Hoggin' the Road: Slaughter Trucks Increase Crashes, Road Damage, and Vehicle Repair Employment

Benjamin Blemings[*], Margaret Bock[†], and Alexandre R. Scarcioffolo[‡]

This Version: November 7, 2022; Most Recent Version: Web Link

Abstract

While it has long been recognized that agricultural production comes with costs and benefits, its effects on transportation have remained under-studied. This paper estimates the effect of pork slaughterhouses on truck traffic and the subsequent consequences such as traffic crashes, road roughness, and auto repair employment. To recover causal estimates, we exploit historic hog population as quasi-random variation in current pork slaughterhouse locations. We document historic hog data using a combination of historical data sources - recorded Census numbers from 1945 and maps which we process to produce data as far back as 1840. Using two-stage least squares, we find a one unit increase in slaughter volume increases truck traffic by 17.6%, fatal traffic crashes by 20.9%, and auto repair employment by 77%. Furthermore, estimates suggest that 95% of slaughter volume on crashes is mediated by truck traffic and 100% of the effect on auto repair is due to trucks. These estimates are important for quantitatively assessing the optimal tax to address negative truck externalities resulting from slaughter and other industries.[1]

Keywords: truck traffic, road damage, pork slaughterhouses

JEL Classification: R4, Q18, J2, N5

[*]Postdoctoral Researcher, Dyson School of Applied Economics and Management, Cornell University, Ithaca, New York 14850. E-mail: btb77@cornell.edu

[†]Margaret Bock, Assistant Professor, Department of Economics, Goucher College, Baltimore, MD 21204. E-mail: margaret.bock@goucher.edu

[‡]Alexandre R. Scarcioffolo, Assistant Professor, Department of Economics and Finance, Georgia College & State University, Milledgeville, GA 31061. E-mail: alexandre.scarcioffolo@gcsu.edu

[1]We thank Clint Neill, Brad Humphreys, and Josh Hall for helpful comments and suggestions. We thank seminar participants at West Virginia University, the North American Regional Science Conference 2021, and the Agricultural and Applied Economics Association 2022. We thank Matthew Kinzer for his excellent research assistance.

1 Introduction

Throughout the 19th century in the US, there was sustained economic growth which was correlated with rising trends in industrialization and urbanization (Kaldor, 1967). These trends also introduced negative externalities to cities, such as water pollution (Leon, 2008, pg. 5), air pollution (W. W. Hanlon, 2016), crime (United States President's Commission on Law Enforcement & Administration of Justice & Katzenbach, 1967, pg. 5, 17), and congestion (Glaeser, 2014, pg. 3). Modern industries, such as coal-powered energy generation, hydraulic fracturing, and agriculture also generate negative externalities. In response, at least one town in each major US shale formation (Bakken, Marcellus, Barnett) has attempted to ban heavy truck traffic from nearby fracking operations.[2] Similar to fracking, the hog slaughter industry is also associated with heavy truck traffic. The city of Great Falls, Montana attempted to prohibit the opening of a 3,000-acre meat processing facility near the city in 2019. Pollution, traffic, and road damage from trucks are among the major reasons residents cited as justifications to cancel the facility (Shinn, 2019).[3]

This paper quantifies how pork slaughterhouses affect truck traffic, fatal automobile crashes, road roughness, and automotive repair employment. Given the additional planned subsidies of $500 million to meat processing (USDA, 2021), the negative consequences of trucks (M. L. Anderson & Auffhammer, 2014; FHWA, 2000; Muehlenbachs, Staubli, & Chu, 2021; Xu & Xu, 2020), and residents' concerns, this is a highly relevant policy question. Furthermore, the causal identification of negative externalities of heavy industry is a core concern of economic scholarship.

An obstacle that complicates estimating the causal effects of pork slaughterhouses is endogenous location decisions of slaughter operations. If slaughter operations consider road networks when deciding where to locate, which is likely since transportation is costly (Behrens, Brown, & Bougna, 2018; Picard & Zeng, 2005) and highways are likely to increase their productivity (Holl, 2016), then OLS suffers from reverse causality. Our approach addresses this challenge by appealing to variation in contemporary pork slaughter which arises due to historic hog populations.

[2] These concerns have been highlighted in popular media. Landowners in North Dakota were concerned about increased truck traffic from fracking wells (Associated Press, 2017); a Texas resident expressed concern about truck traffic from fracking, noting one of her friends was killed by a fracking truck (The Texas Tribune, 2014); Pennsylvania residents note the problems associated with the increased truck traffic due to fracking (The Allegheny Front, 2017).

[3] Residents are correct that trucks are used by the pork slaughter industry; trucks are the preferred mode of transportation for hogs (Food and Agriculture Organization of the United Nations, 2001) and Brodersen (2015) approximates that 2,000 trucks transport 1,000,000 hogs daily in the US.

These historic hogs are realized prior to interstate construction and major technology-induced, vertical integration in the industry making them appealing for addressing this reverse causality using two-stage least squares (2SLS). By conventional standards, 1945 hogs predict contemporary pork slaughterhouses with adequate strength for minimally biased second-stage estimates and the weak-instrument efficient Anderson-Rubin confidence sets result in reassuringly similar inference (T. Anderson, Rubin, et al., 1949; Andrews, Stock, & Sun, 2019; Stock & Yogo, 2002). The instrument, the historic presence of production inputs, is closely related to previously used sources of variation. Our approach validates and leverages the historic presence of agricultural inputs as a blended version of distinct previous designs.[4]

First, we document the persistence of hog populations over time and show how they evolved. To do this, we make use of historic agricultural censuses in both map and handwritten PDF forms. We extract historic hog populations from 1948 from a map and recorded numbers from the 1945 United States Agricultural Census from a PDF and show that the median of these same populations gathered in different ways is nearly exactly the same. We take advantage of this map extraction technique to aid our empirical analysis by measuring the spatial distribution of the hog population, in 20 years intervals, back to 1840. We do not know of other studies that use this technique which is advantageous when geographic boundaries change over time, data only exists in map form, and/or the phenomenon of interest is sufficiently local that it can be best studied with fully disaggregated point data. Before 1900, there was a weak relationship between historic and contemporary hogs with historic hogs only being associated with an additional 0.570 hogs in 2017. However, between 1880 and 1900, the hog populations changed such that the 1900 hog population is associated with an additional 1.175 hogs in 2017, and by 1945 this again increased regardless of the origin of the hog data source; map (1.632) or census (1.846).

Next, we leverage hog population persistence to estimate the causal effects of pork slaughterhouses on truck traffic and related outcomes. Our results show that an additional 10,000 hogs in 1945 increases 2017 average annual daily truck traffic by at least 6.5% and a 1 unit increase in slaughter volume at contemporary pork slaughterhouses increases truck traffic by 17.6% control-

[4] It is common to instrument for a contemporary endogenous variable using a historic source of variation such as planned interstate maps or historical mine sites (Duranton & Turner, 2011; Glaeser, Kerr, & Kerr, 2015; W. Hanlon & Heblich, 2021). In a different, clever approach, McArthur and McCord (2017) instruments for crop production using distance to fertilizer production.

ling for state-specific urbanicity, alternative transportation modes, and agricultural support industries. The point estimates are nearly identical using historic hog populations measured as early as 1840, which was before the automobile was mass-produced and when only primitive road networks existed, suggesting the results are identified. This is the strongest causal evidence to date on the effects of meat processing on truck traffic, because it appeals to an explicit source of quasi-random variation in slaughter in nationwide data, unlike prior work which examines associations in Kansas (Bai et al., 2007). There is an emerging literature on the impact of hydraulic fracturing trucks on associated outcomes (Muehlenbachs et al., 2021; Xu & Xu, 2020) which we advance by quantifying how much the hog industry also contributes to truck congestion using a defensible identification strategy. This expands the literature that investigates the relationship between industries and their associated trucking requirements.

Having quantified the relationship between hog slaughter and trucking, we turn to other consequences of trucking including crashes, road roughness, and automobile repair employment. We find that increases in pork slaughter volume increase fatal crashes by 20.9% and automobile repair employment by 77%, but do not find statistically significant effects on road roughness at the county level. This offers a lens through which to re-interpret prior results that find effects of agriculture on local labor markets (Sneeringer & Hertz, 2013), air pollution (Sneeringer, 2010), and house prices (Lawley, 2021). With respect to public health, prior work finds that meat production increases air pollution and infant mortality (Sneeringer, 2009, 2010), and we show that one mechanism likely driving this is the increase in air pollution due to more truck traffic. The temporal/anticipation effects of hog barns on house prices are investigated in Lawley (2021) and our results suggest the possibility that trucking is another mechanism through which hog barns suppress housing prices since many find trucks a highly undesirable disamenity (e.g. Shinn (2019)).

Third, prior results show that meat processing increases non-farm jobs in local labor markets (Sneeringer & Hertz, 2013). These types of results are often used to enforce the advantages of using place-based job policies to create employment growth, particularly in distressed regions (Austin, Glaeser, & Summers, 2018; Bartik, 2020; Parker, Tach, & Robertson, 2022). This development strategy has been used in many contexts in the US, from local empowerment zones (Busso, Gregory, & Kline, 2013) to policies with more geographic coverage, such as the Tennessee Valley Authority (Kline & Moretti, 2014). However, our results caution against using meat processing as an economic development strategy since slaughter has a large impact on auto repair employment. Continuing with this logic, pursuing non-farm employment from meat processing could be considered an example of the broken window fallacy; this is because the non-farm employment is at least partly attributable to more frequently broken and wrecked automobiles. Our results on the increase in auto repair employment make the tradeoff between environmental safety and employment less balanced than has been previously noted (Lawley & Furtan, 2008).

Our final results use the instrumental variables-mediation framework of Dippel, Gold, Heblich, and Pinto (2021) to show that of the effects of slaughterhouses on crashes and auto repair employment, truck traffic from slaughter mediates 95-100% of these effects. This extends the findings that fracking trucks are dangerous due to the crashes they cause (Muehlenbachs et al., 2021; Xu & Xu, 2020) and trucks, in general, are dangerous (M. L. Anderson & Auffhammer, 2014). Diesel taxes could be a policy response, though making these optimal is difficult in practice due to the endogenous response of making trucks heavier and therefore deadlier (Nehiba, 2020). A different option is distance taxes which are an effective mechanism for reducing truck traffic (Luechinger & Roth, 2016), though it's debatable whether they are optimal (Mandell & Proost, 2016; Parry, 2008).

We are not aware of other results that decompose the total effect of industry on crashes into the direct effects and indirect effects through trucks. This is possible in this case due to the framework provided by Dippel et al. (2021) and because our research design leverages an excluded instrumental variable for identification. While this is specific to this industry, we believe it offers a significant contribution to the more general literature on trucks in two ways. First, it suggests an approximate unit elasticity of fatal crashes with respect to hog truck traffic since slaughter increase crashes and truck traffic by nearly the same amount, and the entire effect of slaughter on crashes operates through trucks. This is in a similar vein to the fundamental law of road congestion (Duranton & Turner, 2011). Second, structural models that derive estimates of optimal truck taxation necessarily rely on a road damage parameter (Parry, 2008). Yet, the only source of these parameters is from FHWA (2000) which as far as we can tell uses road damage estimates that are not updated despite changes in technology over time. We provide the first causal estimates of this parameter from contemporary observational data and show that future existing estimates need to carefully consider distance when attempting to update this parameter in other settings.

We begin by describing the multiple data sources and method for extracting historic hog populations from old maps in Section 2.[5] Section 3 provides a minimum working model of why slaughterhouse location is endogenous with respect to transportation outcomes and then describes how the research design addresses this concern. Section 4 presents results and Section 5 offers a brief conclusion.

2 Data

The research question is how slaughter operations affect road usage and how changes in road usage affect crashes and infrastructure. It is cost-prohibitive to randomly assign slaughter to certain areas, making it necessary to use an approach that can produce causal estimates from observational data. With data over time, a differences-in-differences (DD) framework could be appealing due to the relatively weak identification assumptions. There are two main issues with a differences-in-differences approach: there is not a very long time series of road-related outcome data (truck and car traffic are not measured separately until 2014 in the publicly available data and it only is available through 2017) and there are very few slaughter openings or closings. In order to address endogenous slaughter location, we also collect historic hog populations from multiple sources at multiple points in time going back as far as 1840, long before our contemporary slaughter and road data. This enables causal effects to be estimated under defensible assumptions using two-stage least squares.

2.1 Road Outcomes

We collect road outcome data from three main sources. First, we collect data on truck and car traffic and road roughness from the Highway Performance Monitoring System (HPMS) to quantify how truck traffic and road roughness are associated with slaughter. Next, trucks are dangerous due to their size and weight, so we collect data on fatal crash outcomes from the Fatal Accident Reporting System (FARS). Finally, the road roughness data from HPMS is not updated frequently, so we use data from County Business Patterns (CBP) that reports the number of automotive repair employees.

[5] Those who are interested in background on the hog industry can see Appendix B.

2.1.1 Highway Performance Monitoring System

HPMS data is published yearly by the Federal Highway Administration (FHWA) after the states submit data. The data are restricted to only two-way roads to focus on the most common roadway facility type in the HPMS and to reduce unnecessary variation in the outcome variables.[6] The 2017 data include both the International Roughness Index (IRI) and Annual Average Daily Traffic (AADT) separately for cars and trucks. For truck AADT, the data is from the HPMS definition of "combination" trucks, which include trucks with four-or-less axles, single-trailer trucks through seven-or-more axles, and multi-trailer trucks.[7] This represents the most likely category for trucks used by industrial pork slaughter operations.

Road roughness is measured using the International Roughness Index (IRI). The IRI is the number of inches the suspension of a typical car moves over one mile of road (Duranton, Nagpal, & Turner, 2020, pg. 6). A small IRI measure is associated with better overall pavement quality and a smoother ride compared to larger IRI measures since a vehicle's suspension moves less over a road with a lower IRI.[8]

Weighting The road segments recorded in the HPMS are 0.08 miles long on average, but vary from 0.0000002 miles to 60 miles in length. Without appropriate weights, there is a risk that a short and a long road contribute equally to the recorded truck miles or IRI. This may not accurately measure the truck traffic or IRI in a county. To more accurately represent truck traffic and road roughness in a county, weights are created for each road segment. The weights, w_{ij}, are based on the length of the road segment relative to the total length of road in a county:

$$w_{ij} = \frac{r_{ij}}{R_j}. \tag{1}$$

[6]Approximately 93% (N = 6,300,319) of the national HPMS universe of data is two-way roads.HPMS data also include information on one-way roads, ramps, non-mainline, and planned roadway segments. These types of road facilities represent very different types of roadways that are not as commonly driven on.

[7]See http://onlinemanuals.txdot.gov/txdotmanuals/tri/classifying_vehicles.htm for a visual representation.

[8]It is worth mentioning that the IRI is collected relatively infrequently; this is possibly due to state and local financial constraints. On average, most states only update their road segments' IRI measurements once a year. However, there is great variation across states in terms of how often this data is reported to the FHWA. Please see https://www.fhwa.dot.gov/policyinformation/statistics.cfm for further details.

For road segment *i* in county *j*, *r* is the segment's length and *R* is the total length of county *j*'s road network. These weights sum to 1 within each county.

The product of the weight and outcome (IRI, truck AADT) for each road segment are then summed within a county to create the HPMS outcome variables used,

$$y_j = \sum_{i=1}^{i=\mathbf{I}} (y_{ij} * w_{ij}), \tag{2}$$

in which y_{ij} is the truck AADT or IRI for each segment and y_j is the (weighted) dependent variable by county used in the analysis. While considering all roads within a county is the most straightforward analysis, its most obvious limitation is that some roads may be in a county, but far away from the slaughterhouse. To address this concern, Section 4.3 conducts a similar analysis that only includes roads within certain distances of slaughterhouses and the results are consistent.

Other Sources We augment the road outcome data that comes from HPMS with crash data from FARS and automotive repair employment from the CBP. From FARS we obtain all, fatal, geolocated crash-level data which contains the number of crashes, number of fatalities, and number of persons involved. From the CBP we gather data at the county level for employees in NAICS code 811111: General Automotive Repair. Illustrative examples of firms in this category are automobile repair garages (except gasoline service stations), general automotive repair shops, and automotive engine repair and replacement shops. The CBP suppresses some data for privacy concerns, we replace this missing county data with zeroes.

2.2 Historic Hog Population

The historical hog population comes from two sources. The United States Department of Agriculture (USDA) Agricultural Census provides publicly available pdfs, in 5-year intervals, dating back to 1840. We use the 1945 Agricultural Census as the historical benchmark for several reasons. Because we are examining several outcomes that are related to roads, we choose a historical census that took place before the construction of the Interstate Highway System which makes the exogeneity more believable with respect to the road network. Additionally, the most intense vertical integration of the hog industry did not begin until the 1940s, so hog locations before the 1940s could be less predictive for the current hog industry.[9] The year 1945 balances these concerns.

2.2.1 Hog Populations Extracted from Maps

To provide a comparison to the USDA Agricultural Census, reduce costs of data acquisition for years earlier in history, to aggregate historical data to contemporary county boundaries, and to enhance our analysis, we also source data from several published maps of hog locations. Figure A.1 illustrates one of these maps which is from a series of livestock and crop maps printed in a *World Geography* textbook (Bradley, 1948).[10] We digitized these maps to extract the number of historic hog points. Using photo editing software and GIS, we converted the black pixels from the map photograph into points with latitude and longitude. Since each point represents 5,000 hogs, the count of points from this map is representative of the hog population in 1948.[11]

As shown in Figure A.3, the distributions of historic hogs from the 1945 agricultural census and the 1948 map are comparable. The 1948 map distribution, however, includes fewer values in the tails of the distribution compared to the 1945 census.[12] This similarity in distributions suggests that the map extraction technique yields useful and accurate (in terms of outlier-robust central tendency) data. At this time we do not observe data from other years of both the recorded Census and maps, but note that it is not straightforward to compare them in years in the distant past due to changing county borders.

2.3 Contemporary Hog Population, Slaughter, and Rural-Urban Area

The contemporary slaughterhouse data come from the United States Department of Agriculture (USDA) Food Safety and Inspection Service (FSIS) in 2019. They are the universe of inspected

[9] See Section B for more details.

[10] This book can be found in open-source format here: `https://openlibrary.org/books/OL6028680M/World_geography`. Additionally, Figure A.2 also presents hog population maps from 1840-1920.

[11] Fully zoomed, each point representing 5000 hogs is approximately 10 black pixels. However, because the points were not drawn exactly the same, some are physically drawn smaller or larger; some points are comprised of 8 black pixels while some had 11. When converting the pixels to points, the points were first divided by 10 before being multiplied by 5000. This fact explains why the 1948 hog counts are not only in intervals of 5000.

[12] Because the map data was sourced by aggregating the number of black pixels in the map, this could explain why the map data is under-counting the right tail of the distribution; several points on top of each other could have been counted as one point. The left tail of the distribution could be under-counting zeros due to fading, smudges, or folds of the physical map.

slaughterhouses and we restrict them to only slaughterhouses that process and/or slaughter pork products. The slaughterhouses are geo-referenced which is used to assign them to counties.

The other contemporary data we use come from 2017 which might raise some concern that our treatment is not measured at the same time as our outcome.[13] Between 2017 and 2019, only 3 out of 569, or 0.005%, of slaughterhouses in the US, closed.[14] Even though the slaughterhouse data and the other contemporary data are from different years, we believe that this has little impact on the analysis, because the years are very close and the number of slaughterhouses changed very little.

Slaughter and processing volumes are discretely categorized in the data as 1-5, with 1 being the smallest slaughter volume and 5 being the largest. We use the slaughter volume as the main endogenous treatment variable, but our results are very similar when we substitute the number of slaughterhouses (i.e. ignoring differences in volume). We believe this is due to the volume skewing towards lower volumes; of the 569 total pork slaughterhouses, 449 of them are categorized as 1 or 2. The main results are reproduced with slaughterhouses instead of slaughter volume in Section A.1. Contemporary measures of the hog population by county come from the USDA's National Agricultural Statistical Service (NASS).[15]

Rural-Urban Continuum Codes The USDA Economic Research Service (ERS) provides Rural-Urban Continuum codes (RUCC) for each county. The most recent year that these were published was 2013 and this is the year we use. These data are based on population and commuting flows which makes them well-suited for our context since population and commuting are both somewhat important factors due to their potential correlations with our treatment and outcomes. The RUCC data are scaled from 1 to 9, with 1 being the most urban and 9 being the most rural. The USDA considers counties in the 1-3 range as urban and other numbers as rural, so we create a dummy variable, according to these ranges, for urban counties in our specifications.[16]

[13]The most recent publicly available HPMS file is in 2017 and we downloaded the hog data in 2019 which was a cross-section without any historical information publicly available.

[14]We gather this information from `https://www.pork.org/facts/stats/u-s-packing-sector/#uspackingplantclosing`.

[15]The NASS data is suppressed for privacy in counties with very few hog farms.

[16]The distribution is shown in Figure A.4.

2.4 Summary Statistics

We aggregate all data at the county level. If a road segment, historic hog point, pork slaughterhouse, or fatal crash is within the geographic boundary of a particular county, then an identifier is attached for that county. After the identifier is attached, it is straightforward to sum up these variables within counties.

Table 1 displays the summary statistics for key variables at the county level. Panel A shows the full sample. There are an average of 0.19 slaughterhouses and a slaughter volume of 0.36 per county with at least 1 county having 4 slaughterhouses and a volume of 13 which is consistent with some very concentrated operations. The hog population from the map and the recorded numbers are very similar, although the maximum from the records is higher due to the map extraction not being able to fully recover dense areas of points. While this limitation skews the average from the records higher (11,502 to 15,089), the median is only different by 63 hogs (7800 to 7863). In terms of road outcomes, the distributions tend to be positively skewed to varying degrees.

3 Method

The relationship of interest is how changes in pork slaughter affect truck traffic. The association can be estimated using the following fixed effects equation via OLS:

$$IHS(Truck\ AADT)_c = \beta Pork\ Slaughter\ Volume_c + \mathbf{X}_c\gamma + \lambda_s + \psi_r + u_c, \tag{3}$$

in which *c* stands for county, *s* for state, *r* for a rural indicator, and **X** is a vector of controls that are chosen either for enhancing precision or to weaken the identifying assumptions. Our outcomes are skewed with some zero-valued observations and we would like to interpret β as a semi-elasticity, so we use the inverse hyperbolic sine (IHS) transformation on truck miles and the other outcomes (for comparability). The IHS has been used in related literature (Muehlenbachs et al., 2021) and is advantageous because it is similar to a log transformation and allows the retention of zero-valued observations due to it being defined at zero (Bellemare & Wichman, 2020).[17]

[17] As shown by Table 1, our primary dependent variables satisfy both rules of thumb for the appropriateness of using this transformation: their averages are above 10 and less than 1/3 of them are zero-valued (Bellemare & Wichman, 2020).

Table 1: Descriptive Statistics, By 1945 Hog Count

Panel A: Aggregate

	Mean	Median	SD	Min	Max	Count
Pork Slaughterhouses	0.19	0.00	0.46	0.0	4.0	3046
Hog Slaughter Volume	0.36	0.00	1.00	0.0	13.0	3046
Truck AADT	1007.06	525.42	1361.09	0.0	13928.7	3046
1945 Hog Population	15089.07	7863.00	20416.93	0.0	183329.0	2999
1948 Hog Population (Map)	11502.05	7800.00	12711.97	0.0	107800.0	3046
2017 Hog Population	26091.68	279.00	102770.81	3.0	1957364.0	2337
Fatal Crashes	11.15	5.00	26.74	0.0	709.0	3046
International Roughness Index (IRI)	103.35	99.33	29.43	0.6	287.9	3046
Auto Repair Employees	115.76	25.00	348.87	0.0	8781.0	3046
Car AADT	414.39	265.19	428.80	0.0	4394.4	3046
USDA Rural-Urban Continuum Code, 2013	4.95	6.00	2.70	1.0	9.0	3045

Panel B: 1945 Hogs > Median

	Mean	Median	SD	Min	Max	Count
Pork Slaughterhouses	0.23	0.00	0.52	0.0	4.0	1546
Hog Slaughter Volume	0.48	0.00	1.19	0.0	13.0	1546
Truck AADT	1117.10	621.22	1399.78	0.0	13928.7	1546
1945 Hog Population	26665.81	17424.00	23696.11	7874.0	183329.0	1499
1948 Hog Population (Map)	18534.22	14950.00	13768.18	0.0	97800.0	1546
2017 Hog Population	47172.25	1104.00	134444.72	4.0	1957364.0	1231
Fatal Crashes	13.18	6.00	33.90	0.0	709.0	1546
International Roughness Index (IRI)	104.51	99.85	27.32	2.1	227.4	1546
Auto Repair Employees	141.35	30.00	437.45	0.0	8781.0	1546
Car AADT	430.05	278.02	436.26	0.0	4380.5	1546
USDA Rural-Urban Continuum Code, 2013	4.67	5.00	2.58	1.0	9.0	1545

Panel C: 1945 Hogs < Median

	Mean	Median	SD	Min	Max	Count
Pork Slaughterhouses	0.14	0.00	0.39	0.0	3.0	1499
Hog Slaughter Volume	0.24	0.00	0.72	0.0	6.0	1499
Truck AADT	893.79	429.66	1311.29	0.0	13859.3	1499
1945 Hog Population	3517.15	3294.00	2146.82	0.0	7836.0	1499
1948 Hog Population (Map)	4255.64	3450.00	5415.17	0.0	107800.0	1499
2017 Hog Population	2630.77	137.00	34100.96	3.0	1094877.0	1105
Fatal Crashes	9.04	4.00	16.10	0.0	208.0	1499
International Roughness Index (IRI)	102.17	98.78	31.41	0.6	287.9	1499
Auto Repair Employees	89.34	20.00	220.57	0.0	2292.0	1499
Car AADT	398.07	255.16	420.58	0.0	4394.4	1499
USDA Rural-Urban Continuum Code, 2013	5.23	6.00	2.78	1.0	9.0	1499

Note: Panel A reports summary statistics for all counties in 2017. Panel B reports summary statistics for those counties above average historical hogs population and Panel C reports summary statistics for those below historical hogs population. Pork slaughterhouses comes from the United States Department of Agriculture (USDA) Food Safety Inspection Service (FSIS). Truck and Car Average Annual Daily Traffic (AADT) and International Roughness Index (IRI) comes from the Federal Department of Transportation's (DOT) Highway Performance Monitoring System (HPMS). It is traffic on road segments, with road segments being weighted by their physical length. IRI is the amount of inches a vehicle's suspension moves over 1 mile. Hog population in 1945 comes from the USDA historic agriculture census. Hog population in 1948 comes from the hog point geographic extraction technique from Figure A.1 which is described in Section 2.2.1. Hog population in 2017 comes from the USDA's National Agriculture Statistical Service (NASS). Total fatal car crashes comes from the Fatal Accident Reports System (FARS). Auto repair employees comes from the Census' County Business Patterns.

Table 2: OLS Estimates of Pork Slaughterhouses Effects on Truck Traffic, Car Traffic, Fatal Accidents, Road Roughness, and Automotive Repair Employees

Panel A: Truck AADT	(1)	(2)	(3)
Hog Slaughter Volume	0.083**	0.072***	0.042
	(0.039)	(0.026)	(0.025)
Semi-Elasticity	0.030**	0.026***	0.015*
	(0.014)	(0.009)	(0.009)
Observations	3046	3046	3046
Panel B: Car AADT			
Hog Slaughter Volume	0.101***	0.046**	0.031
	(0.029)	(0.019)	(0.018)
Semi-Elasticity	0.036***	0.016**	0.011*
	(0.011)	(0.007)	(0.007)
Observations	3046	3046	3046
Panel C: Fatal Crashes			
Hog Slaughter Volume	0.178***	0.113***	0.070***
	(0.038)	(0.019)	(0.017)
Semi-Elasticity	0.064***	0.041***	0.025***
	(0.014)	(0.007)	(0.006)
Observations	3046	3046	3046
Panel D: IRI			
Hog Slaughter Volume	0.015	-0.002	-0.003
	(0.011)	(0.006)	(0.006)
Semi-Elasticity	0.005	-0.001	-0.001
	(0.004)	(0.002)	(0.002)
Observations	3046	3046	3046
Panel E: Auto Repair Employees			
Hog Slaughter Volume	0.447***	0.231***	0.165***
	(0.059)	(0.034)	(0.033)
Semi-Elasticity	0.161***	0.083***	0.059***
	(0.021)	(0.012)	(0.012)
Observations	3046	3046	3046
State FEs	-	X	-
Rural-Urban FEs	-	X	-
State X Urban FEs	-	-	X
Controls	-	-	X

Note: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Cluster-robust standard errors, by state, in parentheses. All regressions estimated by OLS with dependent variables that have been transformed by the inverse hyperbolic sine (IHS) for dealing with outliers and 0 values. The independent variable is the number of USDA-inspected pork slaughterhouses. In Panel A, the dependent variable is truck average annual daily traffic (AADT). In Panel B, the dependent variable is car AADT. In Panel C, the dependent variable is number of fatal road crashes. In Panel D, the dependent variable is the international roughness index (IRI). In Panel E, the dependent variable is the number of automotive repair employees. Column 1 includes no controls. Column 2 includes state fixed effects and the Rural-Urban Continuum Codes (RUCC) fixed effects, of which there are 2. Column 3 includes controls for land area, railway miles, corn grain bushel production, and soy bean bushel production. Additionally, it uses the RUCC indicators to create an indicator for whether a county is urban or not and then interacts that with the state fixed effects.

Table 2 reports results from estimating Equation 3. As shown in Panel A, there is a positive association between truck traffic and pork slaughter, but it is less statistically significant in column 3 in which the state and rural fixed effects are interacted and all control variables are included. This is true for both the raw coefficient on slaughterhouses and the non-linear combination transformed semi-elasticity which is reported in the second row.[18] Similar interpretations can be made for both car traffic (Panel B) and fatal car accidents (Panel C), in which column 3's coefficients are statistically significant at varying levels with relatively small magnitudes. In Panel D, there is not a detectable association between road roughness and slaughter. In Panel E, there is a strong positive association between pork slaughter and auto repair employees in all columns.

3.1 Endogenous Slaughter Location

We do not believe that it is appropriate to interpret the OLS estimates as causal because of endogenous business location. In our context, the estimates could be causal if we claim to observe all things that slaughterhouses care about when deciding where to locate. However, this seems unlikely. Beyond exogenous natural advantages, businesses often make location decisions that increase the potential for knowledge spillovers or decrease transportation costs (Marshall, 1890). For instance, highways have been shown to increase the productivity of manufacturing firms by reducing the transportation costs of both inputs and outputs (Holl, 2016). In general, we are concerned there are location characteristics such as transportation costs (Behrens, Gaigné, & Thisse, 2009) and coagglomeration with other industries (Ellison, Glaeser, & Kerr, 2010) that are not fully observed. Larue, Abildtrup, and Schmitt (2011) and Roe, Irwin, and Sharp (2002) specifically discuss location patterns of the hog industry in Denmark and the US. Both papers find a variety of factors that simultaneously explain the location of the hog industry including, but not limited to, transportation costs, nearby agriculture industries, and local and state regulations. It would be onerous to collect all local regulations across the entire country and even if that was possible, including them in the model would not be straightforward given their interactions.

[18]The raw coefficients have been shown to over/under estimate the true semi-elasticity by 40% in Bellemare and Wichman (2020) which strongly suggests that the transformed semi-elasticity coefficient is the most appropriate policy parameter.

Appendix B details important characteristics of the slaughter industry. Specifically, the temperament of hogs essentially requires the use of trucks to transport live hogs to slaughter. It is natural that slaughterhouses would understand this and attempt to maximize profits by picking a location with low truck transportation costs (Behrens et al., 2009). These low truck transportation cost locations, however, are probably also characterized by higher truck traffic in general.

3.2 Econometric

To overcome the endogenous location of slaughterhouses with respect to transportation networks, our approach relies on variation in pork slaughterhouses that arises due to persistence in local hog populations. The first-stage relationship between historic hog population and contemporary pork slaughterhouses is specified:

$$(4) \qquad Pork\ Slaughter\ Volume_{c,t=2017} = \phi_1 Hogs_{c,t=1945} + \mathbf{X}_{c,t=2017}\gamma + \lambda_s + \psi_r + \epsilon_c,$$

in which the subscripts are the same as Equation 3. The one addition is that *t* has been introduced to represent time at the yearly frequency.

This first stage is expected to exist if hog populations are persistent, specifically that,

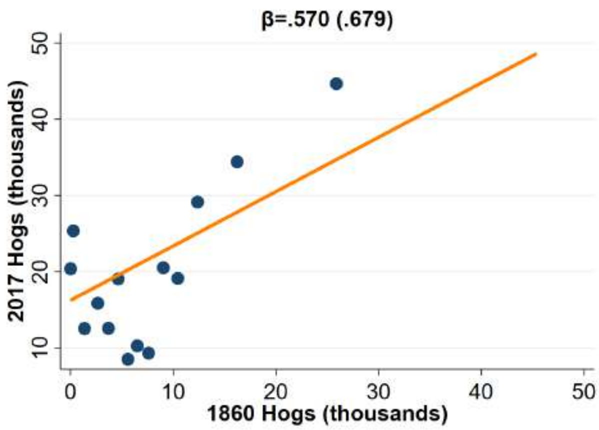
$$Corr(hog\ population_{c,y=1945}, hog\ population_{c,y=2017}) > 0,$$

due to persistent natural regional advantage (Glaeser & Gottlieb, 2009). Indeed, this theory is supported anecdotally by the heavy vertical integration of the industry and the data. As shown by Panels B and C of Table 1, counties with below-average 1945 hog populations have 2,630.77 hogs in 2017, and counties with above-average 1945 hog populations have 47,172.25 hogs in 2017.

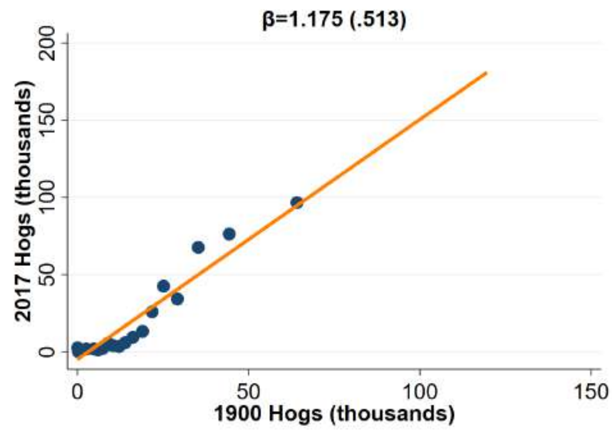
Furthermore, we describe both the historical evolution of persistence and the strength of this relationship in Figure 1. As shown by Figure 1a, an additional hog in 1860 is associated with an additional .57 hogs in 2017. By 1900, Figure 1b shows that an additional 1900 hog is associated with an additional 1.175 hogs in 2017, suggesting hog industry firms had exited the counties that

Figure 1: Binned Scatterplots of The Persistence of Hog Population

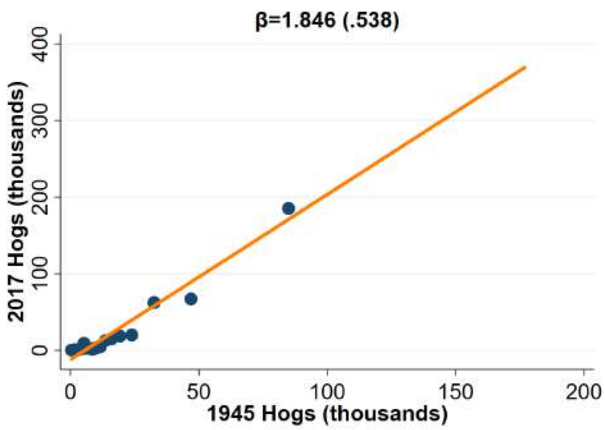
(a) 1860 Hogs



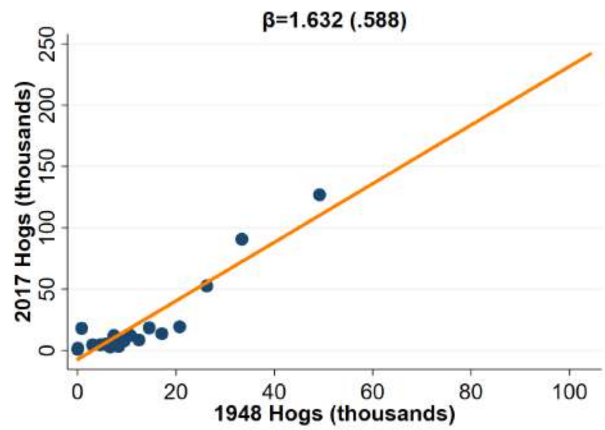
(b) 1900 Hogs



(c) 1945 Hogs (From Census)



(d) 1948 Hogs (from Map)



Note: Scales differ. All hogs are in thousands. (a) shows average 2017 hogs, conditional on 1860 hogs. (b) shows average 2017 hogs, conditional on 1900 hogs. (c) shows average 2017 hogs, conditional on 1945 hogs. (d) shows average 2017 hogs, conditional on 1948 hogs. Equal number of observations in each bin. Number of bins chosen as either the optimal number, in terms of bias-variance tradeoff (Cattaneo, Crump, Farrell, & Feng, 2019), or 10. Procedure selects number of bins to optimize a bias-variance tradeoff in the asymptotic integrated mean square error (IMSE) (Cattaneo et al., 2019). Regression coefficients are from ordinary least squares, standard errors are clustered at the state level, and include controls and fixed effects. No other explanatory variables used in graphs, for those see Figure A.5. To see other years, with and without controls, see and Figure A.6.

they are not present in today by this time. As shown in Figure A.6, the 1920 hogs produce similar results to 1900 and the 1880 hogs produce similar results to 1860.[19]

By 1945, Figure 1c suggests that the hog industry had become even more concentrated with an additional 1945 hog being associated with 1.84 additional hogs in 2017. Using data from the map extraction technique (described in Section 2.2.1), Figure 1d shows that using the data on hogs from the map produces similar results though slightly smaller at 1.63. By predicting contemporary hog population, we believe it is reasonable to expect that historic hog population predicts contemporary areas with lower transport costs and thus a greater volume of pork slaughter.

In the second stage, the relationship of interest is how do contemporary pork slaughterhouses affect contemporary transportation outcomes. To estimate this relationship, the quasi-random assignment from the first stage is leveraged in the following equation:

$$IHS(y)_{c,t=2017} = \beta_1 \widehat{Pork\ Slaughter\ Volume}_{c,t=2017} + X_{c,t=2017}\gamma + \lambda_s + \psi_r + u_c, \tag{5}$$

in which the subscripts are the same and $\widehat{Pork\ Slaughter\ Volume}$ are predicted values from Equation 4. Since pork slaughterhouses use trucks and higher volumes imply more traffic, it is expected that $\beta_1 > 0$. The other outcomes, $IHS(y)$, are fatal crashes, road roughness, and auto repair employment which we expect to be positively associated with slaughter volume

3.3 Identification

For our estimates to be given an interpretation as causal, the goal of this paper, several assumptions must be satisfied (Angrist, Imbens, & Rubin, 1996; Imbens & Angrist, 1994). First, the hog population needs to be sufficiently persistent that the historic hog population is able to predict contemporary slaughterhouse locations with adequate strength. We have already shown suggestive evidence that this is the case and will provide more formal tests in the results. The second key assumption is that historic hogs are conditionally independent of contemporary slaughterhouses. This is plausible due to the historic hog population being realized (at least) 72 years before contemporary slaughterhouses and realized prior to vertical integration and around the end of the industrial

[19] The 1840 hogs produce large but imprecise results which are of similar magnitude to the 1940s. This could be due to the Civil War or the 1840 map does not include many points on the west coast.

revolution. If this is so, then the reduced form regression of contemporary traffic on historic hogs can be interpreted as an intent-to-treat effect.

3.3.1 Exclusion

Third, the exclusion restriction requires that the historic hog population is not correlated with the error term in the second stage,

$$corr(Hogs_{c,t=1945}, u_{c,t=2017}) = 0. \tag{6}$$ [20]

In other words, the historic hog population affects contemporary truck traffic only through its ability to predict contemporary pork slaughterhouse locations. Instead of relying on this unnecessarily strong assumption of no unconditional correlation, the causal interpretation of our estimates requires the weaker conditional exclusion assumption.

First, we highlight the appropriateness and importance of our fixed effects in satisfying exclusion. It is likely that hogs and/or traffic vary across states. For instance, hogs are known to be raised in Iowa and the Carolinas and there tends to be more traffic in states with Interstate highways. We account for these correlations and their potential threat to the exclusion restriction by including state fixed effects which remove across-state differences from the error term.[21] Next, traffic and agricultural production tend to differ across rural and urban areas. Without addressing this, our results could instead be driven by other locational characteristics that differ by urbanicity, thus violating the exclusion restriction. To account for this, we include an indicator variable for whether a county is considered to be rural (RUCC>3) according to the USDA's RUCC codes and threshold for being considered urban.

Finally, one's concerns about the rural-urban divide affecting the results are likely to vary across states. For instance, it could matter whether one is in a rural or urban area in Iowa, where hogs are raised; however, it is highly unlikely that the urban-rural divide matters in Alaska, where hogs are not raised due to the climate. In order to account for this we interact the state fixed effects with

[20] The error, $u_{c,t=2017}$ is not necessarily the 2017 error perse. We just mean the unexplained variation in contemporary truck traffic and we apologize for this shortcut from abuse of notation.

[21] HPMS data originates from states and therefore might vary slightly in its collection, state fixed effects have the additional benefit of accounting for this.

the urban indicator. With this new set of fixed effects the conditional exclusion restriction that now needs to be satisfied is:

$$corr(Hogs_{c,t=1945}, u_{c,t=2017} \mid \mathbf{S}, \mathbf{R}) = 0, \tag{7}$$

in which **S** stands for a vector of state fixed effects and **R** stands for a rural indicator. It is worth re-emphasizing that the RUCC codes are defined by the United States Department of Agriculture and this is a question fundamentally related to the agriculture industry. Furthermore, these RUCC codes are based on population and commuting flows. This probably absorbs a lot of unwanted, threatening variation in the error term, because the dependent variable is "transportation".

Still, it may be possible to formulate a third factor that varies across state-specific rural-urban areas in which historical hogs cause contemporary truck traffic, violating the assumption in Equation 7. One such factor could be the size of a county because perhaps larger counties have more space for trucks and/or hogs.[22] To address this, county land area is used as a control variable.

Another possible issue is that historic hogs lead to the differential development of modern transportation infrastructure. While trucks are the dominant mode of transportation for live pigs, it is possible to transport finished products via rail without reducing product quality as noted in Appendix B and Bai et al. (2007). In our modeling approach, we address this possibility by including the miles of rail in a county as a control variable to shut down this avenue for exclusion violations.[23]

A third way that exclusion could be violated is if historic hogs are also correlated with the development of hog support industries. The important hog support industries include soybean and corn production since these are the major inputs into feeding hogs. Our regressions also control for soybean and corn grain bushels production to remove the possibility that these hog support in-

[22]In a panel setting, this would be subsumed by county fixed effects since county area is time-invariant, but we have a cross-section of counties making county dummies impossible to include.

[23]Geo-referenced railroad data come from Homeland Infrastructure Foundation-Level Data (HIFLD) using GIS. Rail miles strictly used for passenger travel are not included in the analysis.

dustries lead to exclusion restriction violations.[24] With the inclusion of the aforementioned control variables, the conditional exclusion restriction is weakened to:

$$corr(Hogs_{c,t=1945}, u_{c,t=2017} \mid \mathbf{S}, \mathbf{R}, \mathbf{X}_a, \mathbf{X}_o) = 0, \tag{8}$$

in which land area and rail miles are included in $\mathbf{X}_o$ (o stands for other) and $\mathbf{X_a}$ (a stands for agriculture). This conditioning strategy makes it much more plausible that the remaining variation in $u_{c,t=2017}$ is uncorrelated with the historic hog population.

Still, automobiles were being mass-produced by 1945, so perhaps road networks had developed too much by then for exclusion to be believable, even conditional on these other factors. To guard against this, our analysis also makes use of hogs from before 1945, including back to 1840. In general, we find the most similar results back to 1880, which would be identified under the even weaker conditional exclusion restriction of:

$$corr(Hogs_{c,t=1880}, u_{c,t=2017} \mid \mathbf{S}, \mathbf{R}, \mathbf{X}_a, \mathbf{X}_o) = 0. \tag{9}$$

This a weaker assumption in an important historical way, cars were not being mass produced in 1880 which means road networks had not developed.[25]

Additional Assumptions Furthermore, the estimated effects are valid for compliers. Compliers are counties that have slaughterhouses because they have historic hogs or don't have slaughterhouses due to the absence of historic hogs. The assumption of weak monotonicity requires that contemporary slaughterhouses don't decrease with additional historic hogs. Finally, the stable unit value treatment assumption requires no spillovers across counties. We attempt to address each of these concerns in the results.

[24] Our main specifications use separate controls for production from NASS. For corn, we use bushels of corn grain production. For soybeans, we use bushels of production. For both of these variables, there are many missing values from privacy protection, so we fill these in with zeros. The controls enter the specification as the log of the variable plus 1 to allow for zero-valued observations.

[25] Note that the exclusion restriction, and possibly its plausibility, changes with different outcomes.

4 Results

To better understand the upcoming regressions, the results begin with binned scatter plots shown in Figure 2. As shown by Figure 2a and Figure 2b, there is a noticeable, positive relationship between historic hog population (from 1840 or 1945) and contemporary pork slaughterhouses. We also show the first stage relationship spatially, mapping the 1945 hog population against present-day pork slaughterhouses. Figure A.7a and Figure A.7c both reveal that pork slaughterhouses are almost never located in counties with low historic hog counts and very often located in areas with many historic hogs. This suggests the strong and weakly monotonic instrument requirements, described in Section 3.3, are satisfied. Given the positive persistence of hog population which is shown in Figure 1, Panels B and C of Table 1, and the reduced transport costs of locating near inputs, this positive correlation is unsurprising. Weak monotonicity seems reasonable for both 1840 hogs (Figure 2a) and 1945 hogs (Figure 2b) since increases in historic hogs do not lead to reductions in contemporary slaughterhouses.

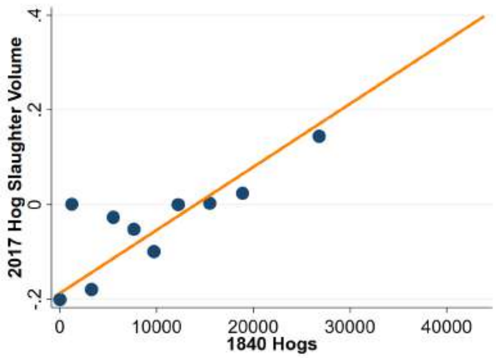
There is a difference in the shape of the relationship between 1840 hogs and 1945 hogs. The 1840 hogs first stage seems more closely approximated by a linear relationship while the 1945 hogs first stage looks to be more concave. With the concave relationship shown in Figure 2b, one might expect more error in the estimates when linear regressions are used. Furthermore, after some low number of 1945 hogs ($\approx$ 10,000), almost all the points are above the linear regression fit, so the standard errors will be robust to heteroskedasticity and robust to arbitrary correlation within states.

Next, the outcomes of interest are substituted for pork slaughterhouses on the y-axes. As shown by Figure 2c, Figure 2d, and Figure 2f, contemporary truck traffic, fatal car crashes, and auto repair employees increase with hog population in 1945.[26] The shape of these positive relationships is concave just like the historic hog-contemporary slaughterhouse relationship. This suggests it is more than just the contemporary hog population, that is driven by slaughter activity. As shown by Figure 2e, there is also a positive relationship between historic hogs and road roughness, yet the linear regression line is less close to these points suggesting more error compared to the other

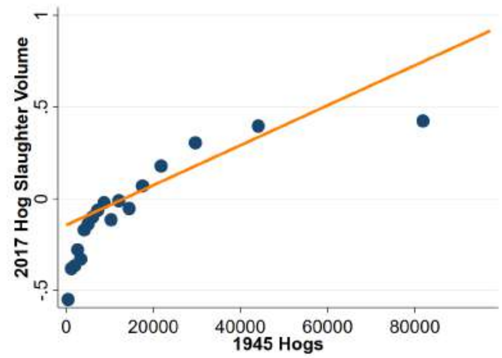
[26]We illustrate this reduced form relationship visually. Figure A.7b and Figure A.7d show the relationship between 1945 hog counts and contemporary truck traffic on a map. Of 3,000 counties, 1,137 are consistent with the expected story, 892 are inconsistent, and the rest are borderline.

Figure 2: Binned Scatterplots of the First Stages and Reduced Forms

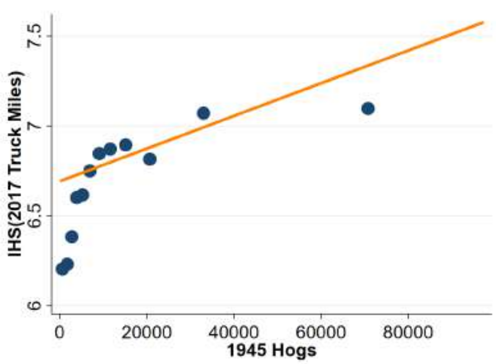
(a) 1840 Hogs First Stage



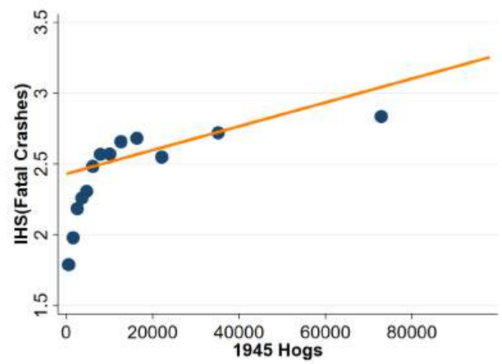
(b) 1945 Hogs First Stage



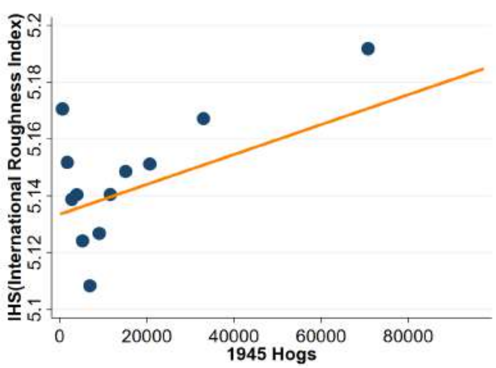
(c) Truck Miles Reduced Form



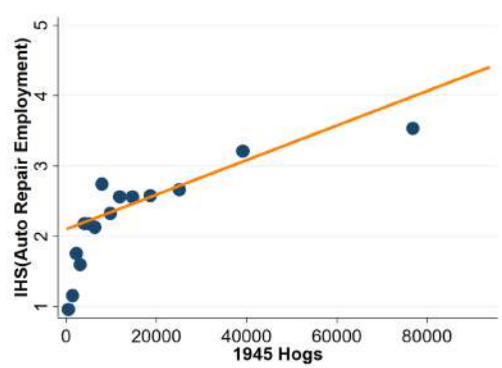
(d) Fatal Crashes Reduced Form



(e) Road Roughness Reduced Form



(f) Auto Repair Employees Reduced Form



Note: Scales differ. All hogs are in thousands. (a) shows average 2017 pork slaughterhouses, conditional on 1840 hogs. (b) shows average 2017 pork slaughterhouses, conditional on 1945 hogs. (c) shows average 2017 truck average annual daily traffic (AADT), conditional on 1945 hogs. (d) shows average 2017 fatal automobile crashes, conditional on 1945 hogs. (e) shows average road international roughness index, conditional on 1945 hogs. (f) shows average auto repair employment, conditional on 1945 hogs. Equal number of observations in each bin. Number of bins chosen as either the optimal number, in terms of bias-variance tradeoff (Cattaneo et al., 2019), or 10 if the optimal number was less than 10. Procedure selects number of bins to optimize a bias-variance tradeoff in the asymptotic integrated mean square error (IMSE) (Cattaneo et al., 2019). All figures control for urban by state fixed effects which can lead to negative values. In (b)-(f) the x-axis range is restricted to 100,000 due to some outliers.

binned scatter plots. We present results that account for non-linearity and outliers and the results are unaffected.

Next, we turn to estimate the first stage, reduced form, and two stage regressions. Table 3, Panel A begins with regressions that include approximately 100 interacted state and rural fixed effects. As shown in column 1, an increase in the 1945 hog population by 10,000 is associated with 12.7% higher 2017 truck traffic and this is statistically significant at 99% confidence.

Our hypothesis for why the historic hog population increases contemporary truck traffic is that it predicts contemporary pig meat industrial activity which uses trucks. Column 2 of Panel A shows that even conditional on state-by-urban fixed effects, a 10,000 hog increase in 1945 hogs is associated with an additional 0.109 contemporary hog slaughter volume and this is also statistically significant at 99% confidence. Column 3 reports the two stage results and implies that a 1 unit increase in slaughter volume increases truck traffic by 27.7%, holding state by rural fixed effects constant.

In column 1, the semi-elasticity has an intent-to-treat (ITT) effect interpretation under the weakest assumption of conditional independence. So far, we use an extensive set of controls that accounts for state-specific urbanicity. Nonetheless, one might be concerned that additional controls are needed to achieve independence. In Panel B, control variables for county land area and rail miles are added and the estimated semi-elasticity drops from 12.7% to 10.2%. Next, contemporary hog feed industries' production, soybeans and corn grain bushels, are included, and the estimated semi-elasticity shrinks to 6.5%. An increase of 10,000 1945 hogs would be an increase equal to half the standard deviation or 2/3 of the mean, this translates into a 1 standard deviation in 1945 hogs being responsible for an additional 130 annual daily truck miles or roughly 1/10th of a standard deviation of truck traffic increase. While this is a sensibly sized effect, it is also a large effect as this is roughly an additional 48,000 truck miles yearly in a county.

Despite shrinking due to the inclusion of controls, these intent-to-treat (with hog processing) estimates remain statistically significant at 95% confidence. One possible interpretation is that these estimates are crucial for identification. However, as shown by the small increases in R^2 the agricultural variables also explain little additional variation in the outcomes. So, an alternative explanation is that the agricultural production variables are measured with error due to disclosure

Table 3: 2SLS Estimates of Slaughterhouses on Average Daily Truck Miles, Cumulative Additive Slaughter Volume as Treatment

Dependent Variable:	(1) Reduced Form IHS(Truck AADT)	(2) First Stage Slaughter Volume	(3) Second Stage IHS(Truck AADT)
Panel A: Fixed Effects			
1945 Hogs (10,000's)	0.084***	0.109***	
	(0.024)	(0.022)	
Hog Slaughter Volume			0.769***
			(0.182)
Observations	2991	2991	2991
Kleibergen-Paap F			24.32
A-R 95% Confidence Set			[0.45, 1.32]
Semi-Elasticity	0.127***		0.277***
	(0.036)		(0.066)
Panel B: Rail and Land			
1945 Hogs (10,000's)	0.068***	0.104***	
	(0.021)	(0.022)	
Hog Slaughter Volume			0.649***
			(0.175)
Observations	2991	2991	2991
Kleibergen-Paap F			23.14
A-R 95% Confidence Set			[0.32, 1.15]
Semi-Elasticity	0.102***		0.234***
	(0.032)		(0.063)
Panel C: Soy & Corn			
1945 Hogs (10,000's)	0.043**	0.087***	
	(0.018)	(0.020)	
Hog Slaughter Volume			0.489**
			(0.192)
Observations	2991	2991	2991
Kleibergen-Paap F			19.05
A-R 95% Confidence Set			[0.13, 1.08]
Semi-Elasticity	0.065**		0.176**
	(0.027)		(0.069)

Note: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Cluster-robust standard errors, by state, in parentheses. The table displays 2SLS regressions of slaughter volume on contemporary truck traffic, using historic hog population as an instrument. Columns 1, 2, and 3 display the reduced form, first stage, and second stage respectively. Panel A includes state X urbanicity fixed effects. Panel B adds land area and miles of railway infrastructure as control variables. Panel C adds soybean and corn grain bushel production as control variables. All panels show the Kleibergen-Paap first stage F-statistic for historic hogs. All panels show the corresponding Anderson-Rubin 95% confidence sets for the IV estimate, which are efficient for potentially weak instruments, as suggested by Andrews et al. (2019) for just-identified structural equations. All panels also show the corresponding semi-elasticity transformation for inverse hyperbolic sine transformations that is suggested by Bellemare and Wichman (2020).

protection and are a result of surveys, causing their inclusion to mechanically bias the coefficients of interest (Bound, Brown, & Mathiowetz, 2001; Millimet, 2011).

While the interpretation of the reduced form estimates as causal ITT effects requires the weakest assumptions, the usefulness and interpretation of the estimates could be improved by understanding the actual impacts of contemporary meat processing. For that analysis, we need to establish that historic hogs are significantly related to contemporary slaughter. As shown by column 2, there is a strong, positive, and statistically significant (at 99% confidence), within a state-rural county (Panel A) and holding agricultural production (Panel C), land area, and alternative transportation constant (Panel B and C), between 1945 hog population and contemporary slaughterhouses. The magnitude of this association ranges from 0.046 to 0.035 which is relatively small, but not unexpected given there are only 569 slaughterhouses across nearly 3,000 counties. The effect is large since a 1 standard deviation increase in historic hogs leads to an increase in pork slaughter volume of 0.2, equal to 1/5 of a standard deviation in slaughter volume. The first stage produces a Kleibergen-Paap F statistic that ranges from 19.05 to 24.32 which suggests that 1945 historic hogs are a strong enough predictor for minimally biased second stage estimates (Stock & Yogo, 2002).

Given the strong first stage, we present the two stage results in column 3. With only fixed effects, a 1 unit increase in slaughter volume is associated with a 27.7% increase in truck traffic and this decreases to 17.6% by the time all the control variables are added. This effect is statistically significant at 95% (Panel C) and 99% (Panel A and B). An additional slaughterhouse increases truck traffic by 17.6% which is equal to about 177 additional daily truck miles or about 13% of a standard deviation. The instrument is not weak, but if it was, then the Anderson-Rubin (AR) confidence sets are efficient and none of the 95% AR confidence sets include zero. Also, the AR confidence sets are generally wider than the valid t-ratio inference sets which suggest this inference may even be slightly conservative (Lee, McCrary, Moreira, & Porter, 2022).

4.1 Alternative Historic Hog Years and Sources

There are two related concerns that one might have. First, one might wonder how robust the results are to using historic hogs from different points in time as the instrument. Second, one might not be confident that our controls are sufficiently rich to be able to claim that the conditional exclusion restriction holds. These concerns can be, at least partially, addressed by using historic hogs from other years. Earlier years of hogs can showcase the robustness of the results and the plausibility of the conditional exclusion restriction by increasing the gap between the historic realization and contemporary treatment. With this increasing plausibility of the conditional exclusion restriction, a tradeoff is that it does make it less likely that the historic hog population has a strong enough association with contemporary slaughter.

Prior to using hogs from years in the more distant past, we reproduce our results using a similar year but collected differently. Our 1948 hog data is extracted from a map, instead of coming from a census. As shown in Figure 3a, the Kleibergen-Paap first stage F-statistic is lower, but still high enough using this alternative collection technique. This is evidence that the map data extraction yields nearly identical results, not just in summary statistics as discussed in Section 2.4, but also in the analyses that make use of it. As shown in Figure 3b, the 2SLS point estimate of the effect of slaughter, using 1948 hogs semi-elasticity is nearly the same.

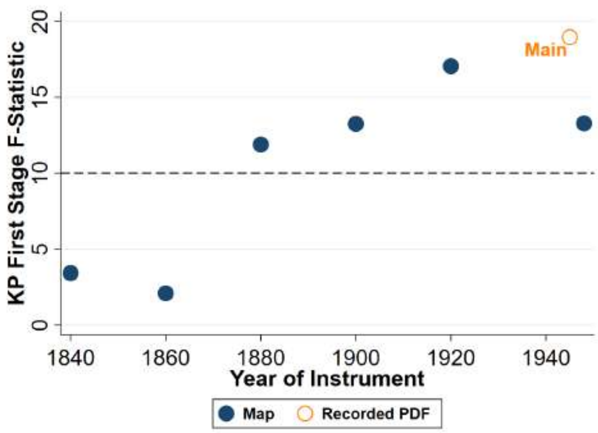
As one goes back in 20-year intervals from the 1945 population, the instrument's first stage F-statistic remains above 10 until 1860. The lower F-statistics farther back may be because from 1880-1900 the relationship between historic and contemporary hogs was relatively weak, however as Figure 1 shows, over the years it became stronger, increasing from 0.57 (1860) to 1.843 (1948).

The conditional exclusion restriction requires that historic hogs only cause contemporary truck traffic through contemporary slaughterhouses. This is made believable by the hogs used in the main specifications being realized prior to the construction of the interstate system and the most intense vertical integration of the hog industry along with reasonable controls. Nonetheless, by 1945, automobiles were becoming the dominant mode of transportation with advances in technology, so one could be concerned that 1945 is not far enough in the distant past.[27] As shown by Figure 3b, the point estimate for the effect of slaughterhouses on truck traffic barely changes as one substitutes older years of hogs as the instrument. In 1860 and 1840, the instrument is less predictive and the standard errors grow. In 1860, the point estimate is nearly identical, but the larger standard

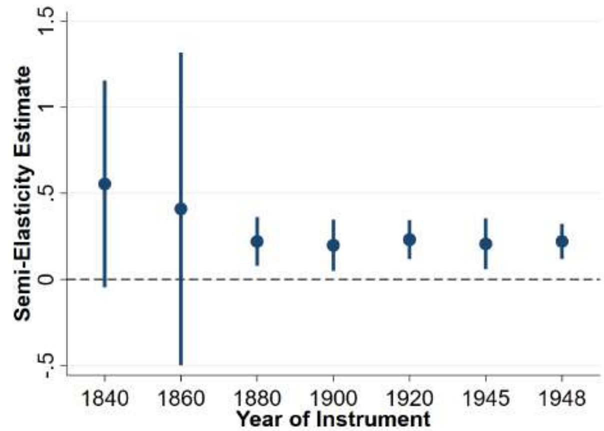
[27] For example, between 1900 and 1915, the number of cars in the US jumped from only 8,000 to more than 2 million. See Hadjilambrinos (2021) for more details.

Figure 3: First Stage F-Statistic and Semi-Elasticity Estimates by Year of Instrument

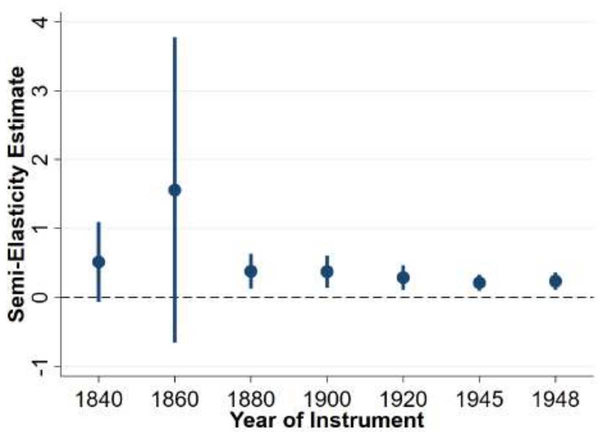
(a) Kleibergen-Paap First Stage F-Statistics



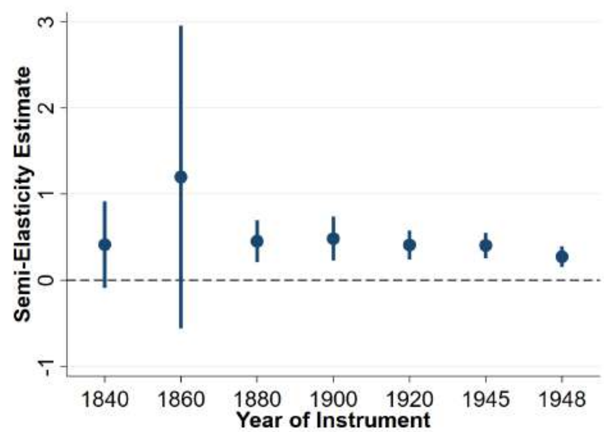
(b) Truck Miles



(c) Fatal Car Crashes



(d) Auto Repair Employment



Note: Scales differ. Figures diagnose the sensitivity of estimates to using just-identified (i.e. a single year of historic hogs as the instrumental variable) regressions with other years of historic hogs as the instrument. All regressions include interacted state-urbanicity fixed effects and controls (land area, rail miles, and crop production). Standard errors are clustered at the state level. (a) shows the first-stage Kleibergen-Paap F-statistics by year with an orange open dot representing the main specifications. (b)-(d) show the second stage estimate after it has been transformed to be interpreted as a semi-elasticity. The whiskers show 95% Wald confidence intervals. (b) shows the effects on truck miles, (c) shows the effects on fatal crashes, and (d) shows the effects on auto repair employment.

errors straddle 0. In 1840, the point estimate is larger, causing the larger standard errors to still not include 0.

4.2 Robustness

Next, we turn to assess the robustness of the estimates. First, nothing prevents us from using all of the historic years of hogs as instruments simultaneously. In theory, this could increase the precision of each instrument and contribute additional explanatory power. As shown in row 1 of Figure 4, using an over-identified setup slightly reduces the confidence intervals and slightly increases the point estimate.

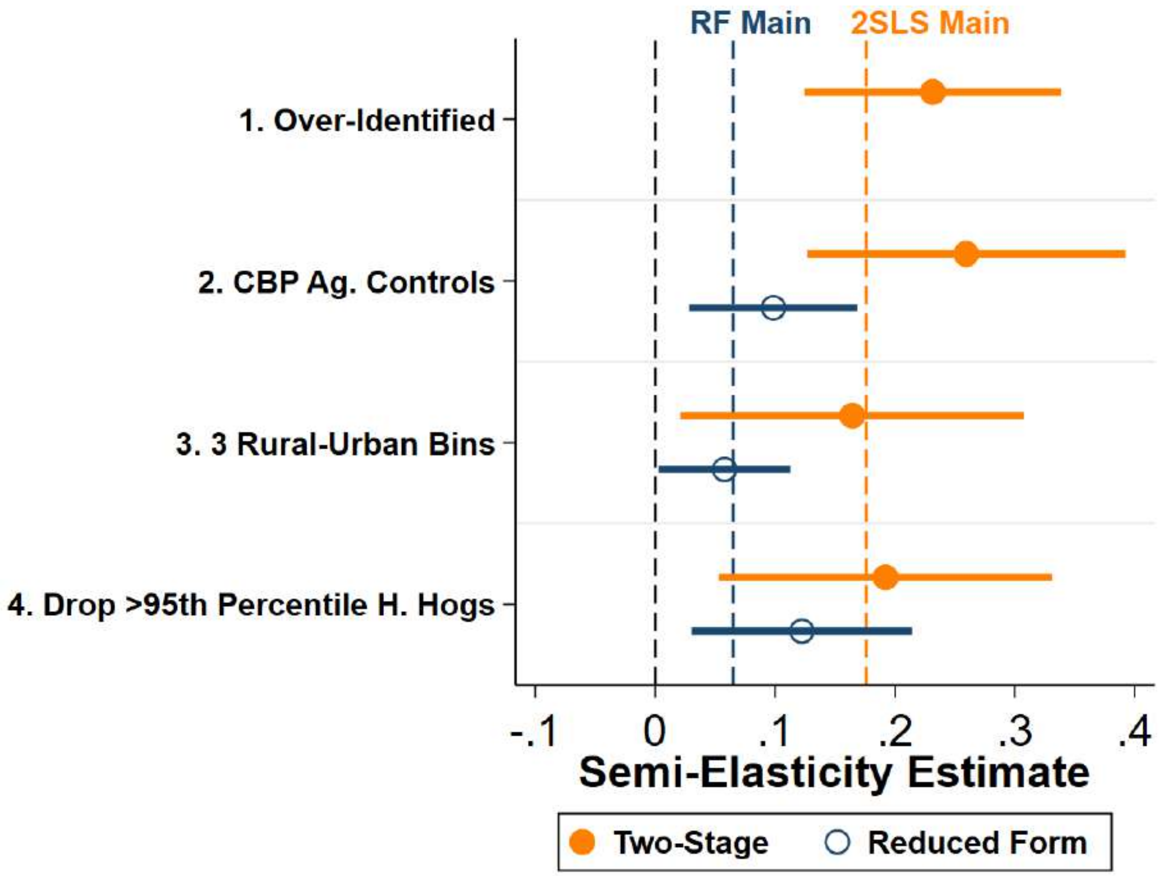
Second, the agricultural variables nearly halved the treatment effects in the reduced form and reduced the two stage effect from 0.234 to 0.176. This could arouse suspicion that the results are sensitive to the inclusion of additional agricultural factors. In order to empirically assess this concern, we replace the NASS agricultural controls with controls from CBP. These alternative controls are the employment numbers of the following industries: grain and bean wholesale, support for animal production, support for crop production, and non-slaughter meat processing. As shown in row 2 of Figure 4, the reduced form coefficient grows from 0.065 to 0.098 and the second stage coefficient grows from 0.176 to 0.259. This provides reassurance that the results are not overly sensitive to the inclusion of other agricultural controls.

Third, one might be concerned that classifying areas into dichotomous rural and urban areas are insufficiently fine to address potential third factors which could cause bias or worse, unidentified estimates. To show that this does not affect the results, the rural-urban indicator is further disaggregated into urban (RUCC codes 1-3), suburban (4-6), and rural (7-9).[28] As shown in the third row of Figure 4, this slightly reduces the reduced form (navy, open) and two stage (orange, closed) estimates relative to the main estimates (reduced form shown by the navy dotted line and two stage shown by the orange dotted line); yet, the estimates remain statistically different than 0.

The next issue that requires additional robustness is in the specification of the equations because Figure 2 shows there may be some non-linearity in both the first stage and reduced forms. Our first robustness check drops historic hog outliers, which we define as historic hogs above the 95th percentile. This addresses some of the non-linearity and certainly addresses whether the high

[28] We cannot use the fully disaggregated codes due to small cell sizes.

Figure 4: Robustness of Estimates



Note: Figure displays the robustness of the reduced form and two stage estimates to various issues. All estimates have been transformed so that they are interpretable as a semi-elasticity (Bellemare & Wichman, 2020) and are shown with 95% Wald confidence intervals. All regressions use state-urbanicity interacted fixed effects and the full set of controls and use standard errors that are clustered at the state level. The dashed lines represent the main point estimates from the reduced form and second stage respectively. In row 1, the first stage is over-identified by using every year of hog population that we observe as an instrument. In row 2, the agriculture controls are changed from NASS variables (corn grain bushel and soybean bushel production) to County Business Patterns employment controls (grain and bean wholesale, support for crop production, support for animal production, and non-slaughter meat processing). In row 3, the RUCC codes are further disaggregated into urban (1-3), suburban (4-6), and rural (7-9) and then interacted with the state fixed effects. In row 4, counties that are above the 95th percentile in historic hogs are dropped.

leverage points of high historic hogs are driving the results. The results are presented in row 4 and show that removing the high-leverage historic hogs leads to a larger, nearly doubled reduced form estimate. Nonetheless, the two stage estimate remains virtually unchanged suggesting that the results are not driven by outlier historic hogs.

Our final check explicitly addresses the apparent non-linearity of the reduced form by including a quadratic term for historic hogs. While this is useful for reducing concerns about misspecification errors, it does make the second stage estimates uninterpretable. Table A.1 shows that including a squared term does not reduce the statistical significance of the raw coefficients in either the reduced form or the second stage.

Outcome Distributions by Historic Hog Quartiles Nonetheless, the preceding regressions still must specify the functional forms of the instrument and treatment. Although it comes at the expense of not producing magnitude, a way to circumvent specifying the functional form is to inspect the differences in the distributions of the outcomes across different historic hog quartiles. As shown by Figure A.9b, the cumulative distribution shows clear differences across hog quartiles. In particular, the differences are largest in the middle and slightly towards the lower ends of the distribution.

4.3 Local Effects and the Intensive Margin

To this point, our truck traffic-dependent variable has been a county-level weighted average. While the weighting is likely to be helpful in eliminating some issues, one could still be concerned about roads that are far away from the slaughterhouse, but in the same county, having undue influence on the results. Since our main variables, historic hog population, slaughterhouses, and truck traffic are all geo-referenced, we are able to change the unit of analysis from a county to a slaughterhouse. This highlights the advantages of using our map extraction of historic hogs which provides the exact spatial distribution as opposed to numbers recorded at the county level. Furthermore, since we are changing to the slaughterhouse level, this also will provide insights into how much of our results are driven by the intensive margin of slaughter as opposed to the county level which conflates the intensive and extensive margin by using counties without slaughter as controls.

We construct distance rings around each slaughterhouse to isolate roads that are more likely to be traveled by trucks in the slaughter industry. By doing this, we can examine any magnitude differences in treatment by distance. This technique has been used in several papers (e.g. Miguel & Kremer, 2004; Muehlenbachs, Spiller, & Timmins, 2015) to highlight the difference in treatment effects as distance increases. We use equal-distance rings at 25-mile intervals, from 25 miles to 75 miles, and isolate the roads that are within each ring. Figure A.10 illustrates an example of the 25-mile slaughterhouse rings. Previous surveys motivate our choice of distance rings. For example, Beam et al. (2015) note that 95% of farms surveyed in the US Department of Agriculture's (USDA) National Animal Health Monitoring System in 2011 reported the farthest distance from farm to slaughter was 90 miles or less. The median travel distance for hogs from farm to slaughter was around 55 miles (Beam et al., 2015). At this level, county-level controls such as state and rural fixed effects or corn production no longer make sense; however, we are able to control for a plant's processing volume which is separate from its slaughter volume. While we do view this as a limitation, it is worth noting that states without hog slaughter, such as Alaska, are excluded by definition and our prior results have not been sensitive to controls or fixed effects.

Table 4 shows the effect of slaughterhouse-level slaughter volume on truck traffic at increasingly larger rings around slaughterhouses. Panel A, column 1 shows that an additional 10,000 hogs within 25 miles of a slaughterhouse increase truck traffic by 1.1%. In Panel B, the effect of those hogs decreases to 0.25% and in Panel C it decreases again to 0.1%. In Panel A the estimate is statistically significant at 99% confidence and in Panels B and C this is slightly reduced to being significant at 95% confidence. As shown by column 2, the association between historic hogs and slaughter volume also drops in magnitude as hogs progressively farther away are considered, but the coefficient remains statistically significant. Column 3 shows the Kleibergen-Paap first-stage F-statistic. It is lower than what might be desirable but ranges from 5.7-8.8; we use weak-instrument efficient AR confidence intervals to address this issue. One possible conclusion from this exercise is that some of the strength of the instrument relies on the extensive margin such that removing areas with no slaughter reduces predictive power.

We have provided extra detail on the first stage and reduced form estimates because the second stage estimate of the effect of slaughterhouses depends on both of these. As shown in column 3, Panel A, a 1 unit increase in slaughter volume increases truck traffic by 36.7% on roads within 25

Table 4: 2SLS Estimates of Slaughterhouse-Level Slaughter Volume on Truck Traffic within Distance Buffers without County Controls

Dependent Variable:	(1) Reduced Form IHS(Truck AADT)	(2) First Stage Slaughter Volume	(3) Second Stage IHS(Truck AADT)
Panel A: Within 25 Miles			
1948 Hogs (10,000's)	0.0593***	0.0301**	
	(0.0215)	(0.0125)	
Slaughter Volume			1.9687*
			(1.0368)
Observations	568	568	568
R^2	0.0124	0.5455	
Kleibergen-Paap F			5.782
A-R 95% Confidence Set			[.613947, ...]
A-R P-value			0.0041
Semi-Elasticity	0.0110***		0.3671*
	(0.0040)		(0.1933)
Panel B: Within 50 Miles			
1948 Hogs (10,000's)	0.0131**	0.0152***	
	(0.0063)	(0.0054)	
Slaughter Volume			0.8633*
			(0.4888)
Observations	568	568	568
R^2	0.0083	0.5492	
Kleibergen-Paap F			7.811
A-R 95% Confidence Set			[.108579, ...]
A-R P-value			0.0273
Semi-Elasticity	0.0025**		0.1610*
	(0.0012)		(0.0911)
Panel C: Within 75 Miles			
1948 Hogs (10,000's)	0.0056**	0.0075***	
	(0.0027)	(0.0025)	
Slaughter Volume			0.7474*
			(0.4227)
Observations	568	568	568
R^2	0.0098	0.5506	
Kleibergen-Paap F			8.815
A-R 95% Confidence Set			[.094597, ...]
A-R P-Value			0.0329
Semi-Elasticity	0.0010**		0.1394*
	(0.0005)		(0.0788)

Note: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Cluster-robust standard errors, by state, in parentheses. The table displays 2SLS regressions of slaughter volume on contemporary truck traffic at the slaughterhouse level, using digitized historic hog populations from 1948 as an instrument. Columns 1, 2, and 3 display the reduced form, first stage, and second stage respectively. Each panel represents a different distance buffer. Panels A, B, and C examine the truck traffic on roads within 25 miles, 50 miles, and 75 miles of a slaughterhouse respectively. All panels include controls for slaughterhouse processing volume. All panels show the Kleibergen-Paap first stage F-statistic for historic hogs. All panels show the corresponding Anderson-Rubin 95% confidence sets for the IV estimate, which are efficient for potentially weak instruments, as suggested by Andrews et al. (2019) for just-identified structural equations. All panels also show the corresponding semi-elasticity transformation for inverse hyperbolic sine transformations that is suggested by Bellemare and Wichman (2020).

miles of a slaughterhouse. In contrast, that effect is lowered to 16.1% at 50 miles (Panel B) and 13.9% at 75 miles (Panel C). These estimates are statistically significant at 90% confidence using standard inference, but using weak instrument-robust inference the effects are significant at 95% confidence. Our estimate of the effect of slaughterhouses on roads progressively farther away is consistent with our expectations: the effects are smaller when roads farther away are considered.

4.4 Consequences of Truck Traffic

Additional truck traffic raises the prospects of other consequences. For instance, trucks are known to cause deadly accidents and are known to be much more damaging to roads than cars since they are heavier. As shown in Panel A of Table 5, 1 unit increase in slaughter volume is associated with an additional 20.9% fatal crashes. This is close to the point estimates for the effect on trucks.

Next, we run the same regression with road roughness (IRI) as the dependent variable. As shown in Panel B, there is no detectable effect of slaughterhouses on road roughness which is also true for every year of historic hog instrument (Figure A.11). We believe this may be due to poor IRI data, so we use a different proxy for road damage: the number of automobile repair employees. As shown in Panel C, historic hogs and contemporary slaughterhouses have large associations with contemporary auto repair employees at 28.2% and 77% respectively. These are the largest effects of any outcome, but it is not entirely surprising, given that the same was true of the OLS estimates. As shown in Figure 3c and Figure 3d, these interpretations are valid going back to at least 1880.

4.4.1 Local Road Roughness

It is odd that slaughterhouses increase truck traffic, fatal crashes, and auto repair employment, but have no effects on road roughness at the county level. One reason for this might be that the standard deviation of the road roughness is only 28.4% of its average, while our other outcomes have much larger standard deviations in relation to their mean. We believe that this lower amount of variation might be driving the null result on road roughness at the county level.

As such the results at the county level might not find any effect of slaughterhouses on trucks, because roads in the county, but far away from the slaughterhouse, drown the signal. To investigate whether this may be the case, we repeat our slaughterhouse-level analysis with road roughness as

Table 5: 2SLS Estimates of Slaughter on Truck Consequences, Cumulative Additive Slaughter Volume as Treatment

	(1) Reduced Form	(2) First Stage	(3) Second Stage
Panel A: Fatal Crashes Dependent Variable:	IHS(Crashes)	Slaughter	IHS(Crashes)
1945 Hogs (10,000's)	0.050*** (0.015)	0.087*** (0.020)	
Slaughter Volume			0.577*** (0.164)
Observations	2991	2991	2991
Kleibergen-Paap F			19.05
A-R 95% Confidence Set			[0.28, 1.11]
Semi-Elasticity	0.076*** (0.022)		0.209*** (0.059)
Panel B: Roughness Dependent Variable:	IHS(IRI)	Slaughter	IHS(IRI)
1945 Hogs (10,000's)	0.008 (0.006)	0.087*** (0.020)	
Slaughter Volume			0.087 (0.076)
Observations	2991	2991	2991
Kleibergen-Paap F			19.05
A-R 95% Confidence Set			[-0.06, 0.30]
Semi-Elasticity	0.011 (0.009)		0.031 (0.027)
Panel C: Auto Repair Employees Dependent Variable:	IHS(Employees)	Slaughter	IHS(Employees)
1945 Hogs (10,000's)	0.187*** (0.029)	0.087*** (0.020)	
Slaughter Volume			2.136*** (0.403)
Observations	2991	2991	2991
Kleibergen-Paap F			19.05
A-R 95% Confidence Set			[1.44, 3.46]
Semi-Elasticity	0.282*** (0.044)		0.770*** (0.145)

Note: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Cluster-robust standard errors, by state, in parentheses. The table displays 2SLS regressions of consequences of truck traffic, using historic hog population as an instrument. Dependent variables vary by panel. Columns 1, 2, and 3 display the reduced form, first stage, and second stage respectively. All regressions include state X urban fixed effects, land area, non-passenger railway miles, 2017 corn grain bushels production, and 2017 soybean bushel production as additional control variables. All panels show the Kleibergen-Paap first stage F-statistic for historic hogs. All panels show the corresponding Anderson-Rubin 95% confidence sets for the IV estimate, which are efficient for potentially weak instruments, as suggested by Andrews et al. (2019) for just-identified structural equations. All panels also show the corresponding semi-elasticity transformation for inverse hyperbolic sine transformations that is suggested by Bellemare and Wichman (2020).

the outcome. Column 1 of Table 6 shows the reduced form, and there are no statistically significant effects at 25 (Panel A) or 50 (Panel B) miles. However, there is a statistically significant, at 99% confidence, the effect of historic hogs within 75 miles of a slaughterhouse on road roughness of roads within 75 miles. The magnitude of 0.0003 at 75 miles is lower than at 50 miles (0.0004) or 25 miles (0.0008), but the standard error is much lower which drives the statistical significance up. This is consistent with our hypothesis that road roughness just varies less. While column 2 shows the first stage is exactly the same, the estimated effect of slaughterhouses on road roughness at 75 miles increases to 4% rougher roads from 2.5% at lower distances. This is because the reduced form estimate in column 1 drops less than the first stage estimate in column 2.

Table 6 shows the effect of slaughterhouse-level slaughter volume on road roughness (IRI) at different distances. Despite not finding significant results on road roughness using all roads in Table 5, examining roads within a certain distance of a slaughterhouse yields significant results. Specifically, Panel C of Table 6 shows a significant reduced form semi-elasticity.Additionally, as shown in Panel C, a 1 unit increase in slaughterhouse-level slaughter volume increases road roughness by 4.1% within 75 miles.

4.5 Falsification

We find several interesting consequences of pork slaughterhouses, yet wish to confirm that our findings are not driven purely by chance. In order to do this, we use several other dependent variables which are from the same sources yet have no strong expectation that they are affected by slaughterhouses. Our first falsification exercise changes the dependent variable to car miles traveled. As shown by the first row of Figure 5, there is no statistically significant effect of slaughterhouses on car miles traveled. Furthermore, this suggests that the effect of slaughterhouses on fatal crashes is not due to some abnormal car traffic around slaughterhouses.

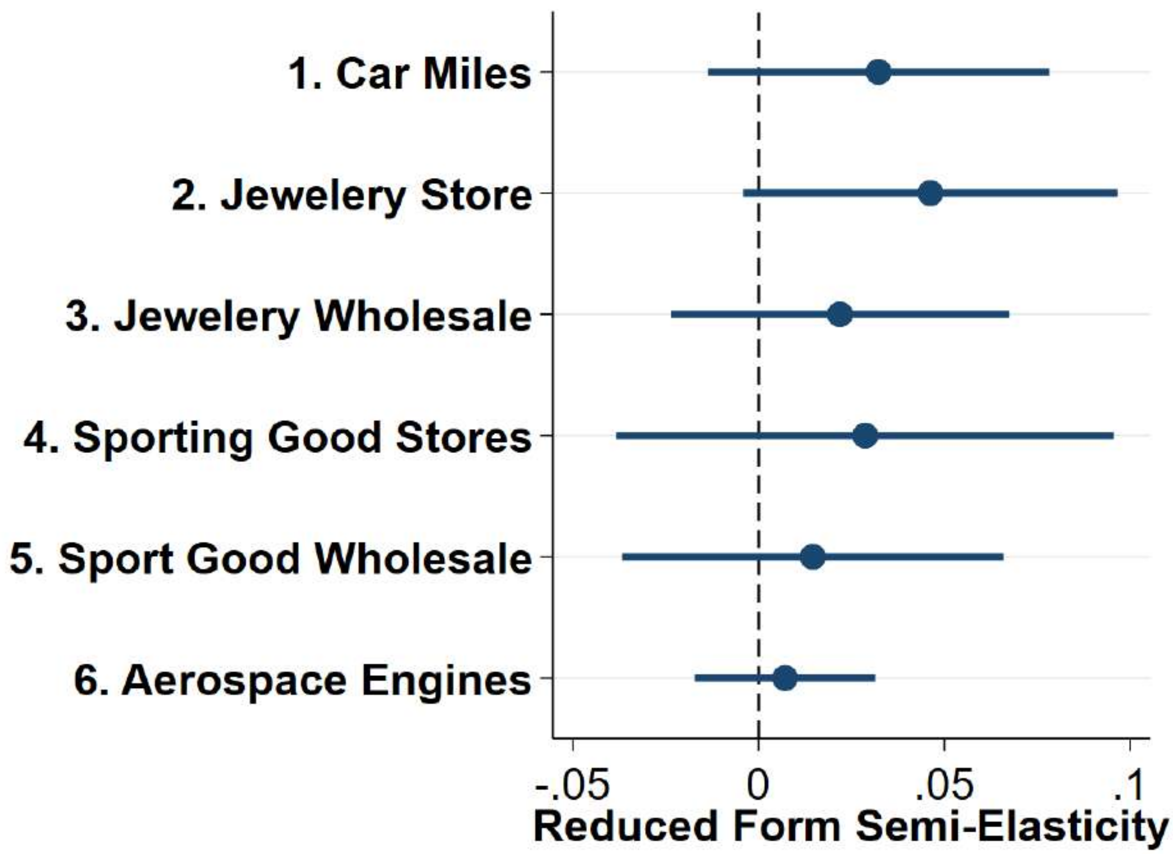
Next, we look at the employment of other industries that are unrelated to hog populations under the logic that they should be unaffected by the historic presence of hogs. To source these industries, we reference the clustering of industries in Porter (2003) and map them into current NAICS codes. The first industry that we examine is jewelry stores and jewelry/watch, precious stones, and precious metal wholesaling. As shown by rows 2 and 3 of Figure 5, historic hogs do

Table 6: 2SLS Estimates of Slaughterhouse-Level Slaughter Volume on Road Roughness within Distance Buffers without County Controls

Dependent Variable:	(1) Reduced Form IHS(IRI)	(2) First Stage Slaughter Volume	(3) Second Stage IHS(IRI)
Panel A: Within 25 Miles			
1948 Hogs (10,000's)	0.0040	0.0301**	
	(0.0048)	(0.0125)	
Slaughter Volume			0.1342
			(0.1706)
Observations	568	568	568
R^2	0.0097	0.5455	
Kleibergen-Paap F			5.782
A-R 95% Confidence Set			[-.210305, ...]
A-R P-value			0.3961
Semi-Elasticity	0.0008		0.0250
	(0.0009)		(0.0318)
Panel B: Within 50 Miles			
1948 Hogs (10,000's)	0.0022	0.0152***	
	(0.0015)	(0.0054)	
Slaughter Volume			0.1421
			(0.1076)
Observations	568	568	568
R^2	0.0129	0.549	
Kleibergen-Paap F			7.811
A-R 95% Confidence Set			[-.041034, ...]
A-R P-value			0.1270
Semi-Elasticity	0.0004		0.0265
	(0.0003)		(0.0201)
Panel C: Within 75 Miles			
1948 Hogs (10,000's)	0.0017***	0.0075***	
	(0.0006)	(0.0025)	
Slaughter Volume			0.2197**
			(0.1091)
Observations	568	568	568
R^2	0.0238	0.5507	
Kleibergen-Paap F			8.815
A-R 95% Confidence Set			[.068487, ...]
A-R P-Value			0.0032
Semi-Elasticity	0.0003***		0.0410**
	(0.0001)		(0.0204)

Note: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Cluster-robust standard errors, by state, in parentheses. The table displays 2SLS regressions of slaughter volume on contemporary road roughness at the slaughterhouse level, using digitized historic hog populations from 1948 as an instrument. Columns 1, 2, and 3 display the reduced form, first stage, and second stage respectively. Each panel represents a different distance buffer. Panels A, B, and C examine the road roughness of roads within 25 miles, 50 miles, and 75 miles of a slaughterhouse respectively. All panels include controls for slaughterhouse processing volume. All panels show the Kleibergen-Paap first stage F-statistic for historic hogs. All panels show the corresponding Anderson-Rubin 95% confidence sets for the IV estimate, which are efficient for potentially weak instruments, as suggested by Andrews et al. (2019) for just-identified structural equations. All panels also show the corresponding semi-elasticity transformation for inverse hyperbolic sine transformations that is suggested by Bellemare and Wichman (2020).

Figure 5: Falsification for Car Miles and Unrelated Industries



Note: Figure shows the reduced form effects of historic hogs on employment numbers in industries that are unrelated to slaughterhouses and car traffic. All estimates have been transformed so that they are interpretable as a semi-elasticity (Bellemare & Wichman, 2020) and are shown with 95% Wald confidence intervals. All regressions use state-urbanicity interacted fixed effects and the full set of controls and use standard errors that are clustered at the state level. Row 1 uses car average annual daily traffic as the dependent variable. For rows 2-6, we use the following as the dependent variable: jewelry store employment (NAICS code 448310), jewelry/watches, precious metals, precious stones wholesaler employment (NAICS code 423940), sporting good store employment (NAICS code 451110), sporting and recreational goods and supplies merchant wholesaler employment (NAICS code 423910), and aircraft engine and engine part manufacturing employment (NAICS code 336412) not have statistically significant effects on jewelry. The second industry that we consider is sporting goods stores and sporting/recreational goods wholesalers. As shown by rows 4 and 5 of Figure 5, there are no statistically significant effects of hogs on the employment of either of these industries. Finally, we consider aerospace engines and parts manufacturing in row 6 and find no statistically significant effects. These falsification exercises are consistent with the results presented so far not being a result of chance and rather due to the mechanisms advanced.

4.6 Trucks as the Mechanism

It could be considered unexpected that pork slaughter is positively associated, in a way that is defensibly interpreted as causal, with fatal crashes and auto repair employment. Yet, our first results show that slaughterhouses cause truck traffic which is dangerous and damaging to roads which in turn damage cars. Thus, we expect that much of the effect of slaughterhouses on crashes and auto repair employment is due to the positive association between trucks and slaughterhouses. In order to empirically test this, we apply the instrumental variables-mediation framework of Dippel et al. (2021). In our setting the instrumental variable is historic hog population, the treatment is pork slaughter volume, and the mediator is truck traffic, meaning that we can empirically assess how much of the effect of pork slaughter on crashes operates through truck traffic. This framework makes the decomposition of the total effect of slaughterhouses into direct (unmediated) and indirect (through trucks) effects possible without any additional instruments.[29]

The decomposition of the total effect of slaughterhouses is implemented through a series of separate two-stage least squares regressions. These estimate the effect of slaughterhouses on truck traffic (which we have already shown), the effect of slaughterhouses on fatal crashes (which we have already shown), and the effect of trucks on crashes, conditional on slaughterhouses. The

[29]This is despite the under-identification issue in which we have two explanatory variables of interest (slaughterhouses and truck traffic), but only a single instrument (historic hog population). It does not require assuming away any of the endogenous relationships that apply this framework; rather, omitted variables concerns provide a different solution. If slaughter is endogenous when truck traffic is regressed on slaughter due to confounders that jointly affect slaughter and traffic, and slaughter is endogenous when crashes are regressed on slaughter because of the same confounders that affect slaughter primarily through truck traffic, then identification is possible with a single instrument. More formally, slaughter is the endogenous treatment, but endogeneity cannot be due to confounders that jointly influence slaughter and crashes, only from confounders that jointly affect slaughter and truck traffic. The identifying assumption is that the correlation between slaughter and crashes is 0 in a covariance matrix of unobserved error terms.

results are shown in Table 7. The reported estimates (Total) and statistics (First Stage F-Statistic -T on Z) which are duplicated from prior results are nearly identical.

Our main interest in these estimates is in the indirect effects. As shown by Panel A, there is a small direct effect of slaughterhouses on fatal crashes, but this is not statistically significant. However, there is a large indirect effect of slaughterhouses, through truck traffic. This effect is not statistically different from 0, though it is close at conventional levels with a p-value of 0.126. The main takeaway is that the indirect effect is much larger than the direct effect. This estimates that truck traffic accounts for 94.93% of the effect of slaughterhouses on fatal car crashes. As shown in Panel B of Table 7, trucks also mediate 100.7% of the effect of slaughterhouses on automobile repair employment. These suggestive results could be somewhat biased due to the relatively low first stage F-statistic when truck traffic is regressed on historic hogs conditional on slaughterhouses, but some mild bias is unlikely to be consequential to the main conclusion of the exercise.

5 Conclusion

It is policy-relevant how much truck traffic is affected by the operation of slaughterhouses. Despite this, existing results either do not focus on slaughter or are insufficiently identified to provide useful policy parameters which can inform upcoming subsidization of the meat processing industry. We overcome endogenous slaughter location by appealing to variation in pork slaughter that arises due to persistent historic hog populations which are theoretically uncorrelated with contemporary truck traffic except through contemporary slaughter. To increase the historic years of hog population that are available, we use a map extraction technique that produces data from as far back as 1840.

We document several important results, beginning with quantifying how much additional truck traffic can be attributed to slaughter operations. We follow these results by showing that slaughterhouses also increase fatal crashes and auto repair employment. Both of these results are robust to using older versions of the instrument, suggesting that the identification assumptions are met and the estimates can be given a causal interpretation. The effect of slaughterhouses on fatal crashes and auto repair employment can be entirely attributed to the effects of slaughterhouses on truck traffic.

Table 7: Mediation Effects of Trucks on Crashes and Auto Repair Employment

Panel A: Fatal Crashes	
Total	0.575***
	(0.169)
Direct	0.023
	(0.027)
Indirect	0.546
	(0.357)
Observations	2991
First Stage F-Statistic (T on Z)	19.05
First Stage F-Statistic (M on Z | T)	5.167
Mediation Effect (% of Total)	94.93
Panel B: Auto Repair Employment	
Total	2.136***
	(0.403)
Direct	-0.021
	(0.108)
Indirect	2.150*
	(1.176)
Observations	2991
First Stage F-Statistic (T on Z)	19.05
First Stage F-Statistic (M on Z | T)	5.167
Mediation Effect (% of Total)	100.7

Note: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Cluster-robust standard errors, by state, in parentheses. This table applies the procedure from Dippel et al. (2021) to estimate how much of the effect of slaughter volume on fatal crashes and automobile repair employees operates through the mediator of truck traffic. In Panel A, the outcome of interest is fatal crashes. In Panel B, the outcome of interest is automobile repair employment. Total is the same as in previous tables. Direct is the effect of slaughterhouses on the dependent variable that is a direct result of slaughterhouses. Indirect is the effect of slaughterhouses that operates through the mediator variable, truck traffic. Coefficients are not transformed to be interpreted as semi-elasticities.

There are some limitations that are worthy of consideration. First, there are two key data limitations. The slaughter data only includes USDA-FSIS-inspected slaughterhouses and the crash data is only for fatal crashes. Next, these causal estimates are valid for compliers: counties with contemporary slaughter due to historic hog presence or vice-versa.

These estimates are unmistakably relevant for policy, including the planned subsidies for meat processing. Vindicating the Montanans, we show that meat processing does lead to costs from additional truck traffic and fatal crashes. The fact that slaughterhouses also increase automobile repair employment could be considered bad if they are repairing cars that were in these crashes or are damaged faster due to driving on the same roads as trucks which are mechanically known to cause a disproportionate amount of road damage compared to cars; however, typically higher employment is seen as positive. Thus, slaughterhouses are good for the job prospects of mechanics and those who work in slaughterhouses but are harmful to others in the community.From a less place-based perspective, additional meat processing capacity can lead to lower meat prices and less food insecurity. These considerations about the negative traffic effects of slaughterhouses should be accounted for when calculating the optimal subsidies for meat processing.

References

Anderson, M. L., & Auffhammer, M. (2014). Pounds that kill: The external costs of vehicle weight. *The Review of Economic Studies*, *81*(2), 535-571. [1, 4]

Anderson, T., Rubin, H., et al. (1949). Estimation of the parameters of a single equation in a complete system of stochastic equations. *The Annals of Mathematical Statistics*, *20*(1), 46–63. [2]

Andrews, I., Stock, J. H., & Sun, L. (2019). Weak instruments in instrumental variables regression: Theory and practice. *Annual Review of Economics*, *11*, 727–753. [2, 23, 31, 33, 35, 61, 62, 64, 66]

Angrist, J. D., Imbens, G. W., & Rubin, D. B. (1996). Identification of causal effects using instrumental variables. *Journal of the American Statistical Association*, *91*(434), 444-455. [16]

Aradom, S., & Gebresenbet, G. (2013). Vibration on animal transport vehicles and related animal behaviours with special focus on pigs. *Journal of Agricultural Science and Technology. A*, *3*(3A), 231. [68]

Associated Press. (2017). *Commission delays decision on using river water in oilfields.* `https://apnews.com/6e94ad14f7e042a5915ce5f64bcd8c09`. (Accessed: June 2020) [1]

Austin, B. A., Glaeser, E. L., & Summers, L. H. (2018). *Jobs for the heartland: Place-based policies in 21st century america* (Tech. Rep.). National Bureau of Economic Research. [3]

Bai, Y., Oslund, P. C., Mulinazzi, T. E., Tamara, S., Liu, C., Barnaby, M. M., & Atkins, C. E. (2007). *Transportation logistics and economics of the processed meat and related industries in Southwest Kansas* (Tech. Rep.). University of Kansas Center for Research, Inc. [3, 18, 68]

Bartik, T. J. (2020). Using place-based jobs policies to help distressed communities. *Journal of Economic Perspectives*, *34*(3), 99-127. [3]

Beam, A., Thilmany, D., Pritchard, R., Garber, L., Metre, D., & Olea-Popelka, F. (2015, 04). Distance to slaughter, markets and feed sources used by small-scale food animal operations in the United States. *Renewable Agriculture and Food Systems*, *31*, 1-11. [30]

Behrens, K., Brown, W. M., & Bougna, T. (2018). The world is not yet flat: Transport costs matter! *The Review of Economics and Statistics*, *100*(4), 712-724. [1]

Behrens, K., Gaigné, C., & Thisse, J.-F. (2009). Industry location and welfare when transport costs are endogenous. *Journal of Urban Economics*, *65*(2), 195-208. [13, 14]

Bellemare, M. F., & Wichman, C. J. (2020). Elasticities and the inverse hyperbolic sine transformation. *Oxford Bulletin of Economics and Statistics*, *82*(1), 50-61. [10, 13, 23, 28, 31, 33, 35, 36, 61, 62, 64, 65, 66]

Bound, J., Brown, C., & Mathiowetz, N. (2001). Chapter 59 - Measurement Error in Survey Data. In J. J. Heckman & E. Leamer (Eds.), (Vol. 5, p. 3705-3843). Elsevier. [24]

Bradley, J. H. (1948). *World Geography*. Boston: Ginn. [8]

Brodersen, R. (2015). *One million pigs on the road every day.* `https://www.aasv.org/shap/issues/v23n6/v23n6pm.html`. (Accessed: June 2020) [1]

Busso, M., Gregory, J., & Kline, P. (2013, April). Assessing the incidence and efficiency of a prominent place based policy. *American Economic Review*, *103*(2), 897-947. [3]

Cattaneo, M. D., Crump, R. K., Farrell, M. H., & Feng, Y. (2019). On binscatter. *arXiv preprint arXiv:1902.09608*. [15, 21, 52, 53]

Chen, Q., Madson, D., Miller, C. L., & Harris, D. H. (2012). Vaccine development for protecting swine against influenza virus. *Animal Health Research Reviews*, *13*(2), 181–195. [69]

Colomer, M. A., Margalida, A., & Fraile, L. (2020). Vaccination is a suitable tool in the control of aujeszky's disease outbreaks in pigs using a population dynamics P Systems Model. *Animals*, *10*(5), 909. [69]

Dippel, C., Gold, R., Heblich, S., & Pinto, R. (2021). The effect of trade on workers and voters. *The Economic Journal*, *132*(641), 199-217. [4, 37, 39, 67]

Duranton, G., Nagpal, G., & Turner, M. (2020). Transportation infrastructure in the US. *NBER Working Paper Series*(w27254). [6]

Duranton, G., & Turner, M. A. (2011). The fundamental law of road congestion: Evidence from US cities. *American Economic Review*, *101*(6), 2616-52. [2, 4]

Ellison, G., Glaeser, E. L., & Kerr, W. R. (2010). What causes industry agglomeration? Evidence from coagglomeration patterns. *American Economic Review*, *100*(3), 1195-1213. [13]

FHWA. (2000). *Addendum to the 1997 Federal Highway Cost Allocation Study Final Report*

U.S. Department of Transportation Federal Highway Administration (Tech. Rep.). Federal Highway Administration. [1, 4]

Fitzgerald, R. F., Stalder, K. J., Matthews, J. O., Schultz Kaster, C. M., & Johnson, A. K. (2009). Factors associated with fatigued, injured, and dead pig frequency during transport and lairage at a commercial abattoir. *Journal of Animal Science*, *87*(3), 1156-1166. [69]

Food and Agriculture Organization of the United Nations. (2001). *Guidelines for Humane Handling, Transport and Slaughter of Livestock.* http://www.fao.org/3/x6909e/x6909e00.htm. (Accessed: June 2020) [1, 68]

Gajana, C., Nkukwana, T., Marume, U., & Muchenje, V. (2013). Effects of transportation time, distance, stocking density, temperature and lairage time on incidences of pale soft exudative (pse) and the physico-chemical characteristics of pork. *Meat Science*, *95*(3), 520–525. [68, 69]

Glaeser, E. L. (2014). A world of cities: The causes and consequences of urbanization in poorer countries. *Journal of the European Economic Association*, *12*(5), 1154–1199. [1]

Glaeser, E. L., & Gottlieb, J. D. (2009). The wealth of cities: Agglomeration economies and spatial equilibrium in the United States. *Journal of Economic Literature*, *47*(4), 983-1028. [14]

Glaeser, E. L., Kerr, S. P., & Kerr, W. R. (2015). Entrepreneurship and urban growth: An empirical assessment with historical mines. *The Review of Economics and Statistics*, *97*(2), 498-520. [2]

Goldman, M., & Kaplan, D. M. (2018). Comparing distributions by multiple testing across quantiles or cdf values. *Journal of Econometrics*, *206*(1), 143–166. [56]

Gosálvez, L., Averós, X., Valdelvira, J., & Herranz, A. (2006). Influence of season, distance and mixed loads on the physical and carcass integrity of pigs transported to slaughter. *Meat Science*, *73*(4), 553 - 558. [69]

Guàrdia, M., Estany, J., Balasch, S., Oliver, M., Gispert, M., & Diestre, A. (2005). Risk assessment of DFD meat due to pre-slaughter conditions in pigs. *Meat Science*, *70*(4), 709 - 716. [69]

Hadjilambrinos, C. (2021). Reexamining the automobile's past: What were the critical factors that determined the emergence of the internal combustion engine as the dominant automotive technology? *Bulletin of Science, Technology & Society*, *41*(2-3), 58-71. [25]

Hall, J. D., Palsson, C., & Price, J. (2018). Is Uber a substitute or complement for public transit? *Journal of Urban Economics*, *108*, 36–50. [68]

Hanlon, W., & Heblich, S. (2021). History and urban economics. *Regional Science and Urban Economics*, 103751. [2]

Hanlon, W. W. (2016). Coal smoke and the costs of the industrial revolution. *NBER Working Paper*(w22921). [1]

Holl, A. (2016). Highways and productivity in manufacturing firms. *Journal of Urban Economics*, *93*, 131-151. [1, 13]

Huynh, T., Aarnink, A., & Verstegen, M. (2005). Reactions of pigs to a hot environment. In *Livestock environment VII, 18-20 May 2005, Beijing, China* (p. 544). [68]

Imbens, G. W., & Angrist, J. D. (1994). Identification and estimation of local average treatment effects. *Econometrica*, *62*(2), 467–475. [16]

Kaldor, N. (1967). *Strategic factors in economic development*. New York State School of Industrial and Labor Relations. [1]

Kemp, B., Da Silva, C. L. A., & Soede, N. M. (2018). Recent advances in pig reproduction: Focus on impact of genetic selection for female fertility. *Reproduction in Domestic Animals*, *53*(S2), 28-36. [69]

Key, N. (2004). Agricultural contracting and the scale of production. *Agricultural and Resource Economics Review*, *33*(2), 255. [69, 70]

Kline, P., & Moretti, E. (2014). Local economic development, agglomeration economies, and the big push: 100 years of evidence from the tennessee valley authority. *The Quarterly Journal of Economics*, *129*(1), 275–331. [3]

Larue, S., Abildtrup, J., & Schmitt, B. (2011). Positive and negative agglomeration externalities: Arbitration in the pig sector. *Spatial Economic Analysis*, *6*(2), 167-183. [13]

Lawley, C. (2021). Hog barns and neighboring house prices: Anticipation and post-establishment impacts. *American Journal of Agricultural Economics*, *103*(3), 1099-1121. [3]

Lawley, C., & Furtan, H. (2008). The political trade-off between environmental stringency and economic development in rural America*. *Journal of Regional Science*, *48*(3), 547-566. [4]

Lee, D. S., McCrary, J., Moreira, M. J., & Porter, J. (2022). Valid t-ratio inference for IV. *American Economic Review*, *112*(10), 3260-90. [24]

Leon, D. A. (2008). *Cities, urbanization and health.* Oxford University Press. [1]

Luechinger, S., & Roth, F. (2016). Effects of a mileage tax for trucks. *Journal of Urban Economics*, *92*, 1 - 15. [4]

Mandell, S., & Proost, S. (2016). Why truck distance taxes are contagious and drive fuel taxes to the bottom. *Journal of Urban Economics*, *93*, 1-17. [4]

Marshall, A. (1890). *Principles of Microeconomics*. London: Macmillan. [13]

McArthur, J. W., & McCord, G. C. (2017). Fertilizing growth: Agricultural inputs and their effects in economic development. *Journal of Development Economics*, *127*, 133–152. [2]

McBride, W. D., & Key, N. (2013). US hog production from 1992 to 2009: Technology, restructuring, and productivity growth. *USDA Economic Research Report*(158). [69]

Miguel, E., & Kremer, M. (2004). Worms: Identifying impacts on education and health in the presence of treatment externalities. *Econometrica*, *72*(1), 159-217. [30]

Millimet, D. L. (2011). The elephant in the corner: a cautionary tale about measurement error in treatment effects models. In *Missing data methods: Cross-sectional methods and applications.* Emerald Group Publishing Limited. [24]

Miranda-De La Lama, G., Villarroel, M., & María, G. A. (2014). Livestock transport from the perspective of the pre-slaughter logistic chain: A review. *Meat Science*, *98*(1), 9–20. [68]

Muehlenbachs, L., Spiller, E., & Timmins, C. (2015). The housing market impacts of shale gas development. *American Economic Review*, *105*(12), 3633-59. [30]

Muehlenbachs, L., Staubli, S., & Chu, J. (2021). The accident externality from trucking: Evidence from shale gas development. *Regional Science and Urban Economics*, 103630. [1, 3, 4, 10]

Nehiba, C. (2020). Taxed to death? freight truck collision externalities and diesel taxes. *Regional Science and Urban Economics*, *85*, 103577. [4]

Parker, E., Tach, L., & Robertson, C. (2022). Do federal place-based policies improve economic opportunity in rural communities? *RSF: The Russell Sage Foundation Journal of the Social Sciences*, *8*(4), 125–154. [3]

Parry, I. W. (2008). How should heavy-duty trucks be taxed? *Journal of Urban Economics*, *63*(2), 651 - 668. [4]

Picard, P. M., & Zeng, D.-Z. (2005). Agricultural sector and industrial agglomeration. *Journal of Development Economics*, *77*(1), 75–106. [1]

Pig Progress. (2015). *Preventing 5 major pig diseases in a breeding herd.* https://www.pigprogress.net/Health/Articles/2015/10/Preventing-five-major-pig-diseases-in-the-breeding-herd-2685176W/. (Accessed: June 2020) [69]

Pork Checkoff. (2015). *Quick facts: The pork industry at a glance.* http://porkgateway.org/wp-content/uploads/2015/07/quick-facts-book1.pdf. (Accessed: June 2020) [70]

Porter, M. (2003). The economic performance of regions. *Regional Studies*, *37*(6-7), 549–578. [34]

Randall, J. M., & Bradshaw, R. H. (1998). Vehicle motion and motion sickness in pigs. *Animal Science*, *66*(1), 239–245. [68]

Rhodes, V. J. (1995). The industrialization of hog production. *Review of Agricultural Economics*, 107–118. [69]

Roe, B., Irwin, E. G., & Sharp, J. S. (2002). Pigs in space: Modeling the spatial structure of hog production in traditional and nontraditional production regions. *American Journal of Agricultural Economics*, *84*(2), 259–278. [13, 70]

Shinn, L. (2019). *These Montanans Don't Want an Industrial Slaughterhouse in Their Backyard.* https://www.nrdc.org/stories/these-montanans-dont-want-industrial-slaughterhouse-their-backyard?fbclid=IwAR0Diss7fr2Rp1R9jNpHVQBDPCLUSh_ck21DbpWTqrONKOjI3k3FMOj9cJk. (Accessed: January 2021) [1, 3]

Sneeringer, S. (2009). Does animal feeding operation pollution hurt public health? A national longitudinal study of health externalities identified by geographic shifts in livestock production. *American Journal of Agricultural Economics*, *91*(1), 124-137. [3]

Sneeringer, S. (2010). A national, longitudinal study of the effects of concentrated hog production on ambient air pollution. *American Journal of Agricultural Economics*, *92*(3), 821-835. [3]

Sneeringer, S., & Hertz, T. (2013). The effects of large-scale hog production on local labor markets. *Journal of Agricultural and Applied Economics*, *45*(1379-2016-113788), 139–158. [3]

Stock, J. H., & Yogo, M. (2002). *Testing for weak instruments in linear IV regression.* National Bureau of Economic Research Cambridge, Mass., USA. [2, 24]

The Allegheny Front. (2017). *On health effects, blame the trucks, not the fracking?* https://www.alleghenyfront.org/on-health-effects-blame-the-trucks-not-the-fracking/. (Accessed: June 2020) [1]

The Texas Tribune. (2014). *Dissecting Denton: How one city banned fracking.* https://www.texastribune.org/2014/12/15/dissecting-denton-how-texas-city-baned-fracking/. (Accessed: June 2020) [1]

United States President's Commission on Law Enforcement & Administration of Justice, & Katzenbach, N. d. (1967). *The challenge of crime in a free society: A report by the President's Commission on Law Enforcement and Administration of Justice*. United States Government Printing Office. [1]

USDA. (2021). *USDA Announces $500 Million for Expanded Meat & Poultry Processing Capacity as Part of Efforts to Increase Competition, Level the Playing Field for Family Farmers and Ranchers, and Build a Better Food System.* https://www.usda.gov/media/press-releases/2021/07/09/usda-announces-500-million-expanded-meat-poultry-processing. (Accessed: May 2022) [1]

Wang, Y.-F., Huang, J.-J., & Zhao, J.-G. (2017). Gene engineering in swine for agriculture. *Journal of Integrative Agriculture*, *16*(12), 2792–2804. [69]

Xu, M., & Xu, Y. (2020). Fraccidents: The impact of fracking on road traffic deaths. *Journal of Environmental Economics and Management*, *101*, 102303. [1, 3, 4]

Online Appendix

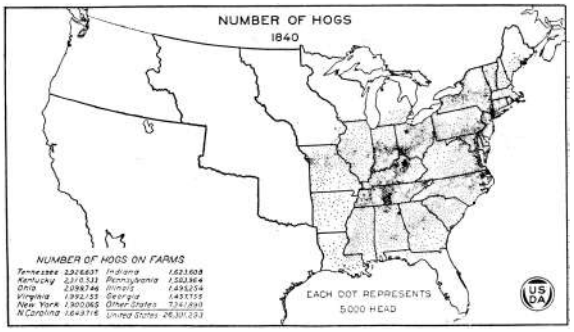
A Additional Tables and Figures

Figure A.1: Hog Population in 1948

Note: Figure shows hog population in 1948. The map comes from the 1948 textbook *World Geography*.

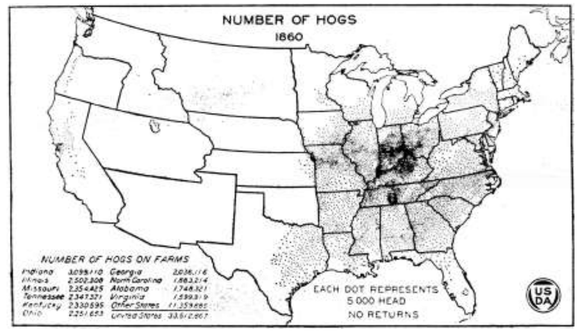
Figure A.2: Hog Population: 1840-1920

(a) 1840 Hog Points



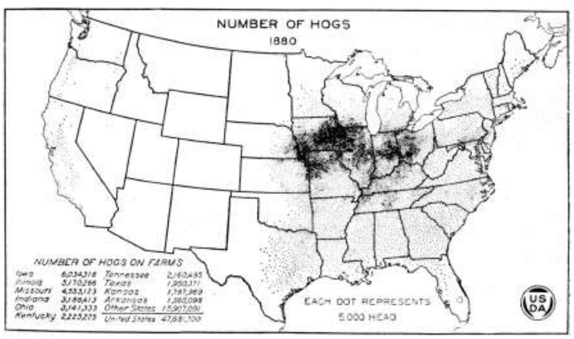
United States Production of Hogs, 1840
United States Department of Agriculture Yearbook 1922, Washington D.C.: Government Printing Office, 1922
Downloaded from *Maps ETC*, on the web at http://etc.usf.edu/maps [map #00157]

(b) 1860 Hog Points



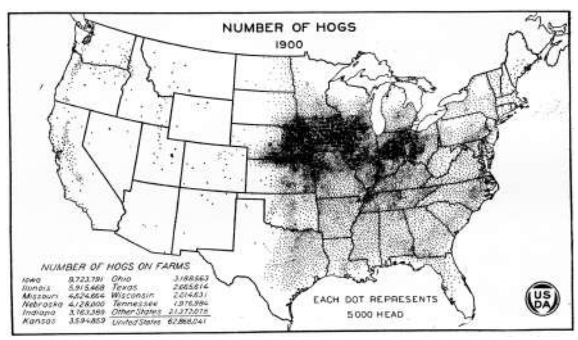
United States Production of Hogs, 1860
United States Department of Agriculture Yearbook 1922, Washington D.C.: Government Printing Office, 1922
Downloaded from *Maps ETC*, on the web at http://etc.usf.edu/maps [map #00158]

(c) 1880 Hog Points



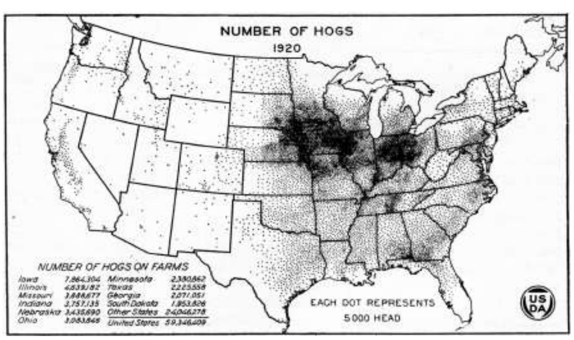
United States Production of Hogs, 1880
United States Department of Agriculture Yearbook 1922, Washington D.C.: Government Printing Office, 1922
Downloaded from *Maps ETC*, on the web at http://etc.usf.edu/maps [map #00159]

(d) 1900 Hog Points



United States Production of Hogs, 1900
United States Department of Agriculture Yearbook 1922, Washington D.C.: Government Printing Office, 1922
Downloaded from *Maps ETC*, on the web at http://etc.usf.edu/maps [map #00160]

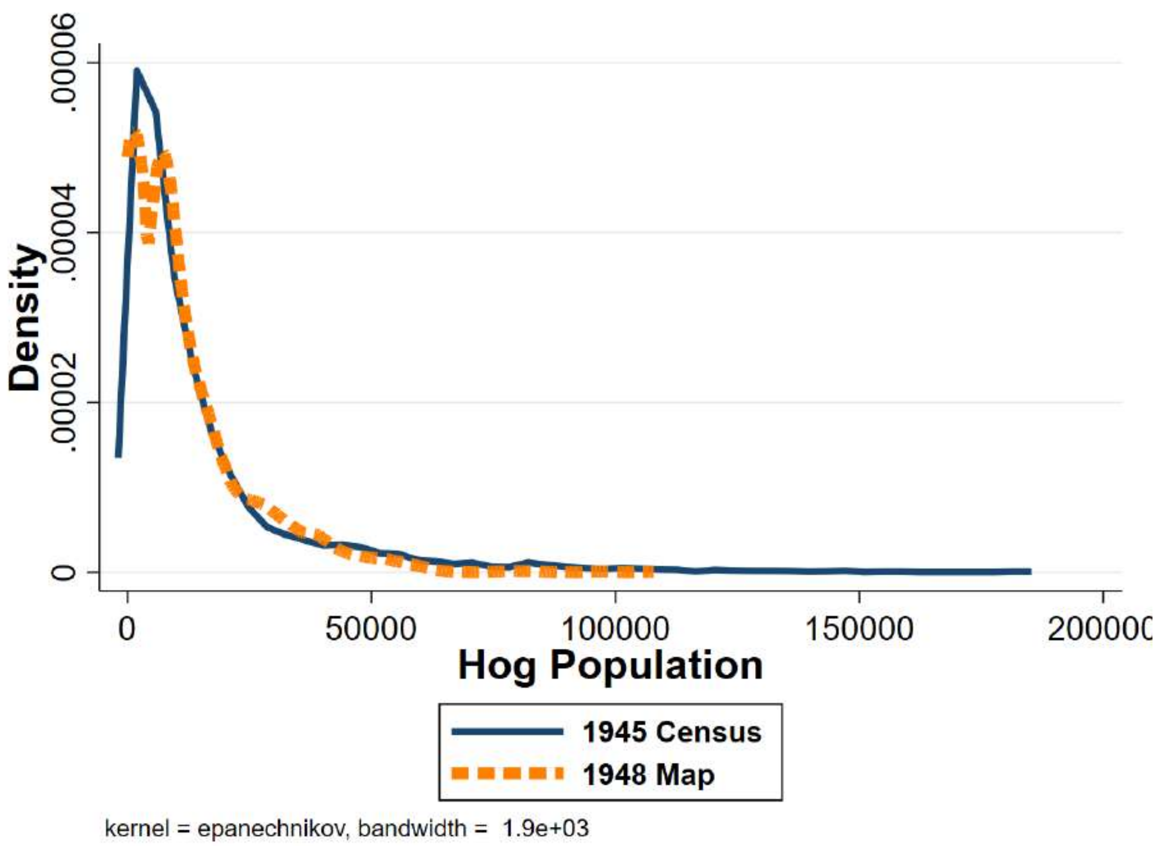
(e) 1920 Hog Points



United States Production of Hogs, 1920
United States Department of Agriculture Yearbook 1922, Washington D.C.: Government Printing Office, 1922
Downloaded from *Maps ETC*, on the web at http://etc.usf.edu/maps [map #00161]

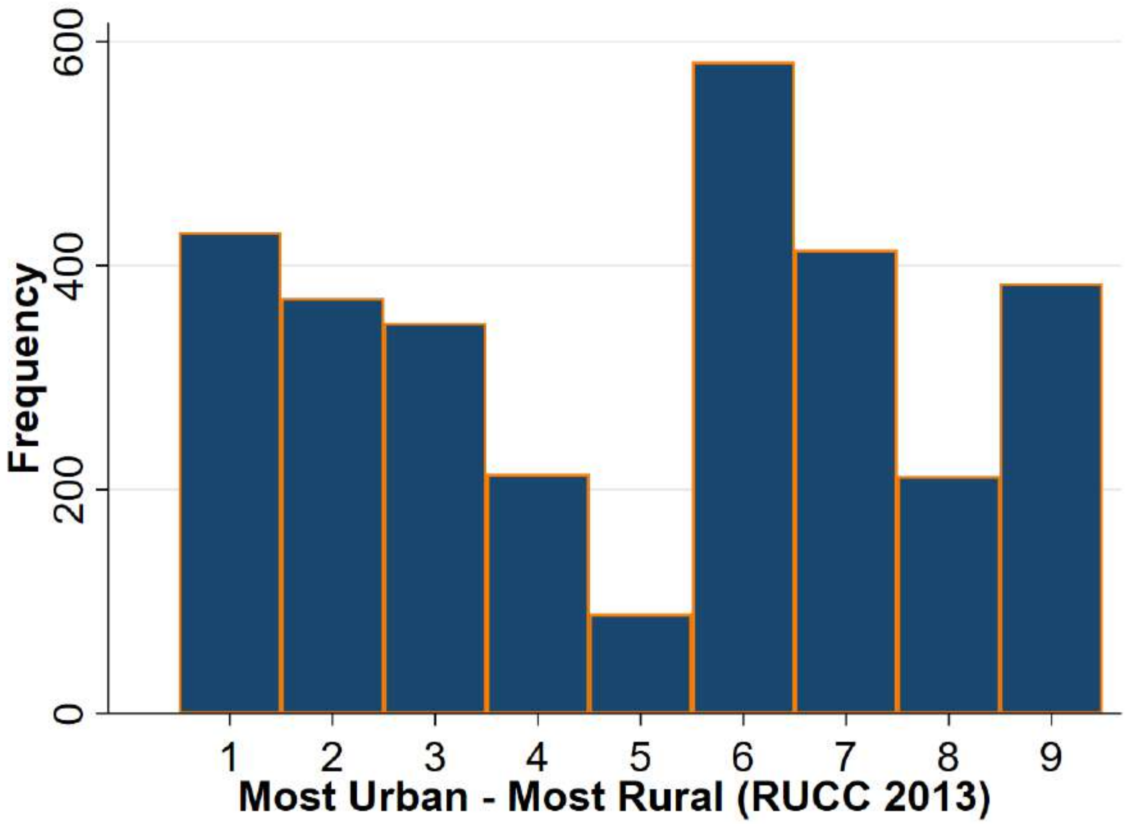
Note: Panels show maps of historic hog densities in the United States. Each dot represents 5000 hogs. Maps are from the 1922 US Department of Agriculture Yearbook.

Figure A.3: Distributions of Hogs in 1945 (Census) and 1948 (Map)



Note: Figure compares the distributions of hog population counts from the 1945 USDA Agricultural Census and the 1948 *World Geography* textbook map. For details of how the hog data was extracted from Figure A.1, see Section 2.2.1.

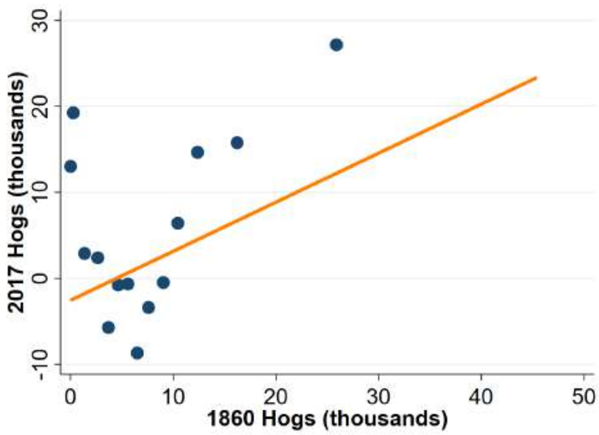
Figure A.4: Number of Counties in Each Rural Urban Continuum Code (2013)



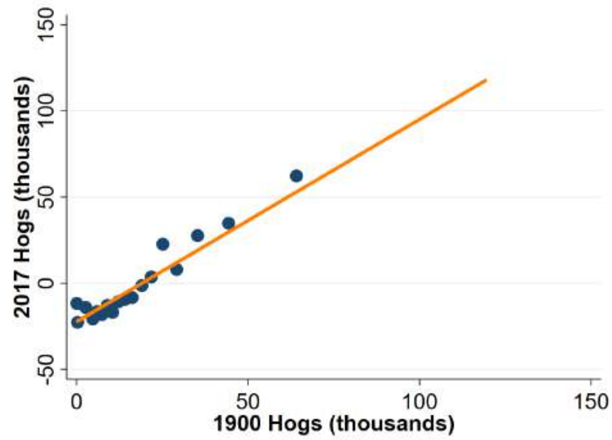
Note: The Rural-Urban Continuum Codes classifies metropolitan counties by the population size of their metro area (codes 1,2 and 3), and nonmetropolitan counties by the degree of urbanization and adjacency to a metro area (codes 4,5,6,7,8, and 9). For the metro area, code 1 refers to counties with 1 million population or more. Code 2 refers to counties areas of 250,000 to 1 million population, and lastly, code 3 refers to counties with fewer than 250,000 population. For the nonmetro countries, code 4 refers to counties with 20,000 urban population or more adjacent to a metro area, while code 5 is for counties with 20,000 urban population or more, but not adjacent to a metro area. Code 6 refers to counties with 2,500 to 19,999 urban population adjacent to a metro area, while code 7 is for counties with 2,500 to 19,999 urban population, but not adjacent to a metro area. Code 8 refers to counties that are completely rural or have less than 2,500 urban population adjacent to a metro area, while code 9 is for counties that are completely rural or have less than 2,500 urban population, not adjacent to a metro area.

Figure A.5: The Persistence of Hog Population, With Controls

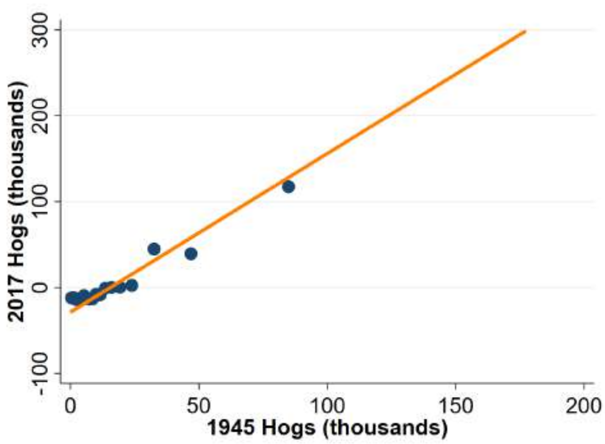
(a) 1860 Hogs



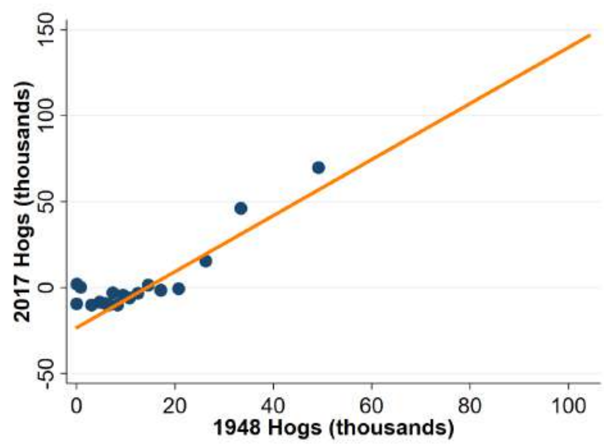
(b) 1900 Hogs



(c) 1945 Hogs (From Census)



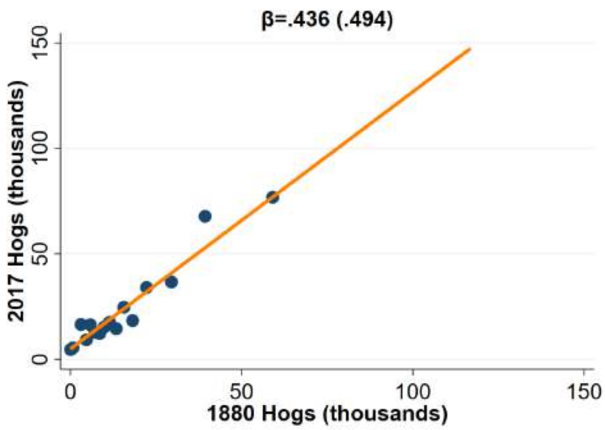
(d) 1948 Hogs (from Map)



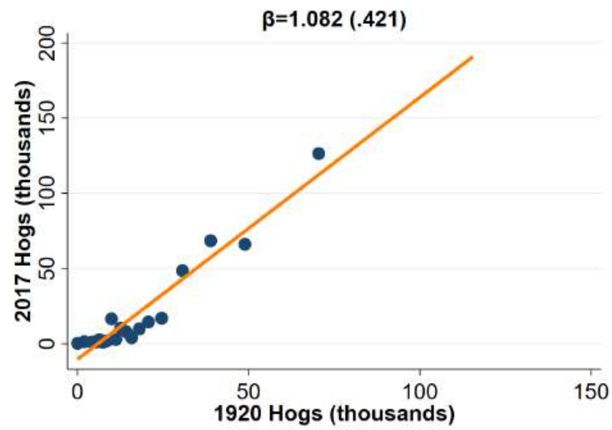
Note: Scales differ. All hogs are in thousands. (a) shows average 2017 hogs, conditional on 1840 hogs. (b) shows average 2017 hogs, conditional on 1945 hogs. (c) shows average 2017 hogs, conditional on 1948 hogs. There are an equal number of observations in each bin. The number of bins chosen as either the optimal number, in terms of bias-variance tradeoff (Cattaneo et al., 2019), or 10. The procedure selects the number of bins to optimize a bias-variance tradeoff in the asymptotic integrated mean square error (IMSE) (Cattaneo et al., 2019). Controls variables include: state X urban fixed effects, land area, rail miles, and crop (corn grain and soybean) production

Figure A.6: The Persistence of Hog Population, Other Years

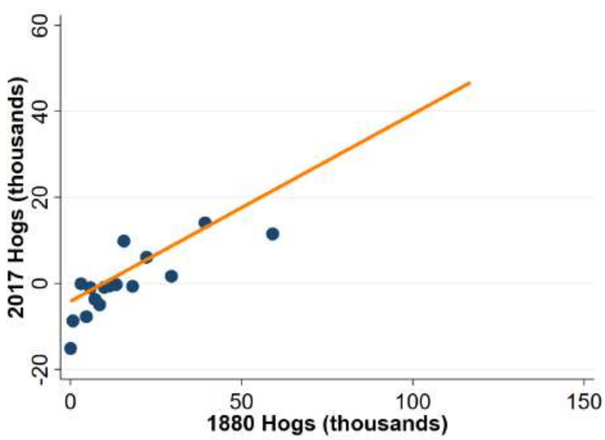
(a) 1880 Hogs



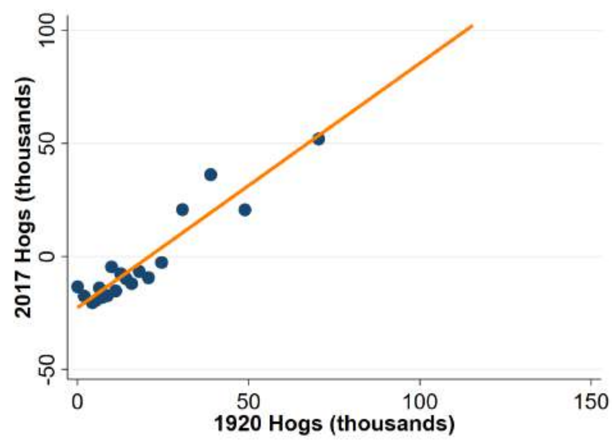
(b) 1920 Hogs



(c) 1880 Hogs, With Controls



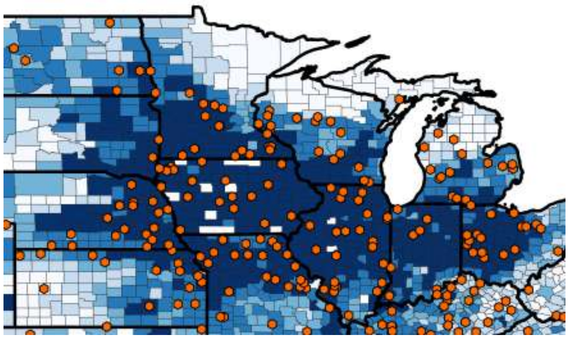
(d) 1920 Hogs, With Controls



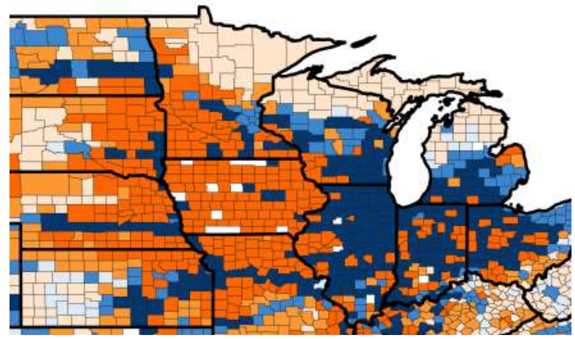
Note: Scales differ. All hogs are in thousands. (a) shows average 2017 hogs, conditional on 1840 hogs. (b) shows average 2017 hogs, conditional on 1945 hogs. (c) shows average 2017 hogs, conditional on 1948 hogs. Equal number of observations in each bin. Number of bins chosen as either the optimal number, in terms of bias-variance tradeoff (Cattaneo et al., 2019), or 10. Procedure selects number of bins to optimize a bias-variance tradeoff in the asymptotic integrated mean square error (IMSE) (Cattaneo et al., 2019). Regression coefficients are from ordinary least squares, standard errors are clustered at the state level, and include controls and fixed effects. No other explanatory variables used in graphs.

Figure A.7: 1945 Hog Population, 2019 Pork Slaughterhouses, and 2017 Truck AADT

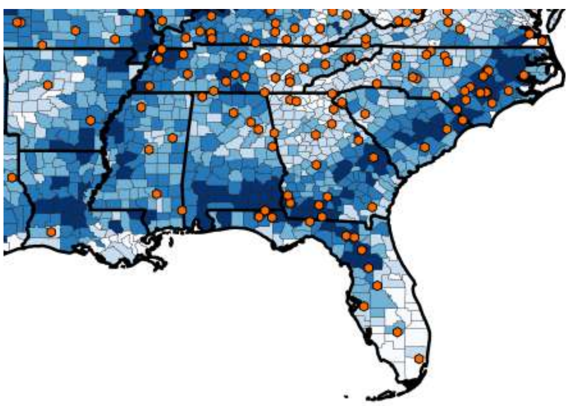
(a): Midwest North, First Stage



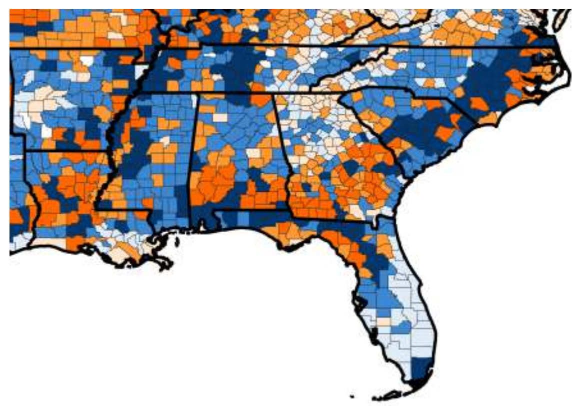
(b): Midwest North, Reduced Form



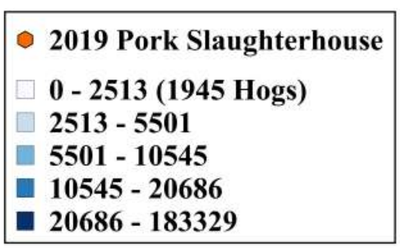
(c): East South, First Stage



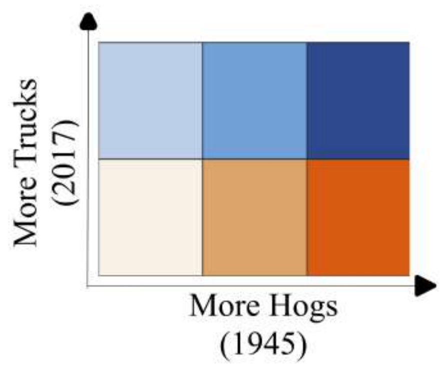
(d): East South, Reduced Form



(e): First Stage Legend



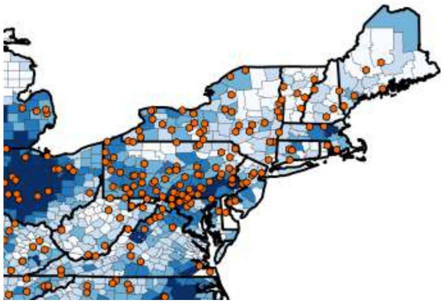
(f): Reduced Form Legend



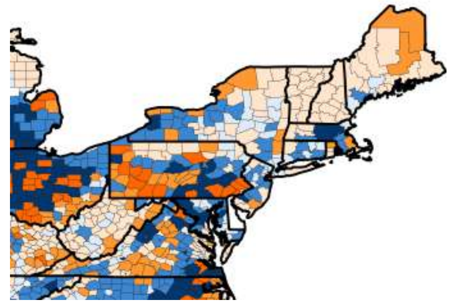
Note: Figure visually shows the first stage relationship between 1945 hogs and 2019 pork slaughterhouses at the county level in the left column and the reduced form relationship between 1945 hogs and 2017 truck AADT in the right column. An orange point represents one pork slaughterhouse in 2019. Darker shades of blue in the left column are associated with more hogs in the 1945 agricultural census. Cutoffs for the first stage legend split the hog data into equal quintiles. For the reduced form legend, hog groups: $0 < 4299$; $4299 \leq 13021$; > 13021; truck groups: $0 < 525$; ≥ 525.

Figure A.8: 1945 Hog Population, 2019 Pork Slaughterhouses, and 2017 Truck AADT

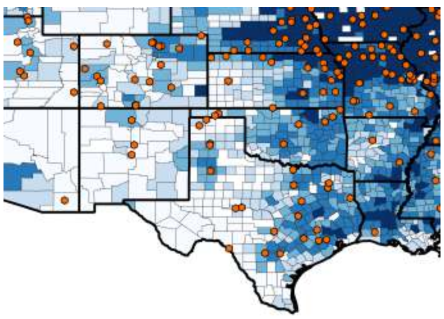
(a): First Stage: East North



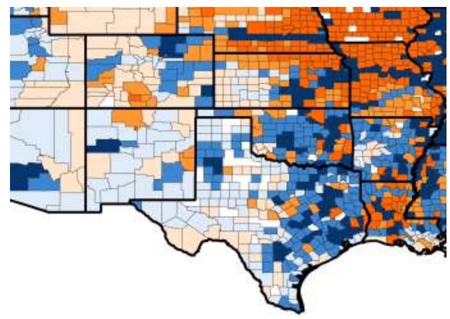
(b): Reduced Form: East North



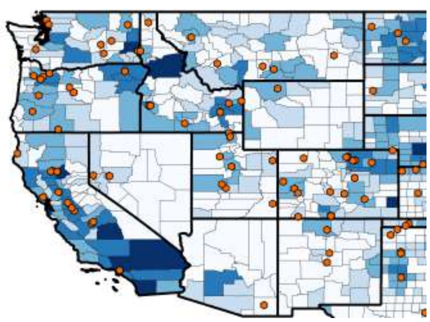
(c): First Stage: Midwest South



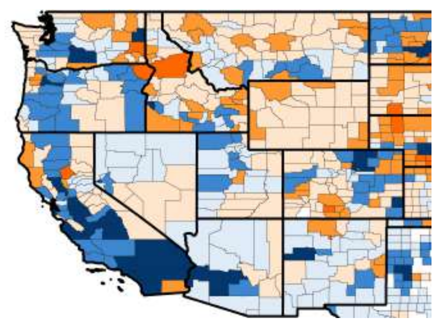
(d): Reduced Form: Midwest South



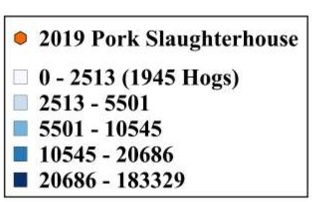
(e): First Stage: West



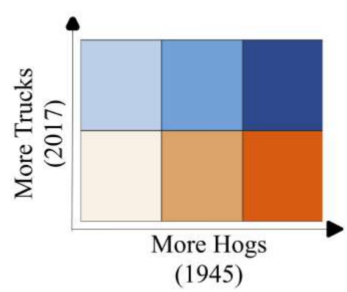
(f): Reduced Form: West



(g): First Stage Legend



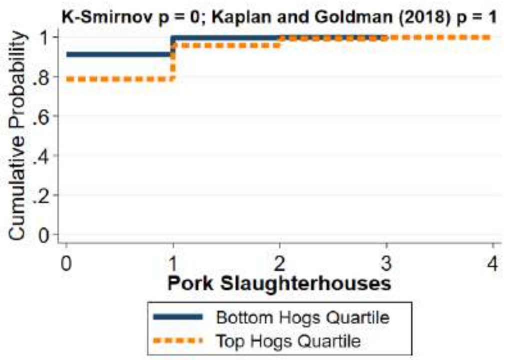
(h): Reduced Form Legend



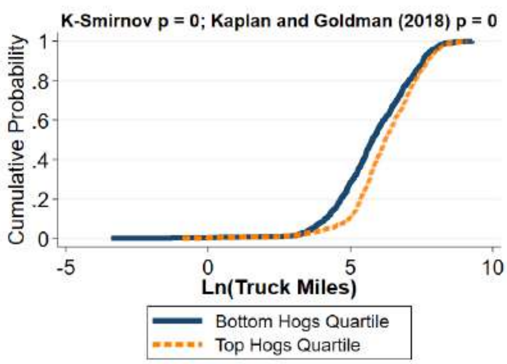
Note: Figure visually shows the first stage relationship between 1945 hogs and 2019 pork slaughterhouses at the county level in the left column and the reduced form relationship between 1945 hogs and 2017 truck AADT in the right column. An orange point represents one pork slaughterhouse in 2019. Darker shades of blue in the left column are associated with more hogs in the 1945 agricultural census. Cutoffs for the first stage legend split the hog data into equal quintiles. For the reduced form legend, hog groups: $0 < 4299$; $4299 \leq 13021$; > 13021; truck groups: $0 < 525$; ≥ 525.

Figure A.9: Cumulative Distribution Functions by 1945 Hog Quartile

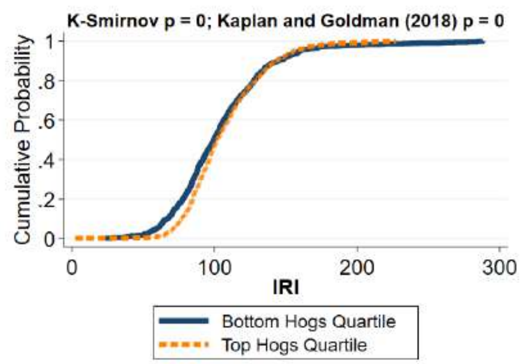
(a): First Stage: Pork Slaughterhouses



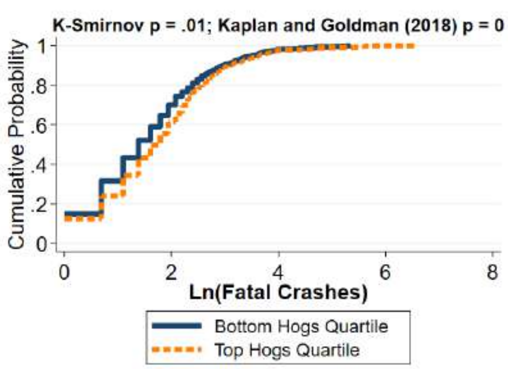
(b): Reduced Form: Ln(Truck AADT)



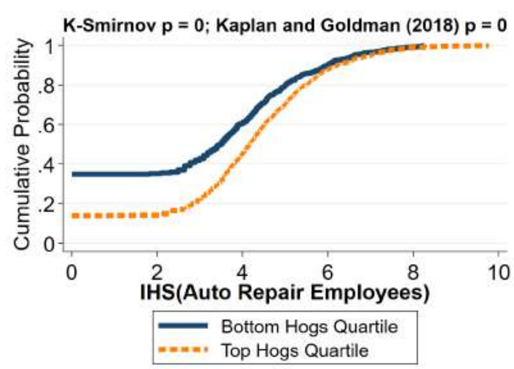
(c): Reduced Form: Road Roughness



(d): Reduced Form: Fatal Car Crashes



(e): Reduced Form: Auto Repair Employment



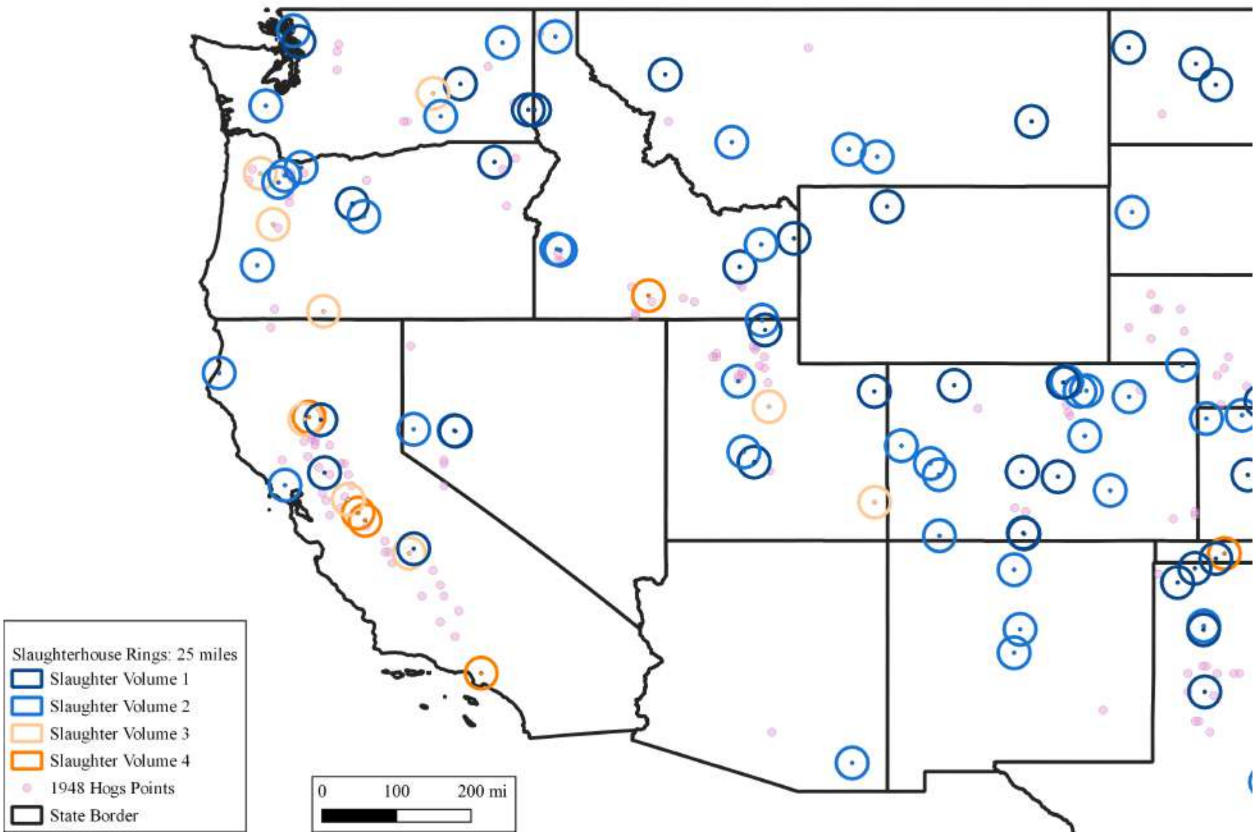
Note: Figures show the cumulative distributions of the dependent variables by the 1945 hogs quartile. Above the graphs are p-values from two tests for the equality of distributions. The first is from the two-sample Kolmogorov–Smirnov test. The second test is also a test for equality of distributions from Goldman and Kaplan (2018).

Table A.1: Robustness to Quadratic Historic Hogs

	Reduced Form	First Stage
1945 Hogs (10,000's)	0.104**	0.166***
	(0.042)	(0.035)
1945 Hogs (10,000's), Squared	-0.005*	-0.008**
	(0.003)	(0.003)
Observations	2999	2999

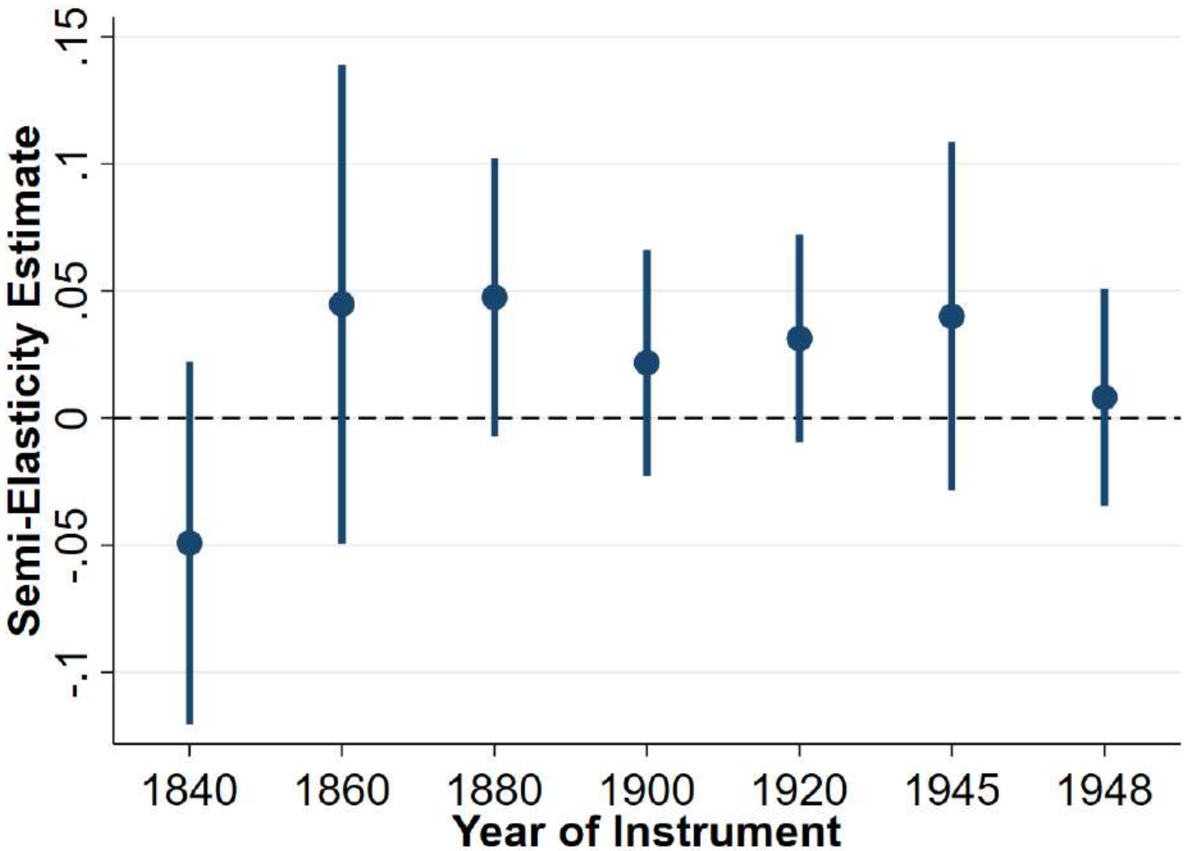
Note: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Cluster-robust standard errors, by state, in parentheses. All regressions are estimated by OLS. All regressions include state X urbanicity fixed effects, land area, rail miles, and crop (corn grain and soybeans) production. In column 1 (Reduced Form), the dependent variable is truck average annual daily traffic. In column 2 (First Stage), the dependent variable is hog slaughter volume.

Figure A.10: Example Slaughterhouse Rings: 25 miles



Note: Figure maps contemporary slaughterhouses with 25-mile distance rings. Different colors represent different slaughter volumes. The figure also shows the 1948 historic hog locations.

Figure A.11: IRI Results by Year



Note: Figures diagnose the sensitivity of estimates to using just-identified regressions with other years of historic hogs as the instrument. All regressions include interacted state-urbanicity fixed effects and controls. Standard errors are clustered at the state level. The second stage estimate, after it has been transformed to be interpreted as a semi-elasticity, is shown. The whiskers show 95% Wald confidence intervals. The dependent variable is the international roughness index (IRI).

A.1 Slaughterhouse as Treatment

Table A.2: OLS Estimates of Pork Slaughterhouses Effects on Truck Traffic, Car Traffic, Fatal Accidents, Road Roughness, and Automotive Repair Employees

Panel A: Truck AADT	(1)	(2)	(3)
Pork Slaughterhouses	0.133* (0.078)	0.154*** (0.054)	0.087 (0.057)
Semi-Elasticity	0.025* (0.015)	0.029*** (0.010)	0.016 (0.011)
Observations	3046	3046	3046
Panel B: Car AADT			
Pork Slaughterhouses	0.198*** (0.049)	0.103** (0.040)	0.074* (0.040)
Semi-Elasticity	0.037*** (0.009)	0.019*** (0.007)	0.014* (0.007)
Observations	3046	3046	3046
Panel C: Fatal Crashes			
Pork Slaughterhouses	0.378*** (0.058)	0.236*** (0.039)	0.151*** (0.039)
Semi-Elasticity	0.071*** (0.011)	0.044*** (0.007)	0.028*** (0.007)
Observations	3046	3046	3046
Panel D: IRI			
Pork Slaughterhouses	0.039 (0.023)	-0.008 (0.010)	-0.009 (0.009)
Semi-Elasticity	0.007* (0.004)	-0.001 (0.002)	-0.002 (0.002)
Observations	3046	3046	3046
Panel E: Auto Repair Employees			
Pork Slaughterhouses	0.960*** (0.102)	0.498*** (0.080)	0.371*** (0.075)
Semi-Elasticity	0.179*** (0.019)	0.093*** (0.015)	0.069*** (0.014)
Observations	3046	3046	3046
State FEs	-	X	-
Rural-Urban FEs	-	X	-
State X Urban FEs	-	-	X
Controls	-	-	X

Note: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Cluster-robust standard errors, by state, in parentheses. All regressions are estimated by OLS with dependent variables that have been transformed by the inverse hyperbolic sine (IHS) for dealing with outliers and 0 values. The independent variable is the number of USDA-inspected pork slaughterhouses. In Panel A, the dependent variable is truck average annual daily traffic (AADT). In Panel B, the dependent variable is car AADT. In Panel C, the dependent variable is the number of fatal road crashes. In Panel D, the dependent variable is the international roughness index (IRI). In Panel E, the dependent variable is the number of automotive repair employees. Column 1 includes no controls. Column 2 includes state fixed effects and the Rural-Urban Continuum Codes (RUCC) fixed effects, of which there are 2. Column 3 includes controls for land area, railway miles, corn grain bushel production, and soybean bushel production. Additionally, it uses the RUCC indicators to create an indicator for whether a county is urban or not and then interacts that with the state fixed effects.

Table A.3: 2SLS Estimates of Slaughterhouses on Average Daily Truck Miles

	(1)	(2)	(3)
Dependent Variable:	Reduced Form IHS(Truck AADT)	First Stage Slaughterhouses	Second Stage IHS(Truck AADT)
Panel A: Fixed Effects			
1945 Hogs (10,000's)	0.084***	0.046***	
	(0.024)	(0.011)	
Pork Slaughterhouses			1.827***
			(0.438)
Observations	2991	2991	2991
Kleibergen-Paap F			17.26
A-R 95% Confidence Set			[1.08, 3.12]
Semi-Elasticity	0.127***		0.341***
	(0.036)		(0.082)
Panel B: Rail and Land Area			
1945 Hogs (10,000's)	0.068***	0.044***	
	(0.021)	(0.011)	
Pork Slaughterhouses			1.540***
			(0.422)
Observations	2991	2991	2991
Kleibergen-Paap F			15.93
A-R 95% Confidence Set			[0.75, 2.75]
Semi-Elasticity	0.102***		0.287***
	(0.032)		(0.079)
Panel C: Corn and Soy Bushels			
1945 Hogs (10,000's)	0.043**	0.035***	
	(0.018)	(0.010)	
Pork Slaughterhouses			1.224**
			(0.482)
Observations	2991	2991	2991
Kleibergen-Paap F			12.53
A-R 95% Confidence Set			[0.32, 2.73]
Semi-Elasticity	0.065**		0.228**
	(0.027)		(0.090)

Note: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Cluster-robust standard errors, by state, in parentheses. The table displays 2SLS regressions of pork slaughterhouses on contemporary truck traffic, using historic hog population as an instrument. Columns 1, 2, and 3 display the reduced form, first stage, and second stage respectively. Panel A includes state X urbanicity fixed effects. Panel B adds land area and non-passenger railway miles as control variables. Panel C adds contemporary corn grain bushel and soybean bushel production as additional control variables. All panels show the Kleibergen-Paap first stage F-statistic for historic hogs. All panels show the corresponding Anderson-Rubin 95% confidence sets for the IV estimate, which are efficient for potentially weak instruments, as suggested by Andrews et al. (2019) for just-identified structural equations. All panels also show the corresponding semi-elasticity transformation for inverse hyperbolic sine transformations that is suggested by Bellemare and Wichman (2020).

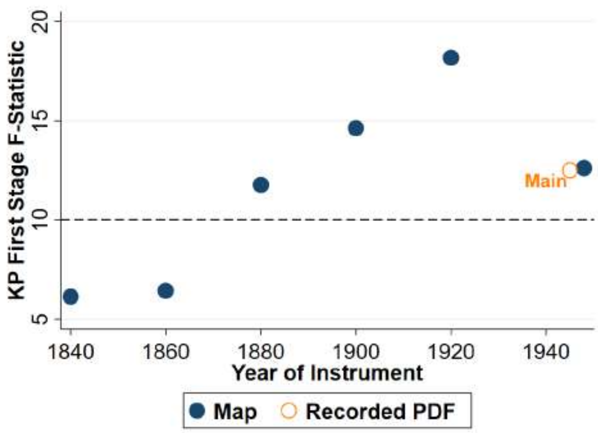
Table A.4: 2SLS Estimates of Slaughterhouses on Average Daily Truck Miles, Untransformed Historic Hogs

Dependent Variable:	(1) Reduced Form IHS(Truck AADT) (1)	(2) First Stage Slaughterhouses (2)	(3) Second Stage IHS(Truck AADT) (3)
1945 Hog Population	0.0000043**	0.0000035***	
	(0.0000018)	(0.0000010)	
Pork Slaughterhouses			1.2237163**
			(0.4817463)
Observations	2991	2991	2991
Kleibergen-Paap F			12.53
A-R 95% Confidence Set			[.327198, 2.73063]
Semi-Elasticity	0.065**		0.228**
	(0.027)		(0.090)

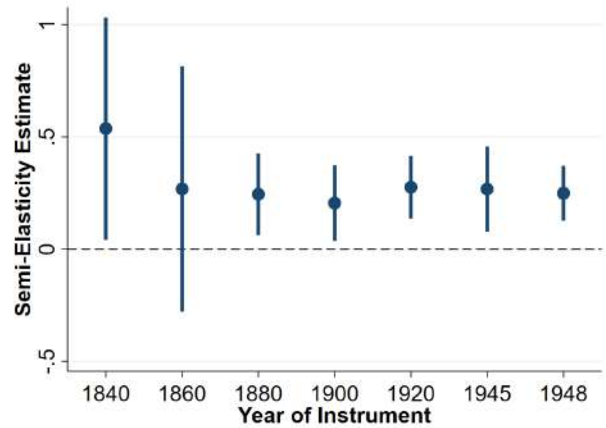
Note: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Cluster-robust standard errors, by state, in parentheses. The table displays 2SLS regressions of pork slaughterhouses on contemporary truck traffic, using historic hog population as an instrument. Columns 1, 2, and 3 display the reduced form, first stage, and second stage respectively. All panels show the Kleibergen-Paap first stage F-statistic for historic hogs. All panels show the corresponding Anderson-Rubin 95% confidence sets for the IV estimate, which are efficient for potentially weak instruments, as suggested by Andrews et al. (2019) for just-identified structural equations. The instrument is unscaled, since Bellemare and Wichman (2020) finds unscaled regressors leads to more stable estimates when using inverse hyperbolic sine transformations. All regressions use state X urban fixed effects, land area, rail miles, and crop production (corn grain and soybeans) as controls.

Figure A.12: First Stage F-Statistic and Semi-Elasticity Estimates by Year of Instrument

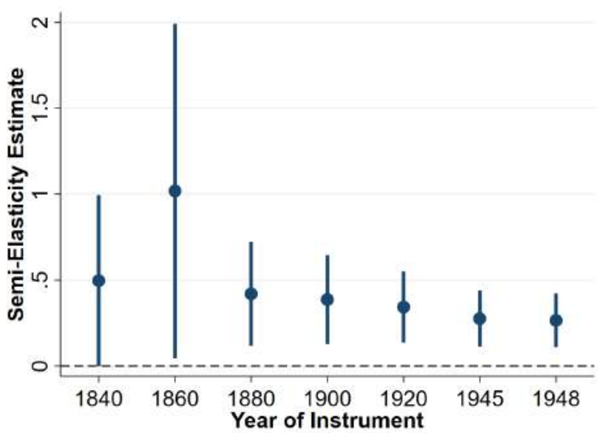
(a): Kleibergen-Paap First Stage F-Statistics



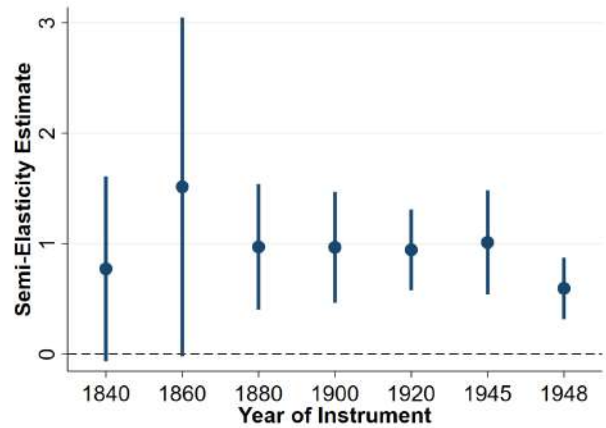
(b): Truck Miles



(c): Fatal Car Crashes



(d): Auto Repair Employment



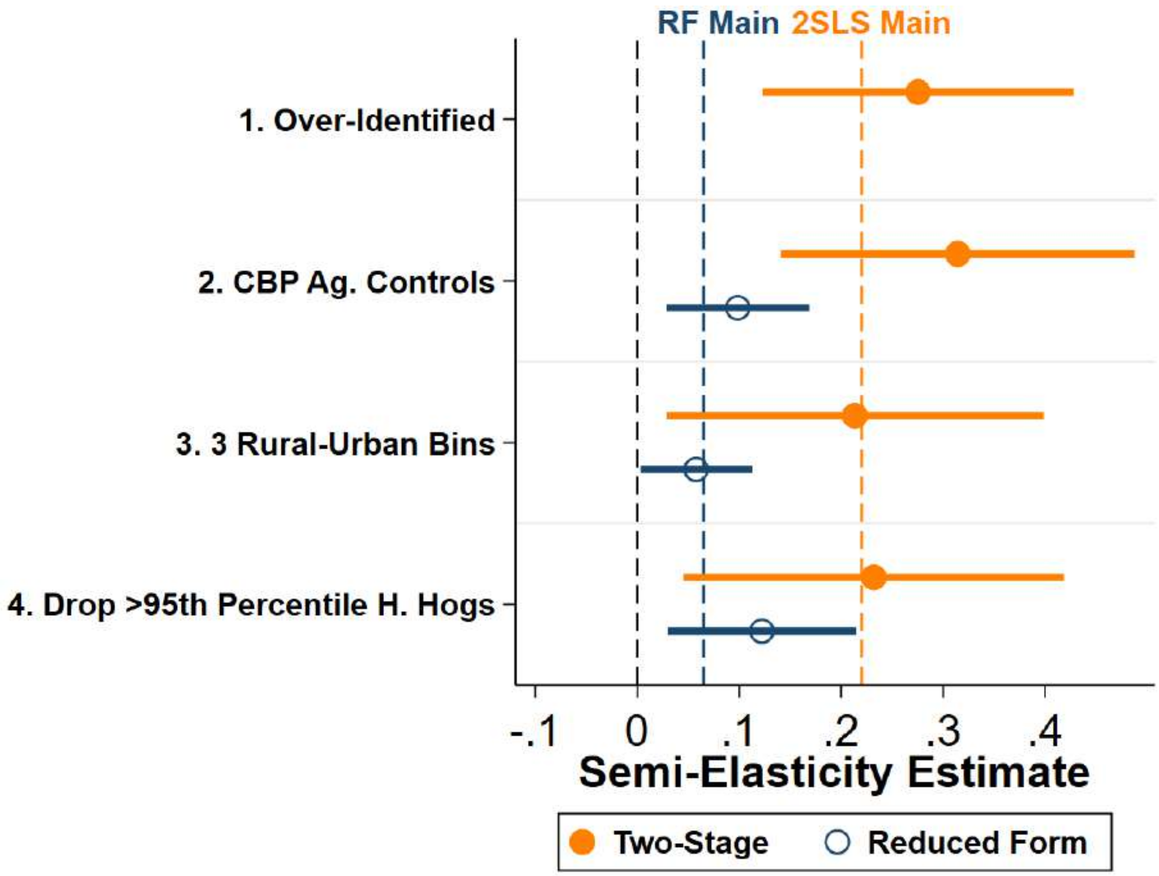
Note: Figures diagnose the sensitivity of estimates to using just-identified regressions with other years of historic hogs as the instrument. All regressions include interacted state-urbanicity fixed effects and controls. Standard errors are clustered at the state level. (a) shows the first-stage Kleibergen-Paap F-statistics by year with an orange open dot representing the main specifications. (b)-(d) show the second stage estimate after it has been transformed to be interpreted as a semi-elasticity. The whiskers show 95% Wald confidence intervals. (b) shows the effects on truck miles, (c) shows the effects on fatal crashes, and (d) shows the effects on auto repair employment.

Table A.5: 2SLS Estimates of Slaughterhouses on Average Daily Truck Miles, Other Hog Years

Dependent Variable:	(1) Reduced Form IHS(Truck AADT)	(2) First Stage Slaughterhouses	(3) Second Stage IHS(Truck AADT)
Panel A: 1840			
1840 Hogs (10,000's)	0.145***	0.048**	
	(0.035)	(0.020)	
Pork Slaughterhouses			2.984**
			(1.414)
Observations	3038	3038	3038
Kleibergen-Paap F			5.967
A-R 95% Confidence Set			[1.13, ...]
Semi-Elasticity	0.071***		0.556**
	(0.017)		(0.264)
Panel B: 1880			
1880 Hogs (10,000's)	0.060***	0.046***	
	(0.021)	(0.013)	
Pork Slaughterhouses			1.293**
			(0.521)
Observations	3038	3038	3038
Kleibergen-Paap F			11.82
A-R 95% Confidence Set			[0.36, 2.87]
Semi-Elasticity	0.074***		0.241**
	(0.025)		(0.097)
Panel C: 1920			
1920 Hogs (10,000's)	0.049***	0.040***	
	(0.016)	(0.009)	
Pork Slaughterhouses			1.227***
			(0.414)
Observations	3038	3038	3038
Kleibergen-Paap F			18.05
A-R 95% Confidence Set			[0.42, 2.39]
Semi-Elasticity	0.085***		0.229***
	(0.029)		(0.077)
Panel D: 1948			
1948 Hogs (10,000's)	0.066***	0.056***	
	(0.021)	(0.016)	
Pork Slaughterhouses			1.180***
			(0.311)
Observations	3038	3038	3038
Kleibergen-Paap F			12.90
A-R 95% Confidence Set			[0.47, 1.98]
Semi-Elasticity	0.076***		0.220***
	(0.025)		(0.058)

Note: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Cluster-robust standard errors, by state, in parentheses. The table displays 2SLS regressions of pork slaughterhouses on contemporary truck traffic, using different years of historic hog populations as an instrument. Columns 1, 2, and 3 display the reduced form, first stage, and second stage respectively. All regressions use state X urban fixed effects, land area, rail miles, and crop production (corn grain and soybeans) as controls. Panel A uses 1840 hogs, Panel B uses 1880 hogs, Panel C uses 1920 hogs, and Panel D uses 1948 hogs. All panels show the Kleibergen-Paap first stage F-statistic for historic hogs. All panels show the corresponding Anderson-Rubin 95% confidence sets for the IV estimate, which are efficient for potentially weak instruments, as suggested by Andrews et al. (2019) for just-identified structural equations. All panels also show the corresponding semi-elasticity transformation for inverse hyperbolic sine transformations that is suggested by Bellemare and Wichman (2020).

Figure A.13



Note: Figure displays the robustness of the reduced form and two stage estimates to various issues. All estimates have been transformed so that they are interpretable as a semi-elasticity (Bellemare & Wichman, 2020) and are shown with 95% Wald confidence intervals. All regressions use state-urbanicity interacted fixed effects and the full set of controls and use standard errors that are clustered at the state level. The dashed lines represent the main point estimates from the reduced form and second stage respectively. In row 1, the first stage is over-identified by using every year of hog population that we observe. In row 2, the agriculture controls are changed from NASS variables (corn grain bushel and soybean bushel production) to County Business Patterns employment controls (grain and bean wholesale, support for crop production, support for animal production, and non-slaughter meat processing). In row 3, the RUCC codes are further disaggregated into urban (1-3), suburban (4-6), and rural (7-9) and then interacted with the state fixed effects. In row 4, counties that are above the 95th percentile in historic hogs are dropped.

Table A.6: 2SLS Estimates of Slaughterhouses on Consequences of Truck Traffic

	(1) Reduced Form	(2) First Stage	(3) Second Stage
Panel A: Fatal Crashes Dependent Variable:	IHS(Crashes)	Slaughterhouses	IHS(Crashes)
1945 Hogs (10,000's)	0.050*** (0.015)	0.035*** (0.010)	
Pork Slaughterhouses			1.443*** (0.442)
Observations	2991	2991	2991
Kleibergen-Paap F			12.53
A-R 95% Confidence Set			[0.69, 2.93]
Semi-Elasticity	0.076*** (0.022)		0.270*** (0.083)
Panel B: Roughness Index Dependent Variable:	IHS(IRI)	Slaughterhouses	IHS(IRI)
1945 Hogs (10,000's)	0.008 (0.006)	0.035*** (0.010)	
Pork Slaughterhouses			0.217 (0.188)
Observations	2991	2991	2991
Kleibergen-Paap F			12.53
A-R 95% Confidence Set			[-0.16, 0.74]
Semi-Elasticity	0.011 (0.009)		0.040 (0.035)
Panel C: Auto Repair Employees Dependent Variable:	IHS(Employees)	Slaughterhouses	IHS(Employees)
1945 Hogs (10,000's)	0.187*** (0.029)	0.035*** (0.010)	
Pork Slaughterhouses			5.345*** (1.276)
Observations	2991	2991	2991
Kleibergen-Paap F			12.53
A-R 95% Confidence Set			[3.17, 9.74]
Semi-Elasticity	0.282*** (0.044)		0.997*** (0.238)

Note: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Cluster-robust standard errors, by state, in parentheses. The table displays 2SLS regressions of pork slaughterhouses on the consequences of truck traffic, using historic hog population as an instrument. Dependent variables vary by panel. Columns 1, 2, and 3 display the reduced form, first stage, and second stage respectively. All regressions include state X urbanicity fixed effects, land area, non-passenger railway miles, contemporary corn grain bushel, and soybean bushel production as additional control variables. All panels show the Kleibergen-Paap first stage F-statistic for historic hogs. All panels show the corresponding Anderson-Rubin 95% confidence sets for the IV estimate, which are efficient for potentially weak instruments, as suggested by Andrews et al. (2019) for just-identified structural equations. All panels also show the corresponding semi-elasticity transformation for inverse hyperbolic sine transformations that is suggested by Bellemare and Wichman (2020).

Table A.7: Mediation Effects of Trucks on Crashes and Auto Repair Employment

Panel A: Fatal Crashes	
Total	1.439***
	(0.453)
Direct	0.049
	(0.062)
Indirect	1.376
	(0.897)
Observations	2991
First Stage F-Statistic (T on Z)	12.52
First Stage F-Statistic (M on Z | T)	5.252
Mediation Effect (% of Total)	95.59

Panel B: Auto Repair Employment	
Total	5.345***
	(1.277)
Direct	-0.029
	(0.239)
Indirect	5.358*
	(2.925)
Observations	2991
First Stage F-Statistic (T on Z)	12.52
First Stage F-Statistic (M on Z | T)	5.252
Mediation Effect (% of Total)	100.3

Note: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Cluster-robust standard errors, by state, in parentheses. This table applies the procedure from Dippel et al. (2021) to estimate how much of the effect of slaughterhouses on fatal crashes and automobile repair employees operates through the mediator of truck traffic. In Panel A, the outcome of interest is fatal crashes. In Panel B, the outcome of interest is automobile repair employment. Total is the same as in previous tables. Direct is the effect of slaughterhouses on the dependent variable that is a direct result of slaughterhouses. Indirect is the effect of slaughterhouses that operates through the mediator variable, truck traffic. Coefficients are not transformed to be interpreted as semi-elasticities.

B Hog Industry Overview

In order to help understand the research design, we explain the basic aspects of the hog industry. First, we review literature that establishes that live hogs are transported via truck. Next, we describe the reason slaughterhouses locate close to hog-raising areas. Finally, we explain factors that contributed to the vertical integration of the hog industry.

B.1 Trucks in The Pork Slaughter Industry

The preferred mode of transporting live hogs is trucks. Two main reasons to use trucks are to reduce financial loss from damaged goods and animal welfare (Food and Agriculture Organization of the United Nations, 2001).[30] Although most hogs are likely transported by truck to slaughter, there is a possibility pork products are transported from the slaughterhouse by transport modes other than trucks, such as rail (Bai et al., 2007, pg. 33).[31] To isolate the relationship between pork slaughterhouses and truck traffic, we control for the amount of non-passenger rail miles.

Trucks are favored to transport live hogs because it is less detrimental to meat quality than rail transport. Hogs are temperamental animals, easily stressed by changing environments.[32] In addition, pigs cannot stand and balance well while moving (Aradom & Gebresenbet, 2013), cannot regulate body temperature (Huynh, Aarnink, & Verstegen, 2005), and pigs easily get motion sickness (Randall & Bradshaw, 1998). Because of environmental stress, the quality of the pork meat has been shown to degrade as stress levels increase (Gajana, Nkukwana, Marume, & Muchenje, 2013).[33]

[30]Under US law, livestock are not allowed to be in a transport vessel for more than twenty-eight consecutive hours. For more temperamental livestock, such as hogs, constant confined conditions limit the consecutive hours of viable transport.

[31]Rail would be a substitute if hogs were moved by rail, instead of a truck. It would be a complement if pigs were trucked into slaughterhouses, then the processed meat was transported out of slaughterhouses via rail. To our knowledge, this relationship has not been explicitly studied yet, although some studies examine if personal transportation choices are complements or substitutes (e.g. Hall, Palsson, and Price (2018)).

[32]To ease the stress of hogs, some slaughter facilities have implemented rules which govern the truck routes to and around slaughterhouses. some slaughterhouses force trucks to take detours to avoid wait times at the slaughterhouse and to keep the truck moving so as to not cause stress for the hogs (Miranda-De La Lama, Villarroel, & María, 2014, pg. 11).

[33]When a hog becomes stressed, it leads to lower lactic acid production in the animal. The lower lactic acid production causes a higher pH in the meat; higher pH levels are associated with lower meat quality (Gajana et al., 2013).

B.2 Why Slaughterhouses Locate Close to Hogs

Slaughterhouses locate near hogs to reduce costs. There is a positive association between travel distance from farm to slaughter and hog mortality (Gosálvez, Averós, Valdelvira, & Herranz, 2006). As the transportation distance via heavy trucks increases, the mortality of hogs also increases. Pig deaths in transit are estimated to cost the US pork industry \$50 to \$100 million annually (Fitzgerald, Stalder, Matthews, Schultz Kaster, & Johnson, 2009, pg. 1156). If not dead from transit, stress and "damage" caused by long transport times decrease pork meat quality (Gajana et al., 2013; Guàrdia et al., 2005).

B.3 Evolution of the US Hog Industry since the 1940s

The hog industry has vertically integrated over the last 70 years. Throughout the 1990s, the pork industry saw rapid use of contracting production. The share of hog production under contract increased from about 18% in 1990 to about 28% in 1995, to almost 60% in 2000. (Key, 2004, pg. 255).

Several reasons exist for why the industry has become more vertically integrated; most relate to economies of scale. Factors that have changed include: industrialization leading to demand for factory-like development with highly specialized labor (Rhodes, 1995), advances in gene practices (Wang, Huang, & Zhao, 2017, pg. 2793), selective breeding led to shorter weaning and bigger litters (Kemp, Da Silva, & Soede, 2018), disease control (Chen, Madson, Miller, & Harris, 2012; Colomer, Margalida, & Fraile, 2020), and improved farm biosecurity practices (Pig Progress, 2015).[34] In sum, hog farms were housing bigger litters with higher survival rates. These advances lead to greater economies of scale and vertical integration followed.

B.3.1 Locational Persistence

In the US, hog farms and producers traditionally located close to corn farms because pigs eat corn (McBride & Key, 2013). Often, farmers would raise both corn and hogs to save on corn transport

[34] Hogs were traditionally bred to be large and produce fatty cuts of meat; advances in gene manipulation allowed the hog industry to cater to consumer demand for leaner cuts of pork (Wang et al., 2017, pg. 2793). The development of hog vaccines for H1N1 and other swine illnesses (Chen et al., 2012; Colomer et al., 2020) specifically decreased hog infection rates.

costs. This explains the large concentration of hogs in the Corn Belt region of the US as shown in Figure A.1.[35]

Over time, corn transportation became cheaper due to increased railroad construction and usage, causing hog producers to move out of traditional hog production areas. Also, the increasing amount of environmental and land use regulations in Corn Belt states pushed out less profitable hog production to other areas, including North Carolina and western states (Roe et al., 2002). Nevertheless, the Corn Belt still remains the key hog-producing region in the US today.[36]

The hog production that remained in the Corn Belt changed from small farms to larger, integrated operations. The integration increased capacity and decreased the number of individual operations. Between 1994 and 1999, "the number of U.S. hog farms fell by more than 50%, from over 200,000 to less than 100,000, while the hog inventory remained relatively stable." (Key, 2004, pg. 255) Despite farms leaving the region, in 2009, the Corn Belt still contained 76% of all feeder-to-finish farms across the United States Department of Agriculture (USDA)'s Agricultural Resource Management Survey.

[35]The "Corn Belt" in the US includes the states of Ohio, Indiana, Illinois, Iowa, and Missouri.
[36]The dispersion of activity can be seen in (Pork Checkoff, 2015, pg. 85).