The Social Costs of Trade: Death and Declining Distance*

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Abstract

We estimate the impact of international competition on suicide and stress related mortality in the United States. Our strategy uses product level Customs data to isolate "pure" transport cost shocks via hedonic regression. We use these plausibly exogenous transport cost shocks to instrument for variation in county level exposure to international competition. Our estimates suggest increased competition from abroad is met with lower rates of suicide as well as lower rates of mortality from causes associated with stress (heart attack, alcohol related disease, etc). To lend credibility to our empirical strategy, we demonstrate our results are robust to concerns regarding endogeneity of the transport cost shocks.

Keywords: Suicide; Mortality; International Trade;

International Exposure; Wellbeing; Health Economics

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1 Introduction

While the United States has traditionally been a vocal leader for increased international economic integration, recently political and economic voices have started to question the benefits, and in particular, the distribution of benefits, from increased globalization. In the most extreme form, arguments have been put forward that the U.S. should decrease its level of international integration going forward. On the academic side, most work in international economics has focused on the overall gains from trade although understanding the distributional consequences of international integration has been a topic of interest since at least Stolper and Samuelson (1941). In both cases however, the emphasis has been placed mostly on "pure" economic outcomes such as wages, employment, and prices.

The 2016 Presidential campaign saw both major party candidates espouse protectionist and anti-trade views, although the degree of emphasis differed. The Trans-Pacific Partnership (TPP) trade agreement was rejected by both parties, while candidate Trump ran on an aggressive anti-trade agenda which included promises to renegotiate or terminate NAFTA. Once in office, the Trump administration has put forward a variety of claims regarding the social ills associated with global integration.

The political language, while frequently exaggerated, is not completely divorced from recent empirical evidence. Autor et al. (2013), for example, find the integration of China into the world trading system lead to substantial manufacturing losses and local labor market disruptions. Magyari (2016) finds evidence contrary to Autor et al. (2013) upon taking the unit of analysis to be the firm rather than the establishment: firms conduct inter-industry reallocation to avoid exposure. Pierce and Schott (2016) similarly attribute large declines in manufacturing employment to Chinese entrance in to the WTO. Furthermore, Pierce and Schott (2019) consider the impact of Chinese integration on mortality outcomes in the US and find a significant increase in suicides in areas more exposed to Chinese trade.

In the present work, we follow this more recent development in the literature by considering the impact of increased globalization on social consequences in the United States. In particular, we consider the impact of increased international integration on mortality rates related to the so-called diseases of despair (suicide, poisoning, alcohol-related liver and pancreas deaths). Contra the political rhetoric and in contrast to the findings of Pierce and Schott (2019), we find that increased international integration, measured by US import transport costs, results in lower mortality. Our findings are consistent with the more traditional view of trade as productivity enhancing. Wealth, trade, and health still appear to be strongly linked for the U.S. In this paper we will refer to increasing "international integration" or increasing "international exposure", which we use interchangeably in reference to declining import transportation costs.

To measure international integration, we estimate industry transport price indices from US customs data for the years 1997-2015. Using hedonic regression and controlling for observable industry, product, and journey characteristics, we estimate yearly changes in transportation costs which are then used to construct an industry-specific price index. These industry price indices capture differences across industries and over time, and form the heart of our measure of enhanced integration. These indices are based on the work on hedonic pricing estimation by Triplett (2004).

As the cost of shipping a product declines, imports become more competitive with domestic industries, reducing the market power of domestic firms and lowering the price of goods for consumers. Declining trade costs are thus productivity enhancing, leading to more efficient allocation of resources in the long run. Melitz (2003) develops the work-horse model of heterogeneous firms in international trade, and shows that declines in trade costs results in a reallocation of resources within an industry away from the least productive firms and towards to most productive firms. More recent work in this vein by Arkolakis et al. (2012), Melitz and Redding (2014), and Feenstra and Weinstein (2017) has focused on measuring aggregate welfare gains from trade using insights from theory to combine (appropriate) aggregate statistics and estimates on import elasticities.

However, as Viner (1937) suggested (and Samuelson (1971), Jones et al. (1971) showed more formally), the existence of aggregate gains from trade does not preclude distributional losses for some. An extensive literature on the impact of trade on earnings inequality is summarized by Goldberg and Pavcnik (2007), who focus primarily on the failure of Stolper-Samuelson empirically.

Trade and expenditure inequality is less well discussed, with the notable exception of Fajgelbaum and Khandelwal (2016) who show how to estimate distributional consequences using aggregate expenditure data combined with trade elasticities estimated with non-homothetic preferences. They find that trade typically tends to favor lower income consumers since trade reduces the cost of tradables, which make up a larger share of the budget for these consumers. Burstein and Vogel (2017) and Galle et al. (2017) provide alternative approaches to quantifying both aggregate and distributional effects of trade. Here we consider the possibility that geographic areas that are particularly exposed to foreign competition may experience distributional losses, resulting in deteriorating measures of well-being and higher mortality.

To convert our industry level transport cost indices into geographic measures of exposure to globalization, we create county-specific measures based on initial manufacturing employment intensity. Our county exposure variable is a fixed weighted average of manufacturing industry transportation price indices, which captures the fact that counties that have more employment in industries that face steeper declines in transportation costs are therefore more exposed to competition from international trade. To address possible measurement error in the trade data on which the transport cost indices are built, we instrument for the transport cost index in a given county with either the average transport cost index in other counties within the state, or the average county transport cost indices in counties in other states.

We then take these time-varying county exposure measures and study the impact of international competition on health outcomes.We focus on deaths of despair: deaths related to suicide, alcohol, and stress related cardiovascular events; all of which may be consequences of coping with stress from changes in economic circumstances. The major takeaway from our estimates is that international integration has a positive impact on health outcomes in each county. We find that overall suicide rates, poisoning suicide rates, and stress-related heart disease death rates all decrease as a county becomes more internationally integrated. Of the causes of death we investigate, we find the largest impact is on stress related heart disease. Also, we find that the measurement error from the trade data provides attenuation bias so significant in OLS estimates that this conclusion may not be reached. Instrumental variable estimates of the impact of international integration on death rates differ by an order of magnitude in comparison to OLS estimates of the same impact.

The rest of the paper proceeds as follows. Section 2 discusses our data and the strategy for isolating pure transportation cost shocks. Section 3 describes our general identification strategy and preferred specifications. Section 4, while brief, demonstrates rubstness of our result. In section 5, we provide concluding remarks.

2 Data

The first step in our analysis is to define a measure of the cost of distance. We rely on the Foreign Trade Data Products from the U.S. Census Bureau, as maintained by Peter Schott. Collected by U.S. Customs, this data contains information on the quantities, dollar values, weights, and shipping costs for all imports disaggregated by HS-10 code, source country, port of entry, district of unlading, method of shipping, and year. Using the methods outlined in Triplett (2004), we construct a transport price index for each of the 4 digit NAICS industry. The estimating equation is given by:

$$\begin{aligned} ln(p_i^t) =& \alpha_0 + \alpha_1 M_i^t + \alpha_2 ln((\frac{KG}{V})_i^t) + \alpha_3 ln(KG_i^t) + \alpha_4 M_i^t \times ln((\frac{KG}{V})_i^t) \\ &+ \alpha_5 M_i^t \times ln(KG_i^t) + \alpha_6 D_i + \underbrace{b_i^{t+1} T_i^{t+1}}_{\text{isolates pure transport cost shock}} + \epsilon_i^t \end{aligned} \tag{1}$$

(1) is run separately by grouping all products in each NAICS industry group (4 digit NAICS) in adjacent years denoted in superscript by t and $t+1$. In each regression, the dependent variable is the log shipping costs per unit for all HS-10 products in concordance with NAICS industry i. A brief discussion of the various control variables follows below.

The coefficient of interest in (1) is b_i^{t+1}, which corresponds to the time dummy that indicates the latter of adjacent years. This coefficient isolates the (log of) the "pure" unit transportation price change for the industry between years t and $t+1$. We refer to this as a pure price change because it captures the variation in unit transportation costs after controlling for both observable and unobservable characteristics of the product, and after controlling for many characteristics of the journey itself.

The weight-to-value ratio is given by $\frac{KG}{V}^t_i$, which contains information about the quality of the good and acts as a key determinant in sourcing and mode of transportation decisions. Total weight being transported is KG_i^t, is included as a control for increasing or decreasing returns in shipping. Both weight and weight-to-value are interacted with mode of transportation, M_i^t, to allow for differential effects by mode of transportation. D_i includes a full set of fixed effects for HS Code, source country, port of entry, district of unloading, as well as a trilateral HS code-source country-mode of transportation fixed effect.

After running these regressions by 4 digit NAICS industry group, we are left with a dataset of time-dummy coefficients, b_i^{t+1}. These are combined to form industry-specific, time varying transportation cost indices over the years 1997 to 2015, normalized to 100 in 1997. Let $\beta_i^t = 100 * \frac{b_i^t}{b_i^{1997}}$ represent the value of this index for industry group i in period t. Figure 1 graphs time-series variation in these transportation price indices for the 3 digit NAICS subsectors.

To map these industry level transportation prices into county-level measures of exposure to declining transportation prices, we rely on county-level employment at the 4 digit NAICS industry group as reported by the U.S. Census County Business Patterns (CBP). To deal with missing and suppressed data, we use the imputation routine employed in Autor et al. (2013) as discussed in their online appendix. Doing so leaves us with total employment, L_{ict} in 4 digit NAICS industry group i, for county c in $t = 2000$. Let $c = 1, \ldots, C$ index the population of counties in the CBP data, and $i = 1, \ldots, J$ index the 4 digit NAICS industry groups. For each county in the year 2000, we construct the county share of national employment in industry i as $s_{ic} = \frac{L_{ict}}{\sum_{c=1}^{C} L_{ict}}$.

To measure variation in the exposure to trade as a result of declining transportation costs, we map the industry-level transport price indices to county-level transport price indices using a weighted average. Let $CTPI_{ct}$ represent the transport price index in county c for year t, while j represents an index for the industry groups present in this county.

$$CTPI_{ct} = \sum_{j} s_{jc} \beta_j^t \tag{2}$$

Our data on county level overall suicide rates and alcohol related liver disease come from the Center for Disease Control's mortality records. Specifically, we use the Public-Use files for Multiple-Cause-of-Death (MCD) records. Data are drawn from all death certificates filed in the United States for the period 1999-2015. Causes of death in the MCD are classified according to International Classification of Disease 10^{th} edition (ICD-10) standards. Use of the CDC mortality data has become increasingly popular in economics contexts, ranging from international trade Pierce and Schott (2019), to gun policy and firearm suicide Vitt et al. (2018), pain epidemics Case and Deaton (2015), and recessions Gordon and Sommers (2016).

For external causes of death, we collect county level data on the suicide rate among all intentional self harm causes, as well as the suicide rates from particular causes like poisoning and firearm suicide. For internal causes of death related to stress and coping, we collect heart disease death rates, specifically the deaths per 100,000 for myocardial infarction (heart attack), cardiomyopathy, and sudden cardiac arrest. Similarly, we collect death rates for alcohol related diseases, by which we mean alcohol related liver and pancreas disease. Figure 2 plots the average suicide rate across counties against the (declining) county transport price index.

To replicate the controls in Pierce and Schott (2019), we collect county-level data on the number of veterans and the number of people without any college education from the 2000 American Community Survey. We combine these with intercensal population estimates in order to create the share of county population with veteran status and the share of the county population without any college education. Additionally, from the 2000 census we collect information on the median income within the county.

3 Empirical Analysis

To motivate our empirical strategy, we initially consider only the graphical evidence. Figure 2 shows the evolution of transport costs incurred with importing along with the evolution of suicide rates (by all methods) over the last 18 years. The import transport price index in the left panel tracks the costs incurred with shipping a single unit of various HS-10 products, averaged over industries within a year. We note that in this figure, there is a sharp decrease in transport costs over the late 90s into the early 2000s, broken by a large spike in transport costs during the early-mid 2000s, and a consistent decrease in from roughly 2005 until 2015. The sharp increase in transport prices coincides with a temporary decline in suicide rates.

The purpose of an identification strategy is to show that caution must be taken before drawing sweeping conclusions from simple charts like in Figure 2. Determining the net effect of exogenous variation in transportation costs on health outcomes is necessary on account of how import exposure could have differing effects on particular channels connected to health and well-being. On the one hand, areas that compete with imports could experience declines in employment and therefore real income. The stress associated with this could result in higher rates of mortality from stress related disease, and of course in higher suicide rates. On the other hand, increased global integration means lower prices across the board, which is an increase in real income. Freeman (2003) estimates the income elasticity of demand for health-care and finds evidence it is a normal good. The implication of this result is that the increase in disposable income that may result from increased international integration may afford people the ability to take better care of themselves and their families.

Rather than rely on conjecture and anecdotes, and to get an initial sense of the strength of the relationship between suicide rates and exposure to trade, we consider an empirical strategy without instruments as specified in (3)

$$\text{Death Rate}_{ct} = \beta_c + \beta_1 CTPI_{ct} + \mathbf{Controls}_{ct}\beta + \epsilon_{ct} \tag{3}$$

where Death Rate_{ct} is the number of deaths for a particular category of mortality per 100,000 population in county c for year t. $CTPI_{ct}$ represents the county transport price index as discussed in the previous section. Included in controls are interactions of the year with the initial year population share without college, veteran share of population, and the median income. Respectively, each of these allow for the possibility that changes in technology may displace workers without college degrees, that the wars in the Middle East may increase suicide rates in the veteran population, and that growing income allows for households to have better access to medical and mental health care.

We present panel data estimates of (3) in Table 2, where we regress population suicide rates on the county transport price index. The observation in this table is that a naive specification without county fixed effects, as in column 1, would suggest that declining transportation costs would be met with higher suicide rates. This anti-trade result could easily be misleading if the researcher fails to use a more credible identification strategy that accounts for time invariant unobserved heterogeneity across counties. In moving to column 2, we note that this anti-trade result is being driven by time invariant characteristics of counties that correlate with suicide rates, as statistical confidence regarding the effect is eroded with the inclusion of county fixed effects in column 2.

In Table 3, we briefly focus our attention on other suicide and stress related death rates. In columns 1-3, we see no significant relationship between county exposure to trade and the death rates for poisoning suicide, firearm suicide, and heart disease. In column 4 we note a small positive coefficient on alcohol related disease deaths.

There are a few sources of endogeneity that warrant a strategy usign instrumental variables. We believe the most concerning source is the high probability of measurement error in the CTPI stemming from general measurement errors recognized in the import data as discussed in GAO (1995). To the degree that the possible measurement error is fixed over time, or follows a secular trend, our county and year fixed effects would solve the measurement error problem. If the measurement error is more idiosyncratic in nature, our instrument discussed below will generate the necessary exogenous variation to overcome possible attenuation bias.

Another possibility is that of omitted variable bias possibly from shipping logistics or shipping power as discussed in Hummels et al. (2007). Consider that counties with heavy representation in some industry in demand will have high employment in that industry, and that high employment in particular industries could mean significant influence over shipping logistics or infrastructure investments to improve shipping to the area. It could also be the case that counties with heavy representation in particular industries may be host to successful firms that have the ability to invest in logistics innovations that will reduce shipping costs in the industry.

With these concerns in mind, our preferred specification below estimates the relationship between variation in suicide rates while controlling for additional factors that may influence suicide rates and be correlated with our instrument.

$$\begin{aligned}\text{Death Rate}_{ct} = \theta_0 + \alpha CT\hat{P}I_{ct} \\ + \mathbf{Controls}_{ct}\beta_z \\ + \mu_c + \mu_t + \epsilon_{ct}\end{aligned} \tag{4}$$

where the dependent variable is the number of deaths from a particular cause per 100,000 population in county c for year t. Our variable of interest is $CT\hat{P}I_{ct}$. Included in $\mathbf{Controls}_{ct}$ are the interactions of the linear trend with various initial year (2000) county characteristics as discussed previously. To generate exogenous variation in the county transport price index, we consider the following first-stage regression

$$\begin{aligned}\text{CTPI}_{ct} = \pi_0 + \pi_1\overline{CTPI_{-c,t-1}} \\ + \mathbf{Controls}_{ct}\delta \\ + \mu_c + \mu_t + r_{ct}\end{aligned} \tag{5}$$

where $\overline{CTPI_{-c,t-1}}$ refers to the average of $CTPI$ in year $t-1$ for counties in state s other than county c. This is a Hausman (1996) style instrument in the sense that we use information about the transport price index in other counties to instrument for the transport price index in a given county. The validity of this approach is discussed in further detail below.

Our identification relies on the idea that any unobserved confounding factors that are common across counties are likely to be controlled for by the combination of the county and year fixed effects. The county fixed effects would control for time invariant common confounding factors, while the year fixed effects would control for all time varying confounding effects common across counties. Remaining sources of bias from measurement error or omitted variables must be idiosyncratic to county c and time varying.

Given the measurement error in the trade data stems from clerical entry errors, this source of error is likely to be independent across counties. To this degree this is true, the average of county transport indices from all the other counties in state s except county c would qualify as an excludable instrument. Furthermore, since counties in the same state are likely to share similar aspects of marginal transport costs, the external county instrument should not suffer from the weak instruments problem. In the robustness checks section, we explore threats to our identification strategy and offer an alternative specifications to check the robustness of our results.

Our initial instrumental variable result is presented in column 2 of Table 4, where the OLS result is presented on column 1. The takeaways from comparing these columns are that the IV estimates are significant and positive, whereas the OLS estimates are not significantly different from zero. The fact that the estimate is positive suggests a "pro-trade" result, meaning that as the county becomes more exposed to foreign competition through declining transport prices, we see that suicide rates also decline. This would be the result of the typical gains from trade story: while employment in some exposed industries may suffer, participating in global markets means lower prices, lower prices mean more disposable income available for leisure and health care.

We can place some economic significance on the point estimate 0.18 in column 2 of Table 4 in the following way. Consider the evidence in Table 1 that the average county is experiencing declining transport prices (average $\Delta CTPI < 0$). Given this secular decrease in transport prices, imagine the county experiences an import exposure shock that brings it from the 75^{th} percentile of the county transport price index to the 25^{th} percentile of the county transport price index.

According to the summary statistics describing CTPI in Table 1, this would mean a change in CTPI of -2.36 (from 0.22 to 2.58). Consequently, we would expect the suicide rate to change by $-0.42(= -2.36 * 0.18)$ deaths per 100,000 population, and is significant at the 95% confidence level.

In Table 5 we compare the OLS versus IV estimates of the impact of exposure on suicides by firearm and poisoning. Comparing columns 1 and 2, we see that the IV estimate of the impact of CTPI on firearm suicides is statistically insignificant. We observe that the IV estimate of the impact of CTPI on poison suicide rates in column 4 is positive and significant, compared to the insignificant OLS estimate in column 3. suggesting that as the county transport price index falls, simultaneously the county experiences fewer intentional overdoses from pills, alcohol, noxious gases, etc. Though the effect is statistically significant, the point estimate is small.

We investigate stress and coping related causes of death in Table 6. Comparing columns 1 and 2, we see that the significance of the OLS point estimate in column 1 does not hold for the IV estimate in column 2. Column 3 presents OLS estimates of the effect of import exposure on stress related heart disease death rates, while column 4 presents the IV estimates. The observation across these is that the OLS estimate is insignificant (and relatively small), while the IV estimate is significant and relatively large. Among the various causes for mortality presented in Table 1, there is an order of magnitude difference in the death rates between heart disease and the other causes.

To understand the economic importance of the point estimate in column 4 of Table 6, again consider a shock that decreases the county transport price index from the 75^{th} percentile to the 25^{th} percentile. Our estimates suggest the stress related heart disease death rate would change by $-5.9(= -2.36 * 2.5)$ deaths per 100,000 population. Evaluated at the mean stress related heart disease death rate, this would constitute an almost 5% reduction in the average heart disease death rate (120 per 100,000).

4 Robustness Checks

In this section, we explore possible threats to identification through failure of the exclusion restriction. One such possibility is the existence of linkages in shipping logistics and shipping market power across counties. There is little reason to believe that the unobserved effect of such linkages is independent across counties. To the degree that these linkages act as determinants of suicide or disease mortality, they pose a threat to identifying our effect of interest. While we do not find this argument particularly convincing, that shipping logistics act as a confounding factor for both suicide rates and transport price indices, we investigate an alternative instrument for robustness against this story.

To motivate a different instrumental variable, we will assume that the state and county level investment decisions that may generate these linkages are clustered within the state, but independent across states. To the degree that this is true, the average value of CTPI in counties in external states would be a valid instrument. The idea is that other states will share similar aspects of marginal import transport prices, and that the spatial aspect of looking at other states will preclude the possibility of the aforementioned spatial linkages introducing bias.

Table 7 provides the result of estimating (4) with a different first stage where CTPI in county c for year t is instrumented with the current and one period lag of of average CTPI in other states. We find that our primary result, that increasing international exposure (meaning decreasing CTPI) has a positive impact on health via falling death rates from suicide, alcohol related diseases, and stress related heart diseases. A Hansen J Test of overidentifying restrictions suggests fails to reject the null, suggesting that our overidentifying restrictions are valid.

5 Conclusions

Our investigation examined the relationship between county-level suicide and disease of despair death rates and international exposure. The story we propose is simple: if trade is indeed welfare enhancing, then it should be reflected in health outcomes, which have well established ties to economic outcomes. We calculate international exposure as an employment weighted average of industry import transportation price shocks for each county. We used these industry transportation prices to create an index of county import exposure. To address measurement error, we instrument for county import exposure using the average of county import exposure in other counties. Our estimate of the relationship between import exposure and mortality relies on an identification strategy that partials out effects of time invariant county characteristics, and uses plausibly exogenous variation in transportation price shocks.

Our results suggest that exposure to declining transportation prices is associated with a decrease in mortality from suicides, alcohol related diseases, and stress related heart disease. These results are consistent with the view that trade is welfare enhancing, and stands in defiance of similar trade impact estimates derived using strategies based on difference-in-difference. We find this pro-trade result is robust to the use of alternative instruments that rely on a spatial dimension to add confidence to the excludability of the instrument.

We believe the most important policy implication of this research is the statement it makes about the consequences of inward oriented trade policies. Our estimates suggest that if the U.S. Government were to take action based on the idea that protectionism is beneficial to our economy, mortality within the United States would rise. Suppose the proposed policy would have the same magnitude effect as a 20% increase in trade costs for the average county, but impacts all 3,007 counties. Our estimates suggest this policy would cause an additional 322 ($= \underbrace{\text{20\% }\Delta\text{CTPI for average county}}_{=0.576} \times \underbrace{\hat{\alpha}}_{=0.186} \times 3,007$ counties) suicides at the margin, every year. Similarly, for stress related heart disease, we would expect the policy would cause an additional 4,330 ($= \underbrace{\text{20\% }\Delta\text{CTPI for average county}}_{=0.576} \times \underbrace{\hat{\alpha}}_{=2.5} \times 3,007$ counties) deaths at the margin, every year.

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6 Appendix

6.1 Figures

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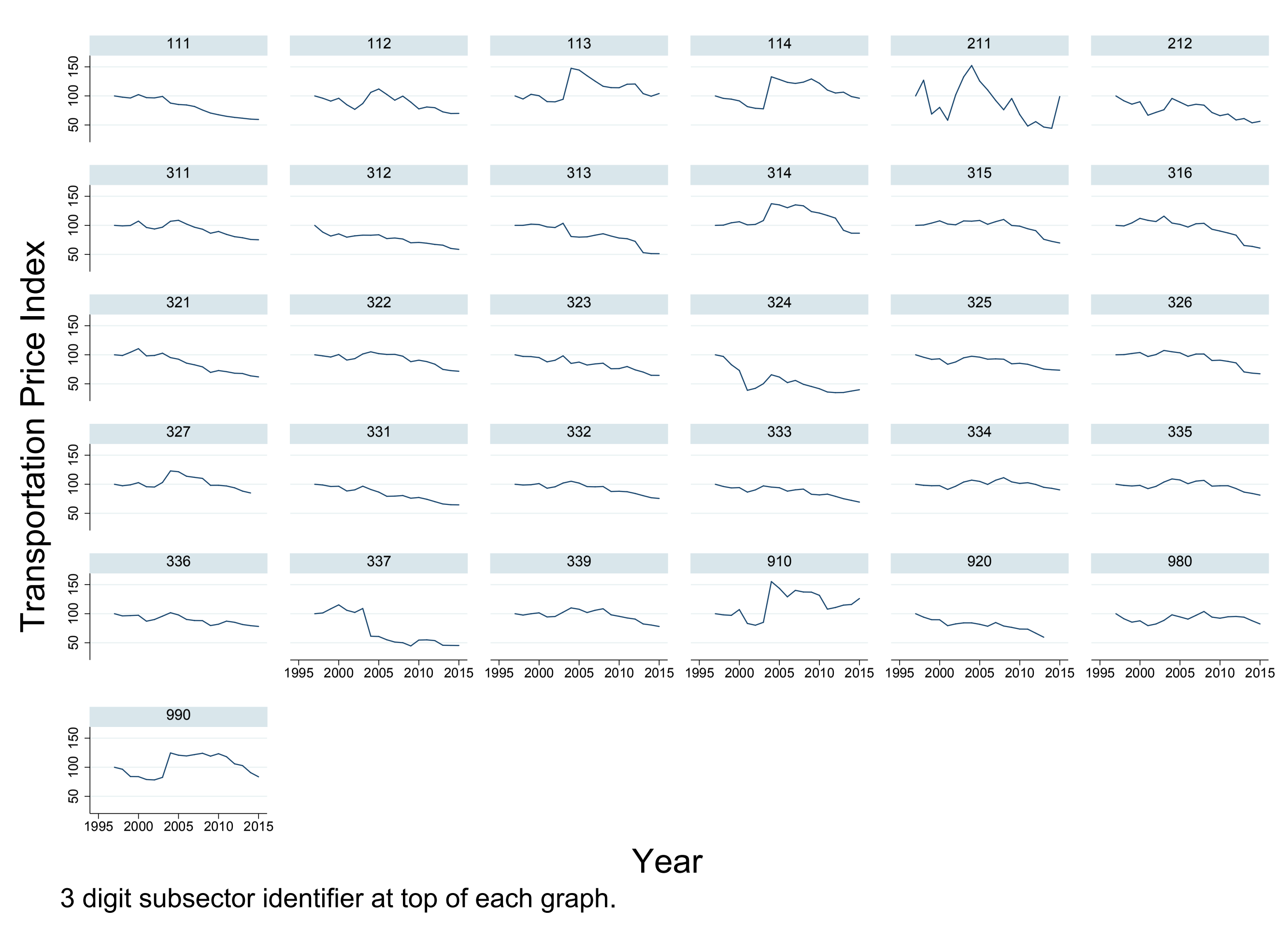

Figure 1: Graphs of time varying pure transport price changes, normalized to 100 in for year 1997.

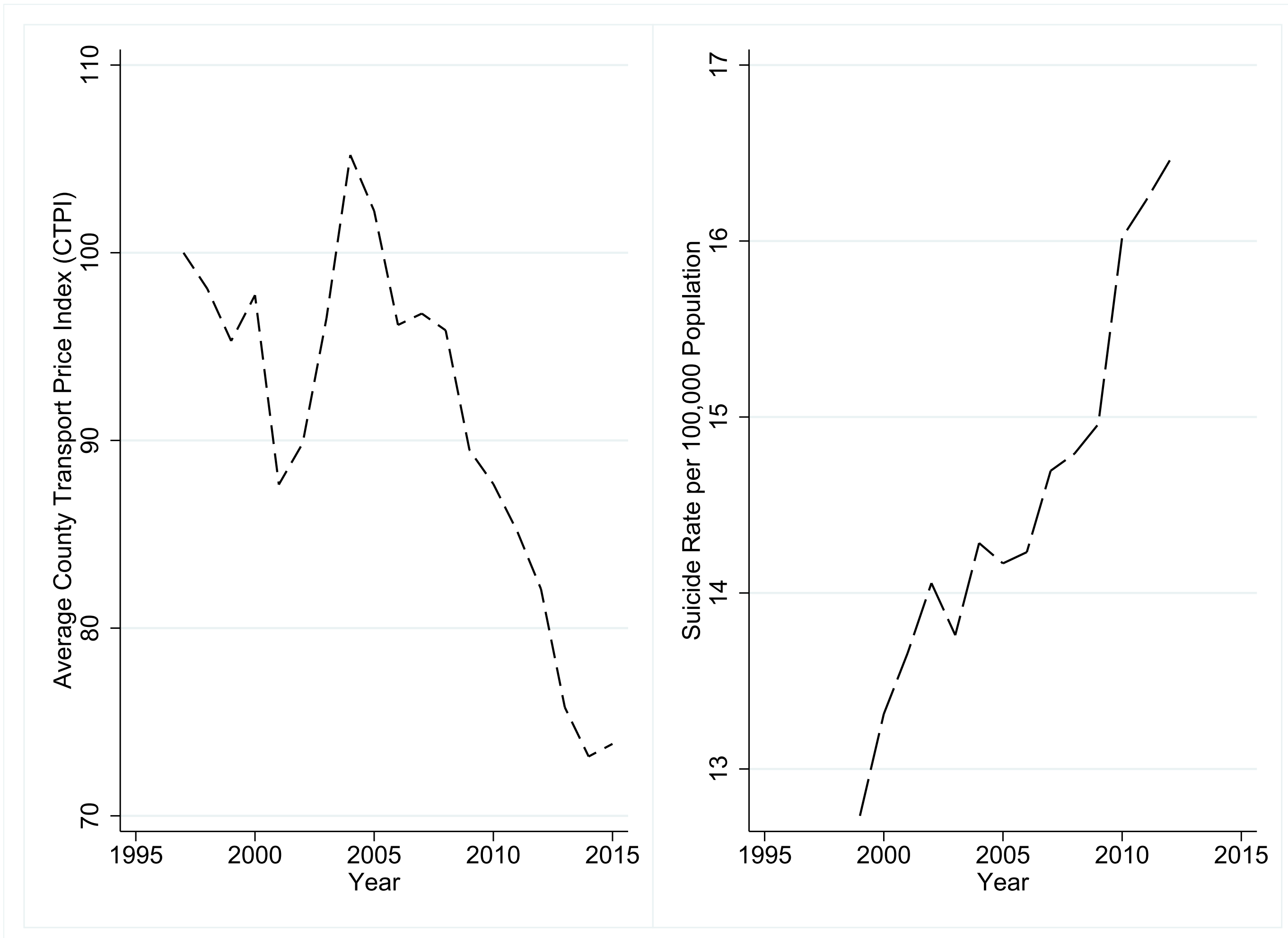

Figure 2: Left panel plots the average of the County Transport Price Index (CTPI) across counties in each year. Right panel plots the average suicide rate across counties according to CDC Multiple Cause of Death data.

6.2 Tables

(Starting on next page)

Table 1: Summary Statistics

	(1)				
	mean	min	max	p25	p75
County Transport Price Index (CTPI)	2.88	0.00	355.45	0.22	2.58
Δ CTPI	-0.02	-29.10	48.61	-0.05	0.02
Population Suicide Rate	14.65	2.13	163.71	10.20	17.37
Population Firearm Suicide Rate	8.21	0.59	55.81	5.07	10.10
Population Poisoning Suicide Rate	3.05	0.45	15.02	1.94	3.81
Population Alcohol Related Disease Rate	8.09	0.82	163.60	4.14	9.76
Population Heart Disease Death Rate	125.90	12.83	974.25	78.76	156.99
Median Income	20150.53	5982.00	41029.00	17511.00	21783.00
Population Share Without College	73.85	55.10	90.10	69.85	77.90
Veteran Share of Population	13.99	3.30	39.10	12.20	15.50

Table 2: OLS of Population Suicide Rate on CTPI

	(1)	(2)	(3)	(4)
	Population Suicide Rate	Population Suicide Rate	Population Suicide Rate	Population Suicide Rate
County Transport Price Index	-0.102**	-0.0536	0.00791	0.00875
	(0.0429)	(0.0395)	(0.00933)	(0.00951)
Year × Population Share Without College				-0.00606*
				(0.00316)
Year × Veteran Share of Population				0.00728*
				(0.00394)
Year × Median Income				0.00000200
				(0.00000241)
Instruments	None	None	None	None
Fixed Effects	None	County	County, Year	County, Year
Std. Error	State Cluster	State Cluster	State Cluster	State Cluster
Observations	10393	10393	10393	10393

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$, **** $p < 0.001$

Table 3: OLS Population Death Rates on CTPI

	(1) Population Poisoning Suicide Rate	(2) Population Firearm Suicide Rate	(3) Population Heart Disease Death Rate	(4) Population Alcohol Related Disease Rate
County Transport Price Index	5.32e-08	0.00429	0.160	0.0361***
	(3.26e-08)	(0.00604)	(0.133)	(0.0113)
Year × Population Share Without College	-2.04e-08	-0.000517	-0.0484*	-0.0375****
	(1.73e-08)	(0.00167)	(0.0264)	(0.00696)
Year × Veteran Share of Population	-1.55e-08	0.00864***	-0.0750**	-0.0207**
	(1.51e-08)	(0.00303)	(0.0300)	(0.00915)
Year × Median Income	1.16e-11	0.00000178	0.0000269	-0.0000183***
	(1.49e-11)	(0.00000140)	(0.0000244)	(0.00000585)
Instruments	None	None	None	None
Fixed Effects	County, Year	County, Year	County, Year	County, Year
Std. Error	State Cluster	State Cluster	State Cluster	State Cluster
KP Stage 1 F stat	N/A	N/A	N/A	N/A
Observations	2012	6008	35671	4340

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$, **** $p < 0.001$

Table 4: Second Stage Regression of Population Suicide Rates on CTPI

	(1) Population Suicide Rate	(2) Population Suicide Rate
County Transport Price Index	0.00875	0.186**
	(0.00951)	(0.0917)
Year × Population Share Without College	-0.00606*	-0.00564
	(0.00316)	(0.00350)
Year × Veteran Share of Population	0.00728*	0.00778**
	(0.00394)	(0.00385)
Year × Median Income	0.00000200	0.00000332
	(0.00000241)	(0.00000254)
Instruments	None	Lagged External County CTPI
Fixed Effects	County, Year	County, Year
Std. Error	State Cluster	State Cluster
KP Stage 1 F stat	N/A	41.3
Observations	10393	9770

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$, **** $p < 0.001$

Table 5: OLS versus IV Regressions of Population Firearm and Poison Suicide Rates on CTPI

	(1) Population Firearm Suicide Rate	(2) Population Firearm Suicide Rate	(3) Population Poison Suicide Rate	(4) Population Poison Suicide Rate
County Transport Price Index	0.00429	0.0542	0.00532	0.0405**
	(0.00604)	(0.0499)	(0.00326)	(0.0195)
Year × Population Share Without College	-0.000517	-0.000236	-0.00204	-0.00186
	(0.00167)	(0.00169)	(0.00173)	(0.00183)
Year × Veteran Share of Population	0.00864***	0.0103***	-0.00155	-0.000481
	(0.00303)	(0.00308)	(0.00151)	(0.00251)
Year × Median Income	0.00000178	0.00000292**	0.00000116	0.00000135
	(0.00000140)	(0.00000145)	(0.00000149)	(0.00000153)
Instruments	None	Lagged External County CTPI	None	Lagged External County CTPI
Fixed Effects	County, Year	County, Year	County, Year	County, Year
Std. Error	State Cluster	State Cluster	State Cluster	State Cluster
KP Stage 1 F stat	N/A	83.1	N/A	79.1
Observations	6008	5616	2012	1903

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$, **** $p < 0.001$

Table 6: OLS versus IV Regressions of Population Disease Death Rates on CTPI

	(1)	(2)	(3)	(4)
	Population Alcohol Related Disease Rate	Population Alcohol Related Disease Rate	Population Heart Disease Death Rate	Population Heart Disease Death Rate
County Transport Price Index	0.0361***	0.340	0.160	2.500**
	(0.0113)	(0.215)	(0.133)	(1.179)
Year × Population Share Without College	-0.0375****	-0.0364****	-0.0484*	-0.0435
	(0.00696)	(0.00633)	(0.0264)	(0.0271)
Year × Veteran Share of Population	-0.0207**	-0.0212***	-0.0750**	-0.0620*
	(0.00915)	(0.00736)	(0.0300)	(0.0317)
Year × Median Income	-0.0000183***	-0.0000248****	0.0000269	0.0000238
	(0.00000585)	(0.00000572)	(0.0000244)	(0.0000253)
Instruments	None	Lagged External County CTPI	None	Lagged External County CTPI
Fixed Effects	County, Year	County, Year	County, Year	County, Year
Std. Error	State Cluster	State Cluster	State Cluster	State Cluster
KP Stage 1 F stat	N/A	69.1	N/A	140.1
Observations	4340	4106	35671	32988

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$, **** $p < 0.001$

Table 7: FEIV Regression Death Rates on CTPI Using Alternative Instrument

	(1)	(2)	(3)	(4)	(5)
	Population Suicide Rate	Population Firearm Suicide Rate	Population Poisoning Suicide Rate	Population Alcohol Related Disease Rate	Population Heart Disease Death Rate
County Transport Price Index	0.124**	-0.0275	0.0284**	0.197***	2.560**
	(0.0543)	(0.0303)	(0.0114)	(0.0616)	(0.984)
Year × Population Share Without College	-0.00572	-0.000458	-0.00205	-0.0379****	-0.0435
	(0.00349)	(0.00160)	(0.00183)	(0.00658)	(0.0271)
Year × Veteran Share of Population	0.00765*	0.00996***	-0.000679	-0.0218***	-0.0619*
	(0.00385)	(0.00307)	(0.00227)	(0.00805)	(0.0313)
Year × Median Income	0.00000344	0.00000324**	0.00000153	-0.0000238****	0.0000239
	(0.00000250)	(0.00000150)	(0.00000152)	(0.00000631)	(0.0000252)
Instruments	Lag(0/1) External State CTPI	Lag(0/1) External State CTPI	Lag(0/1) External State CTPI	Lag(0/1) External State CTPI	Lag(0/1) External State CTPI
Fixed Effects	County, Year	County, Year	County, Year	County, Year	County, Year
Std. Error	State Cluster	State Cluster	State Cluster	State Cluster	State Cluster
KP Stage 1 F stat	202.52	595.17	392.69	286.55	50.62
Observations	9770	5616	1903	4106	32988

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$, **** $p < 0.001$