THEMA Working Paper n°2020-04
CY Cergy Paris Université, France

The Medium Run impact of Non Pharmaceutical Interventions. Evidence from the 1918 Influenza in US cities

Guillaume Chapelle

May 2020

The Medium Run impact of Non Pharmaceutical Interventions. Evidence from the 1918 Influenza in US cities [*]

Guillaume Chapelle [†]

First Version April, 11th 2020, this Version May, 1st, 2020

Abstract

This paper uses a difference in differences framework to estimate the causal impact on the mortality rate of Non Pharmaceutical Interventions (NPIs) used to fight pandemics. The results suggest that NPIs such as school closures and social distancing introduce a trade-off. While they can lower the fatality rate during the peak of the pandemic, they also reduce the herd immunity and significantly increase the death rate in subsequent years. There is no significant association between the implementation of NPIs and cities' growth.

JEL Code: I18, H51, H84

---

[*] The author acknowledges the support from ANR-11-LABX-0091 (LIEPP), ANR-11-IDEX-0005-02 and ANR-17-CE41-0008 (ECHOPPE). I thank Bernard Cohen, Sarah Cohen, Jean Benoît Eyméoud, Philippe Martin, Etienne Wasmer and Clara Wolf for their helpful comments. The English was edited by Bernard Cohen that I thank particularly. All errors remain mine.

[†] CY Cergy Paris Université, THEMA, CNRS, F-95000 Cergy, France and Sciences Po, LIEPP, Paris, email: gc.chapelle@gmail.com; guillaume.chapelle@sciencespo.fr; guillaume.chapelle@cyu.fr

1 Introduction

Since the emergence of the global Covid-19 pandemic, a growing stream of contributions has sought to inform policy makers by analyzing past pandemics. In this context, the 1918 flu might offer an interesting opportunity to evaluate the potential impact of pandemics on economic activity (Barro, Ursúa, and Weng 2020) and the potential benefits of Non Pharmaceutical Interventions (NPIs) such as school closures and social distancing (Correia, Luck, and Verner 2020).

My first contribution is summarized in Figure 1. I estimate with a difference in differences approach the impact of Non Pharmaceutical Interventions to fight against pandemics on the aggregate death rate. I show that cities that responded more aggressively and rapidly to the 1918 pandemic with NPIs managed to decrease the death rate in 1918. However, these cities also ended with relatively higher mortality levels in the subsequent years, in particular when the intervention was long. The net benefit of Non Pharmaceutical Interventions thus seems smaller in terms of mortality. One potential explanation would be the lower immunity of the population generated by these measures making these cities more vulnerable during the following years. Indeed, the subsequent influenza epidemics, with the exception of avian influenza, have been caused by descendants of the 1918 virus (Taubenberger and Morens 2006) up to 1977 (Fine 1993). This finding seems to support that herd immunity[1], as initially advocated in Fox et al. (1971), allows to decrease the spread of influenza. Indeed, Fine (1993) reports that many epidemiological papers argued that herd immunity might be a convenient way to decrease the spread of influenza these include St Groth (1977) and Fine (1982).

I then investigate the impact of NPIs on cities' demographic structure and growth. Unsurprisingly in light of their limited impact on the death rate, I find no impact on their population growth or even on the share of population belonging to the most affected cohort. Moreover, a careful investigation of the long run dynamics of the manufacturing sector does not allow to establish any causal link of NPIs on economic growth given that cities that adopted longer NPIs had different economic dynamics (pre-trends) before 1909.

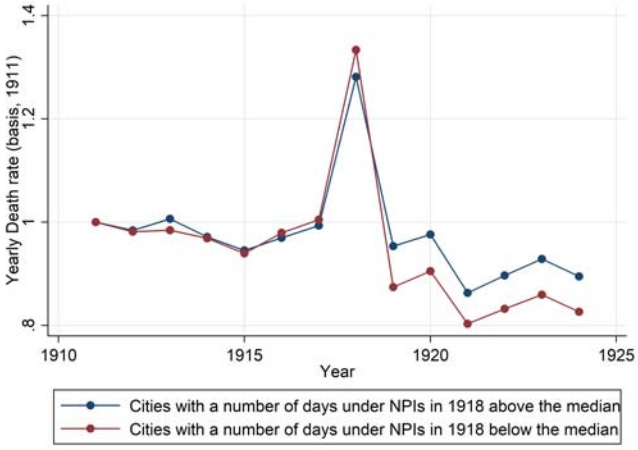
The paper is organized as follows. Section 2 presents the background and the current state of our knowledge on the 1918 pandemic including its potential effect on economic activity. Section 3 presents the data. Section 4 develops a difference in differences approach to estimate the impact of NPIs

---

[1] *"The resistance of a group to attack by a disease to which a large proportion of the members are immune, thus lessening the likelihood of a patient with a disease coming into contact with a susceptible individual"* (Agnew 1965)

on the death rate. Section 5 discusses the impact of NPIs implemented in 1918 on cities' dynamics. Section 6 concludes.

Figure 1: Evolution of the yearly death rate before and after the 1918 flu in 43 cities that implemented Non Pharmaceutical Interventions in 1918 for different length



Reading notes:Cities that implemented NPIs for a longer time saw their death rates increase less than cities that had shorter NPIs in 1918. On the other hand the death rate remained relatively higher during the following years for these cities

Computation of the author from the Bureau of Census mortality Tables published in 1920 and 1925

Data on NPIs come from Markel et al. (2007)

Average death rate computed for a sample of 43 cities: Albany (NY), Baltimore, Birmingham, Boston, Buffalo, Cambridge, Chicago, Cincinnati, Cleveland, Columbus, Dayton, Denver, Fall River, Grand Rapid, Indianapolis, Kansas City, Los Angeles, Louisville, Lowell, Milkwaukee, Minneapolis, Nashville, New Haven, New Orleans, New York, Newark, Oakland, Omaha, Philadelphia, Pittsburgh, Portland, Providence, Richmond, Rochester, Saint Louis, Saintt Paul, San Fransisco, Seattle, Spokane, Syracuse, Toledo, Washington, Worcester.

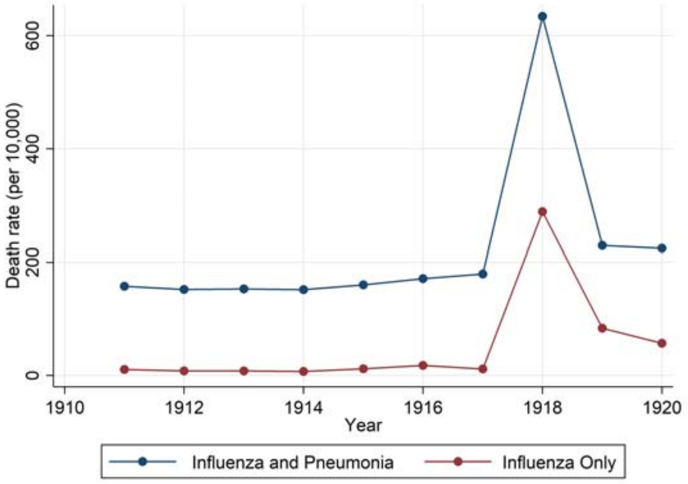
2 Background and literature review

2.1 The Policy responses to the 1918 influenza

The year 2020 has seen a global health crisis with more than 50% of the world population under relatively strict NPIs. The closest crisis from which enough data is available is the 1918 flu that spread throughout the world at the end of the First World War and infected about a quarter of the world population at that time (Taubenberger and Morens 2006). It also

had long run consequences on children born during this period (Almond 2006). The flu mostly affected active people with an unusual casualty rate concentrated for the age groups between 15 and 45.
In the U.S., the flu was probably spread by troups coming back from Europe and increased dramatically the death rate in the autumn of 1918. It is also noteworthy that the death rate due to influenza decreased the next years but remained at higher levels when compared with previous years as illustrated in Figure 2. This might be because doctors were then more likely to report influenza as the cause of some death but also because the virus mutated and continued to affect people in the following years. Indeed, Taubenberger and Morens (2006) stress that the virus at the origin of the 1918 pandemic gave birth to most of the subsequent influenza strains, with the exception of avian flu. Fine (1993) states that *"prior to 1977 only a single major [influenza] virus (shift) subtype was found circulating in the human population worldwide at any time"*.

Figure 2: Evolution of the death rate caused by influenza and influenza and pneumonia



Author's computation from Bureau of the Census, Mortality Statistics 21st Annual Report published in 1920.
Average death rate computed for a sample of 43 cities: Albany, Baltimore, Birmingham, Boston, Buffalo, Cambridge, Chicago, Cincinnati, Cleveland, Columbus, Dayton, Denver, Fall River, Grand Rapids, Indianapolis, Kansas City, Los Angeles, Louisville, Lowell, Milkwaukee, Minneapolis, Nashville, New Haven, New Orleans, New York, Newark, Oakland, Omaha, Philadelphia, Pittsburgh, Portland, Providence, Richmond, Rochester, Saint Louis, Saint Paul, San Fransisco, Seattle, Spokane, Syracuse, Toledo, Washington, Worcester.

The Federal Government did not coordinate a national response (Correia, Luck, and Verner 2020) leaving cities to manage the pandemic by implementing local measures. The timing of the response appears to be correlated with the geographical longitude suggesting that cities located in the West had more time to prepare using the experience of cities in the East that had been more rapidly overwhelmed. Indeed Markel et al. (2007) show that the pandemic waves started in the East during the second week of September 1918, in the Midwest in the last week of September and in the West in the second week of October. They show that all cities they investigated implemented some kind of NPI, such as quarantines, social distancing and school closures, but that some were stricter and faster to take action than others. Their data also documents some heterogeneity in the responses within each region. For example, New York responded rapidly to the pandemic and managed to flatten the epidemic curve implementing strictly enforced isolation and quarantine procedures. According to Markel et al. (2007) this allowed the city to experience the lowest death rate on the East Coast. On the other hand, Pittsburgh only took action on the beginning of October and closed schools at the end of the month. This resulted in the highest excess mortality burden in the sample studied.

2.2 Economic and health consequences of the 1918 pandemic

This paper is intended as a contribution to the economic literature and engages with the epidemiological literature as I study the impact of NPIs implemented in 1918 on health and economic outcomes. I try to extend the epidemiological literature documenting the impact of Non Pharmaceutical Policies (NPIs) as Markel et al. (2007), Bootsma and Ferguson (2007), and Hatchett, Mecher, and Lipsitch (2007) which was carefully reviewed in Aiello et al. (2010) using an econometric approach. My results confirm their estimated impact of the short run consequences of NPIs (i.e during the pandemic) and supplement their results by documenting the medium run impact of the policies once the main wave is over. My findings are in line with the literature on herd immunity (Fine 1993; Fine, Eames, and Heymann 2011) as I document a trade-off between short run benefits of NPIs and their medium run consequences. I show that cities that implemented NPIs incurred higher death rates in the following years. This paper also contribute to the literature documenting the evolution of mortality rates differential in US cities as Feigenbaum, Muller, and Wrigley-Field (2019), Clay, Lewis, and Severnini (2019), and Acuna-Soto, Viboud, and Chowell (2011).

I also contribute to the literature documenting the economic impact of pandemics. For example, Meltzer, Cox, and Fukuda (1999) estimated in 1999 the potential economic impact of the next pandemic without economic disruption and analyzed the benefits of developing vaccines to prevent it. Smith et al. (2009) developed a general equilibrium model to measure the potential impact of a pandemic on the UK economy under different scenarios. The Covid-19 pandemic has also given rise to a wide range of estimates of its potential economic impact as Atkeson (2020), Kong and Prinz (2020), Takahashi and Yamada (2020), Barrot, Grassi, and Sauvagnat (2020), and Chen, Qian, and Wen (2020). This research is more precisely related to the literature that documented the impact of past pandemics and in particular the 1918 pandemic. Barro, Ursúa, and Weng (2020) used a panel of countries and estimate that the flu had negative impacts on GDP and consumption, estimated to be around 6 and 8 percent, respectively. Velde (2020) study the short run dynamics of US economics during the pandemics. I discuss more extensively the recent work of Correia, Luck, and Verner (2020) who document what kind of economic impact one can expect from non pharmaceutical intervention and influenza pandemic on cities' manufacturing and banking sectors. My results argue for caution regarding any inferred causal links between economic activity and the mortality caused by the pandemic in US cities. I find that on the medium run, NPIs seem to have decreased the immunity of the population leaving individuals more sensitive to the following waves of the pandemic and strains of influenza. My findings can also contribute to the economic literature investigating the optimal policy responses to pandemics, e.g. Alvarez, Argente, and Lippi (2020) and Jones, Philippon, and Venkateswaran (2020), as they suggest that optimal policy responses should include an exit strategy when implementing NPIs. My conclusions tend to support the intuition developed in Toda (2020) that argues that countries might rely on herd immunity to fight against the pandemic while limiting the economic slowdown.

3 Data

I construct a panel of 43 cities with precise measures of NPIs in a spirit close to Correia, Luck, and Verner (2020). My data comes from the census bureau archives published online. I digitize the Statistical Abstract of the United States from the Census Bureau to extract information on the number of wage workers, aggregate wages, the total output and the added value for the 43 cities from 1899 to 1923. I end up with a balance panel of 43 cities for the years 1899, 1904, 1909, 1914, 1919 and 1920.

I supplement this dataset with the data compiled by Markel et al. (2007) on NPIs describing the number of days under NPIs and the speed of their implementation after the first case was reported in the city. I also use the mortality tables for large cities published by the Census Bureau from 1906 to 1924.

Table 1: Descriptive Statistics for the 43 US Cities

	Mean	Std.Dev.	Obs	min	max
Demographics					
Population (1900)	328018.60	576706.40	43	36800	3437200
Population (1910)	441201.02	776807.64	43	100292	4770082
Population growth (1900-1910)	0.50	0.56	43	0	2
Sex Ratio (men/women) 1910	1.03	0.12	43	1	1
average age (1910)	28.39	1.32	43	25	31
First decile age (1910)	5.09	0.92	43	4	7
Median Age (1910)	26.42	1.56	43	23	30
Ninth decile age (1910)	53.51	1.88	43	49	58
Health					
NPI days (1918)	88.28	46.43	43	28	170
NPI Speed (1918)	-7.35	7.84	43	-35	11
Death Rate (1917)	179.10	61.53	43	59	380
Death Rate (1918)	647.14	187.53	43	283	1244
Health Expenditures per head (1900)	0.19	0.11	43	0	1
Health Expenditures per head (1917)	1.84	0.61	43	1	3
Manufacturing sector					
Wage Workers (1899)	40886.84	70859.04	43	1060	388586
Value Produced (1899)	114844.51	217164.14	43	3756	1172870
Wages (1899)	18792.91	34528.14	43	616	196656

Author's computation from the Bureau of the Census, Mortality Statistics 21st Annual Report published in 1920 ,the US census Statistical Abstract and Manufacture Surveys (1900-1929) . NPI variables are from Markel et al. (2007).

The cities are Albany, Baltimore, Birmingham, Boston, Buffalo, Cambridge, Chicago, Cincinnati, Cleveland, Columbus, Dayton, Denver, Fall River, Grand Rapid, Indianapolis, Kansas City, Los Angeles, Louisville, Lowell, Milwaukee, Minneapolis, Nashville, New Haven, New Orleans, New York, Newark, Oakland, Omaha, Philadelphia, Pittsburgh, Portland, Providence, Richmond, Rochester, Saint Louis, Saint Paul, San Francisco, Seattle, Spokane, Syracuse, Toledo, Washington, Worcester.

Finally, I use the exhaustive census for the years 1900, 1910, 1920 and 1930 downloaded on the IPUMS website and compiled by Ruggles et al. (2020). The main variables used are summarized in Table 1.

4 The impact of NPIs on the mortality rate in the medium run

4.1 Empirical specification

Epidemiological studies investigate how Non Pharmaceutical Interventions allow to flatten the epidemic curve by examining high frequency (weekly) data (Markel et al. 2007; Bootsma and Ferguson 2007). I follow a different approach in order to study their impact in the medium run. This is performed by an event study following a growing econometric literature (Duflo 2001; Autor 2003; De Chaisemartin and d'Haultfoeuille 2018; Fetzer 2019) to investigate the impact of NPIs on the death rate at the city level:

$$Deathrate_{i,t} = \delta_i + \gamma_t + \sum_{t \neq 1916} \beta^t \times 1_{t(i)=t} \times NPI_{1918,i} + \sum_{t \neq 1916} \lambda^t \times 1_{t(i)=t} \times X_i + \epsilon_{i,t} \tag{1}$$

where I use three different death rates : total death rate, death rate for influenza and pneumonia (used in Bootsma and Ferguson (2007), Markel et al. (2007), and Correia, Luck, and Verner (2020)) and death rate for influenza only. X_i controls for the population in 1910 and health expenditures per capital in 1917. There are two NPI terms reported in Markel et al. (2007). The first term, NPI Speed, measures the rapidity of the response after the first case was discovered in the city, and the second term, NPI Days, measures the duration that NPIs such as social distancing and school closures were implemented. β^t is used to describe if cities that responded more aggressively to the pandemic had different trends from 1911 to 1920.

To compute the net effect, I also estimate a simpler difference-in-differences specification:

$$Deathrate_{i,t} = \delta_i + \gamma_t + \beta \times Post \times NPI_{1918,i} + \sum_{t \neq 1916} \lambda^t \times 1_{t(i)=t} \times X_i + \epsilon_{i,t} \tag{2}$$

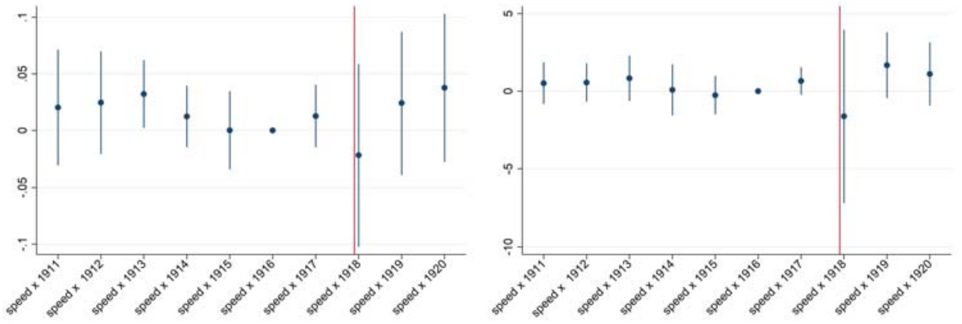
where *Post* takes value one when the year is higher than 1917.β is used to measure the net impact of NPIs implemented in 1918 from year 1918 until the end of the observations (up to 1924 for the long run specifications). Both equations are estimated by ordinary least squares and standard errors are clustered at the city level.

4.2 Results of the event study

Figures 3 and 4 display the estimates of β^t. One can observe that the common trend assumption is fulfilled before the 1918 pandemic and that high and low NPIs cities had similar mortality trends.These policies reduced the mortality rate in 1918, this is consistent with Markel et al. (2007). However, one also observes a significant rebound of mortality in these cities in 1919 and 1920. This tends to suggest that the herd immunity of the population is lower and that more people die from influenza and pneumonia in the two subsequent years than would have been the case with less aggressive NPIs. We observe the same patterns for the two measures of NPI policies with one difference that argues for the herd immunity interpretation. In 1919 and 1920, cities that implemented long NPIs experienced a dramatic increase in their death rate; while this is not so important when they responded rapidly after the first case appeared. This suggests that the longer people were isolated from the virus in 1918, the lower the herd immunity and the higher the death rate the next years. The figures for "death caused by influenza" could be recovered until 1920 but the series for the total death rate and deaths caused by pneumonia and influenza are available through 1924. I provide additional evidence in Figure B.1 and B.2 of the appendix that the total death rate appears to be higher through 1924 in cities that implemented long NPIs in 1918. It is possible that the impact of the influenza may be reflected more in the total death rate if those who die from influenza have other co morbidity factors.

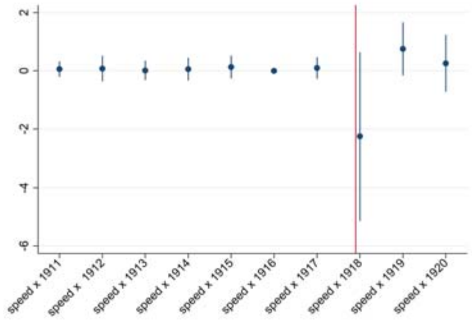
These findings appear to be consistent with the literature on herd immunity. They suggest that the 1918 pandemic acted as a vaccine for the subsequent years in cities that did not implement NPIs. Indeed, Fine, Eames, and Heymann (2011) reported that *"one proposal has been to reduce community spread of [influenza] by concentrating on vaccination of schoolchildren, as transmission within crowded classrooms leads to rapid dispersal throughout the community, and into the homes where susceptible adults reside"*. As a consequence one might think that NPIs as school closures limited the spread of the virus during the pandemic but failed to raise the level of immunity within the city, making the population more susceptible. The impact of the length of NPIs appears to support this interpretation: the longer children stayed at home, the lower their exposure to the influenza and the subsequent immunity of the population.

Figure 3: Event study: Estimates of the aggregate impact of NPI implementation speed on death rates



(a) All causes of death

(b) Influenza and Pneumonia



(c) Influenza Only

Reading notes: Cities having adopted more rapidly NPIs saw their death rates increase less than cities that were slower in 1918. On the other hand the death rate was relatively higher in 1919 and 1920 for these cities

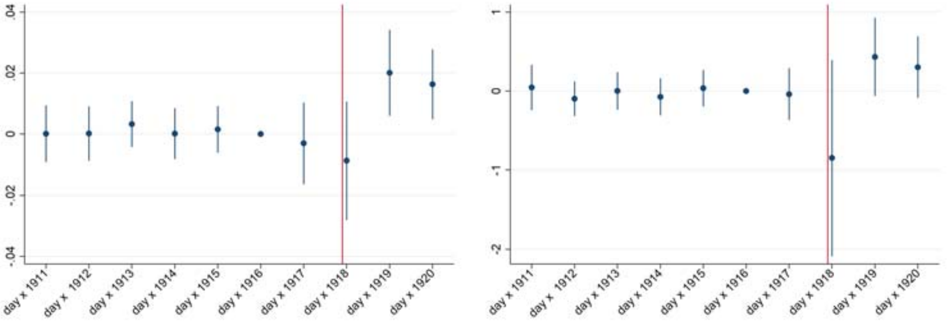
Estimates of the difference in difference equation:

$Deathrate_{i,t} = \delta_i + \gamma_t + \sum_{t\neq 1916} \beta^t \times 1_{t(i)=t} \times NPI_{1918,i} + \sum_{t\neq 1916} \lambda^t \times 1_{t(i)=t} \times X_i + \epsilon_{i,t}$

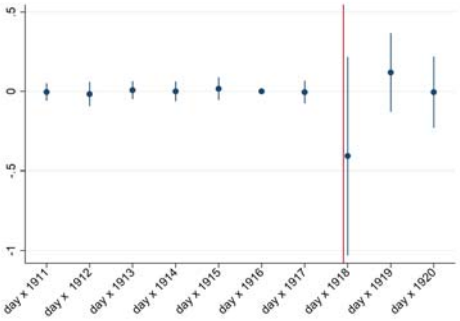
Controls include health expenditures in 1917, population in 1910, years and city fixed effects

95% confidence Interval clustered at the city level

Figure 4: Event study: Estimates of the aggregate impact of NPI implementation duration on death rates



(a) All causes of death (b) Influenza and Pneumonia



(c) Influenza Only

Reading notes: Cities that implemented NPIs for a longer time saw their death rates increase less than cities that had shorter NPIs in 1918. On the other hand the death rate was relatively higher in 1919 and 1920 for these cities

Estimates of the difference in difference equation:

$Deathrate_{i,t} = \delta_i + \gamma_t + \sum_{t \neq 1916} \beta^t \times 1_{t(i)=t} \times NPI_{1918,i} + \sum_{t \neq 1916} \lambda^t \times 1_{t(i)=t} \times X_i + \epsilon_{i,t}$

Controls include health expenditures in 1917, population in 1910, years and cities' fixed effects

95% confidence interval clustered at the city level

4.3 Robustness checks

I perform several robustness checks to verify the underlying hypothesis, to investigate the longer run impact of NPIs, and to control for the influence of the demographic structure of cities before and after the pandemic.

Additional tests of the common trend assumption. I gathered longer time series for the total death rate from 1906. Specific death rates for influenza alone or for influenza and pneumonia were not published in the sources that I consulted. Results remain unchanged as cities with a high and low level of NPIs in 1918 had common trends from 1906 as illustrated in Figure B.3 in the Appendix. I also extend the series for influenza and pneumonia and for the total death rate until 1924 in Figure B.1 and B.2. The results show that the length of NPIs still had a significant impact through 1924 while the impact of the speed of their implementation faded rapidly after 1919.

Cities' weights and differentiated trends between the East and the West. The observations are weighted according to their population in 1910. This does not affect the estimated trends. Moreover, as discussed in Correia, Luck, and Verner (2020) the pandemic spread from the East to the West, giving the West more time to adjust. One potential confounding factor could be that cities on the West Coast started to behave differently from the East Coast after the First World War due to some regional shocks. I control for this eventuality adding regional shocks, i.e., interacting years fixed effects with a fixed effect to indicate to which of the four regions the city belongs (West, South West, East, Midwest), results remain unchanged as illustrated in Figures C.3 and B.4 in the appendix.

Changing demographic structure. An alternate explanation would be that cities with an aggressive policy may undergone different demographic changes that could explain their divergence in terms of mortality after 1918. Appendix C compares the demographic structure of these cities (population, population growth, sex ratio, average age, age distribution, share of each cohort and age groups) in each census year. It is noteworthy that cities that implemented longer and earlier NPIs were younger, had higher population growth rates and had proportionally more males; these demographic trends continued unchanged after 1918. This reflects the fact that these cities tend to be located on the West Coast. If controlling for regional shocks might absorb these differences, I follow the epidemiological literature as Markel et al. (2007) and also control explicitly for the difference in sex ratio, median age and population growth in 1910, before the pandemic, or in 1920, immediately following the pandemic; in all such cases, the results remain unaffected, as illustrated in Figures B.6 and B.7.

4.4 Short run and long run impact of NPIs

In order to get an idea of the net benefits of NPIs, I run a difference in differences specification. The first one displayed in Table 2 only accounts for the year 1918 to estimate the short run impact of NPI, i.e. during their implementation. Columns (1) to (4) do not control for any characteristics beyond year and cities' fixed effects. Columns (5) to (8) also control for health expenditures per capita before the pandemic and city size. The inclusion of controls does not change the point estimate but makes it less precise and not significant. Columns (3), (4), (7) and (8) weight the observations by their population in 1910. Several comments are in order. First, speed appear to be more efficient than the duration of NPIs as the coefficient of the number of days is never statistically significant. Rapid implementation reduced the total death rate by 1.3 per 10,000 population, the death rate for pneumonia and influenza by 7 per 10,000 and the death rate for influenza only by 3 per 10,000. Note that the figures for the net number of lives saved by NPIs vary depending on the rate used. Their estimated impact is higher on the death rate caused by Influenza and Pneumonia than on the total death rate, suggesting that a portion of those saved from influenza by NPIs could have died from other diseases. Another interpretation could be that cities that implemented NPIs attributed a lower share of their deaths to influenza while the other cities tended to assign more deaths in 1918 to the ongoing pandemic.

In Table 3, I run the same specifications but including the year 1919 and 1920. One can observe that the point estimates are divided by two or three and are less significant. Rapid implementation of NPIs reduced the total death rate by 0.06 per 1,000 population, the death rate for pneumonia and influenza by 4 per 10,000 and the death rate for influenza only by 1.1 per 10,000. The impact of the number of days under NPIs is never significant. This suggests that a portion of the people saved by NPIs in 1918 were lost during the following two years.

Finally, Table 4 presents the estimates extending the series through 1924. Data for deaths caused by influenza alone were not available. The impact of speed remains significant in one specification but is even smaller. More interestingly, the impact of the length of the NPIs on the total death rate now turns positive and statistically significant in most of the specifications. This suggests that cities that implemented long periods of NPIs ultimately lost more people, increasing their death rate by 1.2 per 10,000. One potential interpretation of the finding could be that NPIs should not last too long and that their exit strategy should include specific policies to avoid that having a lower herd immunity lead to higher death rates in the subsequent years.

Table 2: Short Run Impact of NPIs (1911-1918)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel a) Dependant variable: Death rate for all causes (per 1,000)								
speed NPI x Post	-0.0570		-0.132***		-0.0627		-0.167*	
	(0.0388)		(0.0339)		(0.0427)		(0.0785)	
days NPI x Post		-0.00982		-0.0149		-0.00935		-0.0231
		(0.00683)		(0.0108)		(0.00766)		(0.0126)
N	343	343	343	343	343	343	343	343
R^2	0.915	0.915	0.908	0.888	0.915	0.915	0.910	0.902
Panel b) Dependant variable: Death rate for Influenza and pneumonia (per 10,000)								
speed NPI x Post	-1.829		-7.405**		-2.852		-11.49	
	(2.894)		(2.593)		(3.240)		(6.273)	
days NPI x Post		-0.867		-1.328		-0.958		-1.899*
		(0.549)		(0.784)		(0.557)		(0.934)
N	343	343	343	343	343	343	343	343
R^2	0.894	0.899	0.906	0.897	0.896	0.900	0.910	0.906
Panel b) Dependant variable: Death rate for Influenza only (per 10,000)								
speed NPI x Post	-2.455		-2.695*		-2.691		-4.475	
	(1.487)		(1.086)		(1.722)		(2.428)	
days NPI x Post		-0.306		-0.305		-0.416		-0.557
		(0.280)		(0.353)		(0.308)		(0.421)
N	343	343	343	343	343	343	343	343
R^2	0.922	0.921	0.945	0.938	0.924	0.923	0.948	0.943
Controls								
City FE	Y	Y	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y	Y	Y
Controls x Years FE	N	N	N	N	Y	Y	Y	Y
Weights	N	N	Y	Y	N	N	Y	Y

Clustered Standard errors in parentheses

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

Post is a dummy indicating observations after 1917 while speed NPI indicates the speed at which the city implemented their NPI. Days NPI describes the length the NPI measures were in place.

Estimates of the difference in difference equation:

$Deathrate_{i,t} = \delta_i + \gamma_t + \beta \times Post \times NPI_{1918,i} + \sum_{t \neq 1916} \lambda^t \times 1_{t(i)=t} \times X_i + \epsilon_{i,t}$

Controls include health expenditures in 1917, population in 1910, years and city fixed effects standard errors clustered at the city level. Cities are weighted with their population in 1910

Table 3: Medium Run Impact of NPIs (1911-1920)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel a) Dependant variable: Death rate for all causes (per 1,000)								
speed NPI x Post	-0.0240		-0.0655***		-0.0284		-0.0569*	
	(0.0176)		(0.0114)		(0.0196)		(0.0217)	
days NPI x Post		0.00906*		0.00585		0.00846*		0.00151
		(0.00407)		(0.00552)		(0.00410)		(0.00535)
N	429	429	429	429	429	429	429	429
R^2	0.881	0.884	0.882	0.871	0.882	0.884	0.883	0.879
Panel b) Dependant variable: Death rate for Influenza and pneumonia (per 10,000)								
speed NPI x Post	-0.0163		-2.996**		-0.361		-3.315	
	(1.122)		(0.967)		(1.229)		(2.168)	
days NPI x Post		0.00828		-0.141		-0.0749		-0.448
		(0.237)		(0.326)		(0.242)		(0.357)
N	429	429	429	429	429	429	429	429
R^2	0.880	0.880	0.886	0.879	0.881	0.881	0.887	0.885
Panel b) Dependant variable: Death rate for Influenza only (per 10,000)								
speed NPI x Post	-0.604		-1.104**		-0.716		-1.256	
	(0.636)		(0.326)		(0.688)		(0.668)	
days NPI x Post		-0.0201		0.0311		-0.106		-0.103
		(0.133)		(0.149)		(0.136)		(0.149)
N	429	429	429	429	429	429	429	429
R^2	0.905	0.905	0.925	0.922	0.908	0.908	0.926	0.925
Controls								
City FE	Y	Y	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y	Y	Y
Controls x Years FE	N	N	N	N	Y	Y	Y	Y
Weights	N	N	Y	Y	N	N	Y	Y

Clustered Standard errors in parentheses

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

Post is a dummy indicating observations after 1917 while speed NPI indicates the speed at which the city implemented their NPI. Days NPI describes the length the NPI measures were in place.

Estimates of the difference in difference equation:

$Deathrate_{i,t} = \delta_i + \gamma_t + \beta \times Post \times NPI_{1918,i} + \sum_{t \neq 1916} \lambda^t \times 1_{t(i)=t} \times X_i + \epsilon_{i,t}$

Controls include health expenditures in 1917, population in 1910, years and city fixed effects standard errors clustered at the city level. Cities are weighted with their population in 1910

Table 4: Long Run Impact of NPIs (1911-1924)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel a) Dependant variable: Death rate for all causes (per 1,000)								
speed NPI x Post	-0.0136		-0.0535^{***}		-0.0140		-0.0268	
	(0.0256)		(0.00928)		(0.0261)		(0.0183)	
days NPI x Post		0.0143^{**}		0.0123^{**}		0.0128^{**}		0.00813
		(0.00417)		(0.00456)		(0.00435)		(0.00415)
N	597	597	597	597	597	597	597	597
R^2	0.863	0.875	0.888	0.885	0.868	0.876	0.892	0.893
Panel b) Dependant variable: Death rate for Influenza and pneumonia (per 10,000)								
speed NPI x Post	0.0976		-2.131^{***}		0.00578		-1.551	
	(0.652)		(0.565)		(0.620)		(1.112)	
days NPI x Post		0.180		0.143		0.0925		-0.123
		(0.132)		(0.195)		(0.127)		(0.197)
N	597	597	597	597	597	597	597	597
R^2	0.880	0.881	0.891	0.886	0.882	0.883	0.893	0.892
Controls								
City FE	Y	Y	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y	Y	Y
Controls x Years FE	N	N	N	N	Y	Y	Y	Y
Weights	N	N	Y	Y	N	N	Y	Y

Clustered Standard errors in parentheses

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

Post is a dummy indicating observations after 1917 while speed NPI indicates the speed at which the city implemented their NPI. Days NPI describes the length the NPI measures were in place.

Estimates of the difference in difference equation:

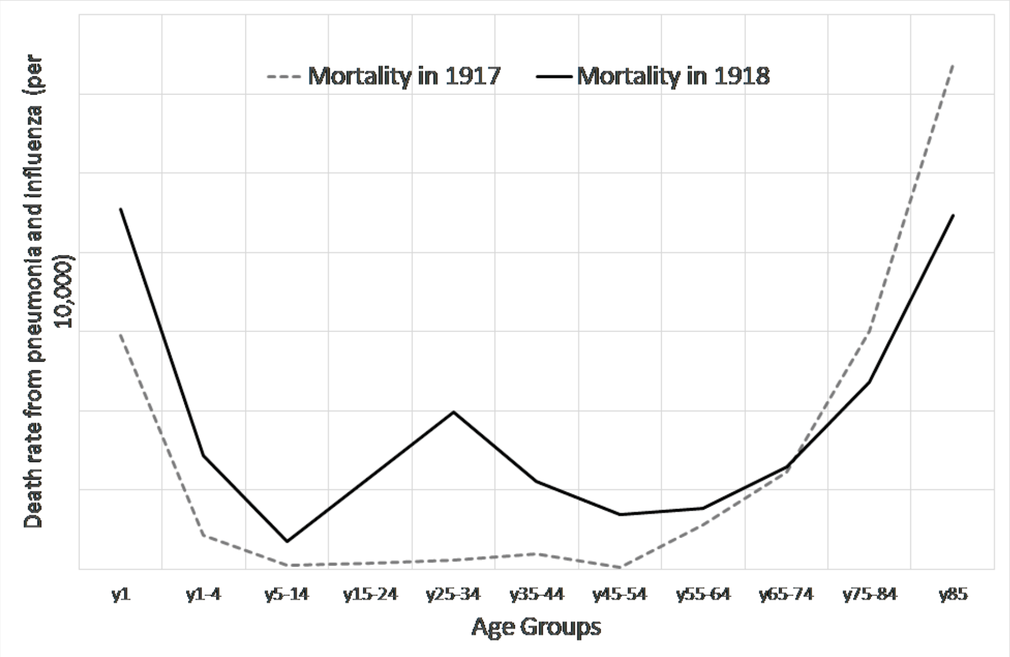
$Deathrate_{i,t} = \delta_i + \gamma_t + \beta \times Post \times NPI_{1918,i} + \sum_{t \neq 1916} \lambda^t \times 1_{t(i)=t} \times X_i + \epsilon_{i,t}$

Controls include health expenditures in 1917, population in 1910, years and city fixed effects standard errors clustered at the city level. Cities are weighted with their population in 1910

5 The impact of NPIs on city growth and demographics

One key measure of a city's dynamics is its demographic population growth, especially during a period of industrialization. It could thus be interesting to investigate the impact of NPIs on population growth in particular in the light of the higher death rates in the following decade. Moreover, the 1918 pandemic had an unusual characteristic in that, unlike earlier and later episodes of influenza, its death rate was particularly high for young workers aged between 24 and 35 years, as stressed in Taubenberger and Morens (2006) and illustrated in Figure 5. One can try to detect whether NPIs managed to preserve this demographic group and city's growth. An event study is conducted using the 1900 to 1930 censuses to document the relative demographic dynamics of cities that implemented NPIs.

Figure 5: Death rate from Influenza and Pneumonia in 1917 and 1918



Source: Bureau of the Census, Mortality Statistics 21st Annual Report published in 1920

5.1 Empirical Specification

I conducted an event study in a spirit close to Correia, Luck, and Verner (2020) to investigate the impact of NPIs on a city's growth and the relative share of the cohort age 24 to 35 years in 1918 accounting for the different levels of fatality rates in the first year of the pandemic.

$$\begin{aligned} y_{i,t} = \delta_i + \gamma_t + \sum_{t \neq 1910} \beta_1^t \times 1_{t(i)=t} \times Mortality_{1918,i} + \sum_{t \neq 1910} \beta_2^t \times 1_{t(i)=t} \times NPI_{1910,i} \\ + \sum_{t \neq 1910} \lambda^t \times 1_{t(i)=t} \times X_i + \epsilon_{i,t} \end{aligned} \tag{3}$$

where $y_{i,t}$ is the population growth rate of cities between year t and t-10 or the share of the cohort aged between 25 and 34 in the first year of the pandemic. β_1^t will estimate the differentiated trend between cities with high or low mortality in 1918. β_2^t will estimate the differentiated trends for cities with different levels of NPIs. X_i controls for the log population in 1900, the amount of health expenditures per capita in 1917 and regional shocks. Standard errors are clustered at the city level.

5.2 Results of the event study

Figure 6 displays the coefficients β_2. β_1s are reported in Figure B.8 in appendix. None is statistically significant at the standard levels. Cities that implemented NPIs appear to have had a slightly higher relative growth rate between 1900 and 1910 and, if anything, lower relative growth rates between 1910 and 1920 and between 1920 and 1930 as illustrated in panels a) and b). Moreover, there is no significant difference regarding the share of the birth cohort mostly affected by the 1918 pandemic.

These results are not so surprising in light of the limited impact of NPIs on mortality when one remembers that cities in the 1920s and 1930s experienced extremely large growth rates because of a massive rural exodus[2] and very high migration flows (with the exception of the period of the First World War) at least until the Immigration Act of 1924 that restricted immigrants from Southern and Eastern Europe. These massive flows of population may have soon erased the demographic impact of the 1918 pandemic on urban population even in the cities most affected. This is evident from the coefficients β_1 on mortality that are never significant as reported in Figure B.8 in the appendix.

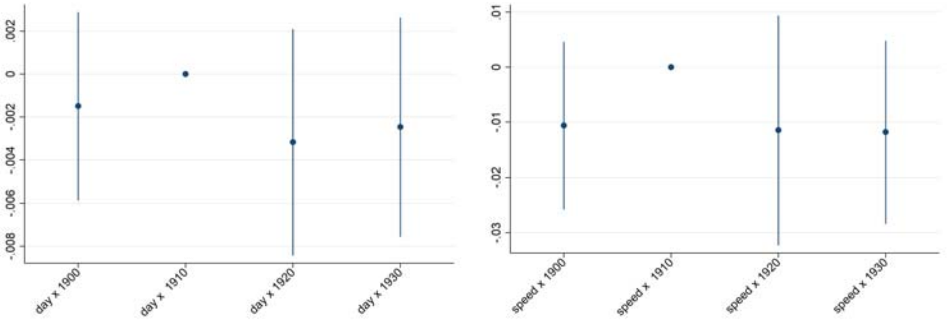
On the other hand, given that population growth is usually a measure of cities' attractiveness and economic performance following the seminal

---

[2] By 1890, twenty-eight percent of Americans lived in urban areas, and by 1920 more Americans lived in towns and cities than in rural areas (Kennedy and Cohen 2015)

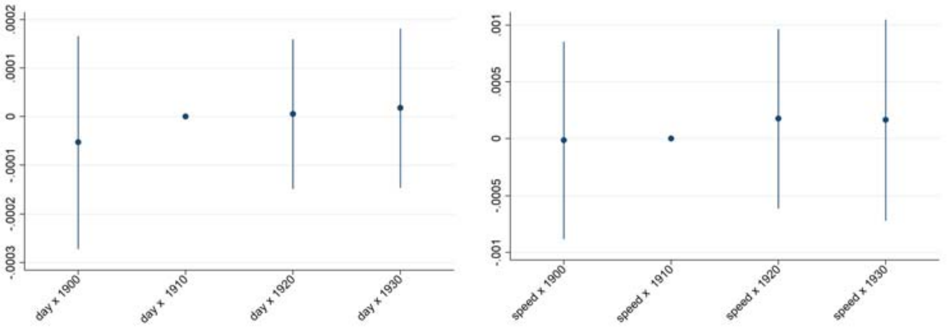
Rosen and Roback model, these results seem at odds with the results provided in Correia, Luck, and Verner (2020). Appendix D extends their series at the city level back to 1899 and explores this issue in details. In a nutshell, their results at the city level might be driven by the fact that cities that implemented faster NPIs and that had lower mortality in 1918 had a different growth rate of their manufacturing sector and maintained that trend after the 1918 pandemic. Nevertheless, it should be noted that our main conclusion on the impact of NPIs on the economy is in line with their findings as Correia, Luck, and Verner (2020) argue that NPIs did not depress the local economy, which is also the result of Figure 6. It is possible that macroeconomic mechanisms still affected the performance of the national economy while leaving the relative growth of cities unaffected as suggested by the state level results in Correia, Luck, and Verner (2020) or the cross country evidence provided in Barro, Ursúa, and Weng (2020).

Figure 6: Event study: Estimates of the aggregate impact of NPI implementation duration on city population growth and the share of the cohort age 25 to 34 in 1918



(a) Impact of NPI duration on population growth between year t and t-10

(b) Impact of NPI speed on population growth between year t and t-10



(c) Impact of NPI length on the cohort age 24 to 35 in 1918

(d) Impact of NPI speed on the cohort age 24 to 35 in 1918

Reading notes: Cities that implemented NPIs for a longer time or faster in 1918 were not found to have any specific population growth or change in the share of the cohort who was 25 to 34 1918.

Estimates of the difference in difference equation:

$y_{i,t} = \delta_i + \gamma_t + \sum_{t\neq 1910} \beta_1^t \times 1_{t(i)=t} \times Mortality_{1918,i} + \sum_{t\neq 1910} \beta_2^t \times 1_{t(i)=t} \times NPI_{1910,i} + \sum_{t\neq 1910} \lambda^t \times 1_{t(i)=t} \times X_i + \epsilon_{i,t}$

Controls include health expenditures in 1917, regional shocks, years and cities' fixed effects

95% confidence interval clustered at the city level

6 Conclusion

In this paper, I investigate the 1918 pandemic in the US to assess the potential economic and health benefits of non pharmaceutical interventions (NPIs) at the city level. My findings can be summarized as follows: first, in the medium run, I estimate that a significant share of the lives saved during the pandemic might be lost during the subsequent years. A potential explanation of this could be that herd immunity becomes lower in cities that implemented NPIs over a long period of time. Second, I do not find any significant impact of these policies on city growth. These findings do not deny the short run benefits of these policies that lower the death rate during the peak of the pandemic and prevent overcrowding of the health system (Markel et al. 2007). However, policy makers should prepare exit strategies to prevent NPIs from leading to higher deaths when they end.

The last word is a word of caution. As any study based on an historical natural experiment, this paper has limited external validity and thus applicability to current public health policies. It would be difficult to draw any inference regarding the predicted impact of NPIs as implemented during the Covid-19 crisis, not least because their magnitude and scale are different. Today NPIs are mainly implemented on a national (or state) scale, rather than at the city level. Moreover, pharmaceutical technologies were less developed than today, and the capacity to produce a new vaccine within a reasonable time was much lower(Ni et al. 2020; Callaway 2020). Finally, the 1918 pandemic was an unprecedented event in the history of health provided that it gave birth to most strains of seasonal influenza until 1977 and which continue to kill up to 650,000 people yearly worldwide (World Health Organization 2007; Paget et al. 2019).

References

Acuna-Soto, Rodolfo, Cecile Viboud, and Gerardo Chowell. 2011. “Influenza and pneumonia mortality in 66 large cities in the United States in years surrounding the 1918 pandemic.” *PLoS One* 6 (8).

Agnew, LR. 1965. *Dorland’s illustrated medical dictionary.* Saunders.

Aiello, Allison E, Rebecca M Coulborn, Tomas J Aragon, Michael G Baker, Barri B Burrus, Benjamin J Cowling, Alasdair Duncan, Wayne Enanoria, M Patricia Fabian, Yu-hui Ferng, et al. 2010. “Research findings from nonpharmaceutical intervention studies for pandemic influenza and current gaps in the research.” *American journal of infection control* 38 (4): 251–258.

Almond, Douglas. 2006. “Is the 1918 influenza pandemic over? Long-term effects of in utero influenza exposure in the post-1940 US population.” *Journal of political Economy* 114 (4): 672–712.

Alvarez, Fernando E, David Argente, and Francesco Lippi. 2020. *A simple planning problem for covid-19 lockdown.* Technical report. National Bureau of Economic Research.

Atkeson, Andrew. 2020. *What will be the economic impact of COVID-19 in the US? Rough estimates of disease scenarios.* Technical report. National Bureau of Economic Research.

Autor, David H. 2003. “Outsourcing at will: The contribution of unjust dismissal doctrine to the growth of employment outsourcing.” *Journal of labor economics* 21 (1): 1–42.

Barro, Robert J, José F Ursúa, and Joanna Weng. 2020. *The coronavirus and the great influenza pandemic: Lessons from the “spanish flu” for the coronavirus’s potential effects on mortality and economic activity.* Technical report. National Bureau of Economic Research.

Barrot, Jean-Noel, Basile Grassi, and Julien Sauvagnat. 2020. “Sectoral effects of social distancing.” *Available at SSRN.*

Bootsma, Martin CJ, and Neil M Ferguson. 2007. “The effect of public health measures on the 1918 influenza pandemic in US cities.” *Proceedings of the National Academy of Sciences* 104 (18): 7588–7593.

Callaway, E. 2020. “The race for coronavirus vaccines: a graphical guide.” *Nature* 580 (7805): 576.

Chen, Haiqiang, Wenlan Qian, and Qiang Wen. 2020. “The impact of the COVID-19 pandemic on consumption: Learning from high frequency transaction data.” *Available at SSRN 3568574.*

Clay, Karen, Joshua Lewis, and Edson Severnini. 2019. “What explains cross-city variation in mortality during the 1918 influenza pandemic? Evidence from 438 US cities.” *Economics & Human Biology* 35:42–50.

Correia, Sergio, Stephan Luck, and Emil Verner. 2020. “Pandemics Depress the Economy, Public Health Interventions Do Not: Evidence from the 1918 Flu.”

De Chaisemartin, Clément, and Xavier d’Haultfoeuille. 2018. “Fuzzy differences-in-differences.” *The Review of Economic Studies* 85 (2): 999–1028.

Duflo, Esther. 2001. “Schooling and labor market consequences of school construction in Indonesia: Evidence from an unusual policy experiment.” *American economic review* 91 (4): 795–813.

Feigenbaum, James J, Christopher Muller, and Elizabeth Wrigley-Field. 2019. “Regional and Racial Inequality in Infectious Disease Mortality in US Cities, 1900–1948.” *Demography* 56 (4): 1371–1388.

Fetzer, Thiemo. 2019. “Did austerity cause Brexit?” *American Economic Review* 109 (11): 3849–86.

Fine, Paul EM. 1982. “Herd immunity.” In *Influenza Models: Prospects for Development and Use,* edited by Philip Selby, 189–194. Lancaster, England: MTP Press Ltd.

———. 1993. “Herd immunity: history, theory, practice.” *Epidemiologic reviews* 15 (2): 265–302.

Fine, Paul, Ken Eames, and David L Heymann. 2011. ““Herd immunity”: a rough guide.” *Clinical infectious diseases* 52 (7): 911–916.

Fox, John P, Lila Elveback, William Scott, LAEL GATEWOOD, and Eugene Ackerman. 1971. “Herd immunity: basic concept and relevance to public health immunization practices.” *American Journal of Epidemiology* 94 (3): 179–189.

Garrett, Thomas A. 2007. “Economic effects of the 1918 influenza pandemic.”

Hatchett, Richard J, Carter E Mecher, and Marc Lipsitch. 2007. “Public health interventions and epidemic intensity during the 1918 influenza pandemic.” *Proceedings of the National Academy of Sciences* 104 (18): 7582–7587.

Jones, Callum J, Thomas Philippon, and Venky Venkateswaran. 2020. *Optimal Mitigation Policies in a Pandemic: Social Distancing and Working from Home.* Technical report. National Bureau of Economic Research.

Kennedy, David M, and Lizabeth Cohen. 2015. *American pageant.* Cengage Learning.

Kong, Edward, and Daniel Prinz. 2020. "The Impact of Non-Pharmaceutical Interventions on Unemployment During a Pandemic." *Available at SSRN 3581254.*

Markel, Howard, Harvey B Lipman, J Alexander Navarro, Alexandra Sloan, Joseph R Michalsen, Alexandra Minna Stern, and Martin S Cetron. 2007. "Nonpharmaceutical interventions implemented by US cities during the 1918-1919 influenza pandemic." *Jama* 298 (6): 644–654.

Meltzer, Martin I, Nancy J Cox, and Keiji Fukuda. 1999. "The economic impact of pandemic influenza in the United States: priorities for intervention." *Emerging infectious diseases* 5 (5): 659.

Ni, Ling, Fang Ye, Meng-Li Cheng, Yu Feng, Yong-Qiang Deng, Hui Zhao, Peng Wei, et al. 2020. "Detection of SARS-CoV-2-specific humoral and cellular immunity in COVID-19 convalescent individuals." *Immunity.* ISSN: 1074-7613.

Paget, John, Peter Spreeuwenberg, Vivek Charu, Robert J Taylor, A Danielle Iuliano, Joseph Bresee, Lone Simonsen, Cecile Viboud, et al. 2019. "Global mortality associated with seasonal influenza epidemics: New burden estimates and predictors from the GLaMOR Project." *Journal of global health* 9 (2).

Ruggles, Steven, Sarah Flood, Ronald Goeken, Josiah Grover, Erin Meyer, Jose Pacas, and Matthew Sobek. 2020. *IPUMS USA: Version 10.0 [dataset].* Minneapolis, MN: IPUMS.

Smith, Richard D, Marcus R Keogh-Brown, Tony Barnett, and Joyce Tait. 2009. "The economy-wide impact of pandemic influenza on the UK: a computable general equilibrium modelling experiment." *Bmj* 339:b4571.

St Groth, SF de. 1977. “The control of influenza.” *Bulletin der Schweizerischen Akademie der Medizinischen Wissenschaften* 33 (4-6): 201.

Takahashi, Hidenori, and Kazuo Yamada. 2020. “When Japanese Stock Market Meets COVID-19: Impact of Ownership, Trading, ESG, and Liquidity Channels.” *mimeo.*

Taubenberger, Jeffery K, and David M Morens. 2006. “1918 Influenza: the mother of all pandemics.” *Emerging infectious diseases* 12 (1): 15.

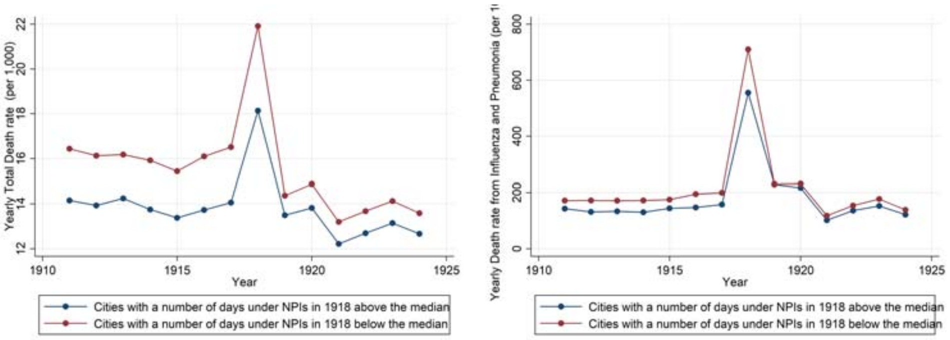
Toda, Alexis Akira. 2020. “Susceptible-infected-recovered (sir) dynamics of covid-19 and economic impact.” *arXiv preprint arXiv:2003.11221.*

Velde, Francois R. 2020. “What Happened to the US Economy During the 1918 Influenza Pandemic? A View Through High-Frequency Data.”

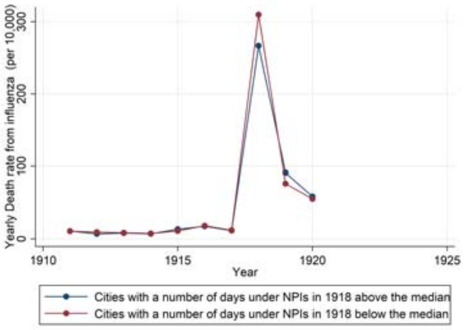
World Health Organization. 2007. “Up to 650 000 people die of respiratory diseases linked to seasonal flu each year.” Accessed April 11, 2020. `https://www.who.int/en/news-room/detail/14-12-2017-up-to-650-000-people-die-of-respiratory-diseases-linked-to-seasonal-flu-each-year`.

A Additional Series

Figure A.1: Evolution of the death rates by level of NPI in 1918



(a) All causes of death (b) Influenza and Pneumonia



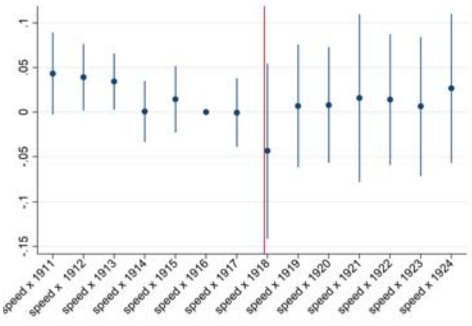
(c) Influenza Only

Reading notes: Cities that implemented NPIs for a longer time saw their death rates increase less than cities that had shorter NPIs in 1918. On the other hand the death rate was relatively higher in the next years for these cities

B Robustness Checks

B.1 Evidence until 1924 and from 1906

Figure B.1: Event study: Estimates of the aggregate impact of NPI implementation speed on death rates



(a) All causes of death (b) Influenza and Pneumonia

Reading notes: Cities having adopted more rapidly NPIs saw their death rates increase less than cities that were slower in 1918. On the other hand the death rate was relatively higher in 1919 and 1920 for these cities

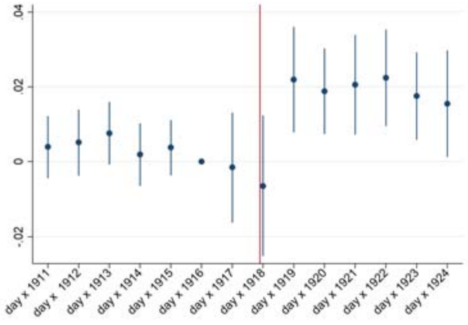
Estimates of the difference in difference equation:

$Deathrate_{i,t} = \delta_i + \gamma_t + \sum_{t \neq 1916} \beta^t \times 1_{t(i)=t} \times NPI_{1918,i} + \sum_{t \neq 1916} \lambda^t \times 1_{t(i)=t} \times X_i + \epsilon_{i,t}$

Controls include health expenditures in 1917, population in 1910, years and city fixed effects

95% confidence Interval clustered at the city level

Figure B.2: Event study: Estimates of the aggregate impact of NPI implementation length on death rates



(a) All causes of death (b) Influenza and Pneumonia

Reading notes: Cities that went through long NPIs period saw their death rates increase less than cities that had shorter NPIs in 1918. On the other hand the death rate was relatively higher from 1919 for these cities

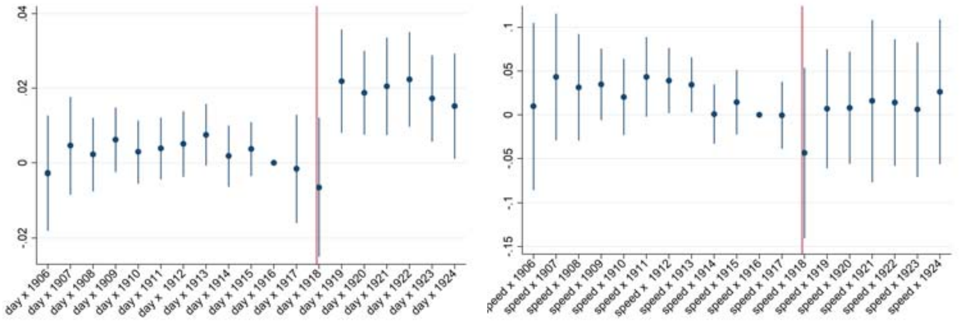
Estimates of the difference in difference equation:

$Deathrate_{i,t} = \delta_i + \gamma_t + \sum_{t \neq 1916} \beta^t \times 1_{t(i)=t} \times NPI_{1918,i} + \sum_{t \neq 1916} \lambda^t \times 1_{t(i)=t} \times X_i + \epsilon_{i,t}$

Controls include health expenditures in 1917, population in 1910, years and city fixed effects

95% confidence Interval clustered at the city level

Figure B.3: Event study: Estimates of the aggregate impact of NPI implementation length on death rates from 1906



(a) All causes of death, number of days

(b) All causes of death, speed of implementation

Reading notes: Cities that implemented NPIs for a longer time saw their death rates increase less than cities that implemented shorter NPIs in 1918. On the other hand the death rate was relatively higher from 1919 for these cities

Estimates of the difference in difference equation:

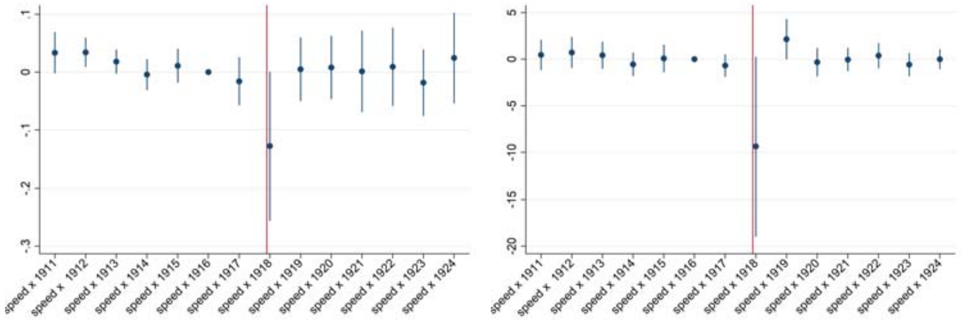
$Deathrate_{i,t} = \delta_i + \gamma_t + \sum_{t \neq 1916} \beta^t \times 1_{t(i)=t} \times NPI_{1918,i} + \sum_{t \neq 1916} \lambda^t \times 1_{t(i)=t} \times X_i + \epsilon_{i,t}$

Controls include health expenditures in 1917, population in 1910, years and city fixed effects

95% confidence Interval clustered at the city level

B.2 Weighting the observation by their population and adding regional shocks

Figure B.4: Event study: Estimates of the aggregate impact of NPI implementation speed on death rates



(a) All causes of death

(b) Influenza and Pneumonia

Reading notes: Cities having adopted more rapidly NPIs saw their death rates increase less than cities that were slower in 1918. On the other hand the death rate was relatively higher in 1919 and 1920 for these cities

Estimates of the difference in difference equation:

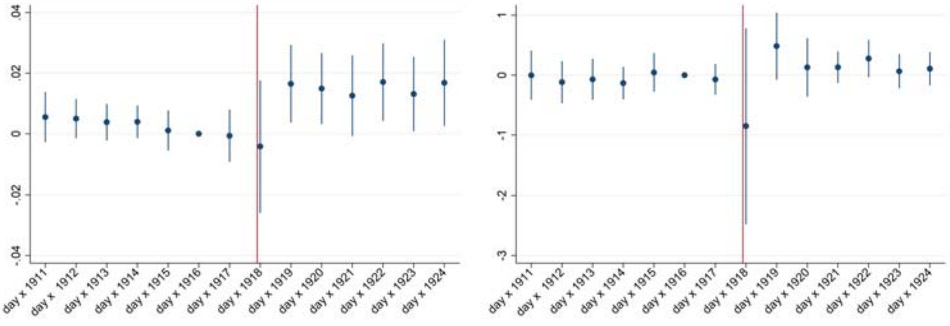
$Deathrate_{i,t} = \delta_i + \gamma_t + \sum_{t \neq 1916} \beta^t \times 1_{t(i)=t} \times NPI_{1918,i} + \sum_{t \neq 1916} \lambda^t \times 1_{t(i)=t} \times X_i + \epsilon_{i,t}$

Controls include health expenditures in 1917, population in 1910, regional shocks, years and city fixed effects

Observations are weighted by their 1910 population

95% confidence Interval clustered at the city level

Figure B.5: Event study: Estimates of the aggregate impact of NPI implementation length on death rates



(a) All causes of death (b) Influenza and Pneumonia

Reading notes:Cities that implemented NPIs for a longer time saw their death rates increase less than cities that had shorter NPIs in 1918. On the other hand the death rate was relatively higher in 1919 and 1920 for these cities

Estimates of the difference in difference equation:

$Deathrate_{i,t} = \delta_i + \gamma_t + \sum_{t \neq 1916} \beta^t \times 1_{t(i)=t} \times NPI_{1918,i} + \sum_{t \neq 1916} \lambda^t \times 1_{t(i)=t} \times X_i + \epsilon_{i,t}$

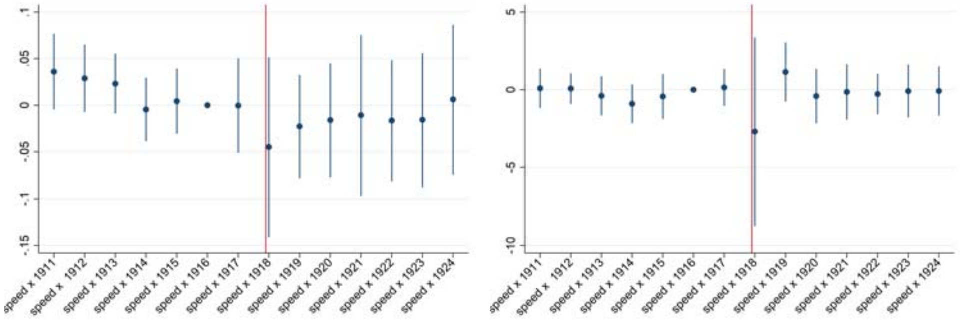
Controls include health expenditures in 1917, population in 1910, regional shocks, years and city fixed effects

Observations are weighted by their 1910 population

95% confidence Interval clustered at the city level

B.3 Controlling for differences in the demographic structures

Figure B.6: Event study: Estimates of the aggregate impact of NPI implementation speed on death rates



(a) All causes of death

(b) Influenza and Pneumonia

Reading notes: Cities having adopted more rapidly NPIs saw their death rates increase less than cities that were slower in 1918. On the other hand the death rate was relatively higher in 1919 and 1920 for these cities

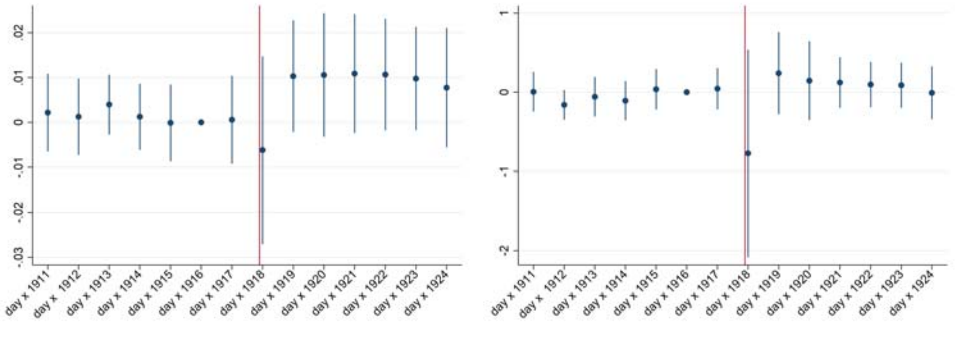
Estimates of the difference in difference equation:

$Deathrate_{i,t} = \delta_i + \gamma_t + \sum_{t\neq 1916} \beta^t \times 1_{t(i)=t} \times NPI_{1918,i} + \sum_{t\neq 1916} \lambda^t \times 1_{t(i)=t} \times X_i + \epsilon_{i,t}$

Controls include health expenditures in 1917, population in 1910, average age, population growth and the sex ratio in 1910, years and city fixed effects

95% confidence Interval clustered at the city level

Figure B.7: Event study: Estimates of the aggregate impact of NPI implementation length on death rates



(a) All causes of death (b) Influenza and Pneumonia

Reading notes: Cities that implemented NPIs for a longer time saw their death rates increase less than cities that had shorter NPIs in 1918. On the other hand the death rate was relatively higher in 1919 and 1920 for these cities

Estimates of the difference in difference equation:

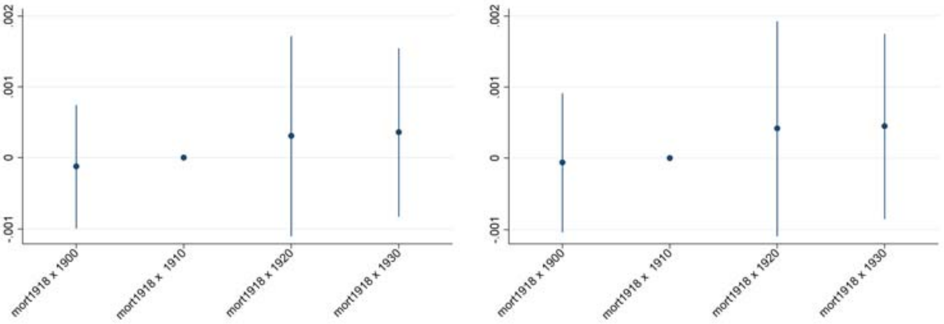
$Deathrate_{i,t} = \delta_i + \gamma_t + \sum_{t \neq 1916} \beta^t \times 1_{t(i)=t} \times NPI_{1918,i} + \sum_{t \neq 1916} \lambda^t \times 1_{t(i)=t} \times X_i + \epsilon_{i,t}$

Controls include health expenditures in 1917, population in 1900, average age, population growth and the sex ratio in 1920, years and city fixed effects

95% confidence Interval clustered at the city level

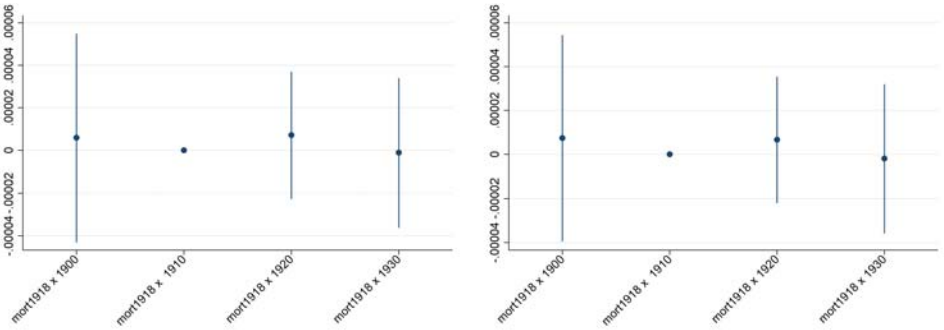
B.4 Coefficient on 1918 Mortality

Figure B.8: Event study: Estimates of the aggregate impact of the 1918 death rate on cities' demographic growth and the share of the cohort aged between 25 and 34 in 1918



(a) Impact of the mortality in 1918 on Population growth between year t and t-10 ,controlling for the speed of implementation of NPIs

(b) Impact of the mortality in 1918 on Population growth between year t and t-10 ,controlling for the length of implementation of NPIs



(c) Impact of the mortality in 1918 on the cohort aged between 24 and 35 in 1918,controlling for the speed of implementation of NPIs

(d) Impact of the mortality in 1918 on the cohort aged between 24 and 35 in 1918,controlling for the length of implementation of NPIs

Reading notes: Cities that implemented NPIs for a longer time saw their death rates increase less than cities that had shorter NPIs in 1918. On the other hand the death rate was relatively higher in 1919 and 1920 for these cities

Estimates of the difference in difference equation:

$Deathrate_{i,t} = \delta_i + \gamma_t + \sum_{t \neq 1916} \beta^t \times 1_{t(i)=t} \times NPI_{1918,i} + \sum_{t \neq 1916} \lambda^t \times 1_{t(i)=t} \times X_i + \epsilon_{i,t}$

Controls include health expenditures in 1917, population in 1910, years and city fixed effects

95% confidence Interval clustered at the city level

C The demographic structure

Table C.1: Balance test, demographics in 1900 by length of NPIs

		Below the Median			Above the Median			Difference		
variable	year	Average	Standard Deviation	Obs	Average	Standard Deviation	Obs	Difference	Tstat	pvalue
POP	1900	247074	274906	22	415965	782282	21	-168891	-0.953	0.346
POPgrowth	1900	.	.	.	.	.	.	.	.	.
ratio	1900	0.961	0.0675	22	1.068	0.218	21	-0.106	-2.186	0.0346
average_age	1900	27.34	1.267	22	27.43	1.335	21	-0.0909	-0.229	0.820
age_q1	1900	4.591	0.666	22	5.048	0.921	21	-0.457	-1.870	0.0686
age_q5	1900	25.32	1.323	22	25.76	1.868	21	-0.444	-0.902	0.372
age_q9	1900	53.05	2.126	22	52.10	2.071	21	0.950	1.483	0.146
share_a0001	1900	0.0207	0.00310	22	0.0184	0.00349	21	0.00229	2.279	0.0280
share_a0104	1900	0.0786	0.00875	22	0.0743	0.0120	21	0.00429	1.345	0.186
share_a0514	1900	0.185	0.0159	22	0.186	0.0201	21	-0.00121	-0.219	0.828
share_a1524	1900	0.200	0.0157	22	0.193	0.0109	21	0.00667	1.612	0.115
share_a2534	1900	0.192	0.0119	22	0.198	0.0198	21	-0.00588	-1.184	0.243
share_a3544	1900	0.142	0.00896	22	0.156	0.0213	21	-0.0138	-2.789	0.00799
share_a4554	1900	0.0915	0.00768	22	0.0914	0.00959	21	0.000129	0.0489	0.961
share_a5564	1900	0.0534	0.00782	22	0.0501	0.00836	21	0.00324	1.314	0.196
share_a6574	1900	0.0264	0.00484	22	0.0240	0.00567	21	0.00248	1.542	0.131
share_a7584	1900	0.00887	0.00207	22	0.00759	0.00192	21	0.00128	2.101	0.0418
share_a8500	1900	0.00193	0.000713	22	0.00144	0.000358	21	0.000492	2.841	0.00698
share_c0001	1900	.	.	.	.	.	.	.	.	.
share_c0104	1900	.	.	.	.	.	.	.	.	.
share_c0514	1900	.	.	.	.	.	.	.	.	.
share_c1524	1900	0.127	0.0139	22	0.120	0.0192	21	0.00697	1.370	0.178
share_c2534	1900	0.181	0.0160	22	0.182	0.0194	21	-0.00104	-0.192	0.849
share_c3544	1900	0.206	0.0170	22	0.197	0.0111	21	0.00884	2.006	0.0515
share_c4554	1900	0.184	0.0110	22	0.192	0.0195	21	-0.00814	-1.693	0.0981
share_c5564	1900	0.132	0.00773	22	0.144	0.0179	21	-0.0123	-2.945	0.00530
share_c6574	1900	0.0842	0.00804	22	0.0829	0.00897	21	0.00130	0.500	0.620
share_c7584	1900	0.0480	0.00755	22	0.0447	0.00806	21	0.00324	1.363	0.180
share_c8500	1900	0.0300	0.00623	22	0.0265	0.00678	21	0.00350	1.766	0.0848
share_c99999	1900	0.00819	0.00558	22	0.0106	0.0132	21	-0.00238	-0.774	0.443

Table C.2: Balance test, demographics in 1910 by length of NPIs

		Below the Median			Above the Median			Difference		
variable	year	Average	Standard Deviation	Obs	Average	Standard Deviation	Obs	Difference	Tstat	pvalue
POP	1910	310610	326523	22	578011	1.057e+06	21	-267402	-1.132	0.264
POPgrowth	1910	0.346	0.436	22	0.655	0.630	21	-0.309	-1.878	0.0675
ratio	1910	0.988	0.0923	22	1.073	0.138	21	-0.0844	-2.364	0.0229
average_age	1910	28.15	1.321	22	28.65	1.300	21	-0.505	-1.262	0.214
age_q1	1910	4.818	0.795	22	5.381	0.973	21	-0.563	-2.081	0.0437
age_q5	1910	26.05	1.463	22	26.81	1.601	21	-0.764	-1.635	0.110
age_q9	1910	53.82	1.967	22	53.19	1.778	21	0.628	1.096	0.280
share_a0001	1910	0.0208	0.00309	22	0.0184	0.00294	21	0.00240	2.607	0.0127
share_a0104	1910	0.0750	0.00850	22	0.0684	0.00924	21	0.00659	2.435	0.0193
share_a0514	1910	0.169	0.0170	22	0.154	0.0201	21	0.0146	2.575	0.0137
share_a1524	1910	0.200	0.0129	22	0.202	0.0108	21	-0.00230	-0.632	0.531
share_a2534	1910	0.192	0.0158	22	0.207	0.0198	21	-0.0154	-2.827	0.00722
share_a3544	1910	0.148	0.00971	22	0.154	0.0113	21	-0.00640	-1.999	0.0522
share_a4554	1910	0.101	0.00769	22	0.105	0.00807	21	-0.00389	-1.619	0.113
share_a5564	1910	0.0553	0.00708	22	0.0541	0.00717	21	0.00125	0.575	0.568
share_a6574	1910	0.0286	0.00536	22	0.0265	0.00490	21	0.00213	1.358	0.182
share_a7584	1910	0.00947	0.00206	22	0.00863	0.00177	21	0.000838	1.431	0.160
share_a8500	1910	0.00157	0.000372	22	0.00138	0.000312	21	0.000198	1.888	0.0661
share_c0001	1910	.	.	.	.	.	.	.	.	.
share_c0104	1910	.	.	.	.	.	.	.	.	.
share_c0514	1910	0.131	0.0153	22	0.119	0.0162	21	0.0124	2.585	0.0134
share_c1524	1910	0.168	0.0156	22	0.156	0.0197	21	0.0127	2.344	0.0240
share_c2534	1910	0.209	0.0143	22	0.217	0.0127	21	-0.00721	-1.743	0.0889
share_c3544	1910	0.183	0.0145	22	0.196	0.0181	21	-0.0129	-2.588	0.0133
share_c4554	1910	0.137	0.00942	22	0.143	0.0104	21	-0.00627	-2.078	0.0440
share_c5564	1910	0.0905	0.00773	22	0.0935	0.00792	21	-0.00298	-1.249	0.219
share_c6574	1910	0.0495	0.00700	22	0.0477	0.00707	21	0.00178	0.830	0.411
share_c7584	1910	0.0236	0.00460	22	0.0218	0.00422	21	0.00177	1.312	0.197
share_c8500	1910	0.00763	0.00173	22	0.00689	0.00143	21	0.000743	1.531	0.134
share_c99999	1910	.	.	.	.	.	.	.	.	.

Table C.3: Balance test, demographics in 1920 by length of NPIs

		Below the Median			Above the Median			Difference		
variable	year	Average	Standard Deviation	Obs	Average	Standard Deviation	Obs	Difference	Tstat	pvalue
POP	1920	369174	385078	22	711416	1.249e+06	21	-342242	-1.226	0.227
POPgrowth	1920	0.187	0.110	22	0.282	0.191	21	-0.0949	-2.003	0.0518
ratio	1920	0.968	0.0607	22	1.015	0.0519	21	-0.0465	-2.693	0.0102
average_age	1920	29.01	1.330	22	29.98	1.520	21	-0.964	-2.216	0.0323
age_q1	1920	4.955	0.899	22	5.476	0.928	21	-0.522	-1.872	0.0683
age_q5	1920	27.18	1.593	22	28.71	1.793	21	-1.532	-2.966	0.00501
age_q9	1920	55.41	1.894	22	55.81	2.089	21	-0.400	-0.659	0.513
share_a0001	1920	0.0198	0.00268	22	0.0167	0.00220	21	0.00307	4.086	0.000199
share_a0104	1920	0.0759	0.0102	22	0.0680	0.00961	21	0.00789	2.607	0.0127
share_a0514	1920	0.173	0.0183	22	0.160	0.0149	21	0.0134	2.624	0.0122
share_a1524	1920	0.176	0.0142	22	0.171	0.0115	21	0.00519	1.315	0.196
share_a2534	1920	0.185	0.0127	22	0.196	0.0105	21	-0.0112	-3.141	0.00312
share_a3544	1920	0.151	0.0114	22	0.161	0.0112	21	-0.0106	-3.083	0.00365
share_a4554	1920	0.112	0.00899	22	0.115	0.0115	21	-0.00349	-1.113	0.272
share_a5564	1920	0.0647	0.00843	22	0.0684	0.00930	21	-0.00374	-1.381	0.175
share_a6574	1920	0.0307	0.00476	22	0.0311	0.00548	21	-0.000414	-0.265	0.793
share_a7584	1920	0.0105	0.00202	22	0.0106	0.00214	21	-8.32e-05	-0.131	0.897
share_a8500	1920	0.00218	0.000378	22	0.00217	0.000447	21	9.49e-06	0.0753	0.940
share_c0001	1920	0.0193	0.00279	22	0.0171	0.00256	21	0.00221	2.706	0.00989
share_c0104	1920	0.0751	0.00934	22	0.0682	0.00865	21	0.00686	2.496	0.0167
share_c0514	1920	0.167	0.0171	22	0.154	0.0137	21	0.0127	2.676	0.0107
share_c1524	1920	0.186	0.0158	22	0.184	0.0113	21	0.00236	0.562	0.578
share_c2534	1920	0.180	0.0126	22	0.194	0.0105	21	-0.0137	-3.875	0.000377
share_c3544	1920	0.142	0.0105	22	0.150	0.0109	21	-0.00758	-2.324	0.0252
share_c4554	1920	0.100	0.00890	22	0.105	0.0116	21	-0.00417	-1.327	0.192
share_c5564	1920	0.0574	0.00757	22	0.0606	0.00864	21	-0.00321	-1.297	0.202
share_c6574	1920	0.0256	0.00424	22	0.0259	0.00491	21	-0.000293	-0.210	0.835
share_c7584	1920	0.00740	0.00145	22	0.00756	0.00157	21	-0.000153	-0.333	0.741
share_c8500	1920	0.00145	0.000337	22	0.00145	0.000339	21	7.99e-07	0.00774	0.994
share_c99999	1920	0.0386	0.00510	22	0.0336	0.00450	21	0.00503	3.421	0.00143

Table C.4: Balance test, demographics in 1930 by length of NPIs

		Below the Median			Above the Median			Difference		
variable	year	Average	Standard Deviation	Obs	Average	Standard Deviation	Obs	Difference	Tstat	pvalue
POP	1930	408033	411836	22	887415	1.545e+06	21	-479382	-1.404	0.168
POPgrowth	1930	0.115	0.118	22	0.238	0.219	21	-0.123	-2.313	0.0258
ratio	1930	0.952	0.0509	22	0.978	0.0372	21	-0.0262	-1.918	0.0621
average_age	1930	30.33	1.342	22	31.14	1.378	21	-0.808	-1.948	0.0583
age_q1	1930	5.773	0.813	22	6.286	0.644	21	-0.513	-2.288	0.0274
age_q5	1930	28.50	1.739	22	29.81	1.692	21	-1.310	-2.501	0.0165
age_q9	1930	57.59	2.039	22	57.86	1.905	21	-0.266	-0.442	0.661
share_a0001	1930	0.0149	0.00168	22	0.0140	0.00169	21	0.000988	1.922	0.0616
share_a0104	1930	0.0639	0.00686	22	0.0590	0.00648	21	0.00495	2.431	0.0195
share_a0514	1930	0.174	0.0194	22	0.158	0.0127	21	0.0163	3.232	0.00243
share_a1524	1930	0.177	0.0112	22	0.174	0.00867	21	0.00283	0.920	0.363
share_a2534	1930	0.169	0.0159	22	0.179	0.00991	21	-0.00904	-2.227	0.0315
share_a3544	1930	0.155	0.0106	22	0.165	0.00791	21	-0.00930	-3.246	0.00233
share_a4554	1930	0.117	0.00937	22	0.122	0.0104	21	-0.00501	-1.657	0.105
share_a5564	1930	0.0748	0.00966	22	0.0748	0.00897	21	-2.73e-05	-0.00959	0.992
share_a6574	1930	0.0393	0.00626	22	0.0405	0.00686	21	-0.00116	-0.581	0.564
share_a7584	1930	0.0122	0.00213	22	0.0127	0.00263	21	-0.000491	-0.674	0.504
share_a8500	1930	0.00207	0.000453	22	0.00208	0.000436	21	-3.50e-06	-0.0258	0.980
share_c0001	1930	0.0178	0.00226	22	0.0158	0.00155	21	0.00199	3.349	0.00175
share_c0104	1930	0.0675	0.00758	22	0.0616	0.00516	21	0.00594	2.987	0.00474
share_c0514	1930	0.179	0.0138	22	0.181	0.00886	21	-0.00145	-0.407	0.686
share_c1524	1930	0.169	0.0145	22	0.178	0.00916	21	-0.00885	-2.378	0.0222
share_c2534	1930	0.148	0.0102	22	0.157	0.00872	21	-0.00949	-3.280	0.00212
share_c3544	1930	0.108	0.00938	22	0.111	0.0103	21	-0.00302	-1.007	0.320
share_c4554	1930	0.0674	0.00939	22	0.0676	0.00862	21	-0.000279	-0.101	0.920
share_c5564	1930	0.0324	0.00525	22	0.0339	0.00626	21	-0.00154	-0.878	0.385
share_c6574	1930	0.00869	0.00169	22	0.00906	0.00196	21	-0.000371	-0.666	0.509
share_c7584	1930	0.00113	0.000243	22	0.00115	0.000250	21	-1.88e-05	-0.250	0.804
share_c8500	1930	8.54e-05	4.32e-05	22	7.90e-05	2.41e-05	21	6.30e-06	0.587	0.561
share_c99999	1930	0.201	0.0216	22	0.184	0.0163	21	0.0171	2.921	0.00566

Table C.5: Balance test, demographics in 1900 by speed of NPIs

		Below the Median			Above the Median			Difference		
variable	year	Average	Standard Deviation	Obs	Average	Standard Deviation	Obs	Difference	Tstat	pvalue
POP	1900	258556	271404	22	403936	786094	21	-145380	-0.818	0.418
POPgrowth	1900	.	.	.	.	.	.	.	.	.
ratio	1900	0.968	0.0657	22	1.061	0.221	21	-0.0936	-1.899	0.0646
average_age	1900	27.28	1.221	22	27.49	1.373	21	-0.207	-0.523	0.604
age_q1	1900	4.500	0.598	22	5.143	0.910	21	-0.643	-2.750	0.00883
age_q5	1900	25.36	1.329	22	25.71	1.875	21	-0.351	-0.710	0.482
age_q9	1900	52.91	2.022	22	52.24	2.234	21	0.671	1.034	0.307
share_a0001	1900	0.0208	0.00300	22	0.0183	0.00351	21	0.00248	2.496	0.0167
share_a0104	1900	0.0791	0.00852	22	0.0738	0.0119	21	0.00532	1.689	0.0988
share_a0514	1900	0.185	0.0167	22	0.185	0.0194	21	-0.000401	-0.0726	0.942
share_a1524	1900	0.198	0.0155	22	0.195	0.0119	21	0.00330	0.778	0.441
share_a2534	1900	0.193	0.0121	22	0.197	0.0200	21	-0.00411	-0.819	0.417
share_a3544	1900	0.143	0.0112	22	0.154	0.0211	21	-0.0110	-2.143	0.0381
share_a4554	1900	0.0914	0.00767	22	0.0915	0.00960	21	-5.34e-05	-0.0202	0.984
share_a5564	1900	0.0529	0.00738	22	0.0507	0.00895	21	0.00220	0.882	0.383
share_a6574	1900	0.0259	0.00460	22	0.0246	0.00607	21	0.00134	0.817	0.419
share_a7584	1900	0.00858	0.00190	22	0.00789	0.00224	21	0.000689	1.090	0.282
share_a8500	1900	0.00179	0.000527	22	0.00160	0.000693	21	0.000192	1.024	0.312
share_c0001	1900	.	.	.	.	.	.	.	.	.
share_c0104	1900	.	.	.	.	.	.	.	.	.
share_c0514	1900	.	.	.	.	.	.	.	.	.
share_c1524	1900	0.127	0.0137	22	0.119	0.0190	21	0.00827	1.641	0.108
share_c2534	1900	0.181	0.0165	22	0.182	0.0190	21	-0.000922	-0.170	0.865
share_c3544	1900	0.204	0.0170	22	0.199	0.0123	21	0.00483	1.061	0.295
share_c4554	1900	0.185	0.0113	22	0.191	0.0198	21	-0.00572	-1.168	0.249
share_c5564	1900	0.133	0.00944	22	0.143	0.0178	21	-0.0101	-2.344	0.0240
share_c6574	1900	0.0839	0.00773	22	0.0832	0.00929	21	0.000684	0.263	0.794
share_c7584	1900	0.0474	0.00709	22	0.0453	0.00868	21	0.00214	0.886	0.381
share_c8500	1900	0.0292	0.00579	22	0.0274	0.00751	21	0.00180	0.883	0.382
share_c99999	1900	0.00888	0.00605	22	0.00985	0.0131	21	-0.000963	-0.311	0.757

Table C.6: Balance test, demographics in 1910 by speed of NPIs

		Below the Median			Above the Median			Difference		
variable	year	Average	Standard Deviation	Obs	Average	Standard Deviation	Obs	Difference	Tstat	pvalue
POP	1910	326922	320429	22	560922	1.063e+06	21	-234001	-0.987	0.329
POPgrowth	1910	0.365	0.436	22	0.636	0.639	21	-0.271	-1.635	0.110
ratio	1910	0.994	0.0903	22	1.067	0.143	21	-0.0736	-2.028	0.0491
average_age	1910	28.10	1.259	22	28.70	1.342	21	-0.603	-1.519	0.136
age_q1	1910	4.864	0.834	22	5.333	0.966	21	-0.470	-1.709	0.0949
age_q5	1910	26.05	1.430	22	26.81	1.632	21	-0.764	-1.635	0.110
age_q9	1910	53.64	1.733	22	53.38	2.061	21	0.255	0.441	0.662
share_a0001	1910	0.0208	0.00311	22	0.0184	0.00294	21	0.00239	2.586	0.0134
share_a0104	1910	0.0750	0.00853	22	0.0684	0.00924	21	0.00653	2.408	0.0206
share_a0514	1910	0.170	0.0173	22	0.154	0.0194	21	0.0157	2.805	0.00767
share_a1524	1910	0.199	0.0122	22	0.203	0.0114	21	-0.00399	-1.108	0.274
share_a2534	1910	0.192	0.0160	22	0.206	0.0203	21	-0.0135	-2.433	0.0194
share_a3544	1910	0.149	0.0101	22	0.153	0.0114	21	-0.00454	-1.384	0.174
share_a4554	1910	0.101	0.00795	22	0.105	0.00774	21	-0.00411	-1.716	0.0937
share_a5564	1910	0.0548	0.00646	22	0.0547	0.00781	21	9.90e-05	0.0454	0.964
share_a6574	1910	0.0281	0.00485	22	0.0270	0.00559	21	0.00108	0.675	0.503
share_a7584	1910	0.00922	0.00188	22	0.00889	0.00204	21	0.000331	0.553	0.583
share_a8500	1910	0.00151	0.000348	22	0.00144	0.000365	21	7.47e-05	0.687	0.496
share_c0001	1910	.	.	.	.	.	.	.	.	.
share_c0104	1910	.	.	.	.	.	.	.	.	.
share_c0514	1910	0.131	0.0154	22	0.119	0.0161	21	0.0126	2.628	0.0120
share_c1524	1910	0.169	0.0160	22	0.155	0.0191	21	0.0133	2.489	0.0170
share_c2534	1910	0.209	0.0138	22	0.217	0.0128	21	-0.00876	-2.156	0.0370
share_c3544	1910	0.184	0.0147	22	0.195	0.0186	21	-0.0111	-2.167	0.0361
share_c4554	1910	0.138	0.00971	22	0.142	0.0106	21	-0.00424	-1.368	0.179
share_c5564	1910	0.0902	0.00790	22	0.0938	0.00760	21	-0.00358	-1.512	0.138
share_c6574	1910	0.0489	0.00629	22	0.0483	0.00784	21	0.000595	0.275	0.785
share_c7584	1910	0.0231	0.00417	22	0.0223	0.00480	21	0.000816	0.596	0.555
share_c8500	1910	0.00740	0.00158	22	0.00713	0.00169	21	0.000279	0.561	0.578

Table C.7: Balance test, demographics in 1920 by speed of NPIs

		Below the Median			Above the Median			Difference		
variable	year	Average	Standard Deviation	Obs	Average	Standard Deviation	Obs	Difference	Tstat	pvalue
POP	1920	388825	377175	22	690830	1.257e+06	21	-302005	-1.078	0.287
POPgrowth	1920	0.193	0.106	22	0.275	0.197	21	-0.0828	-1.729	0.0913
ratio	1920	0.978	0.0609	22	1.005	0.0588	21	-0.0262	-1.433	0.159
average_age	1920	29.04	1.402	22	29.95	1.469	21	-0.911	-2.080	0.0438
age_q1	1920	5	0.976	22	5.429	0.870	21	-0.429	-1.517	0.137
age_q5	1920	27.27	1.723	22	28.62	1.746	21	-1.346	-2.545	0.0148
age_q9	1920	55.27	1.882	22	55.95	2.061	21	-0.680	-1.130	0.265
share_a0001	1920	0.0196	0.00290	22	0.0169	0.00221	21	0.00264	3.340	0.00180
share_a0104	1920	0.0751	0.0107	22	0.0689	0.00974	21	0.00622	1.994	0.0528
share_a0514	1920	0.172	0.0192	22	0.160	0.0145	21	0.0119	2.296	0.0269
share_a1524	1920	0.177	0.0137	22	0.170	0.0116	21	0.00682	1.753	0.0871
share_a2534	1920	0.186	0.0127	22	0.195	0.0115	21	-0.00942	-2.549	0.0146
share_a3544	1920	0.151	0.0115	22	0.161	0.0115	21	-0.00988	-2.821	0.00734
share_a4554	1920	0.112	0.0106	22	0.115	0.0102	21	-0.00243	-0.769	0.446
share_a5564	1920	0.0644	0.00889	22	0.0687	0.00871	21	-0.00426	-1.587	0.120
share_a6574	1920	0.0303	0.00448	22	0.0316	0.00566	21	-0.00126	-0.814	0.421
share_a7584	1920	0.0104	0.00187	22	0.0107	0.00227	21	-0.000378	-0.597	0.554
share_a8500	1920	0.00218	0.000384	22	0.00216	0.000442	21	2.19e-05	0.174	0.863
share_c0001	1920	0.0191	0.00287	22	0.0173	0.00263	21	0.00182	2.161	0.0366
share_c0104	1920	0.0743	0.00987	22	0.0691	0.00866	21	0.00520	1.833	0.0741
share_c0514	1920	0.166	0.0177	22	0.155	0.0133	21	0.0119	2.491	0.0169
share_c1524	1920	0.187	0.0154	22	0.183	0.0115	21	0.00419	1.004	0.321
share_c2534	1920	0.181	0.0125	22	0.193	0.0115	21	-0.0122	-3.316	0.00192
share_c3544	1920	0.142	0.0104	22	0.150	0.0111	21	-0.00723	-2.202	0.0334
share_c4554	1920	0.101	0.0111	22	0.104	0.00964	21	-0.00282	-0.885	0.381
share_c5564	1920	0.0571	0.00772	22	0.0609	0.00834	21	-0.00388	-1.585	0.121
share_c6574	1920	0.0252	0.00390	22	0.0263	0.00514	21	-0.00106	-0.763	0.450
share_c7584	1920	0.00735	0.00139	22	0.00761	0.00162	21	-0.000264	-0.575	0.569
share_c8500	1920	0.00146	0.000351	22	0.00143	0.000324	21	2.34e-05	0.227	0.821
share_c99999	1920	0.0383	0.00546	22	0.0340	0.00445	21	0.00430	2.820	0.00736

Table C.8: Balance test, demographics in 1930 by speed of NPIs

		Below the Median			Above the Median			Difference		
variable	year	Average	Standard Deviation	Obs	Average	Standard Deviation	Obs	Difference	Tstat	pvalue
POP	1930	430678	403520	22	863691	1.555e+06	21	-433013	-1.263	0.214
POPgrowth	1930	0.111	0.112	22	0.242	0.220	21	-0.131	-2.479	0.0174
ratio	1930	0.952	0.0496	22	0.977	0.0393	21	-0.0252	-1.844	0.0725
average_age	1930	30.29	1.351	22	31.18	1.341	21	-0.890	-2.167	0.0361
age_q1	1930	5.682	0.780	22	6.381	0.590	21	-0.699	-3.304	0.00199
age_q5	1930	28.45	1.654	22	29.86	1.740	21	-1.403	-2.710	0.00979
age_q9	1930	57.55	2.110	22	57.90	1.814	21	-0.359	-0.598	0.553
share_a0001	1930	0.0150	0.00159	22	0.0139	0.00176	21	0.00105	2.060	0.0458
share_a0104	1930	0.0644	0.00678	22	0.0585	0.00613	21	0.00589	2.985	0.00477
share_a0514	1930	0.174	0.0193	22	0.158	0.0129	21	0.0163	3.249	0.00231
share_a1524	1930	0.177	0.0104	22	0.175	0.00974	21	0.00226	0.732	0.469
share_a2534	1930	0.170	0.0161	22	0.178	0.0103	21	-0.00707	-1.701	0.0965
share_a3544	1930	0.155	0.0100	22	0.165	0.00857	21	-0.00949	-3.331	0.00184
share_a4554	1930	0.116	0.00896	22	0.123	0.0104	21	-0.00650	-2.204	0.0332
share_a5564	1930	0.0746	0.00994	22	0.0750	0.00863	21	-0.000464	-0.163	0.871
share_a6574	1930	0.0392	0.00670	22	0.0406	0.00638	21	-0.00146	-0.731	0.469
share_a7584	1930	0.0122	0.00226	22	0.0127	0.00251	21	-0.000536	-0.737	0.465
share_a8500	1930	0.00207	0.000455	22	0.00208	0.000434	21	-1.91e-05	-0.141	0.888
share_c0001	1930	0.0176	0.00231	22	0.0160	0.00167	21	0.00168	2.729	0.00930
share_c0104	1930	0.0670	0.00766	22	0.0621	0.00558	21	0.00497	2.421	0.0200
share_c0514	1930	0.179	0.0129	22	0.181	0.0103	21	-0.00157	-0.440	0.663
share_c1524	1930	0.170	0.0147	22	0.177	0.00972	21	-0.00701	-1.837	0.0735
share_c2534	1930	0.148	0.00938	22	0.158	0.00935	21	-0.00995	-3.485	0.00119
share_c3544	1930	0.107	0.00913	22	0.112	0.0102	21	-0.00465	-1.577	0.122
share_c4554	1930	0.0672	0.00969	22	0.0678	0.00826	21	-0.000571	-0.208	0.837
share_c5564	1930	0.0324	0.00568	22	0.0339	0.00585	21	-0.00156	-0.885	0.381
share_c6574	1930	0.00866	0.00176	22	0.00909	0.00188	21	-0.000434	-0.781	0.439
share_c7584	1930	0.00113	0.000251	22	0.00115	0.000240	21	-1.74e-05	-0.232	0.818
share_c8500	1930	8.70e-05	4.38e-05	22	7.74e-05	2.24e-05	21	9.60e-06	0.899	0.374
share_c99999	1930	0.202	0.0211	22	0.183	0.0158	21	0.0191	3.351	0.00174

D Revisiting the impact of the 1918 flu on local output and employment growth

D.1 Purpose of the section

This section revisits a recent study that exploits the 1918 flu and the policies implemented in large US cities to document the impact of pandemics on the economic activity at the state and the city level and assess the benefits of NPIs. They use a difference-in-difference framework to compare cities that aggressively fought against the pandemic with these that adopted a more passive behaviour. Their main finding can be summarized in panel a) of Figure D.1. They show that there is a correlation between NPIs and Mortality suggesting that NPIs might have mitigated mortality. Moreover, they also show that cities that applied stricter NPIs didn't suffer from an economic loss and tended to grow faster in the medium term. My first contribution is summarized in panel b) of Figure D.1 where I show that the correlation between NPIs, growth and mortality in 1918 was the same before the flu. This suggests that cities that applied stricter NPIs had different trends from laxer cities even before the flu. As a consequence the common trend assumption to estimate the impact of NPIs comparing both group of cities might be violated making any inference much more challenging.

D.2 Empirical Specifications

I follow Correia, Luck, and Verner (2020) and run an event study at the city level in order to compare the growth rate of cities with high or low fatality rate before and after the 1918 flu. I estimate the following equation.

$$log(y_{i,t}) = \delta_i + \gamma_t + \sum_{t \neq 1918} \beta^t \times 1_{t(i)=t} \times Mortality_{1918,i} + \sum_{t \neq 1918} \lambda^t \times 1_{t(i)=t} \times X_{i,1900} + \epsilon_{i,t} \tag{D.1}$$

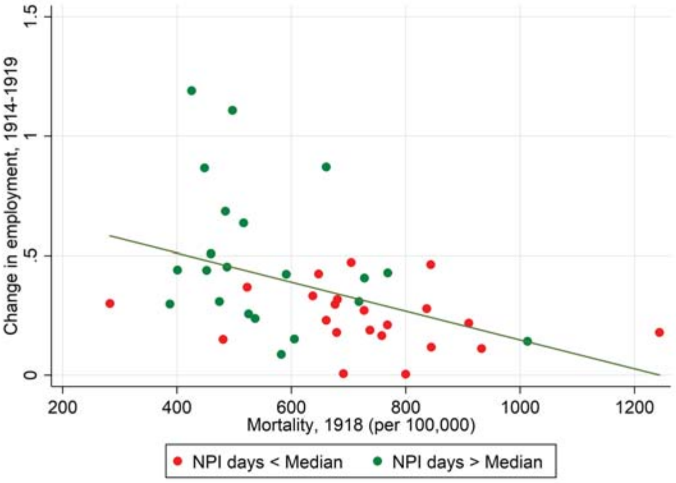
where $y_{i,t}$ are the different outcomes gathered from 1899 to 1923 as total output, total added valued of the manufacturing sector, number of wage workers or the sum of wages for each city i at time t. β^t will estimate the differentiated trend between placed that faced a high or a low mortality in 1918. The added value is not available for 1923. X_i control for the log population in 1900, the amount of health expenditures per capita in 1917, the mortality in 1917, the ratio of manufacturing job to population in 1900. Standard errors are clustered at the city level.

I proceed similarly to identify the impact of NPIs:

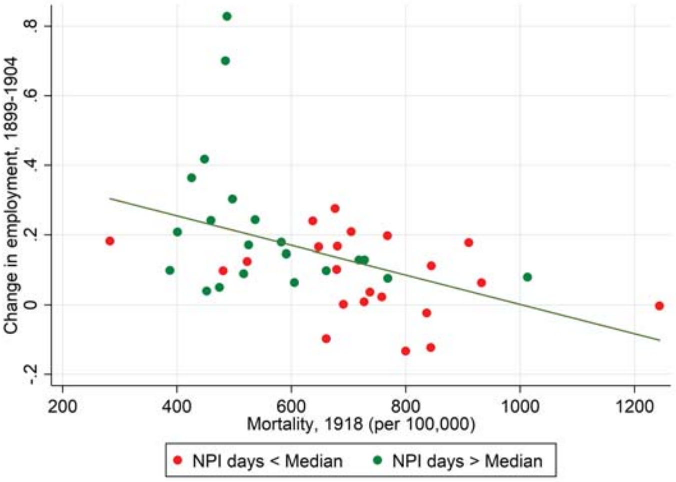
$$log(y_{i,t}) = \delta_i + \gamma_t + \sum_{t \neq 1918} \beta^t \times 1_{t(i)=t} \times NPI_{1918,i} + \sum_{t \neq 1918} \lambda^t \times 1_{t(i)=t} \times X_{i,1900} + \epsilon_{i,t} \tag{D.2}$$

I use the same controls as in equation D.1

Figure D.1: Correlation between change in employment before and after 1918 with Mortality in 1918 in 43 US cities



(a) Change in employment from 1914 to 1919, after the Flu and the implementation of NPIs



(b) Change in employment from 1899 and 1904, before the Flu and the implementation of NPIs

D.3 Balance tests for economic structure

I control for the comparability of low and high NPI cities with balance tests reported in Table D.1 and D.2. Overall, there are few significant differences between the two groups, apart from their level of NPI (by construction) and their level of mortality.

Table D.1: Balance test, manufacturing and health by length of NPIs

	Below the Median			Above the Median			Difference		
variable	Average	Standard Deviation	Obs	Average	Standard Deviation	Obs	Difference	Tstat	pvalue
citypop1900	246259	274059	22	413671	777509	21	-167412	-0.950	0.347
NPI_day	49.82	10.09	22	128.6	32.99	21	-78.75	-10.69	0
NPI_SPEED	-12.09	7.374	22	-2.381	4.631	21	-9.710	-5.142	7.09e-06
MORT_1917	199.7	65.79	22	157.5	49.53	21	42.13	2.363	0.0229
MORT_1918	730.2	184.8	22	560.1	149.8	21	170.2	3.307	0.00197
MANUF_1899	34965	44458	22	47091	91596	21	-12126	-0.556	0.581
VP_1899	84172	111908	22	146978	289427	21	-62807	-0.947	0.349
Wages_1899	15149	18083	22	22611	46156	21	-7462	-0.704	0.485
Health_perhead	0.203	0.125	22	0.184	0.105	21	0.0189	0.535	0.595
HEALTH_17	1.989	0.656	22	1.689	0.519	21	0.301	1.660	0.104

Table D.2: Balance test, manufacturing and health by length of NPIs

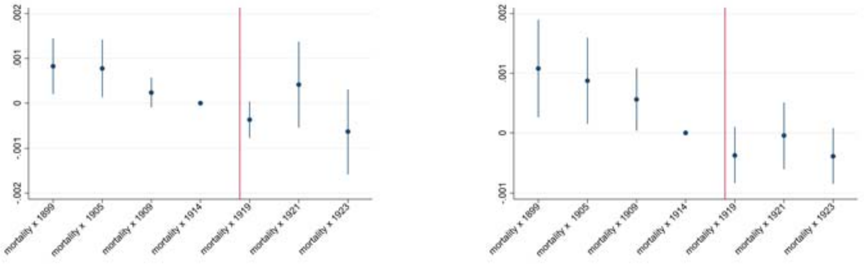
	Below the Median			Above the Median			Difference		
variable	Average	Standard Deviation	Obs	Average	Standard Deviation	Obs	Difference	Tstat	pvalue
citypop1900	257736	270547	22	401648	781318	21	-143911	-0.815	0.420
NPI_day	56.86	24.94	22	121.2	40.63	21	-64.33	-6.290	1.68e-07
NPI_SPEED	-12.82	6.558	22	-1.619	4.080	21	-11.20	-6.685	4.59e-08
MORT_1917	197.2	67.14	22	160.2	49.83	21	36.99	2.044	0.0475
MORT_1918	723.1	184.2	22	567.5	158.8	21	155.6	2.961	0.00509
MANUF_1899	35092	44287	22	46958	91701	21	-11867	-0.544	0.589
VP_1899	86974	110528	22	144042	290619	21	-57069	-0.859	0.396
Wages_1899	15274	17965	22	22479	46226	21	-7205	-0.680	0.501
Health_perhead	0.194	0.121	22	0.193	0.111	21	0.00123	0.0348	0.972
HEALTH_17	1.940	0.674	22	1.740	0.521	21	0.200	1.085	0.284

D.4 Results of the event study

D.4.1 Differentiated trends between cities with different mortality in 1918

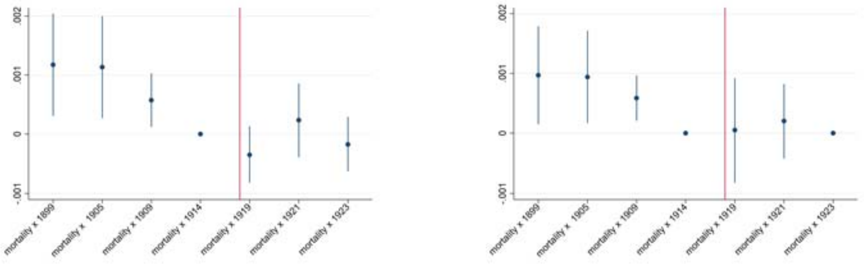
Figure D.2 presents the coefficients estimated using equation D.1. These figures are in line with the results presented in Correia, Luck, and Verner (2020) for states and cities, as we observe a stronger decline in employment after the influenza of 1918 in cities with higher mortality rate and there is no particular trend between 1909 and 1914. However, the addition of data points from 1899 and 1904 changes the picture. One can observe than the cities with lower mortality rates in 1918 used to behave differently in 1899 and 1904 with a growth rate significantly higher than cities with higher mortality in 1918. This findings is in line with panel b) of Figure D.1. While one potential interpretation of the change of sign of the growth rate could be the impact of the 1918 flu, this differentiated trend casts doubt on the possibility of treating the two groups of cities as comparable and of deriving any causal link. Panel b) has no counterpart in Correia, Luck, and Verner (2020) did not include any result on wages. One can observe that the sign of the growth rate of the sum of the wages also becomes negative. While this could be attributed to the impact of the flu, the differentiated positive growth rates at the beginning of the century would also cast serious doubts on this interpretation. Moreover, the sign of the impact is not in line with previous studies; Garrett (2007)for instance finds a positive impact on wages potentially explained by a shortage of labor. Panels c) and d) offer a very similar picture, as employment, total output and value added decline but their trends were also different in 1899 and 1904. To summarize, cities more affected by the flu had different trends before 1918 when compared with those less affected. It is thus difficult to infer any causal relationship between the 1918 pandemics and cities' manufacturing sector dynamics.

Figure D.2: Event study: Estimates of the differentiated trends in the manufacturing sector between cities with High mortality and low mortality in 1918



(a) log(employment)

(b) log(Wages)



(c) log(Total Output)

(d) log(Added Value)

Reading notes: Cities having higher mortality rate had higher growth rate for employment, wage bills, output and added value in 1899 and 1805 and lower in 1819. The growth rates were declining before

Estimates of the difference in difference equation:

$log(y_{i,t}) = \delta_i + \gamma_t + \sum_{t\neq 1918} \beta^t \times 1_{t(i)=t} \times Mortality_{1918,i} + \sum_{t\neq 1918} \lambda^t \times 1_{t(i)=t} \times X_{i,1900} + \epsilon_{i,t}$

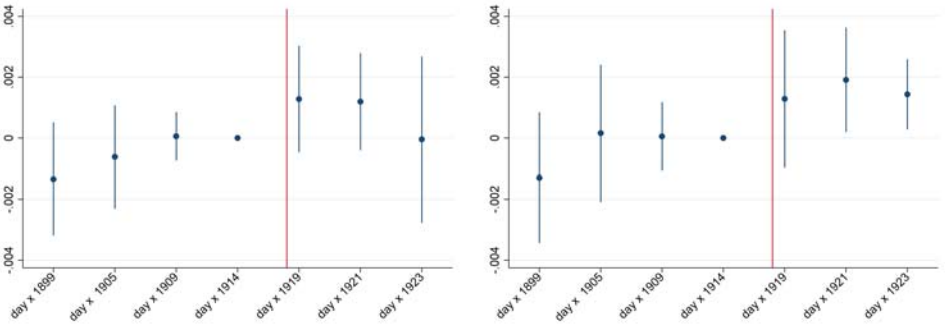
Controls include health expenditures in 1917, population in 1900, the ratio for wage workers to population in 1900, and the mortality in 1917, years and city fixed effects

95% confidence Interval clustered at the city level

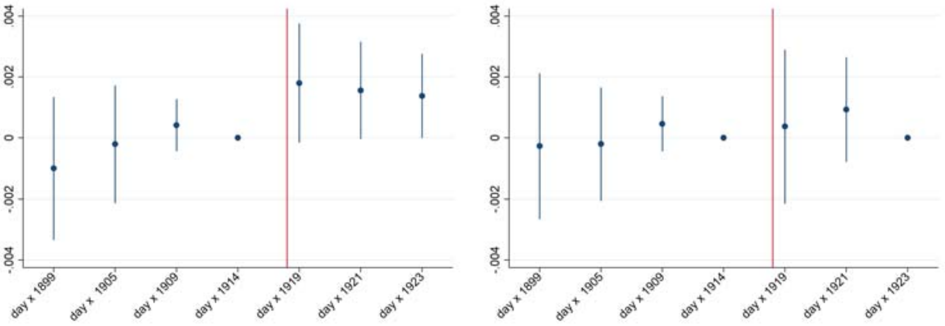
D.5 Differentiated trends between cities with different NPIs policies

Figures D.3 and D.4 respectively the differentiated trends of cities that adopted NPIs either earlier or for a longer period of time, and cities with laxer policies. There is no particular trend in mortality between 1909 and 1914, but for all dependant variables a clear trend of the opposite sign appears before the flu, casting doubt on the causal interpretation of the impact of NPIs on economic activity. Moreover the evidence presented in the previous section documents that these cities also experienced higher death rates in 1919 and 1920 casting doubt on the potential channels that might explain the rebound, given that part of the human capital preserved in 1918 was lost in the subsequent years.

Figure D.3: Event study: Estimates of the differentiated trends in the manufacturing sector between cities High number of days and low number of days under NPIs in 1918



(a) log(employment) (b) log(Wages)



(c) log(Total Output) (d) log(Added Value)

Reading notes:Cities that implemented NPIs for a longer time in 1918 had lower growth rates for employment, wage bills, output and added value in 1899 and 1805 and higher in 1819. The growth rates were rising before 1918

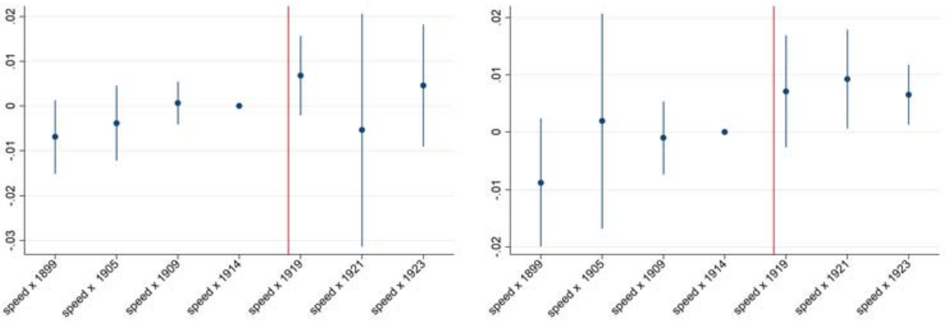
Estimates of the difference in difference equation:

$log(y_{i,t}) = \delta_i + \gamma_t + \sum_{t \neq 1918} \beta^t \times 1_{t(i)=t} \times NPI_{1918,i} + \sum_{t \neq 1918} \lambda^t \times 1_{t(i)=t} \times X_{i,1900} + \epsilon_{i,t}$

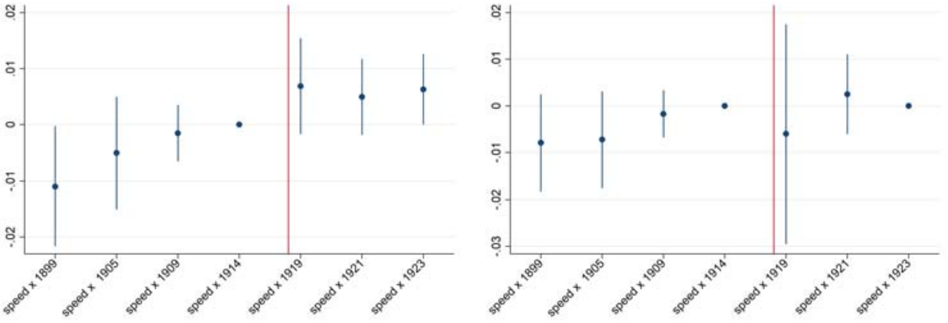
Controls include health expenditures in 1917, population in 1900, the ratio for wage workers to population in 1900, and the mortality in 1917, years and city fixed effects

95% confidence Interval clustered at the city level

Figure D.4: Event study: Estimates of the differentiated trends in the manufacturing sector between cities which were faster and slower to implement NPIs in 1918



(a) log(employment) (b) log(Wages)



(c) log(Total Output) (d) log(Added Value)

Reading notes: Cities having adopted NPIS faster in 1918 had lower growth rates for employment, wage bills, output and added value in 1899 and 1805 and higher in 1918. The growth rates were rising before 1918

Estimates of the difference in difference equation:

$log(y_{i,t}) = \delta_i + \gamma_t + \sum_{t\neq 1918} \beta^t \times 1_{t(i)=t} \times NPI_{1918,i} + \sum_{t\neq 1918} \lambda^t \times 1_{t(i)=t} \times X_{i,1900} + \epsilon_{i,t}$

Controls include health expenditures in 1917, population in 1900, the ratio for wage workers to population in 1900, and the mortality in 1917, years and city fixed effects

95% confidence Interval clustered at the city level