Investigating the effect of the 2018-2019 tariffs from Trump Administration on the Human development of American citizens

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Abstract

During the 2016 U.S. presidential campaign, the future 45th President Donald Trump, appealed to growing protectionist sentiments among voters. Starting from 2018, he concretized his promises in a multiphase tariffs plan on imports according to the 'America First' principle. While numerous studies argue for an economic failure of these measures, the foundation of our study relies in assessing their impact on human development variables to identify a potential trade-off. By analyzing the tariffs impact at the county level, we find no economical or statistical relevant effects. Counties more exposed to tariffs, do not display causal changes in self-reported health, bad mental health days or graduation rates in the short-run. Such results refute the existence of a trade-off between economic and human development which can bring relevant insights to future debate regarding protectionism.

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Introduction

Most international trade theories that are taught in universities point towards a consensus regarding protectionist policies outcomes. Regardless of their political motivations and the gains that some factors of production may experience, these policies are the source of inefficiencies usually expressed in monetary terms and labelled as dead-weight-losses. These losses have already been thoroughly discussed and quantified in the literature (Fajgelbaum, Goldberg, Kennedy & Khandelwal, 2020) treating of the United States unprecedented rise in tariffs imposed in 2018 during Trump's presidency. This can often be interpreted as a deterrence towards the implementation of tariffs which seem to fail in achieving their labor market targets, while creating additional costs spread over the entire population.

As stated above, these costs are always expressed in monetary terms and follow the usual practice of economic studies, focusing on the gross domestic product (GDP) evaluation of outcomes. This paper differs from that approach, inspired by the recent trend consisting in looking at more comprehensive economic indicators, such as the Human Development Index (HDI), to assess the implications of these tariffs. Indeed, this index focuses on different aspects of Human advancement by including the following variables: life expectancy at birth, expected years of schooling, and mean years of schooling to the more classical GNI per capita PPP $ (Human Development Report, 2023). This study will not be considering the monetary aspects and consequences of tariffs, as they have already been thoroughly investigated with a general agreement for a negative relationship (Flaaen & Pierce, 2019). Instead, we evaluate proxy variables within the field of health and education to assess the following question:

Does a county suffering from import competition, experience a shift in health and education variables after implementing protectionist measures?

In this scenario, two hypotheses are possible. In the first, a county that can attribute a major share of its downfall to import competition would experience lower education and health statistics due to the crumbling of its main industries. These can take the form of high school dropouts, harder to meet out-of-pocket payments for healthcare and insurance, or infrastructure degradation. Nevertheless, if the industry can be revived or saved by implemented tariffs, it can bring economic activity to the county and counteract these negative effects. For example, if an industry is protected and faces less competition from foreign companies it could maintain or increase employment. If citizens safeguard their jobs or become hired, they will have additional income available for healthcare as well as employment benefits such as health insurance. Moreover, not having to face the consequences of unemployment and being able to afford leisure activities should have a positive impact on mental health. As for the children of the working adults, their ability to graduate could also be related to these increased employment prospects. They would be less likely to drop-out and take a job to help with family expenses, but also be more motivated to graduate into a healthy labor market. Theoretically, the protected industry could also be flourishing as the main supplier and attracts investments to develop the county's infrastructure with additional hospitals and schools to heal and form the future labor force.

The second hypothesis would be that setbacks from tariffs such as retaliations and increased input prices would in reality worsen the situation or nullify its potential benefits. Indeed, protected industries could not experience a positive employment shock as their costs would start to increase due to imported inputs. In worst cases, this could lead to cost-cuts which are often expressed through lay-offs. Furthermore, retaliations could also negatively affect the purchasing power of citizens with respect to imported goods. Both effects would generate the opposite of hypothesis 1, with less available income to satisfy physical and mental health needs of citizens. Similarly high schoolers' graduation prospects would decline, as they face the consequences of a deteriorating labor market. Therefore, with the help of the research question and these hypotheses, we investigate if a trade-off exists between the monetary costs of tariffs and the Human development of the population.

To achieve this goal, we compile data on the U.S. industries affected by the change in tariffs and evaluate the extent to which they are affected. This measurement is formed on the share of domestic absorption affected by the introduced tariffs, as theorized by Flaaen and Pierce (2019). Subsequently, U.S. counties are attributed their own import protection rate which is a weighted average of the industries rates by each industry's local employment. Using this indicator, we divide control and treated counties with zero and positive protection rates respectively. Finally, we evaluate the treatment effect through an ordinary least squares regression and a difference-in-difference. We also make sure to check for the robustness of our tools with linearity, autocorrelation and parallel trends tests.

We do not identify a short-run significant treatment effect on either of our variables. Indeed, results show that an increase in protectionism is not causally associated with an improvement in Human development for American citizens nor that it worsens it. Moreover, shifting a county's industries from not protected to tariffs exposed, results in a close to zero shift in dependent variables of health. With p-values far over the targeted 0.05, these results are not only economically but also statistically unsignificant. As for education, we find hints of economic significance with a result approaching 10%. Nevertheless, the p-value also points towards a statistical unsignificant result and forbids us to draw any inference.

Related Literature

This paper complements two areas of economic literature, the more developed topic of the 2018 United States tariffs, as well as the less investigated relationship between international trade policy and Human development. The latter shows the most similarities with this study by exploring the impact of different international trade policies and events directly on the HDI or similar Human development measures. Peneva and Ram (2012) study a case close to ours as they explore the relationship between world countries' trade policy restrictiveness on six Human development measures in the fields of health and education. Contrary to their expectation of a negative relationship, comparable to our second hypothesis, their findings point towards no statistical significance with their model's outputs close to zero. On a smaller geographical scale, Kumar (2017) conducts a study on the Association of the Southeast Asian nations (ASEAN) trade openness and its impact on their HDI score. The results display a positive relationship, matching the second hypothesis by proving its opposite. Following the same logic, Jawaid and Waheed (2017) analyze multiple trade variables and their impact on the HDI score of Pakistan which was ranked 145 amongst 187 countries in 2014. They find a positive relationship with most variables confirming again the second hypothesis by opposition. However, exceptions such as imports of consumer goods as a percentage of GDP, display a negative relationship with HDI that echoes the US-China dynamic and would follow the first hypothesis.

Regarding literature concerning the 2018-19 U.S. tariffs, Flaaen and Pierce (2019) question the ability of the tariffs to serve their goal of improving manufacturing employment, output, and producer prices. The key to reach their conclusion resides in disentangling the three main channels of impact from the tariffs, namely: protection for domestic industries, higher imported input costs and harmed international competitiveness. Indeed, they conclude that the goals of the tariffs are not met since the protection of the industries is offset by rising input costs and retaliatory tariffs. As a result, their paper was a source of inspiration for the second hypothesis, and our methodology in the devoted section. Pierce has also studied the effect of older US trade policies when investigating the 2000's trade liberalization towards China (Pierce & Schott, 2020). The dependent variables were mortality measures known as "deaths of despair" (p.47), which displayed a positive relationship with liberalization especially for fatal drug overdose. This study would favor hypothesis 1 and appears as the polar opposite of our question. Finally, there is evidence in literature that workers facing greater import competition from China suffer from worse physical, mental, and general health (Lang, McManus & Schaur, 2018). Therefore, based on available literature both hypotheses are plausible, adding purpose and relevance to our study.

Data

A. Human Development Measures

The main concern that arose during the conception of this paper is the lag in variables. While studying the 2018 tariffs is relevant, being one of the only examples in recent history of such policy change, it however covers a period close to the covid pandemic. It is fair to assume that health, education, and trade variables would display exogenous irregularities during this period, thus limiting our range of study to the years preceding 2020 to avoid distortions. However, the usual HDI measures mentioned above would certainly feature a lag of a few years for the impact of protectionism to be reflected in the data. For instance, rising economic activity that would attract budget for building additional schools and hospitals are projects that take a few years to realize and have an impact on the population.

To solve this issue, we opted for proxies of the variables that could display less lags and thus more direct effects. Regarding citizen's health, we use county level data from the County Health Rankings & Roadmaps (CHR&R) by the University of Wisconsin Population Health

Institute. Their data is a comprehensive summary of the annual Behavioral Risk Factor Surveillance System (BRFSS) survey from the Centers for Disease Control and Prevention (CDC). The key resides in self-reported figures, namely the percentage of adults reporting poor or fair health as well as poor mental health days per month. The university states that among the benefits of self-reported statistics such as its comprehensive and inclusive nature, an association analysis also found that people who reported poor self-rated health had a mortality risk twice as high as people who reported excellent self-rated health. Moreover, this approach solves our aforementioned lag issue as it allows for an anticipation effect regarding the impact of future policies and react faster to changes than to wait for shifts in measures such as life expectancy. We realize that surveyed measures may come with a certain bias, but this can also be a relevant dimension to be considered in our study. For example, politicians aiming for re-election could target these short-run outcomes to gain additional voters.

To quantify education, we build on our need for more direct variables and look into high school graduation rates. We expect more immediate effect than for the mean year of schooling and expected years of schooling proposed by the HDI. For instance, the news about tariffs implementation and the response from the concerned industry could retain jobs and avoid decisions to drop out of school to bring an additional income to the household. To retrieve these numbers, we look into the governmental source of the United States Department of Education which provides yearly estimates at county level. This data set is also summarized by the CHR&R which will ultimately be used.

B. Measure of protectionism

In order to build our analysis on the methodology of Flaaen and Pierce (2019), we first need to retrieve data on the classification of industries. We identify each sector through the North American Industry Classification System (NAICS) and more precisely at the four-digit level to ensure a complete collection of the data. By focusing solely on the protection implication of the US tariffs, we can guarantee that all other industry level data match this classification, which is harmonized country wide. However, we first collect data on the industries affected by the tariffs through the work of Bown (2019) who references them using HS10 codes. In order to make the desired conversion to NAICS 4, we apply the concordance developed by Pierce and Schott (2012) and proceed with a matching of the relevant sectors.

Additionally, we measure import protection by compiling data on an industry's yearly production, imports, and exports. The two trade related variables are retrieved from the United States International Trade Commission. As for each industry's production, it is proxied by the value of shipment collected by the Census bureau in the Annual Survey of Manufactures (ASM).

Methodology

As indicated above, part of our methodology is inspired by Flaaen and Pierce (2019) and their conception of an import protection formula. Its purpose is to quantify the level at which tariffs can restrict foreign competition for an industry by relating "the scale of imports affected by new tariffs to the level of domestic absorption" (p.11). In other words, we do not directly look at tariffs' rate, but instead the extent to which the total national demand for an industry's output is subjected to the policy change. We calculate the protection based on 2017 numbers to avoid any unwanted correlation with the treatment and the measure components such as imports and exports. It is important to note that by focusing our treatment year on 2018, this measure only includes the first 3 phases of Trump's tariffs as well as exclusively the values related to the trading partners of each phase. Moreover, exempted partners, for example Canada and Korea from the steel and aluminum act, are included from the beginning since their exemptions got removed during the studied year. The level of protection is captured by the following equation:

$$Import\ Protection_i = \frac{\sum_{pc \in \Omega^I} imp_{ipc}}{Q_i + imp_i - exp_i}$$

The subscript *i* refers to each four-digit NAICS industry and its related variables. Thus, an industry *i* rate of protection starts on the nominator with the sum of this industry's imports imp_{ipc} from the list Ω^I of U.S. product-country pairs *pc* subject to the tariffs. This sum is then divided by the absorption of the industry, meaning its production Q_i plus its imports imp_i minus the exports exp_i. Note that due to a lack of county level production data for the NAICS 4 industries between the 1111 – 2123 and the 9100, 9300, 9900 codes, the import protection and the remaining part of this study is focused on the manufacturing sector.

To match counties' Human development data with the industries' import protection we create a weighted average of protection by the degree of activity each industry has in the region. Through the 2017 County Business Pattern (CBP) from the Census Bureau, we calculate the employment share of each industry operating in the county which serves to weigh the industry protection. Then, the total import protection for the county is obtained by summing each weighted industry protection. The county import protection measure will be used in our equation to compute the treatment effect. The outcome of this processes on the top ten protected counties is illustrated down below in Table 1.

Table 1: Top Ten Counties by Weighted Import Protection

Rank	County	Protection
1	Mississippi Pontotoc	26,05%
2	Mississippi Chickasaw	23,25%
3	Alabama Clay	18,87%
4	Kentucky Hancock	18,42%
5	North Carolina Alexander	17,08%
6	Illinois Clay	12,40%
7	Georgia Murray	11,83%
8	Kentucky Washington	10,75%
9	Georgia Whitfield	10,60%
10	Mississippi Itawamba	9,96%

With this information, we then proceed to construct the following regression model:

$$\gamma_{it} = \alpha + \delta * C_i + \theta_k * Y_k + \upsilon * T_i + \beta * T_i t + \varepsilon_{it}$$

With γ_{it} being either one of the three Human development measures for county *i* at time *t* which implies that we will run this model once per variable. C_i represents the weighted import protection calculated above to capture the county fixed effect. T_i is the treatment group indicator which is then interacted with the years' time dummy t to obtain our main variable of interest β. T_i either takes the value 0 or 1 for the control and treatment group respectively. The intuition behind this segmentation is that a large share of counties display zero county protection and are thus equivalent to being non-treated by this intervention. Similarly, *t* takes the values 0 for all the years preceding 2018 and 1 otherwise, to represent the before and after intervention timeline. Since the introduction of new tariffs is in waves and covers most of the year 2018, we decide to use this year as our time of intervention to match our yearly data sets.

Note that t is different from the time fixed effect Y_k that represents each observation year k from 2014 to 2019. Furthermore, to address heteroscedasticity issues we run the equation with robust standard errors in STATA. Other linear regression assumption namely linearity and autocorrelation are used to assess the robustness of the results. While linearity is a common concern, autocorrelation is pertinent in this case, as we collect time series data on each county's Human development measure which might be cyclical and thus autocorrelated. We evaluate this possibility through twenty Durbin-Watson tests, on a random sample of 5 counties from each four quantiles of weighted import protection.

This equation serves two purposes, identify the effect δ of weighted import protection via Ordinary Least Squares (OLS) and the interaction effect β through a difference-in-difference (DiD) statistical analysis in STATA. The DiD fits our study as at a certain point in time we face an aggregate level change in a range of panel data. Simultaneously, it accounts for all intrinsic differences that could occur between industries and locations which are source of biases. However, to benefit from this tool we first need to satisfy its main assumption of parallel trends. Indeed, while the treatment and control group are allowed to differ on their characteristics, they must follow a similar trend before the change in policy in order for our model to capture the treatment effect. To test for parallel trends, we include data for multiple years before the policy implementation and test for the significance of a lead variable. The test is conducted by collapsing the dependent variable by the year variable to outline the overall trend of both groups. We expect the assumption to hold as we study industries that operate in the same country and thus evolve in a similar economic environment. Nevertheless, we also use a synthetic control group via the user written packages synth and synth_runner, to counteract a non-satisfied assumption.

Results

It is important to note that due to the Covid pandemic in 2020 and the limitations of our method, all the results below are exclusively relevant in the short-run. Further long-run effects are plausible as discussed in the data section, but not captured by our model.

Firstly, we look into the effect of the OLS on the relationship between the Human development measures and weighted import protection in Table 2. We find that a 10% increase in weighted import protection is associated with a 0.69% decrease in reported poor or fair health at the 95% confidence level. Continuing from left to right, a 10% increase in weighted import protection is associated with, a 0.113 days (or 2 hours 45 minutes per month), increase of reported poor mental health at the 99% confidence level. Finally, a 10% increase in weighted import protection is associated with a 2.12% increase in graduation rate at the 99% confidence level.

Table 2: Regression and DiD coefficients for Human development measures

Variable	(1) Poor_Fair_Health	(2) Mental_health_days	(3) GraduationHS
County_Protection	- 0.069 (0.028)	1.126*** (0.333)	0.212*** (0.045)
2015	0.000*** (0.002)	0.000 (0.029)	0.016*** (0.003)
2016	-0.004*** (0.001)	0.013*** (0.023)	0.026*** (0.003)
2017	-0.004 (0.001)	0.218*** (0.023)	0.047*** (0.002)
2018	0.001 (0.002)	0.356*** (0.02)	0.056*** (0.002)
2019	0.001 (0.002)	0.356*** (0.03)	0.075*** (0.002)
Treatment	-0.015*** (0.001)	0.022 (0.018)	-0.002 (0.002)
Interaction	0.000 (0.002)	0.024 (0.024)	-0.012*** (0.003)
Constant	0.183*** (0.001)	3.541*** (0.025)	0.816*** (0.003)
Observations	18003	17702	16360
R-squared	0.021	0.04	0.066

*Note: Standard errors are in parentheses; *** p<.01, ** p<.05, * p<.1; observations vary with missing values*

We then observe the linearity and autocorrelation check in Figure 1 and Table 3 respectively, to assess whether these association can be causal. From the shape of the scatter plots in Figure 1, it appears that for all three measures the linearity assumption is unlikely to hold due to the high concentration and variability of data at 0% weighted import protection. Regarding the Durbin-Watson tests in Table 3, on average for all three variables the results are at the left of the center value 2. Therefore, counties' Human development measures display positive autocorrelation according to the test on the sample. As a result, the OLS coefficients obtained by regressing the three Human development measures on the weighted import protection, are only indicative and not causal despite their statistical significance.

Table 3: Durbin-Watson Test for 5 randomly sampled counties per quartile

Quantile	County ID	(1) Poor_Fair_ Health	(2) Mental_health_days	(3) GraduationHS
1	2062	0.241	0.431	1.547
1	2252	0.037	0.118	0.874
1	1631 (1625)	0.004	0.151	1.055
1	438	0.106	0.092	0.036
1	3072	0.026	0.218	0.061
2	2113	0.723	1.241	1.203
2	1568	0.603	0.429	1.013
2	559	0.017	0.15	0.024
2	2981	0.276	0.593	0.387
2	752	0.229	0.4	0.315
3	428	0.400	1.541	0.558
3	1934	0.191	0.879	0.422
3	448	0.287	1.074	0.301
3	3001	0.244	0.017	0.65
3	1502	0.172	0.430	0.149
4	1118	0.602	1.571	0.766
4	2172	0.027	0.110	1.844
4	1482	0.138	0.048	0.303
4	405	1.246	0.67	1.239
4	1961	0.019	0.186	1.313

Note: Due to missing values for county 1631, county 1625 has been randomly selected in (3)

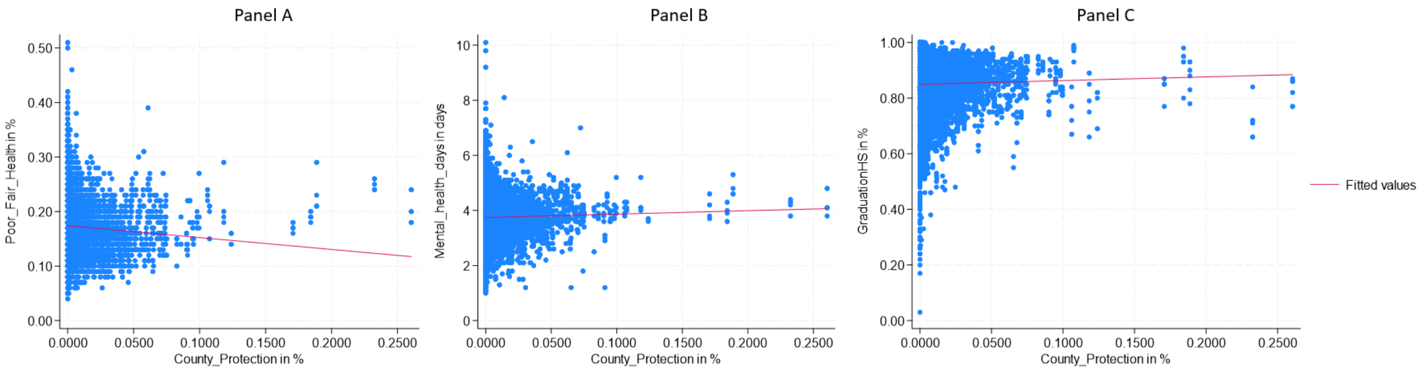

Figure 1: Scatter plot of Human development measure over County Protection with fitted line

Secondly, while we are not able to predict citizen's Human development from import protection based on the above results, we can uncover the treatment effect of becoming a protected county through the DiD results of β. We start by looking at the lead variable significance in Table 4 to determine whether the single butt fundamental assumption of parallel trends holds. We find that for the variables Poor_Fair_Health and Mental_health_days the lead variable is unsignificant while for GraduationHS it is statistically significant at the 99% level. Therefore, the parallel trends assumption holds in two out of three cases and can also be observed in the Figures 3, 4 and 5 of Appendix A. For Poor_Fair_Health and Mental_health_days, we observe interaction terms in Table 2 of 0% and 0.024 days respectively which are unsignificant at the 95% confidence level. The latter is too modest, approximating 30 minutes over a month of mental health, to be economically different from a null effect.

Table 4: DiD regression with lead variable to assess parallel trend assumptions

Variable	(1) Poor_Fair_Health	(2) Mental_health_days	(3) GraduationHS
2015	0.000	0.000	0.016***
	(0.002)	(0.029)	(0.003)
2016	-0.004***	0.112***	0.026***
	(0.001)	(0.023)	(0.003)
2017	-0.004*	0.204***	0.058***
	(0.002)	(0.033)	(0.004)
2018	0.000	0.352***	0.058***
	(0.002)	(0.034)	(0.004)
Lead	0.001	0.023	-0.015***
	(0.002)	(0.031)	(0.005)
Treatment	- 0.016***	0.028	0.004
	(0.001)	(0.023)	(0.003)
Interaction	0.000	0.007	0.000
	(0.003)	(0.032)	(0.005)
Constant	0.184***	3.545***	0.813***
	(0.002)	(0.028)	(0.003)
Observations	14869	14568	13325
R-squared	0.053	0.781	0.089

*Note: Standard errors are in parentheses; *** p<.01, ** p<.05, * p<.1*

Finally for GraduationHS, we instead solve the assumption violation by collapsing the treatment group rates by the years and match it with a synthetic control group formed by the control counties. Note that compared to the DiD method, the user written package cannot account for missing values, thus all counties with at least one missing year must be exempted from the control group. We observe the result of this method in Figure 2 where the synthetic group has been successfully created. Then, with the help of the synth_runner package, STATA runs a series of placebo tests to produce Table 5 outputs where we can find a treatment effect of 9.7% unsignificant at the 95% confidence level. This result also does not appear plausible from a graphical standpoint.

Table 5: Synth_runner estimation of the treatment effect

GraduationrateHS	Coef.	P-value
Treatment effect	.097	0.407

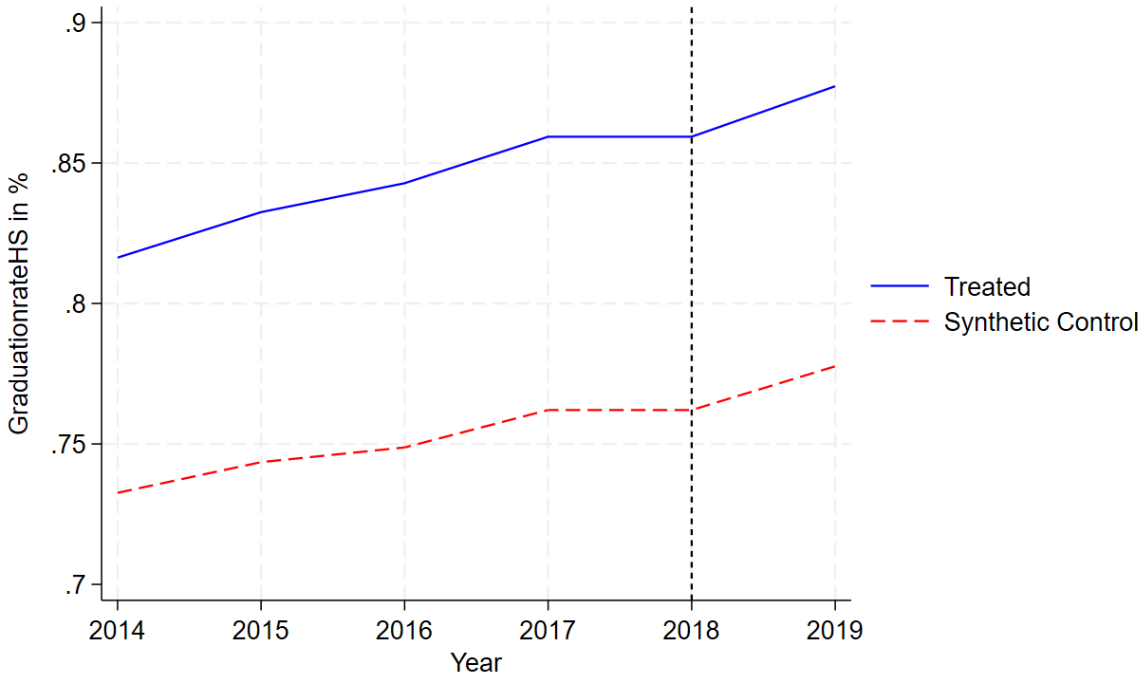

Figure 2: Parallel trend test for high school graduation rate with a synthetic control group

Discussion

A. Robustness and Validity

Before discussing the results, it is first important to evaluate the robustness and validity of the statistical study. In terms of robustness, we identify two possible discussion angles. On the one hand, the DiD method is robust to any dataset that satisfies its fundamental parallel trend assumption and context. This method is free of biases when no major time-varying factors that affect the treatment and control group differently are present and not controlled for. Moreover, it accounts for all time-invariant unobserved factors between the two groups and thus, relaxes the before-and-after and with-and-without crucial assumptions of most statistical methods. Therefore, despite facing linearity and autocorrelation issues with the OLS, we are able to provide robust results for the overall paper. On the other hand, the study's robustness can be affected by the nature of our variables. As previously mentioned, self-reported statistics can be prone to respondents' individual biases and can also be less representative of the county's population depending on the sample selection. Also, the data collection method might be subject to changes from one year to another which could reduce the comparability of the data.

Regarding the internal validity of the results, it appears safe to assume that they are internally valid. The data is collected from the whole territory of the United States and the method accounts for all time-invariant differences between these regions. Nonetheless, the external validity is more complex to prove and our results are most probably not externally valid. Compared to other countries, the United States have their own healthcare and education system that can react differently to such protectionist shocks. For example in the European Union, with less out-of-pocket payments and more subsidies, the health and education of citizens is less prone to changes in the economic environment of the country. Furthermore, in developing economies, protectionism is often used for different purposes such as in the infant industry argument (Hamilton, 1791). Factors such as the growth potential of those economies and their new industries, could impact our studied variables differently.

B. Interpretation

Before reaching our conclusion, we discuss how the results relate to our two hypotheses and the research question. We avoid interpreting the results of OLS as they are not causal and rather focus on the DiD interaction coefficient. Concerning hypothesis 1, the null and unsignificant treatment effects that we have found for do not provide a proof that protectionism can improve the socio-economic status of a county. In the best scenario, there could be a positive effect in that direction which is countered by other factors as discussed in hypothesis 2. Indeed, as we formulated in the introduction, protectionism is often the cause for retaliation and increased input prices that could negatively impact our studied variables. With respect to our findings, the second hypothesis is not confirmed either, and we cannot consider this scenario valid without further proofs.

As a result, our research allows us to affirm that a region suffering from import competition, in this case a United States county, does not experience a net shift in health and education statistics after the implementation of protectionist measures.

C. Proposal for further studies

As mentioned in the external validity section, our study could have different outcomes in developing countries and in a more subsidized system. Thus, it would be relevant to replicate this study in these two other contexts, for instance with a member of the Asian Tigers such as South Korea or a European country. By assessing these different scenarios, one could also analyze if different protectionist measures such as embargo or quotas have effects that vary from tariffs.

Another interesting standpoint for supplementary study, would be to find evidence of the different channels that impact our Human development proxy variables and whether they are the cause of the null treatment. Noteworthy examples would be retaliation or increased output prices as a negative effect, and investment in infrastructure as a positive effect.

Conclusion

This paper examines whether the 2018 -2019 tariffs by the Trump Administration had an impact on the short-run Human development of American citizens. To achieve this goal, we evaluate variables of education and health through the yearly graduation rate, self-reported rate of bad or poor health and the number of bad mental health days in a month. Brought together with the counties' weighted average rate of protection we answer the following question: Does a county suffering from import competition, experience a shift in health and education variables after implementing protectionist measures?

We unveil through three OLS and DiD analyses that the treatment effects are either not robust, null or statistically unsignificant. This echoes our introduction, where we mentioned that a positive effect would serve as an argument for these measures and protectionism in general. Currently tariffs measures are criticized not only ideologically but also due to researches which underline their economic failures. With our contribution to the debate, we were not able to reveal a trade-off between economic outcomes and Human development.

As a result, in light of previous research and our findings, it appears difficult to suggest the use of classical protectionist measures as employed in the U.S. in 2018 to improve socio-economic outcomes. Nonetheless, following the same logic, the results also reflect that the tariffs did not worsen people's health, both mental and physical nor their level of education. Thus, from a political standpoint, this policy could still appear attractive in specific cases such as the protection of a strategic industry.

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Appendix

A. Parallel Trends graphs

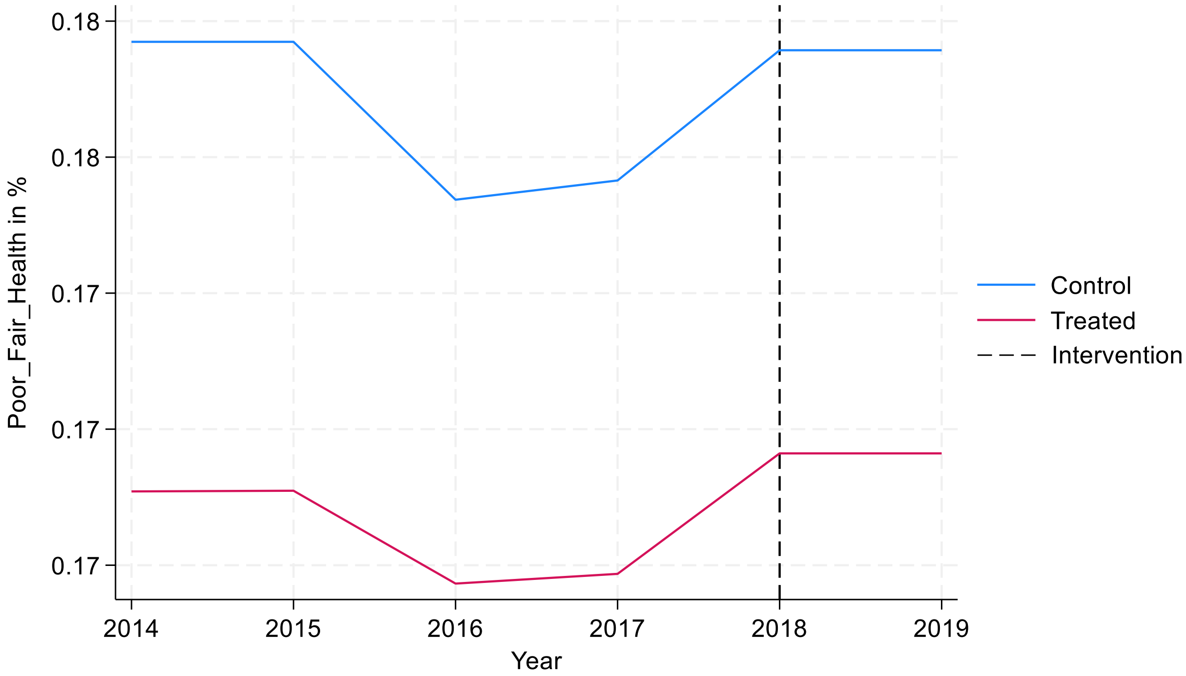

Figure 3: Parallel trend test for reported poor or fair health

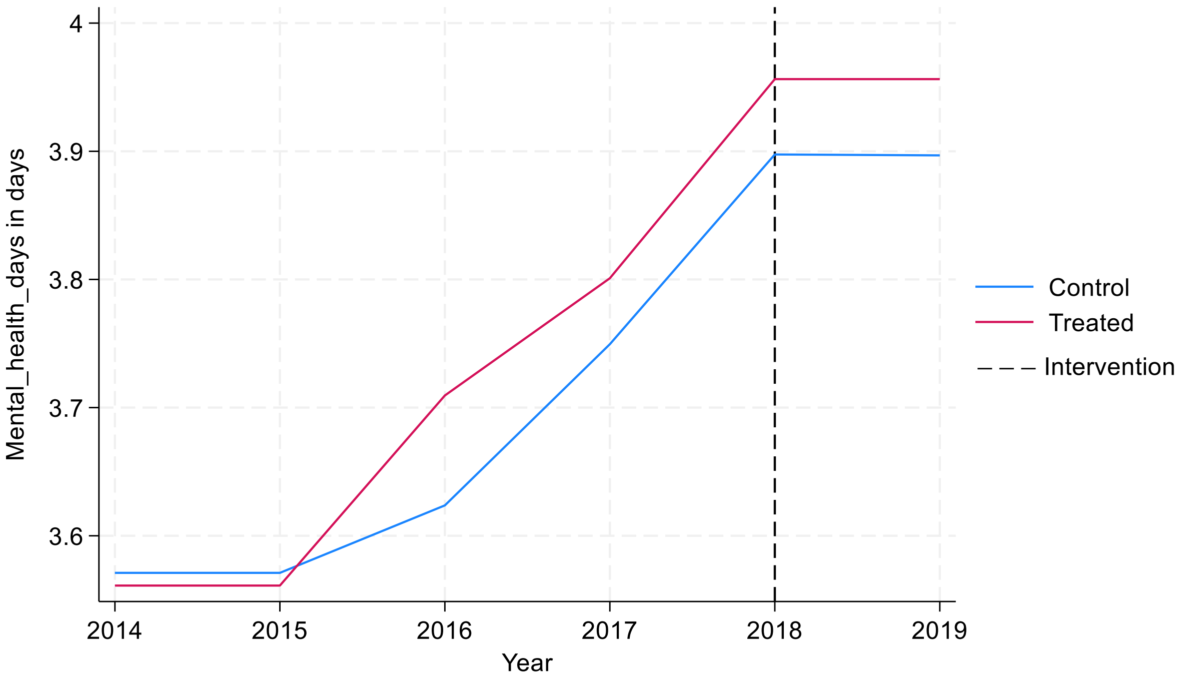

Figure 4: Parallel trend test for reported days of bad mental health

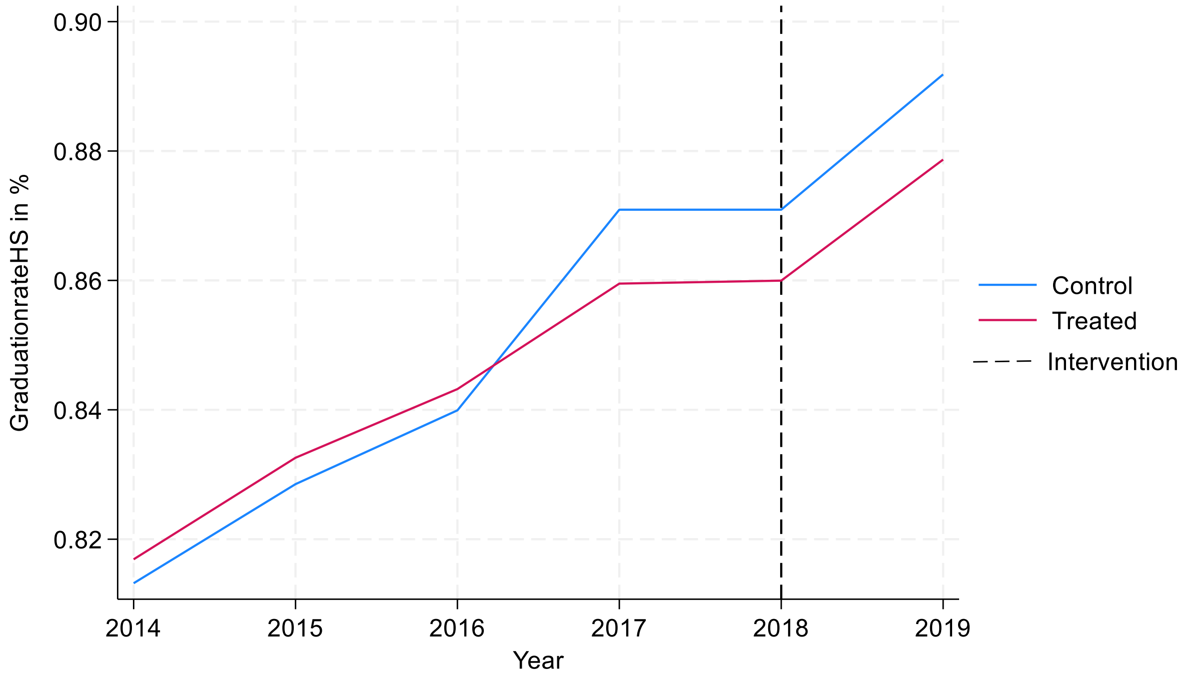

Figure 5: Parallel trend test for high school graduation rate

B. *Variables*

Table 6: Variables descriptions

Variable	**Description**
County_Protection	Employment weighted import protection for each county
Interaction	The interaction between time and the treatment
Intervention	Dummy time variable that equals 0 before the intervention and 1 after the intervention year
GraduationrateHS	Percentage of students in a cohort who graduate in a year
Lead	Dummy time variable that shifts the Intervention variable one year in the past
Mental_health_days	Percentage of people that report bad mental health days over the last month in a survey
Poor_Fair_Health	Percentage of people that report poor or fair health in a survey
Treatment	Dummy indicator for the treatment group. Either 0 or 1 for the control and treatment group respectively
Time	Dummy indicator for the time of intervention. Takes the values 0 for all years preceding 2018 and 1 otherwise
Year	Year of observation. It can represent 2014, 2015, 2016, 2017, 2018 and 2019