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In-utero weather shocks and learning outcomes

Manuel Barron

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Abstract

In the developing world, weather conditions during gestation affect fetal development and birth outcomes, as well as early childhood development, largely because weather fluctuations affect food availability, and accessibility to healthcare facilities. This study estimates the effect of in-utero temperature shocks on learning outcomes in school. To this end, I exploit data on 950,000 second grade students in Peru who took the national student evaluation between 2014 and 2016, paired with data on weather conditions during gestation in their district of birth. In-utero temperature shocks reduce significantly learning outcomes in communication and mathematics. Temperature shocks increase the probability of being classified as remedial in math by 2 percentage points, and decrease the likelihood of obtaining a satisfactory grade by a similar magnitude. I find heterogeneity in these effects, with cool regions more severely affected by cold shocks, and warm regions more severely affected by hot shocks.

JEL Codes: I12, I21, J16, O15

Key words: Climate change, Human capital formation, in-utero shocks.

*Department of Economics, Universidad del Pacífico. E-mail: MF.BarronA@up.edu.pe. I'm thankful to Pia Basurto for insightful comments and Lucina Rodriguez for outstanding research assistance. Special thanks to the Office of Monitoring and Strategic Evaluation at the Ministry of Education for sharing ECE data, and to Sam Heft-Neal for sharing weather data. All errors are mine.

1 Introduction

Weather conditions during gestation affect birth outcomes in developing countries (Yamauchi, 2012; Pereda, Menezes, and Alves, 2014; Rocha and Soares, 2015; Molina and Saldarriaga, 2017; Hu and Li, 2016; Andalón et al., 2014; Kudamatsu, Persson, and Strömberg, 2012), as well as early childhood development (Skoufias and Vinha, 2012; Lokshin and Radyakin, 2012; Rosales, 2014; Kumar, Molitor, and Vollmer, 2014; Mendiratta, 2015; Aguilar and Vicarelli, 2011; Skoufias, Vinha, and Conroy, 2011; Rocha and Soares, 2015; Rose, 1999). There is even evidence that the impacts of these shocks persist through adulthood. Barron, Heft-Neal, and Perez (2018); Fishman, Russ, and Carrillo (2015) show effects on labor market outcomes among among women.

Understanding the long term effects of weather shocks on human capital accumulation, and the mechanisms that drive them, is key in the context of climate change. Our study setting is Peru, which has been considered the third most-affected country by climate change worldwide (Molina and Saldarriaga, 2017). This country is especially interesting because vulnerability to climate change is paired with a weak educational system. The 2012 Program for International Student Assessment (PISA) evaluation placed Peru as last in science, math, and reading comprehension of 65 countries that took the test. Thanks to important efforts conducted by the Ministry of Education, Peru was the most improved country in Latin America in the three subjects by 2015, but the hard-earned gains could be easily wiped out by a number of factors. In this paper I show that weather shocks is one of them.

This paper aims to estimate the effect of in-utero weather fluctuations on learning outcomes, measured by a standardized test. The main outcome variable is the score in ECE (Censal Student Evaluation, or *Evaluacion Censal de Estudiantes*, in Spanish), as well as its main components (communication and mathematics). The main explanatory variables are positive and negative weather shocks during gestation. The empirical specifications account for gender heterogeneity and nonlinear effects of temperature, two features that have been largely established in the literature (see e.g. Barron, Heft-Neal, and Perez, 2018).

The data comes from two main sources. Weather data was obtained from the Climatic Research Unit at the University of East Anglia, and has been previously used in Barron, Heft-Neal, and Perez (2018). The dataset includes monthly precipitation and temperature data on a 0.5×0.5 degree resolution. Standardized test data, paired with date and district of birth, was provided by the Ministry of Education.

I find that temperature shocks have negative effects on learning outcomes, and that these effects differ by average temperature during gestation. Both cold and hot shocks reduce overall test scores, but cold shocks have stronger effects than hot shocks on students exposed to average in-utero temperature below 15C (average reductions of 25.2 and 11.4 points respectively), while for students exposed to average in-utero temperature above 15C, the effects of hot shocks are stronger than the effects of cold shocks (with average reductions of 14.8 and 6.9 points, respectively). The effects are roughly similar across genders. Despite their statistical significance, these effects are small, as the average score is around 1160 points.

To unveil potential effect heterogeneity across the distribution of student skills, I estimate the probability of being classified as remedial or satisfactory.

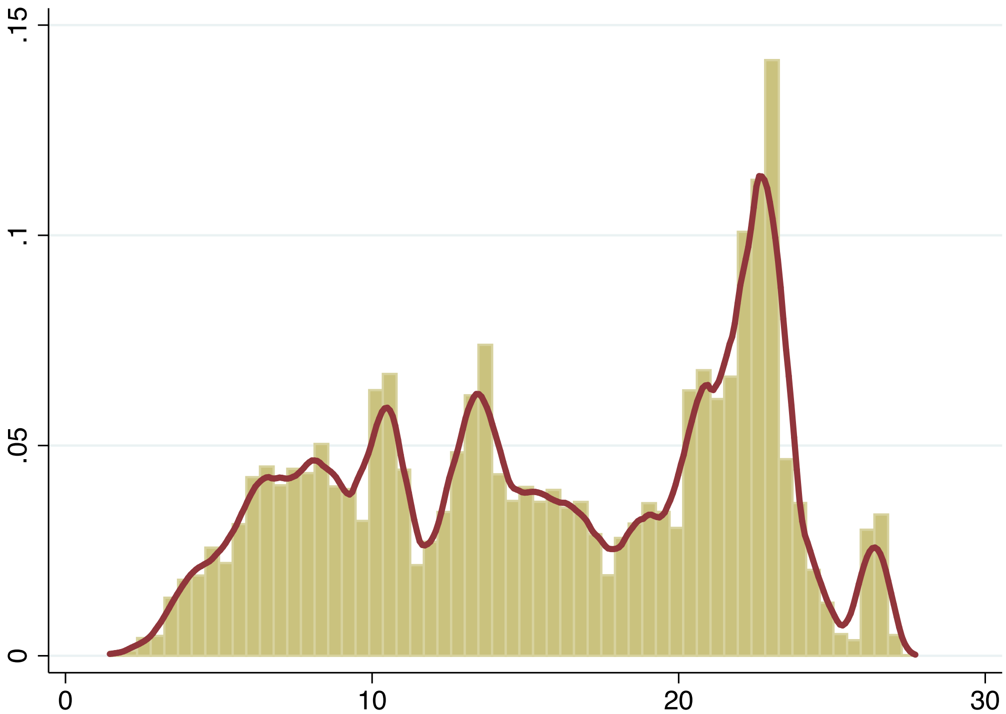
I Investigate if the impact of weather shocks is constant along the distribution of in-utero temperature and skills, and find that negative shocks are stronger in colder temperatures and that shocks have stronger effects on the tails of the skill distribution. For students exposed to average in-utero temperature below 15C, cold shocks increase the probability of scoring as remedial in communication by 1.2 percentage points, a 15% increase with respect to the mean. The result is similar for math, with cold shocks increasing the probability of scoring as remedial by 4.6 points, 15% of the mean. For students exposed to average in-utero temperature above 15C, weather shocks do not affect the probability of being classified as remedial, and the coefficients are small in magnitude, suggesting null effects for this subsample.

There are also important effects on the right tail of the distribution. Cold and hot shocks have similar effects in the likelihood of scoring as satisfactory in communication, reducing it by 3 percentage points or 6-7% of the mean. The level of in-utero temperature becomes relevant in mathematics: Among students exposed to average in-utero temperature below 15C, cold shocks decrease the likelihood of scoring as satisfactory by 4 percentage points, or 13% of the mean. The effect of hot shocks is smaller and significant only for males. On the other hand, among students exposed to average in-utero temperature above 15C, hot shocks reduce the likelihood of scoring as satisfactory by 4 percentage points, or 12% of the mean.

This study is part of a growing literature on the long term effects of weather shocks during early life. Previous studies have studied the effects of exposure to pollution shocks (e.g. Jayachandran, 2009; Rau, Urzúa, and Reyes, 2015; Bharadwaj et al., 2014; Miller and Vela, 2013), radiation (Black et al., 2013), Ramadan (Almond, Mazumder, and Ewijk, 2015), and home visits (Butikofer, Løken, and Salvanes, 2015). The study closest to this is Shah and Steinberg (2017). The authors find that rainfall shocks during gestation can increase performance on cognitive tests and the likelihood of being on the right grade-for-age. This study's main contribution is to shed light on the heterogeneity of these effects by gender, average in-utero temperature, and skill level.

The next section describes the context and the data. Section 3 details the empirical approximation and fleshes out the identification strategy. Section 4 presents the results,

Figure 1: In-utero temperature



while section 5 discusses the main conclusions.

2 Context and Data

2.1 Weather data

Weather data comes from the Climatic Research Unit (CRU) at the University of East Anglia. This dataset contains, among other variables, average temperature worldwide in grids of 0.5 by 0.5 degrees. Around the equator, this is resolution is roughly 50 km^2. To construct historic means I use data from 1950 onwards.[1] Average temperature during gestation was constructed assuming nine-month pregnancy periods. For instance, a student born in November 2006 is assigned average temperature from March to November 2006. This may incorporate measurement error in average in-utero temperature, since gestation may have lasted more or less than nine months, which may lead to attenuation bias, in which case the estimated coefficients should be interpreted as lower bounds to the true effects.

Table 1 shows that average temperature during gestation is 15.7 celsius, with a standard deviation of 6.4 degrees. Figure 1 plots the distribution of in-utero tempera-

[1]Results are robust to using different data spans.

ture, showing that it has support from 2 to 27 degrees celsius. One percent of students experienced a heat shock during gestation, and two percent experienced a cold shock.

2.2 The Student Evaluation (ECE)

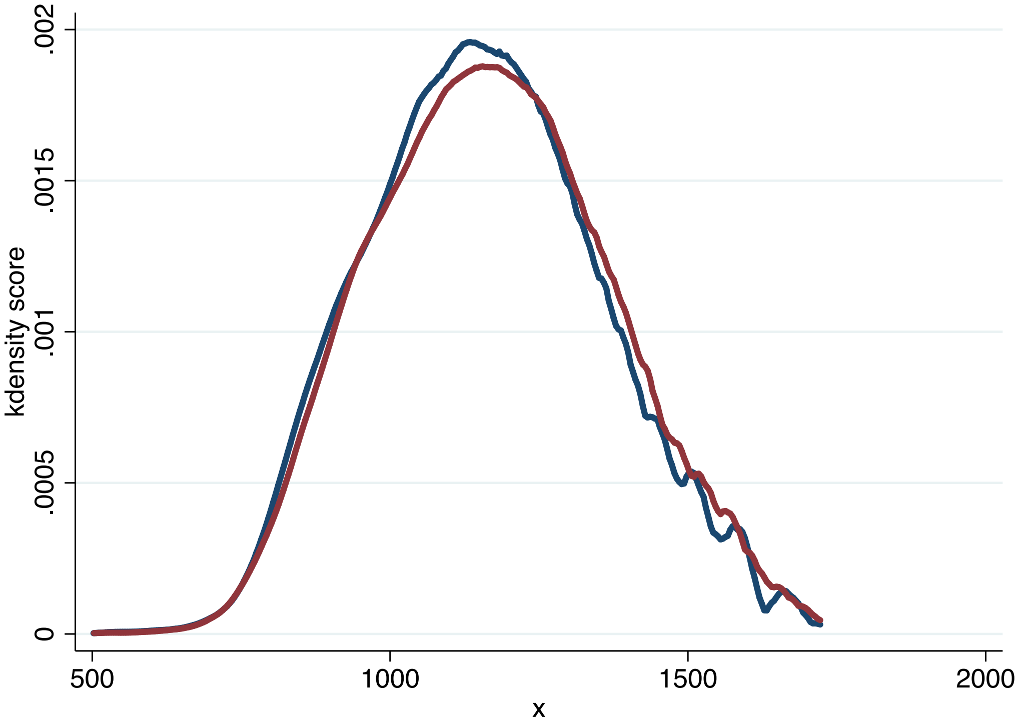
ECE is a standardized test that the Ministry of Education applies annually to measure learning outcomes among second graders. ECE is also applied to fourth graders from indigenous communities, and starting from 2015 it was also applied to eighth graders (second year of high school in the Peruvian system). The evaluation is applied to all students in all private and public schools across the country. Students can be classified as remedial (en inicio), in transition (en proceso), or satisfactory (satisfactorio). The analysis in this paper is performed for second and eighth graders. I used data for 2014, 2015 and 2016 because in these datasets it is possible to match student data to place and date of birth. There was a slight improvement in math between 2014 and 2016. In 2016, there was an increase of 8.2 percentage points in the share of students classified as "satisfactory" with respect to 2014. There is no such trend in reading comprehension. However, there is a reduction of 6.2 percentage points in the share of students classified as "remedial".

Table 1 shows the main descriptive statistics in the sample. 51% of students are male, and their average score is 1,164, with a standard deviation of 197 points. Roughly one third of students was classified as remedial in math, and a similar figure was classified as satisfactory. In communication, only 7 percent was classified as remedial, while almost half of the students where classified as satisfactory.

Table 2 explores differences by gender. Average score among males was 1,161, similar to that of females, at 1,166. The percentage of males and females in each category (remedial, in process, satisfactory) is very similar in mathematics, but females have a higher probability of scoring as satisfactory in communication than males, at 51 and 46 percent, respectively.

Figure 2 compares the density of scores by exposure to shocks. The red line depicts the distribution of scores for students who were not exposed to in-utero temperature shocks, while the blue line depicts the distribution of scores for students exposed to shocks (positive or negative) while in-utero. As can be seen, the former stochastically dominates the latter, implying a strong negative effect of exposure to shocks. A two-sample Kolmogorov-Smirnov test rejects equality of these distributions at the 99% of confidence.

Figure 2: Exposure to Shocks and Test Scores



The horizontal axis measures test scores. The red line is the density for students not exposed to shocks, blue is for students exposed to shocks. Kolmogorov-Smirnov test rejects equality of distributions at 99% of confidence.

Table 1: Descriptive Statistics

	Mean	Standard Deviation
Male (%)	0.51	0.50
Gestation temperature (C)	15.7	6.4
Heat shock (%)	0.01	0.07
Cold shock (%)	0.02	0.13
Score	1164.86	196.56
Remedial, math (%)	0.31	0.46
Satisfactory, math (%)	0.31	0.46
Remedial, communication (%)	0.07	0.26
Satisfactory, communication (%)	0.49	0.5

Sources: Peru's Ministry of Education and Climatic Research Unit, University of East Anglia

Table 2: Learning Outcomes by Gender

	Males	Females
Score	1160.55	1166.1
Remedial, math	0.31	0.32
Satisfactory, math	0.32	0.3
Remedial, communication	0.08	0.06
Satisfactory, communication	0.46	0.51

Sources: Peru's Ministry of Education and Climatic Research Unit, University of East Anglia

3 Empirical Strategy

One of the most common ways to empirically define a positive (negative) temperature shock is by identifying periods were average temperature was one standard deviation above (below) the historic average in a particular region (in this study, a district). I consider "historic average" to be the average from 1950 to 2016. I define an individual experience a positive (negative) weather shock if average temperature during his or her whole gestation period was one standard deviation above (below) the district of birth's historic mean.

The main estimating equation is of the form

$$y_{idbt} = \beta_0 + \beta_1 \times \text{PosShock}_{idbt} + \beta_1 \times \text{NegShock}_{idbt} + \gamma_d + \gamma_b + \gamma_t + \varepsilon_{idbt} \qquad (1)$$

where y is the outcome variable (probability of being graded as "remedial" or "satisfactory" in each of the test components) for individual "i" born in district "d" in year "b", and who took the test in year "t". $PosShock$ and $NegShock$ are indicators for positive and negative weather shocks, respectively. The regression includes fixed effects by district of birth, so β_1 and β_2 are estimated off of within-district variation.

The regression also includes year-of-birth and year-of-test dummies, to control for

Table 3: In-utero temperature shocks and ECE scores

	(1) All	(2) Male	(3) Female	(4) All	(5) Male	(6) Female
Heat shock	-11.727***	-16.548***	-6.506*			
(average during pregnancy)	(4.271)	(6.296)	(3.875)			
Cold shock	-12.926***	-13.623***	-11.994***			
(average during pregnancy)	(3.901)	(3.750)	(4.321)			
Number of hot months				0.253	0.141	0.380
				(0.994)	(1.009)	(1.009)
Number of cold months				-0.859	-1.065	-0.664
				(0.641)	(0.692)	(0.619)
Mean score	1165.0	1162.3	1167.8	1165.0	1162.3	1167.8
SD score	197	198	195	197	198	195
Observations	944113	481460	462607	944113	481460	462607
R squared	0.139	0.136	0.145	0.139	0.136	0.144

All regressions include fixed effects for district of birth, year of birth, and year of the test. Standard errors are clustered by province of birth. Statistically significant at the 90(*), 95(**) and 99%(***), respectively.

potential differences across cohorts or special conditions in the year the evaluation took place. To account for spatial correlation of climate, standard errors are clustered at the province level (a province groups approximately 10 districts).

Identification of a causal effect requires weather shocks to be as good as randomly allocated across individuals born in a same district at different points in time. This is the same assumption as Barron, Heft-Neal, and Perez (2018) and similar to Molina and Saldarriaga (2017). This is not a strong assumption, since weather shocks in a district are difficult to predict, and households are not likely to plan their pregnancies based on their expectations about weather shocks.

4 Results

Overall Effect. Table 3 shows the effect of temperature shocks on second grade scores. Column (1) shows the effects of the main explanatory variable: shocks defined by average gestational temperature more than one standard deviation above (or below) the district of birth's long term mean. On average, positive shocks reduce scores by 11.7 points, while negative shocks do so by 12.9. Despite being statistically significant, these magnitudes are small, around 0.05-0.06 standard deviations of the outcome variable. Columns (2) and (3) analyze the effect by gender. The effect seems stronger among males than females. Mean score is similar across groups, but female scores seem to depend to in-utero weather shocks to a lesser degree than males.

Columns (4) through (6) show the results considering the effect of monthly shocks. These effects are smaller than 1/9 of the aggregate value, and are not statistically

Table 4: In-utero weather shocks and test scores, by component

	All		Male		Female	
	(1)	(2)	(3)	(4)	(5)	(6)
	Comm	Math	Comm	Math	Comm	Math
Heat shock	-6.180***	-5.643***	-7.619**	-9.080**	-4.397**	-2.131
	(2.322)	(2.150)	(2.943)	(3.573)	(2.102)	(2.091)
Cold shock	-5.863***	-7.108***	-5.411***	-8.284***	-6.118***	-5.892*
	(1.282)	(2.664)	(1.289)	(2.500)	(1.417)	(2.995)
Average score	583.1	581.8	578.2	584.0	588.2	579.5
SD score	87	124	87	126	88	122
Observations	944587	944309	481728	481558	462813	462705
R squared	0.164	0.106	0.154	0.107	0.177	0.107

All regressions include fixed effects for district of birth, year of birth, and year of the test. Standard errors are clustered by province of birth. Statistically significant at the 90(*), 95(**) and 99%(***), respectively.

Table 5: Temperature shocks and test scores, by district's temperature

	Temp < 15			Temp> 15		
	(1)	(2)	(3)	(4)	(5)	(6)
	All	Male	Female	All	Male	Female
Heat shock	-11.355**	-16.473**	-5.758	-14.738***	-17.715*	-11.329
	(5.664)	(7.711)	(4.559)	(4.971)	(9.600)	(10.585)
Cold shock	-25.221***	-24.249***	-26.090***	-5.887***	-7.502**	-4.033**
	(2.504)	(2.086)	(3.337)	(1.670)	(2.895)	(2.023)
Average score	1156.6	1154.2	1159.1	1172.4	1169.4	1175.5
SD score	197	199	196	195	198	193
Observations	445320	227474	217810	498787	253978	244784
R squared	0.149	0.144	0.157	0.127	0.126	0.131

All regressions include fixed effects for district of birth, year of birth, and year of the test. Standard errors are clustered by province of birth. Statistically significant at the 90(*), 95(**) and 99%(***), respectively.

significant. This seems to indicate that the effects of temperature during gestation on learning outcomes is non linear. A one-month shock does not affect learning outcomes, but being exposed to high (or low) temperatures during the whole gestational period has strong negative effects on learning.

Table 4 breaks down the results from Table 3 by the test components: communication and mathematics. Positive and negative shocks have similar effects on both components. Positive temperature shocks reduce communication scores by 6.2 points on average, and mathematics scores by 5.6 points. On the other hand, negative temperature shocks reduce communication scores y 5.9 points and mathematics by 7.1 on average. Columns (3) through (6) show results by gender. Both types of shocks affect negatively communications and math scores among males, and communication scores among females, but not math scores among females, which are only weakly affected by negative shocks, and not affected by positive shocks.

Heterogeneity by average in-utero temperature. Table 5 analyzes if hot and

Table 6: Probability of being classified as remedial

	Communication			Mathematics		
	(1)	(2)	(3)	(4)	(5)	(6)
	All	Male	Female	All	Male	Female
Heat shock	0.005	0.013	-0.004	0.020**	0.033**	0.007
	(0.007)	(0.008)	(0.007)	(0.009)	(0.013)	(0.009)
Cold shock	0.008***	0.008***	0.008***	0.019**	0.019**	0.020**
	(0.002)	(0.003)	(0.002)	(0.008)	(0.007)	(0.009)
Mean Dep. Var.	0.070	0.076	0.064	0.311	0.307	0.314
Observations	944587	481728	462813	944309	481558	462705
R squared	0.112	0.110	0.119	0.082	0.085	0.083

All regressions include fixed effects for district of birth, year of birth, and year of the test. Standard errors are clustered by province of birth. Statistically significant at the 90(*), 95(**) and 99%(***), respectively.

cold shocks have similar effects in warm versus cool regions. To do so, I split the sample in two: districts with average historical temperature above or below 15C (the median in the sample). People born in cool regions are more strongly affected by cold shocks than by hot shocks, while the reverse is true for people born in warm regions. Negative shocks reduce scores by around 25 points in cool regions, or 0.13 standard deviations, while positive shocks reduce scores by 15 points in warm regions, or 0.08 standard deviations. Thus, students from cool regions seem to be more heavily affected by weather shocks.

Heterogeneity by skill level. To gain a deeper understanding on the nature of the relation between weather shocks and learning outcomes I turn to analyze the effect along the skills distribution. Students who take the test are classified as "remedial" (7% in communications and 32% in math), "in process" (46% and 37%) or "satisfactory" (47% and 31%). Table 6 shows that cold shocks significantly increase the probability of being classified as remedial in communications by 0.8 percent points (11% of the mean). The effect is almost identical by gender. The coefficient of the heat shocks, however, are not significant. Regarding mathematics, cold shocks increase the probability of being classified as remedial by 2 percentage points, both in males and females, while heat shocks affect males (with an effect of 0.03 or 8% of the mean) but not females. Table 7 analyzes the effects on the other side of the skill distribution. The table shows that both heat and cold shocks significantly reduce the probability of males obtaining a satisfactory grade in mathematics and communication by 2-3 percentage points (5% and 7% of the means, respectively). The effect on females is less significant: cold shocks reduce the probability of being categorized as satisfactory by 3 percentage points in communication, but no in mathematics. On the other hand, heat shocks reduce the probability of obtaining a satisfactory grade by 2 percentage points in communication and 1 percentage point in mathematics (significant at the 90% level).

Table 7: Probability of being classified as satisfactory

	Communication			Matemathics		
	(1)	(2)	(3)	(4)	(5)	(6)
	All	Male	Female	All	Male	Female
Heat shock	-0.029**	-0.034**	-0.021*	-0.023***	-0.032***	-0.013*
	(0.013)	(0.017)	(0.012)	(0.007)	(0.011)	(0.007)
Cold shock	-0.026***	-0.023***	-0.028***	-0.017*	-0.022***	-0.012
	(0.003)	(0.004)	(0.004)	(0.009)	(0.008)	(0.011)
Mean Dep. Var.	0.490	0.465	0.515	0.315	0.326	0.303
Observations	944587	481728	462813	944309	481558	462705
R squared	0.103	0.094	0.116	0.052	0.055	0.052

All regressions include fixed effects for district of birth, year of birth, and year of the test. Standard errors are clustered by province of birth. Statistically significant at the 90(*), 95(**) and 99%(***), respectively.

Table 8: Probability of being classified as remedial (temperature < 15)

	Communication			Mathematics		
	(1)	(2)	(3)	(4)	(5)	(6)
	All	Male	Female	All	Male	Female
Heat shock	0.003	0.012	-0.006	0.026**	0.040***	0.011
	(0.009)	(0.009)	(0.009)	(0.011)	(0.015)	(0.010)
Cold shock	0.012***	0.010***	0.014***	0.046***	0.041***	0.051***
	(0.002)	(0.002)	(0.003)	(0.004)	(0.004)	(0.005)
Mean Dep. Var.	0.082	0.087	0.076	0.317	0.315	0.320
Observations	445507	227575	217896	445390	227507	217847
R squared	0.119	0.117	0.126	0.091	0.092	0.093

The three possible test outcomes are: remedial, in transition, and satisfactory. All regressions include fixed effects for district of birth, year of birth, and year of the test. Standard errors are clustered by province of birth. Stars denote statistical significance at the 90(*), 95(**) or 99(***) percent confidence, respectively. Source: Ministry of Education and CRU.

Finally, I analyze whether the effects of shocks on the probability of being classified as remedial or satisfactory varies across cool and warm regions. Table 8 shows that cold shocks have significant effects in regions with average temperatures below 15C, for both males and females. Cold shocks increase the probability of being classified as remedial in communication by 1 percentage point, or 12% of the mean, with similar effects on males and females. Heat shocks are not significant. The effects on mathematics is larger: cold shocks increase the probability of being classified as remedial by 5 percentage points. Heat shocks increase the probability of males being classified as remedial by 4 percentage points, but the effect on females is not statistically significant. In warm regions, the probability of being classified as remedial is largely unaffected by weather shocks, for either communication or mathematics, either for males or females (Table 9).

Table 10 shows the effects of temperature shocks on the probability of being classified as satisfactory, by test component and gender, for people born in cooler regions

Table 9: Probability of being classified as remedial (temperature> 15)

	Communication			Mathematics		
	(1)	(2)	(3)	(4)	(5)	(6)
	All	Male	Female	All	Male	Female
Heat shock	0.005	0.009	0.000	0.011	0.018	0.002
	(0.009)	(0.017)	(0.015)	(0.012)	(0.017)	(0.020)
Cold shock	0.005	0.006	0.003	0.006	0.009	0.002
	(0.004)	(0.005)	(0.004)	(0.004)	(0.006)	(0.005)
Mean Dep. Var.	0.060	0.066	0.053	0.305	0.301	0.309
Observations	499074	254145	244904	498913	254043	244845
R squared	0.102	0.099	0.108	0.075	0.078	0.073

The three possible test outcomes are: remedial, in transition, and satisfactory. All regressions include fixed effects for district of birth, year of birth, and year of the test. Standard errors are clustered by province of birth. Stars denote statistical significance at the 90(*), 95(**) or 99(***) percent confidence, respectively. Source: Ministry of Education and CRU.

Table 10: Probability of being classified as satisfactory (temperature< 15)

	Communication			Mathematics		
	(1)	(2)	(3)	(4)	(5)	(6)
	All	Male	Female	All	Male	Female
Heat shock	-0.032**	-0.038*	-0.023*	-0.017*	-0.026**	-0.007
	(0.016)	(0.021)	(0.014)	(0.009)	(0.012)	(0.010)
Cold shock	-0.030***	-0.023***	-0.035***	-0.041***	-0.041***	-0.042***
	(0.005)	(0.004)	(0.007)	(0.005)	(0.005)	(0.006)
Mean Dep. Var.	0.463	0.442	0.485	0.307	0.316	0.298
Observations	445507	227575	217896	445390	227507	217847
R squared	0.110	0.101	0.125	0.053	0.054	0.055

The three possible test outcomes are: remedial, in transition, and satisfactory. All regressions include fixed effects for district of birth, year of birth, and year of the test. Standard errors are clustered by province of birth. Stars denote statistical significance at the 90(*), 95(**) or 99(***) percent confidence, respectively. Source: Ministry of Education and CRU.

Table 11: Probability of being classified as satisfactory (temperature> 15)

	Communication			Mathematics		
	(1)	(2)	(3)	(4)	(5)	(6)
	All	Male	Female	All	Male	Female
Heat shock	-0.026*	-0.025	-0.027	-0.043***	-0.050***	-0.033**
	(0.013)	(0.017)	(0.019)	(0.007)	(0.017)	(0.013)
Cold shock	-0.025***	-0.023***	-0.026***	-0.002	-0.010	0.007
	(0.005)	(0.007)	(0.006)	(0.006)	(0.009)	(0.005)
Mean Dep. Var.	0.513	0.486	0.542	0.321	0.335	0.308
Observations	499074	254145	244904	498913	254043	244845
R squared	0.092	0.084	0.103	0.051	0.055	0.050

The three possible test outcomes are: remedial, in transition, and satisfactory. All regressions include fixed effects for district of birth, year of birth, and year of the test. Standard errors are clustered by province of birth. Stars denote statistical significance at the 90(*), 95(**) or 99(***) percent confidence, respectively. Source: Ministry of Education and CRU.

(average temperature below 15C). Among males, cold shocks reduce the probability of being classified as satisfactory by 2 percentage points y communication and 4 percentage points in mathematics (5 and 13% of the mean, respectively). Heat shocks redece the probability of obtaining a satisfactory grade by 4 percentage points (significant at the 90%) in communication and 3 percentage points in mathematics (9 and 8% of the mean, respectively). Among women, heat shocks reduce the probability of obtaining a satisfactory grade by 4 percentage points in communication and mathematics, while heat shocks reduce that probability by 2 percentage points in communication (significant at the 90%) and have no effect on mathematics.

5 Conclusions

Peru is one of the most vulnerable countries to climate change worldwide. Moreover, its education system has profound problems that can be worsened by climate change. This study analyzes the impact of in-utero weather shocks on student scores. The main finding is that these shocks affect learning outcomes in mathematics and communications, measured by standardized test scores in second grade. This relation is not linear: temperature shocks affect more strongly students born in cooler regions (those with average temperature below 15C, the sample median), and they affect more strongly the tails of the distribution, both in the remedial and satisfactory categories. The main policy implication is that the government should put in place mitigation mechanisms in response to temperature shocks, to ameliorate the effects of these shocks and try to reduce their persistence. An important mechanism in this context is maternal anemia (Barron, Heft-Neal, and Perez, 2018). Hence, efforts aimed at tackling it could counteract the effects of weather shocks.

The findings presented here allow to reconcile two types of results in the literature. On the one hand, it has been established that in-utero weather shocks affect fetal development and birth outcomes. On other, weather conditions have been found to have effects on labor market outcomes. This study links both findings, showing that the effect of shocks on labor outcomes is not only because of reduced schooling, but also because of poorer learning outcomes.

This study has a number of data-driven limitations, which I list in increasing order of importance. First, there is a potential source of bias: our study sample includes only students that have made it to second grade. However, any bias from this source is not likely large, since most students reach second grade. Second, the analysis is based on a standardized test which, as any test, has limitations on measuring learning outcomes. Third, and most importantly, despite the data is rich in terms of number of observations, there are not enough variables in the dataset to pin down the mechanisms through which these effects arise, so further work is needed in this direction. However, despite these limitations, this study has a clear message: exposure to weather shocks during gestation reduces test scores in outcomes in second grade, and the effects are especially large in the tails of the skill distribution.

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