NORTHWESTERN UNIVERSITY

# Essays on Environmental and Labor Economics

A DISSERTATION

SUBMITTED TO THE GRADUATE SCHOOL

IN PARTIAL FULFILLMENT OF THE REQUIREMENTS

for the degree

DOCTOR OF PHILOSOPHY

Field of Economics

By

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EVANSTON, ILLINOIS

December 2016

# ABSTRACT


Essays on Environmental and Labor Economics

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This dissertations consists of three chapters. The first chapter is on the topic of environmental economics and studies the question of the effects of air pollution on students' school absences, finding significant and positive effects for air pollution, and PM10 in particular, on school absences. The second chapter is on the topic of labor economics and considers the determinants of international migration, with a focus on wage differences as the main explanatory variable. The analysis finds a positive and significant effect for wage differences across countries on the proportion of emigrants to non-emigrants from the source country. Finally, the last chapter analyzes the effects of issuance of cotton dust standards in the US on the productivity of textile industry and finds weak and negative effects for those regulations.

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CHAPTER 1

# Air Pollution and School Attendance

## 1.1. Introduction

In this paper I examine the relationship between air pollution and school attendance. The main question that I try to address is if higher levels of air pollution cause more students to be absent from school. I use one school in city of Tehran as my source of attendance data which enrolls an average of 830 students in all school grades every year. In my attendance data, I observe individual absence instances on every school day from 2001-02 to 2014-2015 academic years at this school. I also observe air pollution levels, measured as concentrations, for a number of "criteria pollutants"[1] on a day by day basis for a large proportion of the days in the 14 years period in my data set. Under the assumption that air pollution is exogenous and after controlling for potentially confounding factors, I exploit the variation in the levels of air pollution to estimate its effect on students' absence from school. My main findings suggest that rises in levels of air pollutants tend to increase school absence. Specifically, in a model that uses daily data high levels of PM10 appear to increase absence rate: an increase of 10 $\mu g/m^3$ in PM10 concentrations is associated with about 50 more absences per 1 million students. Furthermore, in a model which uses

[1]pollutants, as defined by US EPA, are ozone (O3), particulate matter (PM10 and PM2.5), carbon monoxide (CO), nitrogen dioxide (NO2), sulfur diaoxide (SO2) and lead. PM10 is "inhalable coarse particles" of 10 $\mu m$ in diameter or smaller. PM2.5 is "fine particles" that are 2.5 $\mu m$ in diameter or smaller.

data that is aggregated over 7-day periods, three of the pollutants, namely PM10, O3 and NO2, exhibit a positive and significant effect on absence rate.

Air pollution is a source of various types of external costs in terms of health and human capital. It can increase morbidity and mortality among sensitive groups of population or lower labor productivity among workers exposed to air pollution. These costs may be hard to identify and quantify accurately; nevertheless, it is important to be able to provide estimations of these costs in order to inform environmental policy-making in properly regulating air pollution. This may be of even greater significance in the context of developing countries where environmental issues are typically more sever but, at the same time, more often neglected by policy makers (Greenstone and Jack 2015).

Absence from school, the outcome of interest in this paper, can be costly in terms of learning and investment in human capital. For every day that a student misses school he or she will need to try harder to compensate for what they missed on that school day. There are a number of empirical studies that shed some light on these costs. For example, Marburger (2001), Park and Kerr (1990), and Romer (1993) provide evidence on the negative effect of absenteeism on academic performance in undergraduate classes. Although these studies concern college students in North America, their results arguably hold more generally in any classroom-based learning environment. When considered in sum over the academic year and over all the students, school absence can amount to huge losses in the opportunity to learn and investment in human capital. School absence can also be costly in terms of public funds in the case of public schools and in terms of forgone parent wages if they are forced to stay home to look after their offspring.

In addition to the accumulative loss in human capital, students who tend to be more frequently absent may be more likely to perform worse academically and drop out of school, which can result in lower educational attainment or poorer outcomes in the labor market. This hypothesis needs to be empirically tested to demonstrate the potential causal effect; however, the argument is similar in spirit to what Lavy, Ebenstein, and Roth (2014a,b) show when they examine the effects of exposure to ambient air pollution on cognitive performance during high-stake examinations and the long-run human capital consequence of these exams. Absenteeism, too, may have long-run consequences for individuals through increasing the likelihood of poor educational attainment.

There are few papers in economics that inspect the effects of air pollution on school attendance. Ransom and Pope 1992 is probably the closest to this paper in their methodology and type of the data used. They use weekly absence data from Provo School District and daily absence data from one elementary school in Utah Valley to estimate the effects of PM10 on school absenteeism and find that a $100\mu g/m^3$ increase in 28-day moving average PM10 concentration is associated with a rise approximately equal to two percentage points in absence rate. The size of the school in their study (average about 1000) is comparable to that in this paper (average about 850). However, they use only six school years of daily attendance data (from 1985 to 1990) and only for an elementary school as opposed to to 14 years of data used here and for both elementary and high schools of one school complex. Also, in contrast to what I do in this paper, they do not include other pollutants in their regressions which may be correlated with PM10 and affect health and student attendance at the same time.

Another notable study is Currie et al. (2009) who consider absences in 39 of the largest school districts in Texas. Their data set consists of 1,512 schools with students in grades 1 through 8 and throughout schools years of 1996 to 2001. They find that, among the three air pollutants considered, high carbon monoxide evidently increases school absences. They adopt a difference-in-difference-in-differences approach to identify the effects of air pollution controlling for school and time fixed effects. The high variation in the data and the size of the sample enables them to plausibly identify and accurately estimate the effect. However one limitation of the study is that the unit of observation in their sample is six-week attendance period which only can capture effects that may be in force in longer time intervals and not in a matter of days. In the current paper, in contrast, I take advantage of availability of data at daily level which allows me to avoid those concerns.

Other papers in this area can be divided into two broad categories. Papers in the economics literature that study the effects of air pollution on other economic outcomes of interest such as infant mortality or labor productivity, and papers in the epidemiology literature that study school attendance as the outcome variables but do not generally adopt the economics methodology to address concerns with endogeneity of explanatory variables. A comprehensive review of both of these strands of literature can be found in Currie et al. (2009) and Graff Zivin and Neidell (2013). The current paper builds upon the current literature by examining new data and from a new setting, but finds results that are largely consistent with and confirm the current state of knowledge, namely that ambient air pollution does adversely affect students' school attendance and, consequently, accumulation of human capital.

## 1.2. Background and Data

### 1.2.1. School attendance

The absence data comes from Roozbeh school complex, a private all-boys school located in northern part of Tehran, Iran. This school enrolls students in 13 grade levels corresponding to K-12 system in the United States. The data consists of the number of students who are absent in each grade on every school day. The attendance data spans 14 years from 2001-2002 school year until 2014-2015. The number of students enrolled in this school ranges from 809 to 857 with an average of 64 students in each grade. On average 2.1 percent of students are absent on every school day during the whole period.

Air pollution can cause a student not to attend school either through its adverse health effects or by inducing avoidance behavior; that is, inducing his parents to keep him at home to avoid exposure to high outdoor pollution. My focus in this paper though is not on identifying the specific channel of effect, but on estimating the net effect and the costs consequently incurred. Ideally, our explained variable would be the observed rate of absence due only to ill health or avoidance behavior; however, the reason for being absent is not recorded in the data set and only an indicator of whether the absence was "excused" (that is, authorized by school officials) is recorded. Sickness absence is authorized upon providing medical evidence. Since the school is strict about its attendance policy I assume that the majority of excused absences are due to ill health. Therefore I include only excused absences in my estimations, though inclusion of unexcused ones does not alter the results as they make up only 3 percent of the total absences, which is a small fraction.

One concern with the attendance data is that it comes only from one school which may not be representative of the population of students in Tehran. The school, however, is large with more than 800 students spanning all school ages. Also since the school is located in an area of Tehran with relatively clean air; its students come from families with middle to high socioeconomic status; and it enforces a strict attendance policy; any effects of the air pollution estimated using the current sample is probably an underestimation of the effects in the population of students in Tehran.

Finally, in figure 1.1 the monthly averages of absence rates over the years in the sample is plotted. The dots represent monthly average for a specific month and year and the solid line is the mean of monthly averages. The graph suggests a repeating pattern of variation through a year with increasing rates until April and then falling afterwards. The absence rates for the last month of the school years is much lower which can be a result of higher attendance near final examinations.

### 1.2.2. Air pollution and weather

Air pollution is a chronic environmental problem in Tehran, a large metropolitan area confined by Alborz mountain ranges from three sides. Both stationary sources like manufacturing plants and residential buildings, and mobile sources like personal vehicles and motorcycles are significant sources of air pollution in Tehran (Bayat et al. 2012). Tehran is considered a highly polluted city when compared to the large cities in the developed countries and comparable in levels to some of the most highly polluted cities in the developing world.

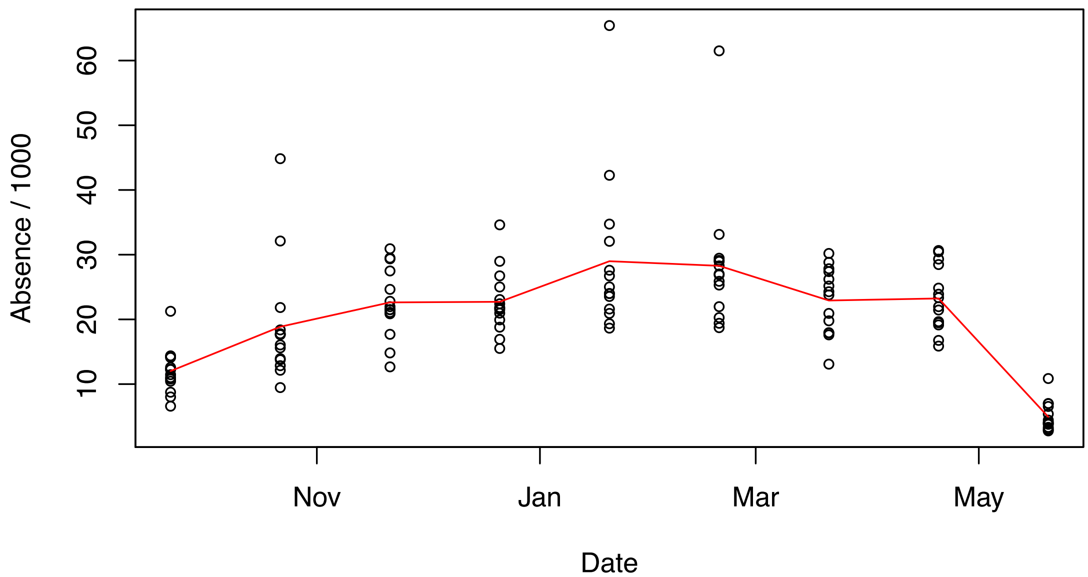


Figure 1.1. Absence rate, monthly averages for 14 years

My source of data for air pollution levels in Tehran is Air Quality Control Company affiliated with City of Tehran who gather and publicly report information on the levels of different pollutants both in concentration and AQI units. They measure air quality using nearly 40 monitoring station that are located around the city, but not all the stations have been active measuring air pollution on all of the days in the time period under study, and some of them have started gathering data relatively recently. The need for multiple monitoring stations arises because Tehran is a large city with an area of 730 $km^2$ and the weather and pollution patterns can be noticeably distinct across its extremities. Figure 1.10 is a map of Tehran with the school and the monitoring stations designated on it.

I use measured daily concentrations from Aghdasyeh station, located in northeast of Tehran, for the four pollutants CO, NO2, O3 and PM10. I choose this particular station because it has the greatest proportion of days for which air pollution data is available. Although this station is not the closest one to the school being studied, it is not too far either, distanced 8.7 kilometers from the school. In table 1.1 I list four of the closest stations to the school sorted by their distance. You can find the correlation coefficient between pollutant concentrations of Aghdasyeh with those of the four closest stations. The correlations are all positive and they are highest for the station that is closest to the school, that is Region 2. This suggests that even though the measured air pollution varies across different regions in Tehran, they generally move in the same direction and taking one station's recorded measurements is a good proxy for the actual level of air pollution that the students have been exposed to.

The weekly average levels of the six pollutants for the period under study (2001 to 2014) are plotted in figure 1.2. All the concentration time series are evidently stationary and pass stationarity tests. Missing data points are dropped from the plots. I do not use the data for PM2.5 even though it is known for its particularly adverse health effects due to its extremely small size and high penetrability into the respiratory system. The reason is that measurment of ambient PM2.5 levels started much more recently compared to the other pollutants hence its related concentration data is available for a relatively small fraction of days. Nevertheless, as one would expect, there is a high correlation between levels of PM10 and PM2.5 and much of the effect of PM2.5 may be captured in the estimated coefficient for PM10. The correlation between concentration levels of different pollutants is reported in table 1.2. I also exclude SO2 because of the small number of days with available data and suspicious data quality prior to 2006, though including SO2 would not turn over the results.

Daily weather data is obtained from Meteorological Organization of Iran and includes daily data on temperature, pressure, humidity, cloud, precipitation and wind speed. Controlling for weather is necessary to absorb the direct effects of weather conditions on absences. For example, low temperature could potentially increase illness-induced absence but, at the same time, thermal inversions where pollution is trapped near ground happen only during cold weather.

Table 1.1. Pollution correlations between Aghdasyeh and other stations

| | CO | NO2 | O3 | SO2 | PM10 | PM2.5 |
|---|---|---|---|---|---|---|
| Region 2 | 0.591 | 0.376 | 0.479 | 0.397 | 0.617 | 0.852 |
| Darous | 0.315 | 0.274 | 0.264 | 0.108 | 0.269 | 0.605 |
| Poonak | 0.211 | 0.367 | 0.354 | 0.377 | 0.693 | 0.822 |
| Setad | 0.378 | 0.337 | 0.084 | 0.232 | 0.516 | 0.685 |

Table 1.2. Correlation table for the six pollutants

| | CO | NO2 | SO2 | PM10 | PM2.5 |
|---|---|---|---|---|---|
| O3 | -0.414 | -0.082 | 0.041 | 0.025 | 0.105 |
| CO | | 0.199 | 0.231 | 0.282 | 0.306 |
| NO2 | | | −0.538 | 0.233 | 0.073 |
| SO2 | | | | 0.185 | 0.363 |
| PM10 | | | | | 0.786 |

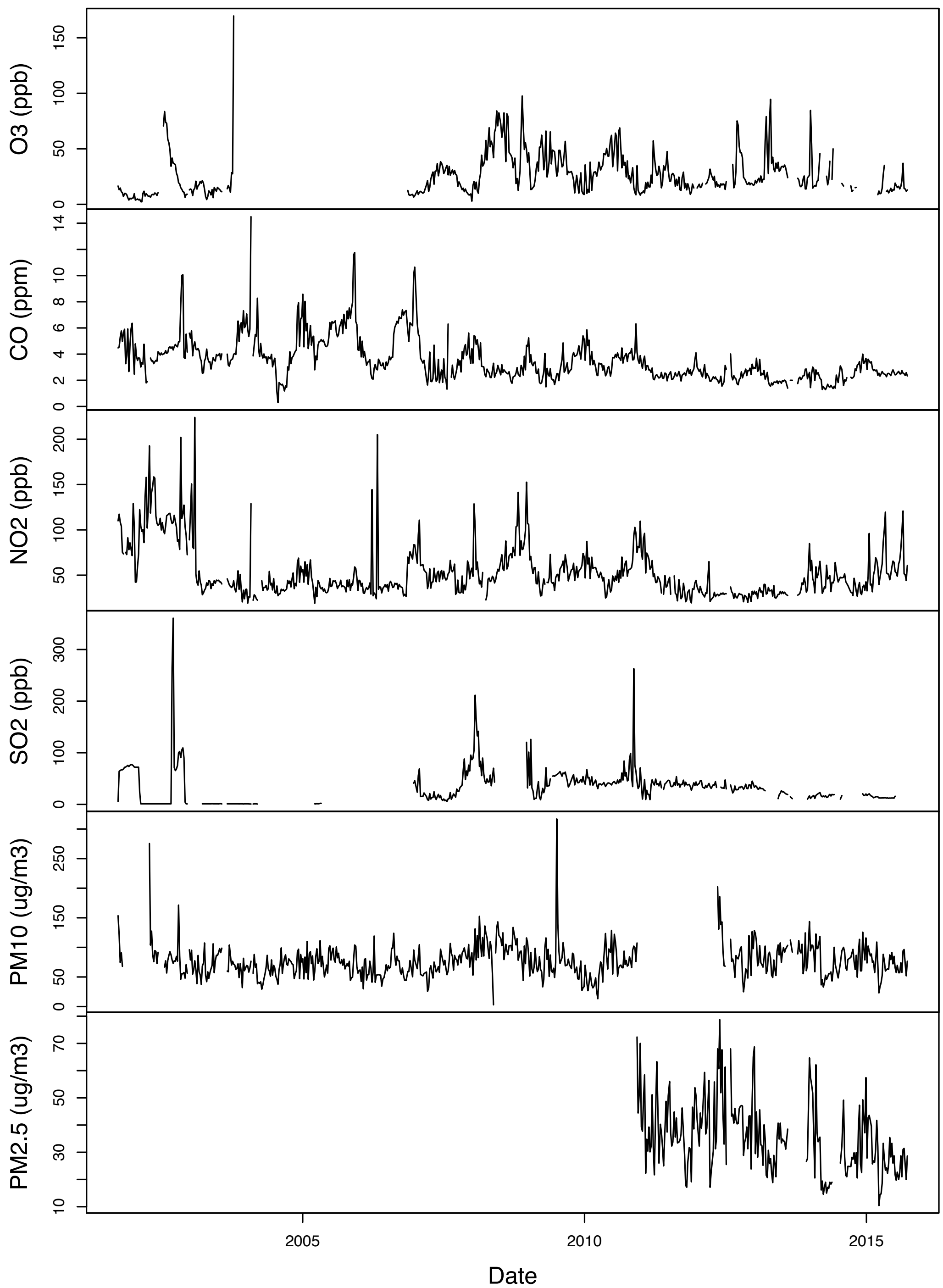


Figure 1.2. Weekly average of pollutant concentrations

## 1.3. Empirical analysis

### 1.3.1. Identification

I exploit the high variability of air pollution concentrations to identify the causal effects of air pollution on student absence. Pollution levels vary greatly even at daily frequency therefore I assume that they are exogenous to school attendance after controlling for weather and cyclical time patterns. This can be seen, for example, in figure 1.3 which plots the residuals from the regression of daily levels of PM10 on the control variables in the model to be described and its own lag for a period of three months in the sample. This is similar in spirit to what Graff Zivin and Neidell (2013) do to argue for the exogeneity of ozone levels in downtown Los Angles. Even after controlling for weather variables and time dummies, a high level of variation remains in the levels of PM10.

Weather is an important variable to control for because it potentially affects student health and attendance but at the same time may be correlated with pollution levels. For example, the CO level is higher at colder days: the correlation coefficient between CO and temperature is $-0.19$ in the sample. But colder weather is also associated with higher incidence of diseases like the flu thus it is important to control for temperature in estimating the effect of CO on attendance. There are other factors as well that may affect attendance and be correlated with pollution levels. One such factor is day of week. Absence rate is usually higher on the final days of the week: table 1.3 shows that absence rate on Thursdays, the last business day of week in Iran, is higher. On the other hand, air quality also seems to follow some pattern over days of the week. For example, air quality is generally better on final days of the week, as can be seen in figure 1.4, probably due

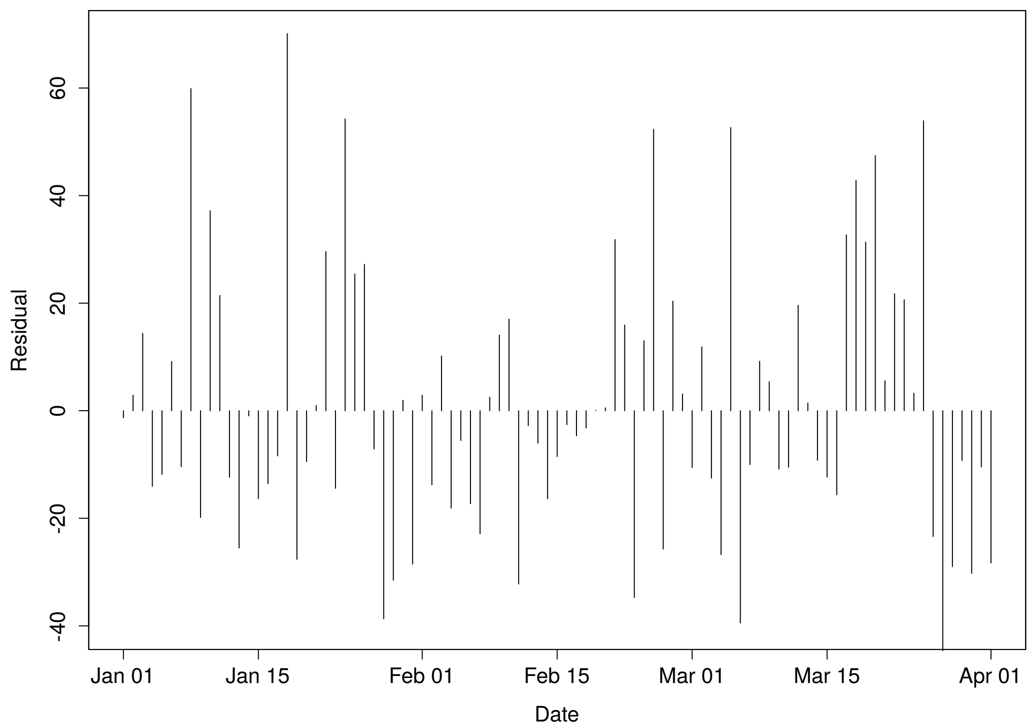


Figure 1.3. Residuals from regression of PM10 on model controls and own lag

to the traffic getting lighter towards the end of the week. This can be seen in table 1.4 which is a regression of PM10 level against day of week dummies and it indicates that PM10 levels are highest on Sundays through Tuesdays. Not controlling for day of week, then, can lead to a biased estimation of the effect of air pollution. Similarly, attendance may be affected on days just before or just after holidays, during exam weeks, or the flu season. Since these factors exhibit a determined time pattern, properly controlling for these patterns can absorb their effects.

Table 1.3. Absences by day of week

| | *Dependent variable:* |
|---|---|
| | Absence per 1000 |
| Sunday | 3.020*** (1.071) |
| Monday | 0.922 (1.073) |
| Tuesday | 1.302 (1.072) |
| Wednesday | 1.666 (1.071) |
| Thursday | 4.383*** (1.077) |
| Constant | 19.692*** (0.760) |
| Observations | 2,677 |
| *Note:* | *p<0.1; **p<0.05; ***p<0.01 |
| | Saturday is the first day of the week. Friday is the weekend. |

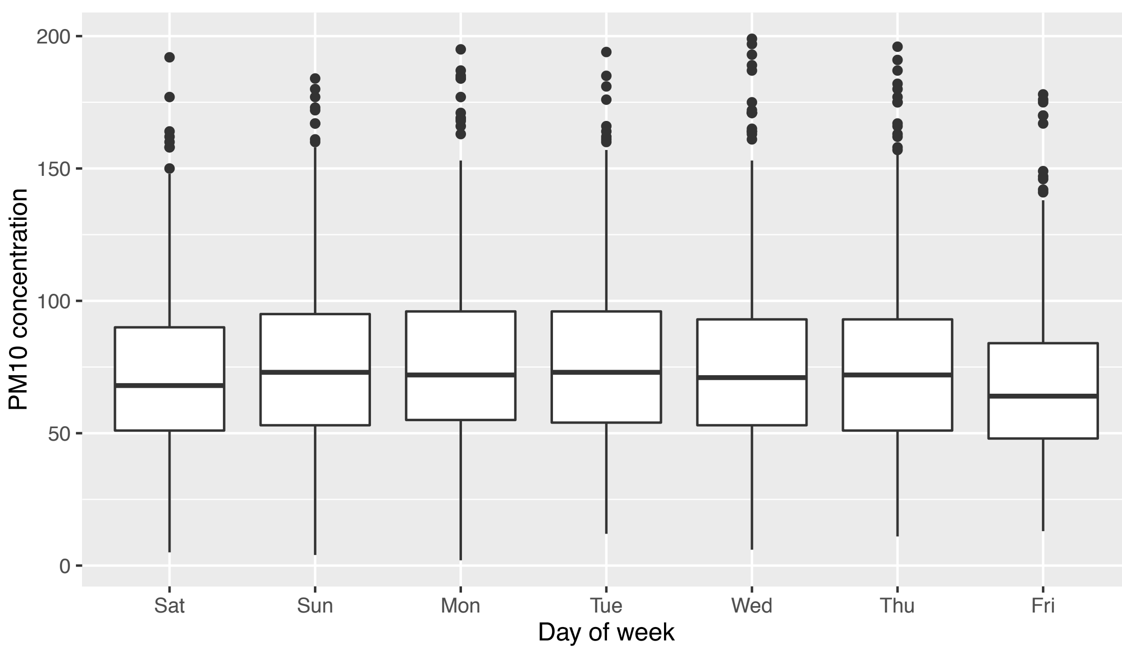


Figure 1.4. Distribution of PM10 concentration by day of week

Table 1.4. PM10 by day of week

| | *Dependent variable:* |
|---|---|
| | PM10 level |
| Sunday | 5.778** (2.437) |
| Monday | 6.247** (2.434) |
| Tuesday | 5.463** (2.423) |
| Wednesday | 3.624 (2.433) |
| Thursday | 3.111 (2.434) |
| Friday | 0.001 (2.450) |
| Constant | 73.336*** (1.720) |
| Observations | 3,874 |
| *Note:* | *p<0.1; **p<0.05; ***p<0.01 |
| | Saturday is the first day of the week. Friday is the weekend. |

### 1.3.2. Model

These ideas can be summarized in the following regression model that states absence rate in terms of air pollution and other potential factors

$$y_t = \mathbf{q_t}'\beta + \mathbf{w_t}'\alpha + \tau_{\mathbf{t}}'\delta + \sum_{j=1}^{L} \lambda_j y_{t-j} + u_t \tag{1.1}$$

The outcome variable $y_t$ is the absence rate on day $t$. It can represent the absence rate for the whole school or a subset of grade levels corresponding to different age groups. $\mathbf{q_t}$ is a vector of pollution concentrations on day $t$. The identification assumption here is that $\mathbf{q_t}$ is uncorrelated with the error term $u_t$. $\mathbf{w_t}$ and $\tau_{\mathbf{t}}$ are vectors of weather and time controls. More specifically, $\mathbf{w_t}$ consists of daily average temperature, wind speed, humidity and precipitation. Finally, $\tau_{\mathbf{t}}$ contains dummies for day of week, every half of a month, and school year to control for other factors with specific time patterns that may affect absences and be correlated with air pollution levels.

To incorporate some of the possible non-linearity in effects, $\mathbf{q_t}$ and $\mathbf{w_t}$ also include squares of the variables within them. In addition, school absence tends to be highly autocorrelated; therefore, it is necessary to control for autocorrelation in the error term by including lag(s) of the dependent variable or the standard error estimates will be biased. These lags are included in the sum $\sum_{j=1}^{L} \lambda_j y_{t-j}$ up to $L$ lags.

### 1.3.3. Whole school effects

The results of the estimation for the absence rate at the whole school level is presented in table 1.6. Each column represents a regression specification. Estimated coefficients are reported in each cell with their (heteroskedasticity robust) standard errors in brackets. Model 1 (first column) is the simple linear model with only pollutant levels and time controls included. The main explanatory variables are concentrations of four pollutants in ppb[2] units. Model 2 (second column) adds weather controls in linear form, and Model 3 adds two lags of the dependent variable. The days on which the pollution data for either of the pollutant is not available or the school was closed (like weekends and holidays) are regarded as missing and removed from the sample.

Comparing the results of the first and the last column and noting the difference between the magnitudes and standard errors implies that including these controls is important for getting consistent estimates. Furthermore, when lags of the dependent variable are added the magnitude of the coefficients become smaller. This is due to the fact that

[2]parts per billion

absences are auto-correlated (as seen in figure 1.5 and if one does not control for the lags, the effects of the pollutants on the current day's absences may be overestimated.

The main finding of the regression is in line with the hypothesized negative effect of air pollution on students school attendance. I find negative negative and significant first order linear effects for one of the four pollutants being studies, namely PM10. According to the results of Model 3, every 1 ppb increase in PM10 results in 18.97 more absences in 1 million students and these coefficients are significant in at least 5 percent level. The effects of NO2, O3 and CO are not statistically significant and the magnitude of the coefficient for CO is much smaller in scale compared to the other pollutants. This implies that the effects of these pollutants on student health and consequent absenteeism is either non-existent or, if it exists, are not large enough to be detected by the current model and data set. Since by including lags of the dependent variable we are essentially estimating the dynamic responses, the long-run effects can be stated as $\frac{\beta_q}{1-\lambda_1-\lambda_2}$ which is reported for PM10 in Model 3 and is found to be 72.96. This implies that since pollution may induce absences of longer than one day due to autocorrelation of absences, its effects in the longer run are actually larger.

Table 1.6: Regression Results – Whole School

| | Model 1 | Model 2 | Model 3 |
|---|---|---|---|
| PM10 | 20.15* | 22.70* | 18.97* |
| | (8.95) | (9.27) | (7.47) |
| O3 | −16.44 | −16.81 | 0.58 |

| | Model 1 | Model 2 | Model 3 |
|---|---|---|---|
| | (19.47) | (19.67) | (15.89) |
| NO2 | 11.69 | 12.89 | 0.50 |
| | (12.14) | (12.22) | (9.87) |
| CO | $-0.24$ | $-0.20$ | 0.00 |
| | (0.26) | (0.26) | (0.21) |
| Temper | | $-254.31^{*}$ | $-174.42$ |
| | | (118.27) | (95.43) |
| Precip | | $264.30^{*}$ | 193.71 |
| | | (128.44) | (103.62) |
| Wind | | $-152.50$ | $-131.36$ |
| | | (259.05) | (208.90) |
| Humid | | $-73.42^{*}$ | $-71.52^{*}$ |
| | | (36.83) | (29.71) |
| $y_{t-1}$ | | | $0.52^{***}$ |
| | | | (0.03) |
| $y_{t-2}$ | | | $0.22^{***}$ |
| | | | (0.03) |
| PM10 LR | | | 72.96 |
| $R^2$ | 0.27 | 0.27 | 0.53 |
| Num. obs. | 1269 | 1266 | 1266 |

$^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$

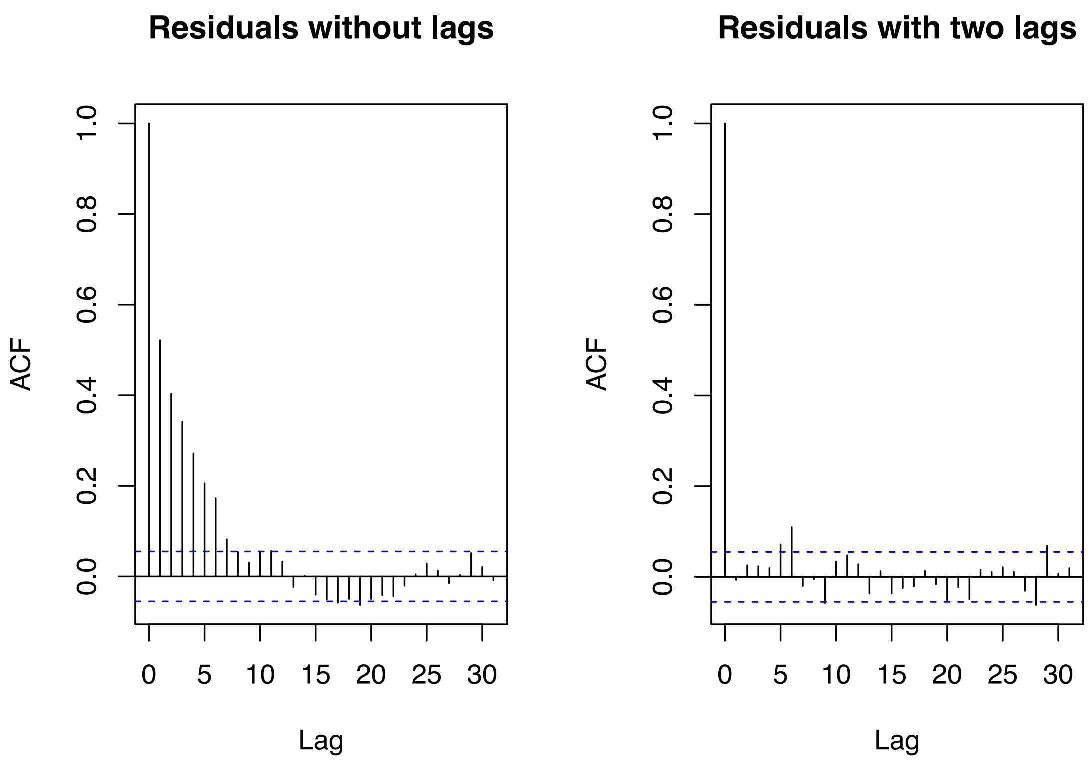


Figure 1.5. Comparing Auto-correlation Function of two models, with and without lags

### 1.3.4. Age group effects

How does the effect of pollution on attendance depend on age? Are younger students more likely to miss school as a result of high air pollution? The attendance data is available at grade level which allows me to investigate the effect of age. This is done in table 1.7 which includes the results of three regressions. Estimated coefficients for the sub-sample of students who are in grades 0 to 6 – aged roughly between 5 and 12 years old – are in column 1 and for the students who are in grades 7 to 12 – roughly aged between 12 and 18 years old – are in column 2.

The general result of the previous estimations still holds: PM10 and NO2 appear to negatively affect attendance. The effects are greater for the younger group compared to the older with the coefficient of PM10 being 62.5 for the younger group versus 42.3 for the older; and the coefficient of NO2 being 80.2 for the younger group versus 20.1 for the older, the latter not being significantly different from zero.

Column 3 is a model run on the combined sample of younger and older groups with a dummy variable for age group and its interactions with pollution levels. According to the results of this model, while belonging to the older group makes it less likely for a student to be absent on a given day by 3.4 percent, the interaction effects between pollution variables and age group are statistically zero. This implies that heterogeneity in response found by comparing models 1 and 2 may just be due to sampling error and the current data cannot reject the hypothesis that the effects are equal across the two groups.

The choice of age groups here is arbitrary and not based on some underlying differences between the two group suggested by biology. Testing the heterogeneity in effect by age for other choices of age groups is easy though using the current data set.

### 1.3.5. Time smoothed effects

Individual days might not be the most appropriate unit of observation for our purpose because the effect of air pollution may not appear until a few days after exposure. Additionally, due to its high frequency, daily data can be quite noisy. One way to overcome this problem is to smooth the data by averaging over periods of longer than one day. This

Table 1.7. Regression Results – Age Groups

| | *Dependent variable:* | | |
|---|---|---|---|
| | Absence per 1 million | | |
| | Grade $< 7$ | Grade $\geq 7$ | Combined |
| | (1) | (2) | (3) |
| PM10 | 62.512** | 42.336* | 53.348*** |
| | (31.550) | (21.722) | (18.194) |
| O3 | −88.384 | 33.293 | −10.470 |
| | (64.416) | (50.735) | (43.400) |
| NO2 | 80.244*** | 20.078 | 51.750** |
| | (29.120) | (33.942) | (23.572) |
| CO | −0.609 | −0.783 | −0.794 |
| | (0.810) | (0.726) | (0.607) |
| Grade $\geq 7$ | | | −3,357.349* |
| | | | (1,906.028) |
| PM10 $\times$ Grade $\geq 7$ | | | −1.281 |
| | | | (12.825) |
| O3 $\times$ Grade $\geq 7$ | | | −35.735 |
| | | | (25.998) |
| NO2 $\times$ Grade $\geq 7$ | | | −3.348 |
| | | | (15.203) |
| CO $\times$ Grade $\geq 7$ | | | 0.180 |
| | | | (0.302) |
| Observations | 1,266 | 1,266 | 2,532 |
| $R^2$ | 0.379 | 0.342 | 0.328 |
| *Note:* | | | *p<0.1; **p<0.05; ***p<0.01 |

can reduce the high frequency noise and, at the same time, take account of potential lags in effects. The new specification can be written in the following form, where an over bar indicates the average over $n$ days

$$\frac{\bar{y}_t}{N} = \bar{\mathbf{q}}'_{\mathbf{t-1}}\beta + \bar{\mathbf{w}}'_{\mathbf{t-1}}\alpha + \tau_t\delta + \sum_{j=1}^{L} \lambda_j \bar{y}_{t-j} + u_t \tag{1.2}$$

In this specification $\bar{y}_t$ is the rate of absence averaged over time intervals of $N$, but I divide it further by $N$ to express the absence rate in days rather than $N$-day averages so the results can be compared to the daily models. In contrast to equation (1.1), in this equation the explanatory variables related to pollution and weather are not contemporaneous with the depended variable but are from the previous period. This is because if the averages of weather and pollution variables from the current time frame are in estimation, then what we are essentially estimating will include the effect of pollution or weather in a future day on today's absences which is meaningless and would make my estimation noisy at best. That is why I focus on the averages of these variables from the previous period and not the current one – for example, the relation between the average pollution in the last 7 days on the average rate of absence in the current 7 days period. I only retain year dummies in $\tau_t$ in this specification since weekdays are no more meaningful for time smoothed sample and it is too coarse for inclusion of half-month dummies. Also the first lag of dependent variable is included to control for possible auto-correlation.

Estimation results are presented in table 1.9. The first three columns show the estimated coefficients of pollution variables averaged over 3-day intervals and the next three columns are for that averaged over 7-day intervals. Columns (1) and (4) are for absence on one day (no averaging); Column (2) and (5) are for average of absence over 3 days; and columns (3) and (6) are for that over 7 days. Models (1) and (4) are presented for the sake of comparison only.

At least two observations can be gleaned from this table. First, by widening the range of days over which absence is averaged, that is from column (1) to (3) and from column (4) to (6), the estimated standard deviation for almost all of the pollutant variables drop in magnitude and the estimated coefficients of some of the pollutant variables become statistically significant. This can taken to imply that averaging actually works to iron out some of the noise and make the estimation more accurate. So that in columns (3) and (6), which denotes the effects for 7-day averaged absence rates, PM10, O3 and NO2 have positive and statistically significant coefficients.

The second observation comes from comparing the 3-day pollution average versus 7-day pollution average models which are in columns (3) and (6) respectively. While the effect of PM10 slightly grows from model (3) to (6) from 17.3 to 23.6, the effect of NO2 jumps more dramatically from 5.2 to 22.7 and the effect of O3 drops from 30.1 to 26.2. This can be used as a clue into to how the different pollutants vary in terms of the speed of their effects on student health and absenteeism. For example, the estimates suggest that the effects of NO2 appear later and only after longer exposures to the gas of 7 days, while the effects of O3 are greater after 3 days compared to 7 days. The effect of PM10, on the other hand, does not show much variation between 3 days and 7 days and shows more consistency across time. This can be viewed better in figure 1.6 which plots the coefficients for PM10, O3 and NO2 estimated for different interval length of averaging pollutants and where the outcome variable is the average 7 day absence rate. This plot shows, for example, that the effect of O3 is highest between 2 and 6 days after exposure, while it is highest after 9 days for PM10 and NO2. Also, while the effect of O3 drops quickly after the first 6 days, it remains relatively high for NO2 after up to 30 days.

Table 1.9. Regression Results – Time smoothed

| | *Dependent variable:* | | | | | |
|---|---|---|---|---|---|---|
| | Absence per 1 million | | | | | |
| | pollution averaged over past 3 days | | | pollution averaged over past 7 days | | |
| | (1) | (2) | (3) | (4) | (5) | (6) |
| PM10 | −15.948 | 9.793 | 17.259*** | −21.575 | 28.004* | 23.557*** |
| | (24.692) | (9.564) | (6.479) | (33.970) | (15.499) | (7.775) |
| O3 | 8.794 | 14.197 | 30.096* | −58.062 | 2.693 | 26.223* |
| | (54.672) | (17.782) | (15.427) | (46.296) | (22.122) | (13.935) |
| NO2 | 77.352** | 8.941 | 5.202 | 114.685*** | 26.974* | 22.720** |
| | (30.660) | (11.545) | (12.773) | (30.973) | (14.235) | (10.037) |
| CO | −0.049 | −0.111 | 0.002 | −0.667 | −0.400 | −0.164 |
| | (0.667) | (0.336) | (0.244) | (0.748) | (0.330) | (0.203) |
| Observations | 1,093 | 534 | 243 | 1,185 | 589 | 262 |
| $R^2$ | 0.548 | 0.490 | 0.447 | 0.525 | 0.521 | 0.490 |
| *Note:* | | | | | | *p<0.1; **p<0.05; ***p<0.01 |

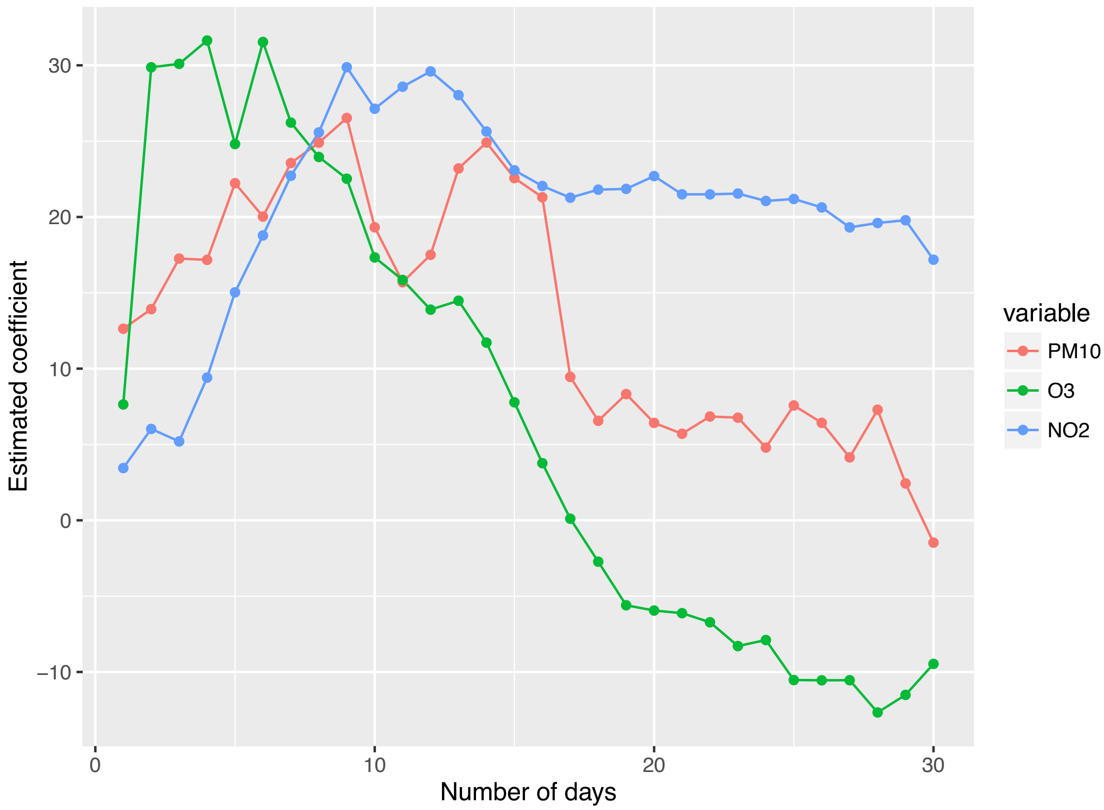


Figure 1.6. Effect of the length of averaging interval on the estimated coefficients

### 1.3.6. Placebo tests

I perform placebo tests to rule out the possibility that the statistically significant effects are purely due to coincidence. The tests involve estimating the same models but with leads or lags of each pollutant variable instead. The rational here is that future pollution should not affect current attendance so we expect the estimated coefficients for leads of pollutants to be not significantly different from zero. Likewise, the level of pollutants in the distant past is not expected to affect the current attendance. I perform these tests for the daily and 7-days time-smoothed models. The results are in figures 1.7 and 1.8.

In figure 1.7 estimated coefficients of the lags and leads of pollutants for up to 60 days are plotted along with their 95 percent confidence interval. Figure 1.8 is the same plot but for the 7-day averaged model and for up to 52 weeks (one year) in the future and in the past. The same day effects of PM10 and NO2 have the highest estimated coefficient. Among their lags, only one or two are significantly different from zero at a 5 percent error level. For O3 and CO no specific pattern can be gleaned other than the increase in the magnitude for the near lags of O3. In the 7-day model, on the other hand, week 0 effect (corresponding to the last 7 days) has a pronounced difference with the other lags in case of PM10, O3 and NO2. But in all of these cases the result holds that distant lags of these variables seldom have coefficients that are statistically significant which can address the concern with capturing false effects.

As for the leads of the pollutants, the estimated coefficients of the daily model are statistically zero for all but one instance (for CO) in the following 60 days. The same result holds for the averaged 7-day model in which virtually all of the leads have coefficients that are statistically zero at 5 percent level. The only notable exception is the 38th lead of O3 which has a positive coefficient and corresponds to roughly 9 months in the future.

It can be concluded that the general picture is consistent with passing of placebo tests that assert the results are not due to statistical fluke. The occasional exceptions can be attributed to some existing correlations in the levels of a pollution over time that are not captured in the current models. As a check for presence of long run correlations (which may be e.g due to cyclicality) in concentrations of air pollutants, in figure 1.9 I plot the auto-correlation functions of the 7-day averages of the four pollutants for a period of 156 weeks (3 years). It is evident from the figure that CO and O3 demonstrate a strong cyclical behavior with the size of the cycles being roughly 1 year. As for PM10, the auto-correlation dies at a faster pace and for NO2 it dampens with the slowest pace and neither PM10 or NO2 show a strong cyclical behavior compared to CO and O3. High levels of auto-correlation may explain the occasional significant coefficients of the far lags and leads of the pollutants.

## 1.4. Conclusion

Environmental pollution exerts external costs that need to be identified and quantified in order for the policy maker to regulate pollution optimally. Air pollution is a prominent form of environmental pollution and a prevalent issue in big cities in many developing and some developed countries. Some types of costs associated with air pollution, such as rises in infant mortality or adult mortality have been widely studied in the economics literature. But there have been relatively few studies regarding the effects of air pollution on other economic outcomes such as human capital, and there is still a lot to be learned about this category of costs of air pollution.

In this paper I studied the effects of air pollution on student school attendance and provided evidence that suggests high air pollution increases students absence from school. Specifically, I showed that the effects are strongest when we consider 7 day average of absence rate rather than the daily rates. This may be due to the fact that 7 days averages smooth out the noise due to weekends and possibly delayed effects of pollution on health. Among the pollutants that I study, I find PM10, NO2 and O3 to be positively affecting absence rate. In terms of costs, I find, for example, that lowering weekly average level of PM10 by 5 $\mu g/m^3$ (which is about 16 percent of its standard deviation) would result in

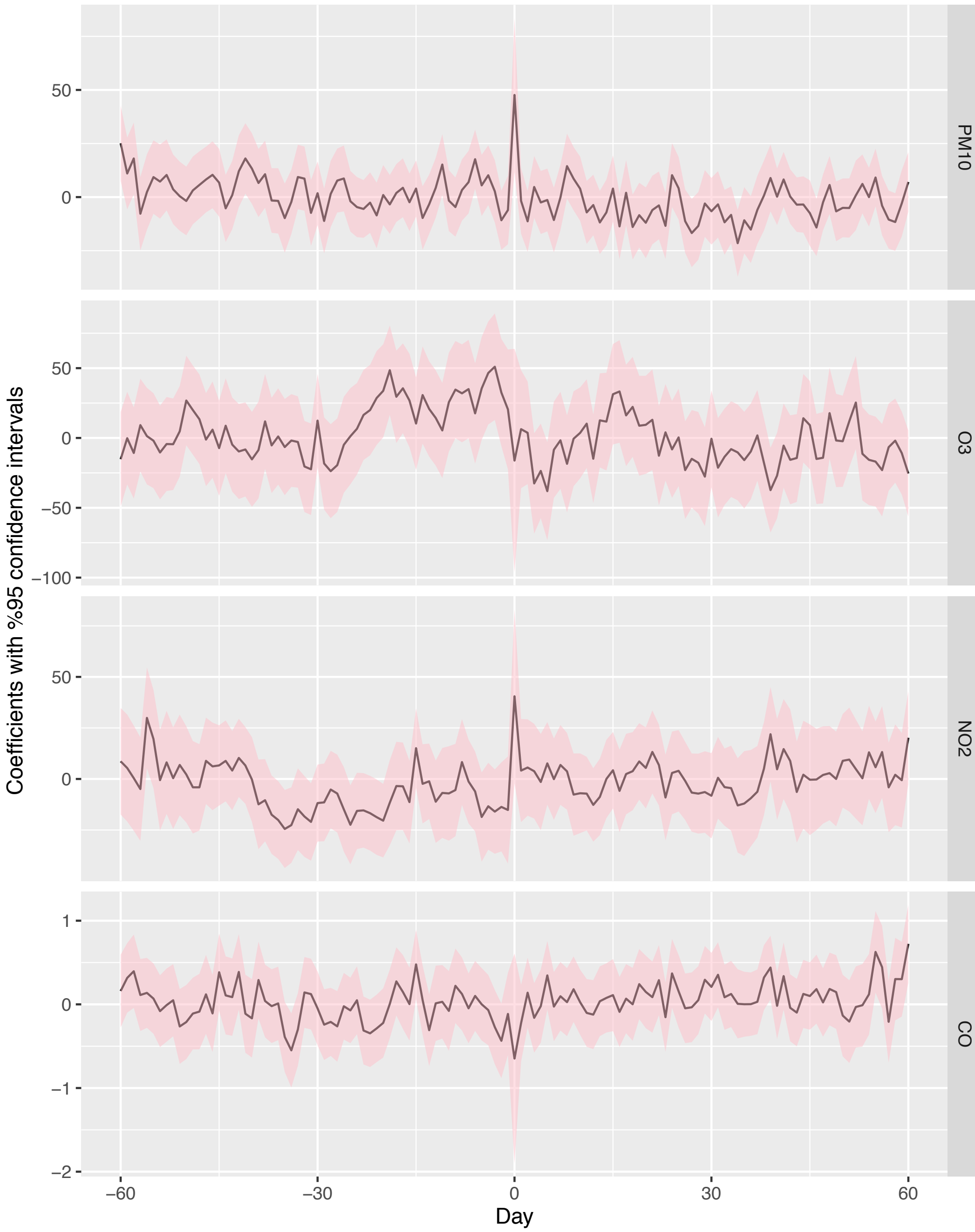


Figure 1.7. Estimated coefficients of lags and leads of pollutant for daily models

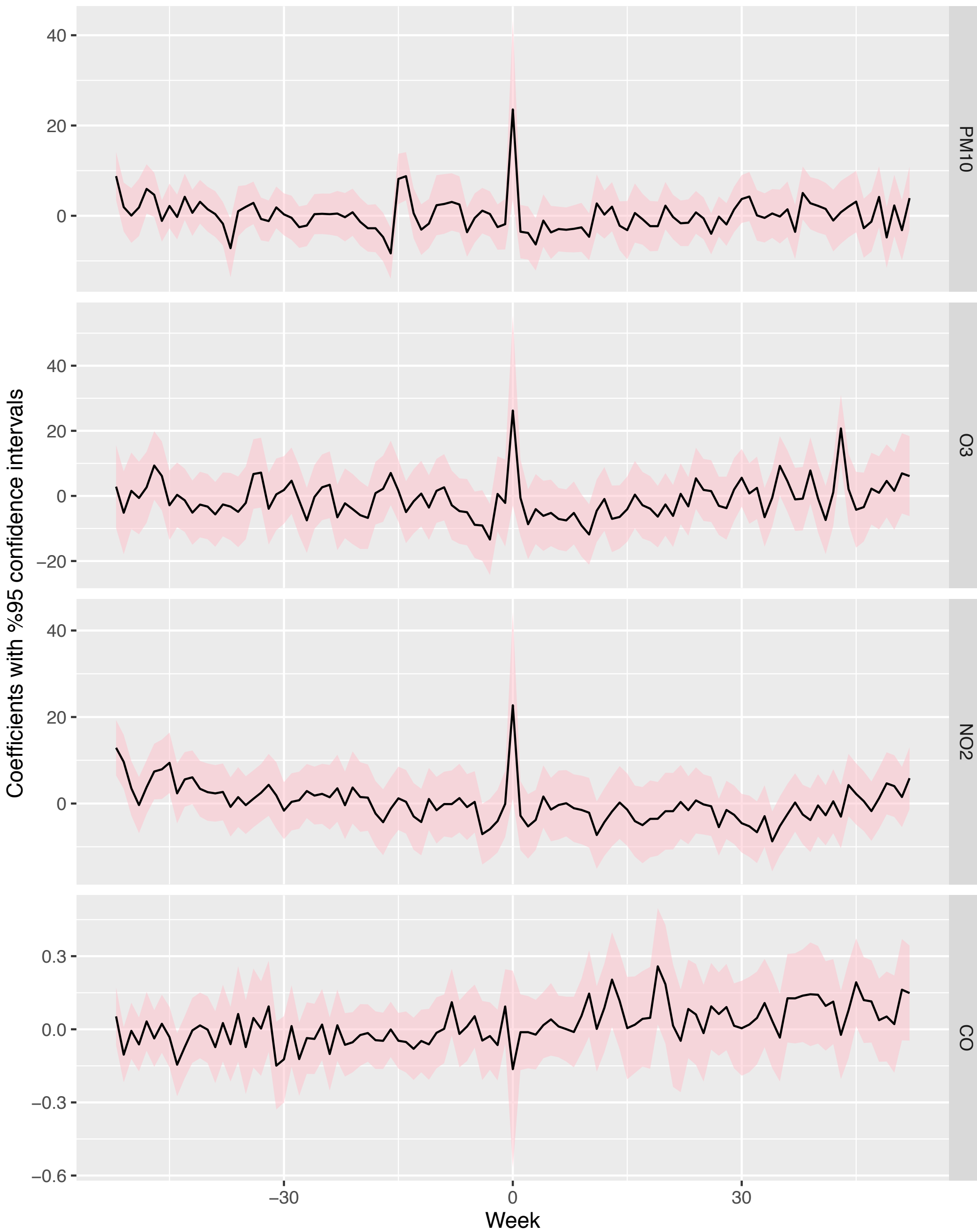


Figure 1.8. Estimated coefficients of lags and leads of pollutant for 7-day time-smoothed models

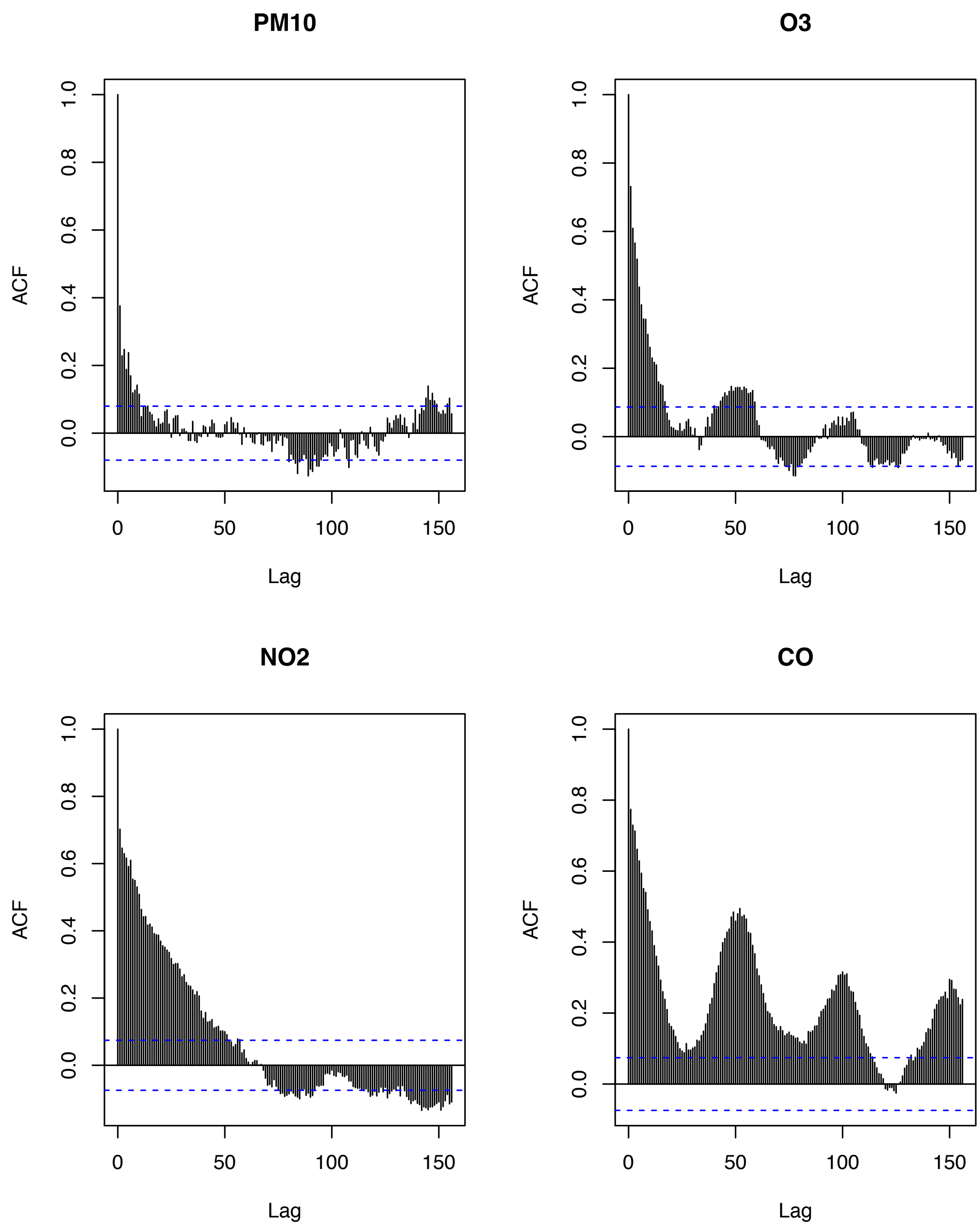


Figure 1.9. Auto-correlation functions – time unit is one week

about 34000 more student-years of school attendance in city of Tehran, which has roughly 1 million school-going students.

There are some important questions that are not addressed in this paper and could be topics for future research in this area. For example, there is still a lot left to be understood about the link between school attendance and formation of human capital: other than the accounting measure of human capital as the number of days a student attends (or misses) school, is there other identifiable links between school attendance and longer term educational attendance? Namely, does frequent absence from school *cause* lower educational attainment? Or is there at least an association between the two so that school attendance may be used as a predictor of human capital investments later in the life? Answering those question would shed further light on the importance of school attendance in formation of human capital and better understanding the costs of absence from school caused by environmental pollution.

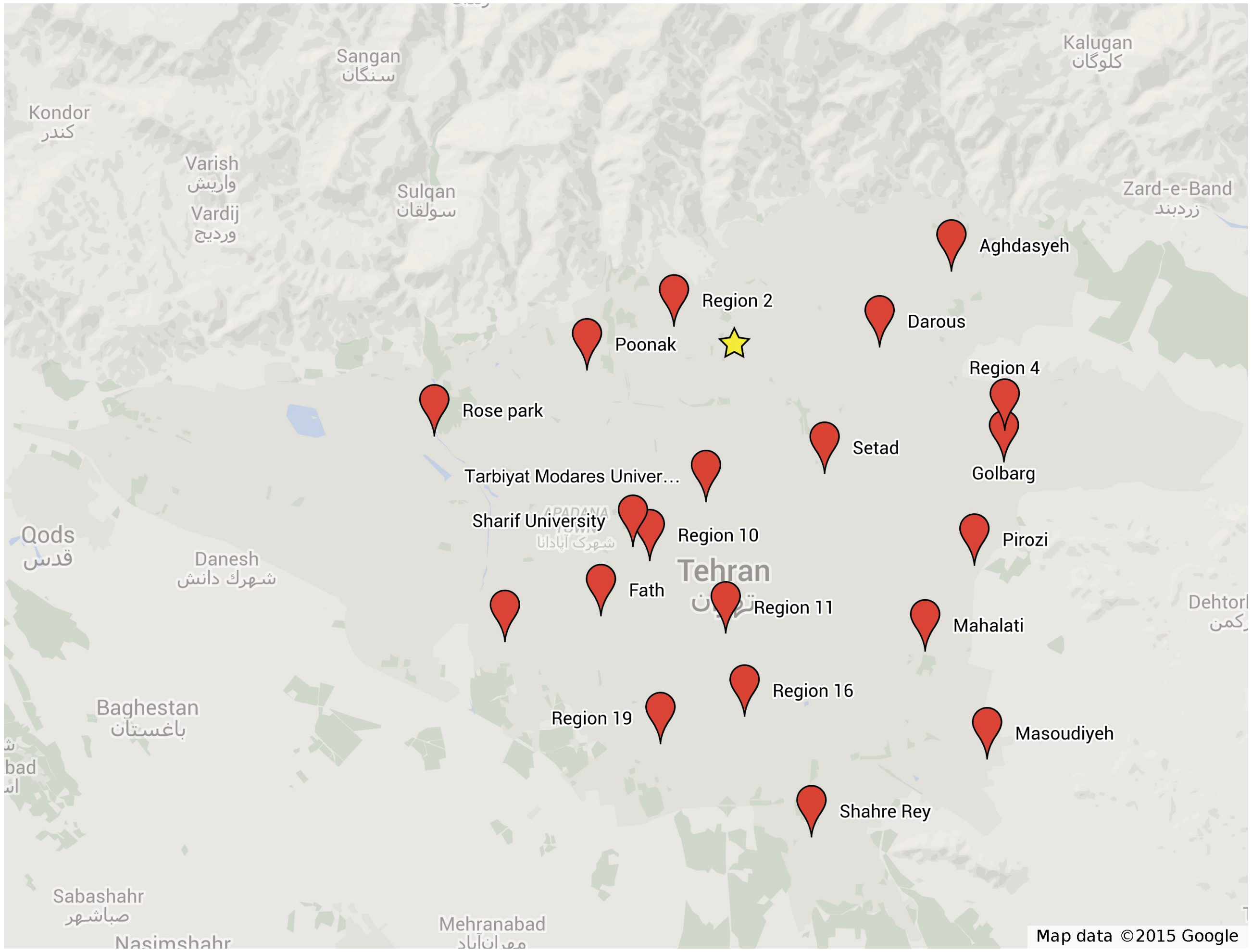


Figure 1.10. Location of the school and pollution monitoring stations

CHAPTER 2

# Determinants of International Migration

## 2.1. Introduction

A sub-strand of the economic literature on international migration has adopted the idea of "gravity" equations from the international trade literature in order to explain the magnitude of international migration between countries. This literature, in a similar way to the gravity models of international trade, assume that the magnitude of migration between two countries should be proportional to the product of some measure of "mass" (corresponding to GDP in the original trade models) in the source and destination countries and inversely proportional to some notion of "distance". However, the gravity models of international migration are typically postulated without specifying a basis in microeconomics theory. In this paper I try to build a micro-based model of international migration that at aggregate country level is similar to the gravity models. So it is not only easy to estimate using available data but also is more justified since it is based on firm theoretical underpinning.

Another point of weakness in this literature is the choice of the mass variables: studies have typically used include GDP or population of the source and destination countries with little theoretical justification for adopting them. In this paper I use wage levels of the source and destination countries instead. There are a few advantages in using wages instead of macro variables such as GDP. First, wages are the proper micro-level factor that theory suggests will affect individual decision to migrate. While GDP may be used to approximate the effect of wages it is not clear how accurate this approximation is since other factors of production (and not just labor) contribute to GDP which can make it a crude and noisy proxy for wages. Second, macro variables are gross measures that do not account for heterogeneity in wages. When wages are used, on the other hand, depending on the level of aggregation, it is possible to gain insight into how differences in wages is affecting individuals differently.

To my knowledge this is the first study that uses wages directly to explain international migration patterns at a more disaggregated level (namely schooling level, sex and age group). The reason wages have not been used before in the literature is mainly that such data have not been historically available; however, thanks to a new data set collected and compiled by the World Bank, I have gained access to a data set that allows me to estimate models using wages as the primary explanatory variable. The data set has an added advantage of including more countries than have typically been studied in the works on international migration. Specifically, it includes data on migration to developing countries which are usually not considered as destinations of immigration in current studies due to lack of data.

In this paper I derive gravity equations for international migration starting from a micro-based model of individual's decision to migrate based on the difference in wages between origin and destination countries. I use the model to estimate the effects of wage differences and other factors on the immigrant population across the world. I find that wage differences are actually an important determinant of migration rates across countries and that, as predicted by theory, the higher is the difference in wages between an origin and a destination country, the higher is the ratio of migrants from the source to the destination country.

Another important contribution of this paper is that the data that I have available allows me to asses the role of heterogeneity in determining the size of migration and test the hypothesis that there is no difference in decision to migrate across groups with different characteristics. Specifically, I look at how education, sex and age can affect the migration rates. My emphasis is on the effect of education as education level as it is an important determinant of worker quality and the analysis of heterogeneity in education allows me to gain insight into the effects of this important characteristic.

## 2.2. Review of literature

There are a number of studies in economics literature that focus on the topic of modeling and estimating the determinants of international migration. Many of these studies are based on early models developed by Sjaastad (1962) and Borjas (1987). The basic idea in these models is that the primary form of migration is labor movement and that the wage differences between the origin and the destination countries are the primary force that drive the labor movement. Borjas (1987) adds the possibility of "self selection" of labor based on the distribution of income in the origin and destination countries. A small strand of the literature on international migration, however, tries to model immigration patterns using the idea of gravity equations adopted from the international trade literature. The gravity equations originated in the trade literature to specify the trade flows between country $i$ and $j$ and take the following form

$$\mathrm{M}_{ij} = \alpha \frac{\mathrm{Y}_i \mathrm{Y}_j}{\mathrm{Distance}_{ij}} \tag{2.1}$$

where $M_{ij}$ is the (value of) trade flow between $i$ and $j$, $Y_i$ and $Y_j$ are some measure of economic size (usually GDP) of countries $i$ and $j$, and $\mathrm{Distance}_{ij}$ is a measure of "distance" between $i$ and $j$ which indicates the costs of trade between $i$ and $j$ due to geographical distance, language or cultural differences, etc[1]. More generally, a gravity model can be specified in the following form

$$\mathrm{M}_{ij} = K_{ij} A_i B_j \tag{2.2}$$

This equation can be reinterpreted and applied to international migration by assuming that $M_{ij}$ is now the migration flow or stock from country $i$ to country $j$ and $A_i$ and $B_j$ are any factors specific to countries $i$ and $j$ that affect migration – we call $A_i$ *supply* or *push* factors and $B_j$ *demand* or *pull* factors. In this form, the notion of the distance between $i$ and $j$ has been generalized and summarized in $K_{ij}$ which encompasses any factors depending on the relation between $i$ and $j$ that affects the migration flow or stock between the countries. These are factors like geographical distance, if the two countries have a common language, or specific regulations in country $j$ regarding admitting immigrants from $i$, etc.

[1]This type of equation is called a "gravity" equation because it resembles the gravity equation in physics where the force attracting two bodies is proportional to the product of their masses and inversely proportional to the square of their distance, namely, $F = G\frac{m_1 m_2}{d^2}$

As an example of using gravity equations for international migration, Lewer and Van den Berg (2008) estimate a gravity model of immigration with populations of the origin and destination countries as "mass" and include other variables such as distance, language, human capital and degree of enforcement of property rights and report the results of their estimations.

Another example of using a gravity-like model to estimate the effects of possible determinants of immigration is Karemera, Oguledo, and Davis (2000) who proposed a reduced form gravity model of immigration flows from 70 countries to North America. Their focus is on estimating the effect of immigration regulation and characteristics of the origin and destination countries like unemployment, inflation, or other factors such as political instability and civil freedom. They also include the incomes and populations of the origin and the destination countries as gravity "mass". They find that population of the origin countries and income of the destination countries are two important factors that determine immigration to North America. In addition, restrictions on political and civil freedoms in the origin countries negatively affect the migration to North America.

One limitation of the current literature is that in almost all of the papers the destination countries are only one or a small set of countries (e.g. the US or Canada or OECD countries). The problem with this approach is that, by omitting the other countries as potential destinations of immigration, the effects of the income differential in explaining the decision to immigrate may be underestimated. This problem could be ignored if the proportion of immigrants to other destinations was negligible relative to those who immigrate to the country (or group of countries) under study. However, a significant proportion of international migration may be towards developing countries which are typically not included as potential immigration destinations in the data sets of existing papers.

Another common problem with the current literature is that the existing studies postulate an empirical estimation model often without a theoretical justification. In those papers, different and often incompatible empirical models have been proposed that are not based on microeconomics theory. For example, the model in Lewer and Van den Berg (2008) specifies a gravity model with populations of the origin and destination countries as the masses, while Karemera, Oguledo, and Davis (2000) proposes a gravity model with both GDPs and populations of the origin and the destination countries as the masses. Beine and Parsons (2015) is probably an exception in that a full micro-based model of international migration is derived and used to estimate the effects of climatic factors as drivers of immigration. In this paper I develop a model of international migration that is based on a microeconomics model of worker's decision to migrate hence addressing this common issue in current studies in this literature.

## 2.3. A Model of International Migration

### 2.3.1. Worker's decision to migrate

I am primarily interested in the effects of income potentials on labor movement across countries. So I focus on the problem of the effect of wages, as the main source of compensation for labor, on the population of migrants in a given country. Consider the problem of a worker's economic decision to migrate. The worker is from country $i$ and his indirect utility from migrating to and working in country $j$ is

$$u_{ij} = f(w_j) + A_j - c_{ij} + \nu_{ij} \tag{2.3}$$

where $w_j$ is the wages in country $j$, and $f(.)$ determines the functional form of the utility of wages (e.g. logarithmic function); $A_j$ is the indirect utility from any non-wage pull factor in the destination country (e.g. amenities or civil rights) common to all individuals; $c_{ij}$ is the (common) total cost of migration from $i$ to $j$; and $\nu_{ij}$ is a random, individual specific residual utility. This includes the utility from staying (not migrating) in which case the indirect utility will be

$$u_{ii} = f(w_i) + A_i + v_{ii} \tag{2.4}$$

in which $c_{ii} = 0$ since there is no immigration costs when the worker chooses to stay.

In deciding which country $j$ to immigrate among the set $S$ of all the countries that the worker can migrate to, or to not immigrate at all and stay in his home country $i$, the worker finds the destination country in which he gets the highest utility, i.e. he solves the maximization problem

$$\max_{k \in S} f(w_k) + A_k - c_{ik} + \nu_{ik} \tag{2.5}$$

Given this migration decision rule, what is the probability that a worker from country $i$ immigrates to country $j$? Calling this probability $p_{ij}$ we can calculate it as the following

$$
\begin{aligned}
p_{ij} &\equiv \Pr\{\bigcap_{k\in S} u_{ij} \geq u_{ik}\} \\
&= \Pr\{\bigcap_{k\in S} f(w_j) + A_j - c_{ij} + \nu_{ij} \geq f(w_k) + A_k - c_{ik} + \nu_{ik}\} \\
&= \Pr\{\bigcap_{k\in S} \nu_{ik} - \nu_{ij} \leq [f(w_j) + A_j - c_{ij}] - [f(w_k) + A_k - c_{ik}]\} \qquad (2.6)
\end{aligned}
$$

Now, in order to further simplify the expression in the last line of equation (2.6) we need to make further assumptions about the distribution of $\nu_{ij}$, that is, the random residual utility of the worker. One possible assumption is that $\nu_{ik}$'s are iid across individuals and distributed according to Type I Extreme Value distribution. In this case, equation (2.6) can be simplified to

$$
p_{ij} = \frac{\exp(f(w_j) + A_j - c_{ij})}{\sum_{k\in S} \exp(f(w_k) + A_k - c_{ik})} \qquad (2.7)
$$

And from equation (2.4) which gives the utility of staying (not migrating), the probability of staying in the home country is given by

$$
p_{ii} = \frac{\exp(f(w_i) + A_i)}{\sum_{k\in S} \exp(f(w_k) + A_k - c_{ik})} \qquad (2.8)
$$

### 2.3.2. Migration rate by wage differences

Now suppose that $N_i$ is the population of country $i$ and $M_{ij}$ is the number of people who migrate from $i$ to $j$. Assuming that the population and the number of migrants are large, by the Law of Large Numbers (LLN), the fraction $\frac{M_{ij}}{N_i}$ converges to $p_{ij}$, so that the number of migrants from $i$ to $j$ can be stated as

$$M_{ij} = p_{ij} N_i \tag{2.9}$$

and the number of people staying at their home country as

$$M_{ii} = p_{ii} N_i \tag{2.10}$$

The odds ratio of migrating to country $j$ then can be stated as

$$\frac{p_{ij}}{p_{ii}} = \frac{M_{ij}}{M_{ii}} = \frac{\exp(f(w_j) + A_j - c_{ij})}{\exp(f(w_i) + A_i)} \tag{2.11}$$

If we further assume that $f()$ is logarithmic then equation (2.11) will simplify to

$$\frac{M_{ij}}{M_{ii}} = w_j \exp(A_j) \times \frac{1}{w_i \exp(A_i)} \times \frac{1}{\exp(c_{ij})} \tag{2.12}$$

This is one derivation of a general form of gravity equation as seen in equation (2.2): the first term $w_j \exp(A_j)$ represents the pull factors or destination mass, the second term $\frac{1}{w_i \exp(A_i)}$ represents the push factors or origin mass, and the last term $\frac{1}{\exp(c_{ij})}$ represents the “distance”. So a gravity-type equation has been derived that can be used to estimate the determinants of international migration based on a microeconomics model of worker's utility maximization.

The advantage of such derivation is that it clearly states the assumptions used in derivation. This way, each assumption can be evaluated in terms of its plausibility and the implications of using alternative assumptions can be assessed. For example, in deriving the gravity-type equation (2.12) I assumed that $\nu_{ij}$ is iid and distributed according to the type I extreme value distribution, that $f()$ is logarithmic, and a separable an additive form for the indirect utility function was specified.

Taking logs of equation (2.11) we get the log-odds-ratio equation

$$\log \frac{M_{ij}}{M_{ii}} = f(w_j) - f(w_i) + A_j - A_i - c_{ij} \tag{2.13}$$

The left hand side of the equation is the (log) ratio of the the number of immigrants who are from $i$ and migrated to $j$ to the population (of non-immigrants) who are from $j$. I call this fraction *migration ratio*. The equation states this ratio as a linear function of $f(w_j) - f(w_i)$, the difference in utility of wages between the origin and the destination countries. I call this difference *wage difference*. But the migration ratio is also a function of other factors in the origin and destination country, namely $A_j$, $A_i$ and $c_{ij}$. This equation is in a convenient form for empirical testing and will be used as the workhorse for my empirical analysis and the variations of the empirical model will be based on this equation.

### 2.3.3. Heterogeneity in response to wage differences

There may be some explanatory power in what we know about a worker's characteristics in determining the immigration patterns. Probably the most important characteristic of the labor that is widely studied in labor economics is a worker's "skill" that is often proxied by his education level and experience. The fact that the wage a worker earns depends on his skill has been widely tested and demonstrated in different countries and settings. The relationship between wage and skill is usually stated using Mincer's equation (Mincer 1974):

$$\log(\text{wage}) = \beta_0 + \beta_1\text{schooling} + \beta_2\text{experience} + \beta_3\text{experience}^2 + \varepsilon \tag{2.14}$$

If worker characteristic is taken into account, then immigration decision equation (2.13) can be updated to include it. The primary characteristic that I am interested in in this paper is education level, $z$. Adding characteristic $z$ to equation (2.3) the indirect utility can be stated as

$$u_{ijz} = f(w_{jz}) + A_{jz} - c_{ijz} + \nu_{ijz} \tag{2.15}$$

In equation (2.15), $u_{ijz}$ is the indirect utility of the worker with characteristic $z$ migrating from $i$ to $j$, $w_{jz}$ is the wage of workers with schooling $z$ in country $j$, and same for pull factors $A_{jz}$, migration costs $c_{ijz}$ and random residual utility $\nu_{ijz}$. The log of odd ratio of migrating versus not migrating of workers with schooling $z$ is then given by

$$\log \frac{M_{ijz}}{M_{iiz}} = f(w_{jz}) - f(w_{iz}) + A_{jz} - A_{iz} - c_{ijz} \tag{2.16}$$

This equation incorporates heterogeneity of workers in terms of their characteristics (primarily education level) and allows us to empirically test if heterogeneity is an important factor in determining the response of labor to wage differences.

## 2.4. Empirical approach

### 2.4.1. Assumptions of the model

In this section I make assumptions that help me in writing an equations that are suitable for empirical estimation of the determinants of migration. The first assumption is regarding the functional form of $f()$ in the indirect utility function. If $f$ is assumed to be a linear function, that is if $f(w) = \beta w$ then that is consistent with underlying preferences which are quasi-linear in income. On the other hand, a logarithmic function $f(w) = \beta \log(w)$ is consistent with homothetic preferences. In my empirical specification I use both functional forms to be able to compare the coefficients resulting from each assumption.

The immigration cost $c_{ij}$ is also specified as a linear function of variables that affect the costs of immigration between countries $i$ and $j$, for example the geographical distance between $i$ and $j$, whether $i$ and $j$ have common languages, whether $i$ and $j$ have a common border, etc. The resulting specification can be stated as the following

$$
\begin{aligned}
c_{ij} &= k_0 + k_1 dist_{ij} + k_2 comm\_lang_{ij} + k_3 comm\_border_{ij} + \kappa_{ij} \\
&= \boldsymbol{k'x_{ij}} + \kappa_{ij} \qquad (2.17)
\end{aligned}
$$

were the variables in equation (2.17) have been collected in the vector $\boldsymbol{x_{ij}}$ in the second line of the equation and the associated coefficients in the vector $\boldsymbol{k}$. Other factors that can affect the immigration costs but are not accounted for in the empirical specification (2.17) are collected in $\kappa_{ij}$.

Another important assumption is regarding the interpretation of the dependent variable as stock versus flow. What $M_{ij}$ represents is the *population* of the immigrants from country $i$ in country $j$, so it is a *stock* rather than a flow variable while the explanatory variable used on the right hand side is wage levels $w_i$ and $w_j$ which are for a specific period of time (year). Ideally, if data were available, we could write a dynamic model of formation of immigrant populations in terms of wage differences over time. But I make the simplifying assumption here that the model is static: wages are observed in period 0, then migration decisions are made, and in period 1 we are in a steady state where all the migration has happened. So we are using the wages of the year of observation as the wages for all the periods in a dynamic model; that is, I assume that wages do not change over time, which is a strong assumption. But given the availability of data there is no escape from making such simplifying assumption.

### 2.4.2. Do wage differences explain immigration?

Putting all of these assumption together and combining equations (2.13) and (2.17) I derive the following linear regression equation that is suitable for estimation, where to simplify notation I have defined $\Delta_{ji}$ to be the difference in wages in equation (2.13), or $\Delta_{ji} \equiv f(w_j) - f(w_i)$

$$\log \frac{M_{ij}}{M_{ii}} = \alpha + \beta\Delta_{ji} + A_j + A_i + \boldsymbol{k'x_{ij}} + \epsilon_{ij} \tag{2.18}$$

Equation (2.18) states that the log ratio of the population of immigrants to non-immigrants is proportional to the "difference" in wages as well as other factors that affect the costs of immigration. This equation can be used to test the hypothesis that the difference in wages levels between the origin and the destination countries can explain the likelihood of migration to the destination country. If $\beta$ is positive then we can conclude that there is positive correlation between the difference in wages and the likelihood of migration. This equation is the main empirical specification in "gravity" form with the advantage that we are using the wage data here rather than GDP.

### 2.4.3. Modeling heterogeneity

If, in addition, we include immigrant characteristics $z$, such as schooling, then we can rewrite equation 2.18 in the following form

$$\log \frac{M_{ijz}}{M_{iiz}} = \alpha_z + \beta\Delta_{jiz} + \gamma_z\alpha_z\Delta_{jiz} + A_{jz} + A_{iz} + \boldsymbol{k'x_{ijz}} + \epsilon_{ijz} \tag{2.19}$$

where the $z$ subscript indicates belonging to the population subgroup with characteristic $z$. The direct fixed effect effect of $z$ is captured by the dummy variables $\alpha_z$, so any heterogeneity in migration ratio that is solely due to the characteristic $z$ but not its interactive effects with other variables (such as wage differences $\Delta_{ijz}$) is reflected in the estimated coefficients of $\alpha_z$. If, in addition, there is heterogeneity in the effects of wage differences that is due to characteristic $z$, it will be captured by the interaction term $\alpha_z D_{jiz}$ and reflected in its coefficient $\gamma_z$. For example, for different levels of education, $\gamma_z$ tells us if the force of the wage differences varies across education levels, or how workers with different education levels differ in terms of their sensitivity to wage in their immigration decisions.

$A_{iz}$ and $A_{jz}$ as before are country fixed effects that control for country specific pull and push factors. The only difference here is that I allow for these effects to vary with $z$, so for example, the utility of staying in a country can be different for individuals with different education levels or ages. The same is true for the cost factors $x_{ijz}$ which now depend on not only the origin and destination countries but also on $z$ to allow for the fact that the costs of immigration can differ across individuals in different subgroups of $z$.

### 2.4.4. Problem of identification

The problem of identification naturally arises in this setting and is an important issue, namely, the estimation may suffer from bias due to reverse causality and omitted variables. Reverse causality in this case may follow from the fact that wages can be affected by migration. Emigration can lead to a fall in labor supply and put an upward pressure on wages and immigration can cause a rise in labor supply in the destination country and lower the wages. Although theory suggests that migration should, in principle, affect the wages, whether that has been the case in reality has been a subject of hot debate among labor economists. One such debate has occurred between Borjas and Katz on the one side (Borjas 2003; Borjas and Katz 2007) who find that immigrant workers are substitutes for domestic workers which results in lower local wages, and Ottaviano and Peri (Ottaviano and Peri 2008, 2012) who do not find evidence for such substitutability and lowering effect on local wages. The preceding discussion shows that the concern about reverse causality of immigration on wages is relevant and potentially creates identification problems. Of course, if the population of migrants is only a small fraction of the work force in the origin or the destination country, this bias, even if present, may be small and safe to ignore. But the case of a large bias cannot be ruled out a priori and without empirical tests.

Another source of identification problem is that wages in the origin or destination countries are correlated with other factors not included as explanatory variables in equation 2.18; for example if $w_i$ is correlated with factors in the origin country that are not reflected in the push factors $A_i$, or, if the same is true for $w_j$ and pull factors in the destination country. In that case the coefficient $\beta$ may suffer from positive or negative bias and we may arrive at wrong conclusions about the effect of wages on international migration. Additionally, the wage difference $\Delta_{ji}$ may be correlated with factors specific to countries $j$ and $i$ that is not controlled for in the cost vector $c_{ij}$. This can also bias the estimates of $\beta$ positively or negatively.

## 2.5. Data

The data used in this study comes from two sources: immigration data and wage data which I am going to describe in detail in subsection.

### 2.5.1. Immigration data

The immigration data comes from the Database on Immigrants in OECD Countries Extended (DIOC-E) put together by OECD and the World Bank (OECD 2011). The database is an extension of the earlier DIOC database which was based on the 2000 census round in OECD countries and compiled the census data from those countries into one database which includes information on immigrants such as age, gender, duration of stay, educational attainment and place of birth. The DIOC-E database expands upon DIOC by adding non-OECD destination countries using their 2000 round census data. This database covers a total of 100 countries (32 OECD and 68 non-OECE) and 233 countries of origin. The latest release of DIOC-E database (release 3.0) covers immigrant characteristics such as country, country of birth, sex, education, age, labor force status and occupation. Dumont, Spielvogel, and Widmaier (2010) provide an overview of the data and some stylized facts about international migration derived from this database.

This database provides the total number of immigrants from origin countries in the destination countries by the year 2000. So what is available is the immigration *stocks* and not *flows*. Also some useful information about immigration is not observed in this data. For example whether the immigration was illegal, or temporary (return) migration is not observed. So we cannot distinguish among different types of immigration and the reasons for which people migrated.

### 2.5.2. Wage data

The DIOC-E data contains information on the population and characteristics of immigrants but they lack data on the potential earnings in the origin and the destination countries. To overcome this I use another source of data for the wages which is a database compiled by the World Bank as discussed in Montenegro and Hirn (2009). This database standardizes and combines the household survey data of more than 120 countries into one single dataset. Since the data are harmonized and processed to be in comparable format this database is useful for cross-country studies like this paper.

This database also includes wages for different education levels in the economies covered by the data set. The wage data by education level is the key advantage of the current paper which enables me to test the determinants of international migration using actual wages rather than using proxies like GDP per capita, which should be more accurate and also enable estimating the effect for different labor skill levels.

Three other characteristics are observed in both of the databases, namely, sex, age group and education level. The observed age groups consist of three distinct groups corresponding to the what is observed in the data. These age groups are 15 to 24 years, 25 to 64 years, and 65 years or older. There are also three education levels observed in the data that are summarized in the table 2.1 below. In the last column of the table the ISCED [2] code that corresponds to each level is also reported.

[2] International Standard Classification of Education

| Level | Description | ISCED |
|---|---|---|
| 1 | no education, completed primary and uncompleted secondary education | 0/1/2 |
| 2 | completed secondary education | 3/4 |
| 3 | completed tertiary education | 5/6 |

Table 2.1. Education levels observed in the data

### 2.5.3. Country "distance" data

As suggested by the theoretical model there are different notions of "distance" between countries that can affect the costs of migration. The most obvious is geographical distance but there are other measure that can potentially affect the costs of migration. One such measure whether two countries have common languages. Where this is the case, migration is relatively less costly because language (and possibly cultural) barriers to migration will be lower. For measure of distance I use the data provided by CEPII database. This database contains the following measures of distance for 225 countries: *geographical distance* between two countries, whether two countries have are *contiguous*, have a *common language*, have *common colonial* history, and whether one country was or is a *colony* of the other. By including the distance data I will be controlling for the effects that they might have on the decision to migrate.

### 2.5.4. Preparing the data for estimation

The immigration data from DIOC-E database and the wage data from Montenegro and Hirn (2009) should be matched to make them useful for answering the empirical questions in this paper. The DIOC-E database comes with migration data but lacks wage data which Montenegro and Hirn (2009) provide. I perform the matching by country hence the observations are limited to countries that show up in both data sets. But the matching can be performed in a finer and by other characteristics as well, namely, by education level, sex and age group. This allows me to control for these other factors when estimating the effects of wages on migration.

The wages are *monthly wages* and are in local currencies though and need to be converted in order to be comparable across countries. The way I do this is to use PPP exchange rates to convert nominal wages to US dollars in any given year. The reason for using PPP is that I want to control for difference in costs of living across countries which cannot be achieved by only using the exchange rates. The exchage rate data is obtained from the World Bank's World Development Indicators database (Bank 2010).

Since the exchange rate data acquired from the World Bank are the *official* exchange rates, in countries where there are dual exchange rates, that is official and unofficial *market* exchange rates, conversion using the official may result in artificially high wages in US dollars. That is because the official exchange rates are often fixed at a rate lower than the market rate. One such country in the data set is Azerbaijan, with reported exchange rates much lower than the going market exchange rates. Since the data for actual market exchange rates is not available in the World Bank data set, I delete suspicious outliers with very high monthly wages; that is middle or low income countries that with average wages of greater than USD 5000 in a month. For example, Axerbaijan, Turkey in early 2000s and Russia in mid 1990s are among the eliminated outliers.

### 2.5.5. Summary statistics

The size of population covered by the DIOC-E database is a total of $2,481,119,008$ individuals and the population of immigrants is $132,659,637$ or 5.3 percent of the population.

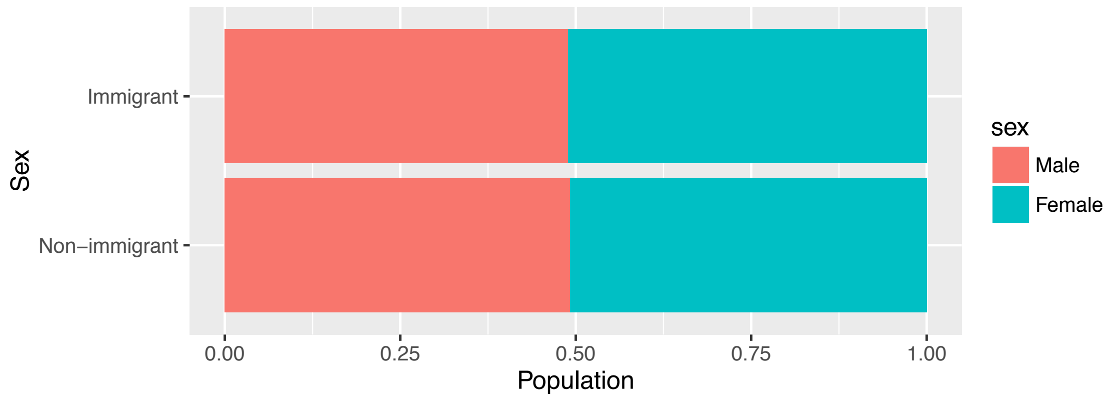


Figure 2.1. Immigrant vs. non-immigrant gender distribution

In the rest of this section I present some summary statistics that provide insight into how the immigrant and non-immigrant population differ in terms of distribution of characteristics, namely age, sex and education level. First I consider the breakdown of population by sex. As can be glimpsed from figure 2.1 The distribution of sexes is almost identical across immigrant and non-immigrant populations. In other words, there does not seem to be any selection with respect to sex in immigration. In addition, the population of the two sexes is almost equal which is to be expected.

The age distribution among immigrants and non-immigrants is displayed in figure 2.2. The population is broken down based on the three age groups introduced earlier, but since for some countries the two age groups of "mid aged" (25-64 years old) and "old aged" (65+ years old) are not separated, I combine them into one group of 25+ year old individuals and assign them to a separate group, as displayed on the figure. The composition of age varies widely across the immigrant and non-immigrant population. The non-immigrant population has a larger fraction population who are "young" (16-24 years old), while the fraction of old aged are larger among immigrant population. Even if this distribution

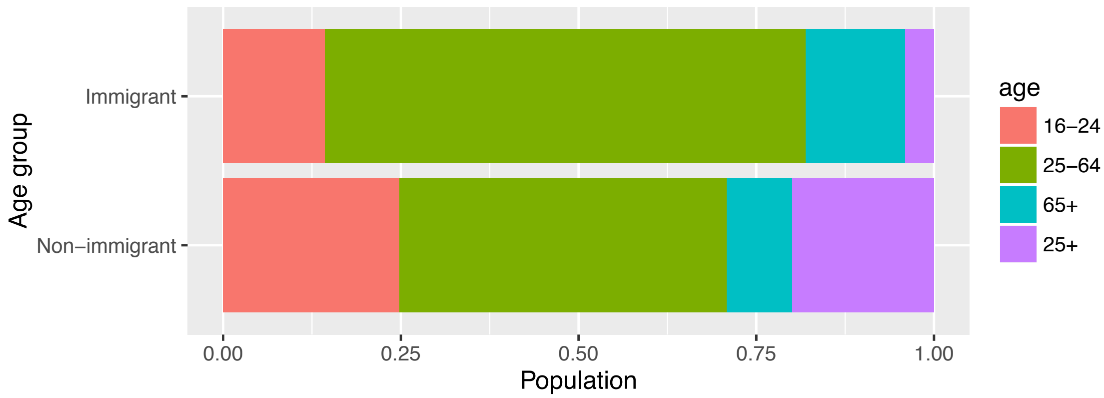


Figure 2.2. Immigrant vs. non-immigrant age distribution

is very coarse, still it can be gleaned from it that the immigrant population is older on average. This is consistent with intuition as it is less likely to be an immigrant in younger age and the probability of being an immigrant increases with age.

Finally the break down of populations based on education level is presented in figure 2.3 where the mapping of levels to schooling attainment was defined in table 2.1. Again there is a large distinction between the population of immigrants and non-immigrants in terms of schooling attainment. While the proportion of population who have completed secondary education (Level 2) is almost equal across the two population, a much larger fraction of non-immigrant population are in education Level 1 while the fraction of population who have completed tertiary education (Level 3) is larger. This suggests that there is selection in education and average level of education of immigrants is higher even after considering the immigration to destination countries that are not developed countries.

This gives an overview of the composition of the population being studied here in terms of the three observed characteristics of sex, age and education level. Finally, to give an overview of the distribution of the real monthly wages across the countries, figure

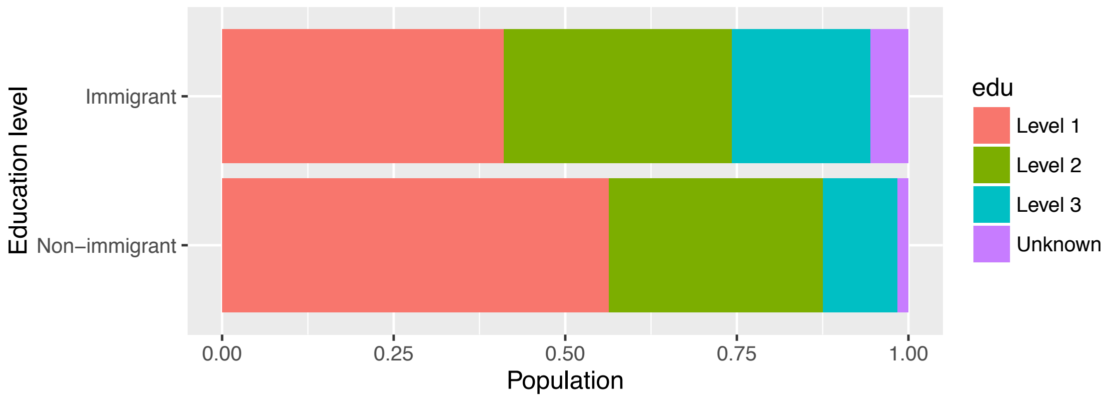


Figure 2.3. Immigrant vs. non-immigrant education level distribution

2.4 provides box plots for log of monthly wages for the three education levels observable in the sample. It is event from the figure that the median wages increase by education level globally. Similar plots have been generated in figures 2.5 and 2.6 for the other two characteristics sex and age group. The median wages are slightly lower and the variance is greater for female workers and among the age groups the mid-aged 25-64 year old workers have the highest median wages. These observations are consistent with the patterns observed in other studies on the relation between wages and education, gender and age.

## 2.6. Estimation

The main equation that I am going to estimate concerns the effect of wage differeces on migration rates. In order to estimate the effect of wage differences I use monthly wages as explained above. But since the monthly wages are available for different subgroups of the sample (by sex, education and age) in the following model I use the (weighted) average over the wages of each group in order to use the wage at a more aggregate level. In addition, for some countries, the wages are available for more than one year. For those

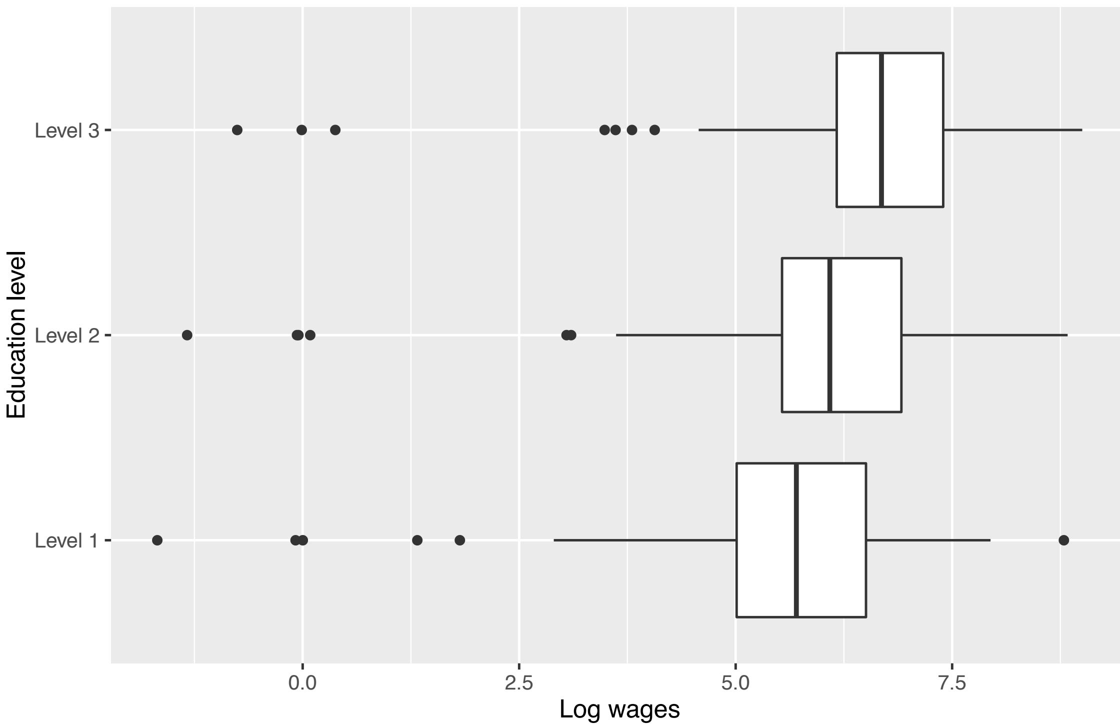


Figure 2.4. Distribution of log wages by education level

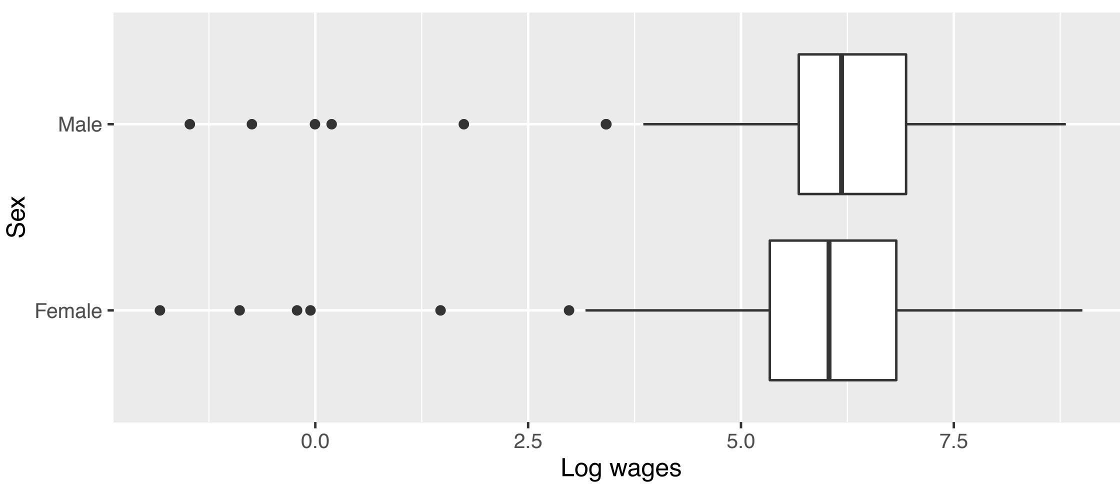


Figure 2.5. Distribution of log wages by sex

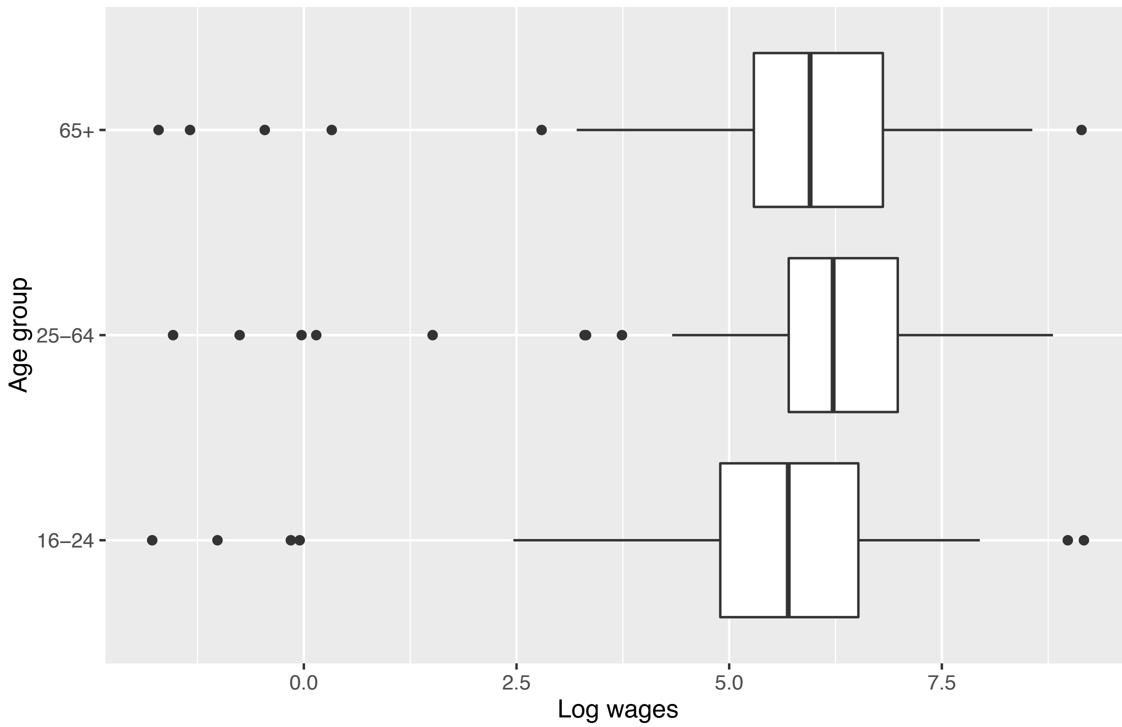


Figure 2.6. Distribution of log wages by age group

countries I use the average over different years for which data is available to make use of as much information as possible.

Wage differences can be defined in two ways. The difference in the wage levels of two countries (after converting both to USD units and adjusting for purchasing power parity), that is $w_j - w_i$. This measure is consistent with underlying quasi-linear preferences in money (wages). Another way to express the differential in log differences $\log(\frac{w_j}{w_i}) = log(w_j) - log(w_i)$ which is consistent with homothetic preferences. I test the model using both of these metrics to see which one, if any of them, are consistent with the theoretical prediction.

### 2.6.1. Country fixed effects

I estimate all of my models twice, with and without country fixed effects. The theory above shows that it is important to control for country fixed effects since they can proxy time invariate country-specific conditions that can effect migrant population. Including fixed effects will not control for time varying country-specific effects but the model here is a static equilibrium model that does not incorporate time.

In addition to the theoretical reason I also show empirically why controlling for country fixed effects is necessary. The primary explanatory variable here is the difference in (log) wages between all country pairs, $\Delta_{ji}$. But if it is correlated with country fixed effects then excluding them can bias the estimates of the coefficient of $\Delta_{ji}$. To see if this holds I look at how much of the variation in $\Delta_{ji}$ is explained by country fixed effects by estimating the following equation

$$\Delta_{ji} = \alpha + A_j + A_i + \epsilon_{ij} \tag{2.20}$$

The $R^2$ of the estimated model for all of the model variations that follow is above .90 which means more than 90 percent of the variation in wage differences is explained by country identities. So, if country fixed effects are not included in an estimation the resulting coefficient will demonstrate not just the effect of wages but also country-specific pull and push factors. But if country fixed effects are controlled for then this bias is removed from estimation. In the estimations that follow I include the results of both including and excluding country fixed effects so its influence can be studied.

### 2.6.2. Base model: effect of wages on immigration

The most basic model is one in which only the average wages of the origin and the destination countries are included but the other characteristics are not. I estimate this model once with country dummies and once without. What the results of the estimation show is the explanatory power of wage differences in determining the extent of international migration.

Figure 2.7 and 2.8 show scatter-plots with log migration ratios $\log(\frac{M_{ij}}{M_{ii}})$ on the vertical axis and the differences in wages $w_j - w_i$ and log wages $\log(w_j) - \log(w_i)$ on the horizontal axis for the country pairs in the data set. The figures suggest that there is a positive relationship between the differences in (log) wages of the destination and origin countries and the migration ratio, that is (log of) the ratio of the number of people who emigrated to $j$ from $i$ to the number of people who remained in $i$, which is in line with the prediction of the model.

The model in equation (2.18) is estimated using OLS and the result of the estimation are reported in table 2.2. The first two columns correspond to a model in which the primary explanatory variable is the difference in log of monthly wages, or $\Delta_{ji} = \log(w_j) - \log(w_i)$, and the following two columns correspond to a model in which it is the difference in wage levels in 100 USD, or $\Delta_{ji} = w_j - w_i$. Columns 2 and 4 include the country fixed effects – both origin and destination – regression while columns 1 and 3 are the models without country fixed effects. On the first row is the primary explanatory variable $\Delta_{ji}$ or "Wage difference". Other rows contain control variables for the costs of migration from $i$ to $j$ and include distance (in 1000 kilometers), whether two countries are contiguous, have a common (official) language, $i$ was a colony of $j$, or they if they had common colonial history.

The estimated coefficients for wage differences in all of the models are positive and statistically significant when using heteroskedasticity consistent standard errors. The magnitude of the estimated coefficients is larger in the models that include country fixed effects. The results confirm the hypothesis that there is a positive correlation between wage differences and the magnitude of immigration between any pair of countries. The model with difference of wages (the second two columns) suggests that the ratio of the migrant to the origin country population increases by 3.5 percent for every 100 USD increase in the difference in wage levels of the destination and origin countries and by 59 percent when country fixed effects are included, which is a high increase in magnitude. The other model states that the elasticity of the ratio of migrant population to wage *ratio*s is about 0.28, so a 10 percent increase in the ratio of the destination to the origin wages results in the ratio of the immigrant population to go up by 2.8 percent. This elasticity is estimated to be 1.89 when country fixed effects are included.

In addition, the coefficients of "distance" variables all have the correct sign and are significant. In particular, geographical distance has a negative sign which means the longer is the distance between two countries, the lower is the migration ratio between them. But the signs of contiguity, common language and colonial variables are all positive which again are expected since these conditions result in lower costs of migration between a pair of countries.

This results confirm the primary hypothesis and the empirical question of the paper that the differences in wage levels can explain the migration ratio between pairs of

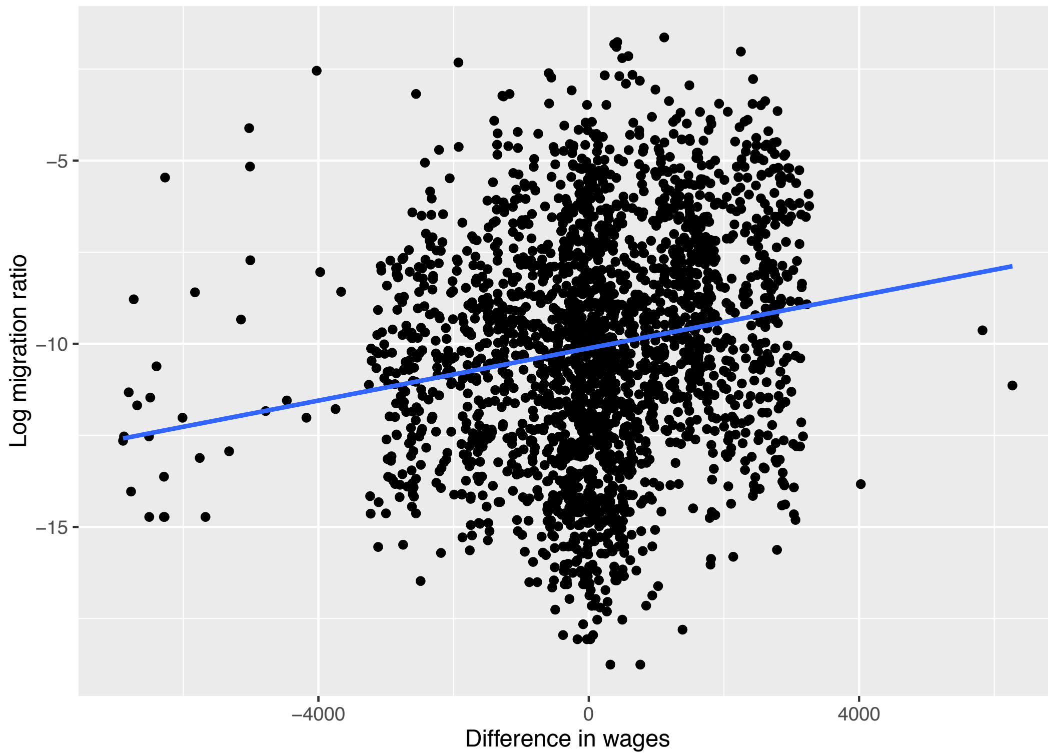


Figure 2.7. Migration ratio vs differences in wages

countries. The advantage of current analysis however is that the set of the destination countries here is wider and included developing countries as destination. In addition, the gravity model here is derived from theory and uses wages rather than GDP as the determining factor which is more in line with theory. In the following sections I include some other characteristics observed in the data in the model. The goal is to find if there is heterogeneity in the effects of wage differences across different characteristics of the immigrants. The two characteristics that I consider are sex and age group, described in section 2.5.2. I will study each characteristic separately and present the results.

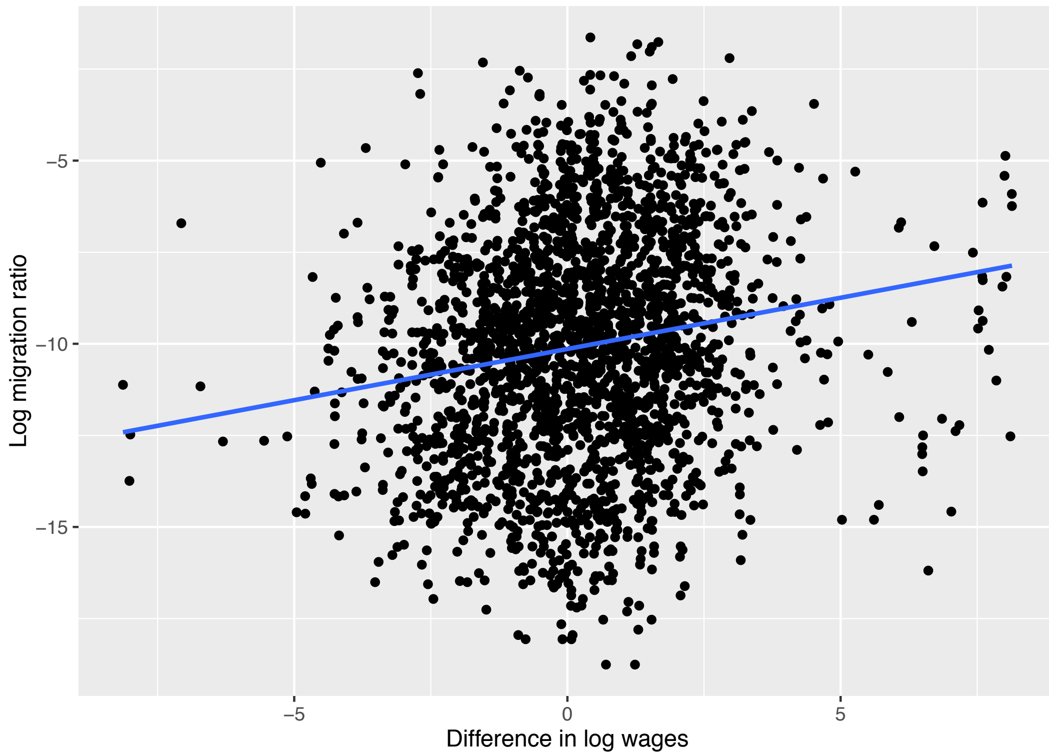


Figure 2.8. Migration ratio vs differences in log wages

### 2.6.3. Comparison with GDP per capita

In absence of wage level data for countries many studies use GDP per capita as proxy for wages. But how is the estimated effects different when GDP per capita is used as a proxy for wages? I address this question by estimating the model above again but with both of these variables included as ex. The data for GDP per capita is acquired from the World Bank and the year used is 2000. To further make the results comparable I use the PPP adjusted GDP per capita data. The results of the regression are in table 2.3. Columns 1 and 2 are for a model with levels of GDP per capita and wages while columns 3 and 4 correspond to ones with log of those variables on the right hand side. Columns 1 and 3 are models without country fixed effects while columns 2 and 4 correspond to ones

Table 2.2. Effect of wage differnces on migration ratios

| | *Dependent variable:* | | | |
|---|---|---|---|---|
| | Log migration ratio | | | |
| | Log wages | | Wages (USD 100) | |
| | (1) | (2) | (3) | (4) |
| Wage diff | 0.311*** | 1.744*** | 0.036*** | 0.478*** |
| | (0.029) | (0.201) | (0.004) | (0.055) |
| Distance | −0.225*** | −0.230*** | −0.221*** | −0.230*** |
| | (0.015) | (0.017) | (0.015) | (0.017) |
| Contiguous | 2.653*** | 2.434*** | 2.643*** | 2.434*** |
| | (0.237) | (0.143) | (0.237) | (0.143) |
| Comm Lang | 1.162*** | 0.566*** | 1.093*** | 0.566*** |
| | (0.190) | (0.134) | (0.191) | (0.134) |
| Colony | 2.430*** | 2.008*** | 2.434*** | 2.008*** |
| | (0.297) | (0.177) | (0.297) | (0.177) |
| Comm Colony | 0.730** | 3.126*** | 0.748** | 3.126*** |
| | (0.302) | (0.206) | (0.302) | (0.206) |
| Constant | −9.501*** | −10.638*** | −9.485*** | −10.638*** |
| | (0.097) | (0.470) | (0.097) | (0.470) |
| Country dummies? | No | Yes | No | Yes |
| Observations | 2,342 | 2,342 | 2,342 | 2,342 |
| $R^2$ | 0.274 | 0.788 | 0.271 | 0.788 |
| *Note:* | | | | *p<0.1; **p<0.05; ***p<0.01 |

with country fixed effects. The results indicate that in the first two models, wage levels always have a positive sign that is greater in magnitude than GDP per capita. In the log level model, on the other hand, the results depend on whether the country fixed effects are included or not. Without country fixed effects GDP per capia have no explanatory power but they are comparable in size (about 2.5 percent). When country fixed effects are included, however, log wages become statistically not significant but GDP per capita become large and highly significant. The general conclusion to draw from this analysis is that the wages (used as level of log level) show a more stable behavior across the models, with a coefficient that is always positive and does not vary widely.

Table 2.3. Comparing the effect of wages vs. GDP per capita

| | *Dependent variable:* | | | |
|---|---|---|---|---|
| | Log migration ratio | | | |
| | Level w/o FE | Level + FE | Log w/o FE | Log + FE |
| | (1) | (2) | (3) | (4) |
| $\Delta_{ij}^{\text{wage}}$ | 0.022*** | 0.612*** | 0.025*** | 0.047 |
| | (0.004) | (0.092) | (0.003) | (0.036) |
| $\Delta_{ij}^{\text{gdp}}$ | 0.016*** | −0.373*** | 0.023 | 2.128*** |
| | (0.004) | (0.081) | (0.040) | (0.462) |
| Distance | −0.228*** | −0.230*** | −0.226*** | −0.230*** |
| | (0.015) | (0.017) | (0.015) | (0.017) |
| Contiguous | 2.665*** | 2.434*** | 2.658*** | 2.434*** |
| | (0.236) | (0.143) | (0.237) | (0.143) |
| Comm Lang | 1.077*** | 0.566*** | 1.156*** | 0.566*** |
| | (0.190) | (0.134) | (0.190) | (0.134) |
| Colony | 2.465*** | 2.008*** | 2.436*** | 2.008*** |
| | (0.296) | (0.177) | (0.297) | (0.177) |
| Comm Colony | 0.788*** | 3.126*** | 0.739** | 3.126*** |
| | (0.301) | (0.206) | (0.302) | (0.206) |
| Observations | 2,342 | 2,342 | 2,342 | 2,342 |
| $R^2$ | 0.276 | 0.788 | 0.274 | 0.788 |
| *Note:* | | | | *p<0.1; **p<0.05; ***p<0.01 |

### 2.6.4. Analyzing heterogeneity in sex

The first characteristic that I consider for analyzing heterogeneity is immigrant sex which is observable in the data set, so that both the number of immigrants from each gender and the average wage for the gender in the origin and destination countries is observable. I run the regression based on the estimation equation (2.19) in which the characteristic dummy $z$ is both added as a fixed effect to capture potential direct correlations and interacted with wage differences. The independent variables in this regression is the difference in wages and and the difference in log wages, similar to the models in the previous section.

The results of the models for linear and log wage differences are reported in table 2.5. In both of these models the effect of differences in (log) wages is still positive and significantly different from zero. The estimated coefficient for the Female dummy is not significantly different from zero which means that being a female does not increase or decrease the likelihood of immigration. The interaction effects between gender and wage differences has mixed signs across the two models and is generally not significantly different from zero, which implies that there is no gap between female and male immigrants in terms of their responsiveness to wage differences in their decision to migrate. The distance variables have expected signs as well, but there is no significant difference between male and female there. Thus, it can be concluded that gender is not a significant source of heterogeneity in explaining migration.

### 2.6.5. Analyzing heterogeneity in age group

Next, I consider the relationship between age and migration using a model similar to the one in section 2.6.4 and using equation (2.19) where $z$ is now the age group. Three age groups are observable in the data set, namely 15 to 24 years old (Young), 25 to 64 years old (Middle), and 65+ years old (Old). The results of the estimation are in table 2.7.

First let's consider the models without country fixed effects (that is, columns 1 and 3 of the table). Wage difference is significant with a positive sign in those models. The

Table 2.5. Effect of wage differnces on migration ratios by sex

| | Log wages | | Wages (USD 100) | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| Female | 0.123 | 0.372 | 0.125 | 0.372 |
| | (0.131) | (0.863) | (0.131) | (0.863) |
| $\Delta_{ji}$ | 0.307*** | 2.018*** | 0.034*** | 0.453*** |
| | (0.029) | (0.251) | (0.003) | (0.056) |
| $\Delta_{ji}\times$ Female | −0.009 | −0.548* | 0.004 | 0.078 |
| | (0.041) | (0.328) | (0.006) | (0.095) |
| Distance | −0.194*** | −0.218*** | −0.193*** | −0.218*** |
| | (0.015) | (0.017) | (0.015) | (0.017) |
| Contiguous | 2.595*** | 2.440*** | 2.580*** | 2.440*** |
| | (0.200) | (0.182) | (0.203) | (0.182) |
| Comm Lang | 1.050*** | 0.567*** | 0.976*** | 0.567*** |
| | (0.196) | (0.139) | (0.196) | (0.139) |
| Colony | 2.430*** | 1.949*** | 2.433*** | 1.949*** |
| | (0.279) | (0.215) | (0.280) | (0.215) |
| Comm Colony | 0.830*** | 2.990*** | 0.853*** | 2.990*** |
| | (0.285) | (0.258) | (0.280) | (0.258) |
| Female × Distance | −0.018 | −0.008 | −0.014 | −0.008 |
| | (0.022) | (0.025) | (0.022) | (0.025) |
| Female × Contiguous | 0.090 | 0.073 | 0.082 | 0.073 |
| | (0.278) | (0.251) | (0.284) | (0.251) |
| Female × Comm Lang | 0.029 | −0.024 | 0.053 | −0.024 |
| | (0.266) | (0.190) | (0.266) | (0.190) |
| Female × Colony | −0.079 | 0.064 | −0.080 | 0.064 |
| | (0.391) | (0.300) | (0.397) | (0.300) |
| Female × Comm Colony | −0.081 | 0.176 | −0.102 | 0.176 |
| | (0.396) | (0.361) | (0.391) | (0.361) |
| Constant | −9.577*** | −10.843*** | −9.554*** | −10.843*** |
| | (0.093) | (0.611) | (0.092) | (0.611) |
| Country dummies? | No | Yes | No | Yes |
| Observations | 4,403 | 4,403 | 4,403 | 4,403 |
| $R^2$ | 0.267 | 0.783 | 0.264 | 0.783 |

*Note:* *p<0.1; **p<0.05; ***p<0.01

"direct" fixed effect of age group is negative for the young and old aged groups and is larger for the old age group. The interaction effect of wage difference with age group is also negative for both young and old aged groups though smaller for the latter group. When country fixed effects are included (column 2 and 4), the age group fixed effects are not longer significantly different from zero. The effect of wage difference stays positive but becomes stronger. The interaction effects, on the other hand, change sign and become positive.

The estimation results suggest a couple of conclusions. First, being young makes it less likely for one to be an immigrant compared to being middle or old aged. This follows from the coefficients of the young aged and old aged groups dummy variables which are negative or statistically equal zero. This is expected because generally the decision to emigrate is a one time decision for the rest of the individual's life, hence the likelihood of being and immigrant increases with age unless there are heterogeneities among different cohorts in terms of their propensity to migrate that make the younger generation more likely to migrate despite the age differences with the older generations, but that hypothesis is not born out by the current data. This distinction become even stronger when the model is estimated using country fixed effects.

The second empirical result is that the young age group immigrants are the most responsive to wage differences between the destination and origin countries. This is also to be expected because the very young have a lower labor participation and the costs of migration (financial, adjustment and difficulty of moving) is higher for that group. Of course, this difference can also be due to cohort effects; that is, the very young in this data set show a lower elasticity of supply because of the specific features and conditions of those cohorts; however, this hypothesis is hard to justify since this pattern is seen across all the countries in the data set and not a specific set of countries only, and it is not very likely that the cohorts in different countries have been subject to similar conditions. But also the considerably larger size of the mid-age group makes this hard to justify.

Table 2.7. Effect of wage differnces on migration ratios by age

| | Log migration ratio | | | |
|---|---|---|---|---|
| | Log wages | | Wages (USD 100) | |
| | (1) | (2) | (3) | (4) |
| Young | $-0.260^{**}$ | $-0.767$ | $-0.251^{*}$ | $-0.767$ |
| | (0.130) | (0.883) | (0.129) | (0.883) |
| Old | $-0.405^{***}$ | 0.117 | $-0.407^{***}$ | 0.117 |
| | (0.131) | (0.996) | (0.131) | (0.996) |
| $\Delta_{ji}$ | $0.373^{***}$ | $1.717^{***}$ | $0.043^{***}$ | $0.453^{***}$ |
| | (0.029) | (0.243) | (0.004) | (0.064) |
| $\Delta_{ji}\times$ Young | $-0.189^{***}$ | $1.044^{**}$ | $-0.024^{***}$ | $0.650^{***}$ |
| | (0.042) | (0.409) | (0.008) | (0.146) |
| $\Delta_{ji}\times$ Old | $-0.117^{***}$ | 0.153 | $-0.015^{**}$ | $0.231^{*}$ |
| | (0.042) | (0.409) | (0.006) | (0.136) |
| Distance | $-0.214^{***}$ | $-0.220^{***}$ | $-0.211^{***}$ | $-0.220^{***}$ |
| | (0.015) | (0.017) | (0.015) | (0.017) |
| Contiguous | $2.373^{***}$ | $2.219^{***}$ | $2.363^{***}$ | $2.219^{***}$ |
| | (0.198) | (0.174) | (0.203) | (0.174) |
| Comm Lang | $1.242^{***}$ | $0.600^{***}$ | $1.149^{***}$ | $0.600^{***}$ |
| | (0.179) | (0.130) | (0.180) | (0.130) |
| Colony | $2.314^{***}$ | $2.015^{***}$ | $2.328^{***}$ | $2.015^{***}$ |
| | (0.283) | (0.218) | (0.287) | (0.218) |
| Comm Colony | $0.843^{***}$ | $3.243^{***}$ | $0.873^{***}$ | $3.243^{***}$ |
| | (0.279) | (0.274) | (0.277) | (0.274) |
| Country dummies? | No | Yes | No | Yes |
| Observations | 6,014 | 6,014 | 6,014 | 6,014 |
| $R^2$ | 0.258 | 0.758 | 0.250 | 0.758 |
| *Note:* | | | | $^{*}$p<0.1; $^{**}$p<0.05; $^{***}$p<0.01 |

### 2.6.6. Analyzing heterogeneity in education level

The last characteristic that I consider for heterogeneity is education. The observed levels of education in the data, as described in section 2.5 consist of three levels: below secondary level (Level 1), secondary level (Level 2), and tertiary level (Level 3). The regression analysis is performed using equation (2.19) with $z$ now representing education level. The results are presented in table 2.8.

The positive coefficients of the Level 2 and Level 3 dummies in columns 1 and 3 suggest that it is more likely for an individual to be an immigrant when he or she has higher levels of education, and that the likelihood is greater the higher is the education level – the ratio of migrant population increases by about about 60 percent when education level rises from Level 1 to Level 2, and more than doubles when it rises to Level 3. This pattern fades away when I include country fixed effects: the coefficients are no more statistically different from zero, so education does not seem to have a level effect on migration ratio once we control for the identity of the origin and destination countries.

The effect of wage differences is positive and significant in all of the models, so the prediction of the theory is confirmed that the higher is the difference in wage of the source and destination countries the large will be the proportion of migrants from the origin country. The interaction effects is, however, negative in the models with country fixed effects and they are larger (more negative) for the highest education levels.

These results are consistent with the hypothesis that the higher educated individuals are more likely to immigrate compared to those with lower levels of education – probably because the costs of immigration decreases with education level. There is no data available in this study to support this claim but it can be justified based on the general observation that the migration process is easier for highly educated individuals in terms of finding a job in the destination country, having the means to cover the costs of travel, and being able to adjust in the destination country setting, hence the highly educated individuals are more likely to respond to the same rate of difference between the wage levels. The current data and results from the regression models do not reject this hypothesis.

The different responses to wage differences by education is harder to justify a priori though. The empirical results indicate that the higher is an individual's education level, the less responsive will they be to wage differences. This may be due to the fact that the individuals with higher education levels in the origin countries do not end up earning the wages of the native population with equivalent education but a lower wage. If that is the case, then the result will be a lower propensity to migrate for the highly educated individuals. It may also point to other costs of migration for the highly educated that is not captured by the model, like some sort of opportunity costs that rises with education level.

Another interesting results however is the heterogeneity with respect to distance variables across education levels. The geographical cost variables (geographical distance and contiguity) exhibit smaller effects as the education level goes up. However, the cultural variable of common language becomes more important with education level. These findings may point to the fact that geographic distance becomes less of a burden to migrate with education but, on the other hand, language plays an increasingly important role with the level of education since the knowing and use of language is more important for the types of jobs that skilled workers perform.

Table 2.8. Effect of wage differnces on migration ratios by education level

| | *Dependent variable:* | | | |
|---|---|---|---|---|
| | Log migration ratio | | | |
| | Log wages | | Wages (100 USD) | |
| | (1) | (2) | (3) | (4) |
| Level 2 | 0.602*** | −0.069 | 0.587*** | −0.069 |
| | (0.140) | (0.901) | (0.140) | (0.901) |
| Level 3 | 1.417*** | 0.767 | 1.404*** | 0.767 |
| | (0.141) | (0.838) | (0.141) | (0.838) |
| $\Delta_{ji}$ | 0.219*** | 2.468*** | 0.028*** | 1.062*** |
| | (0.033) | (0.332) | (0.007) | (0.143) |
| $\Delta_{ji}\times$ Level 2 | 0.094** | −0.602 | 0.014 | −0.521*** |
| | (0.044) | (0.395) | (0.008) | (0.156) |
| $\Delta_{ji}\times$ Level 3 | 0.149*** | −1.348*** | 0.015* | −0.923*** |
| | (0.046) | (0.350) | (0.008) | (0.144) |
| Distance | −0.204*** | −0.233*** | −0.200*** | −0.233*** |
| | (0.018) | (0.021) | (0.018) | (0.021) |
| Contiguous | 3.144*** | 2.825*** | 3.111*** | 2.825*** |
| | (0.208) | (0.190) | (0.212) | (0.190) |
| Comm Lang | 0.743*** | 0.154 | 0.727*** | 0.154 |
| | (0.194) | (0.152) | (0.195) | (0.152) |
| Colony | 2.245*** | 2.250*** | 2.250*** | 2.250*** |
| | (0.345) | (0.287) | (0.354) | (0.287) |
| Comm Colony | 0.981*** | 3.370*** | 0.959*** | 3.370*** |
| | (0.273) | (0.266) | (0.273) | (0.266) |
| Country dummies? | No | Yes | No | Yes |
| Observations | 5,866 | 5,866 | 5,866 | 5,866 |
| $R^2$ | 0.284 | 0.796 | 0.284 | 0.796 |
| *Note:* | | | | *p<0.1; **p<0.05; ***p<0.01 |

## 2.7. Discussion and conclusion

In this paper I studied the role of different factors as potential determinants of international migration. I developed a micro-based model of worker's migration decision to account for inter-country rates of migration based on the difference in wage levels across those countries. This is in contrast to the other attempts in the literature which usually lack a theoretical basis and use gross macro variables like GDP as their explanatory variable. Due to access to a newly compiled data set of wages by country, I can overcome this limitation and use wages as the main determinant, which is a more accurate representation of the true underlying motive variable, that is "potential income" in the source and destination countries. My main finding here is that wage levels do explain the patterns of migration seen between the countries: the larger is the difference in wages of the origin and destination countries, the higher will be the proportion of migrants from the origin in the destination country, confirming the previous findings in the literature. However, while previous studies focus only on developed countries as destinations, this paper extends this to developing countries as immigration destinations and verifies that the previous findings still hold, even when the there are many more destination countries, both developing and developed, in the sample. The quantitative finding here is that every 1 percent difference between the wage levels of the source and destination countries is associated with an increase of 1.7 percent in migration rate from the source country. Alternatively stated in terms of wages converted to US dollars, every USD 100 difference in wages is associated with an increase of about 48 percent in the migration rate from the origin country.

My data set also allows me to look deeper into the role of worker characteristics in determining the effect of wage difference on migration and take care of some of the heterogeneity in the immigrant population. In particular, I study the effects of sex, age and education. I don't find any significant difference between male and female immigrants in terms of their response to wages. The very young and the very old population seems to be less responsive to the wages compared to immigrants in the middle age group. But perhaps the more interesting dimension of heterogeneity to focus on is schooling. I find and increasing relationship between schooling and responsiveness to wage differences in making a decision to migrate: the higher is the education level the more sensitive (elastic) is the rate of migration to wages. This finding should be distinguished from the notably higher rates of migration among educated individuals. According to this empirical finding, not only the more educated workers are more likely to migrate but, *in addition*, they are also more responsive to wages, even after I control for migration cost covariates such as geographical distance.

What is the explanation for this observed disparity? This difference can be attributed to heterogeneity in other costs of migration between education levels that is not captured by the current model. For example, the cost of searching for a job and the risk of unemployment decreases with schooling which makes the highly educated individuals more likely to migrate for the same level of wage motives. Alternatively, individuals who have a higher preference for amenities which are also available to a greater extent in the more developed countries – where wages are generally higher – may be the ones who choose to pursue higher education. This selection effect may partly explain the discrepancy observed in responsiveness between the highly and lowly educated immigrants. The current model and data does not allow me to identify the source of the heterogeneity, and more complete data and finer models are required to distinguish the driving factor. A number of policy implications may also be drawn from the findings in this paper. For example, for a developing country that faces the problem of brain drain, wage appears to be a relatively effective tool to dissuade the most highly educated individuals in there from leaving the country; thus if the goal is to slow down the rate of brain drain, the policy maker might consider tools that aim at increasing the wages (and other benefits) of the "brains" by offering some form subsidy to them.

# CHAPTER 3

# Cotton Dust Standards and Productivity of U.S. Textile Industries

## 3.1. Introduction

The question of what determines productivity of firms is an important and widely studied question in economics. Among the different factors that have been proposed to explain the total factor productivity of firms, government interventions in the form of regulations have been the subject of numerous studies. Standard economic theory suggests that regulations, in the forms of constraints on the choices that profit-maximizing firms can make "should" decrease firm TFP (see section 3.1.2 for a simple theoretical model) and this has also been shown empirically in different contexts (see Syverson (2011) for a review and section 3.1.1 for a few examples).

But is it true that regulations also lead to lower welfare, even if they are institutionalized to protect the labor from hazards of work environment? The answer to this question is less obvious. From a social welfare point of view, an unregulated market could fail to supply sufficient incentives for firms to efficiently provide workplace safety for workers. This could be a consequence of workers having incomplete information about the safety and health hazards they are exposed to in the work environment, so that these costs are not internalized in the wages. An instance of market failure may then exist and there may be room for welfare-improving government intervention.

Unlike welfare effects, the consequence of regulations for firms productivity seems to be more predictable. Profit-maximizing firms take into account all the private costs associated with production and provide the profit-maximizing level of safety. Despite their potential welfare improving role, occupational safety standards and health regulations should diminish productivity by increasing the costs of production or constraining the choices that firms can make regarding the use of their inputs. However, there is another aspect to regulations which is often overlooked, namely the "inducement" effect on firms to adopt new technology sooner than they otherwise would in a market not intervened by government regulations. The faster technology adoption may still not be the optimal outcome from a producer surplus or social welfare point of view; nevertheless, it may have this effect of raising productivity which goes against the assumption that all regulations are bad for productivity.

In this essay I study the question of the effects of workplace safety regulations on productivity of firms. The specific regulation that I am focusing on is the 1978 Cotton Dust Standards issued by Occupational Safety and Health Administration (OSHA). In section 3.2 I go over more details about the background and history of these regulations. Section 3.1.1 is a brief literature review and section 3.1.2 provides a simple theoretical background for the empirical work that follows. For the purpose of this paper I use the industry level production data which is introduced in section 3.3.1. I present the empirical analysis in section 3.3 where I first look at the general trend of productivity growth in the textile industry compared to other industries and then use a differences in differences approach to estimate the effect of the standards on (sub-)industries affected by them. I conclude in section 3.5.

### 3.1.1. Previous work

The topic of productivity and its determinants is the focus of a large literature in economics. One recent review of this literature is presented in Syverson (2011). Among other factors, government regulations have been widely studied for their potential effects on firm productivity. One example of empirical work that seeks to estimate the effect of labor regulations on economic performance in general, and on firm productivity in particular, is Besley and Burgess (2004) who find that regulations negatively impact firm productivity (among other economic outcomes) in Indian states which had stricter regulations compared to the ones with more lenient ones.

Regarding the effects of occupational safety and health regulations, there have been a few studies but most belong to the 1980's. Gray (1987) examines the slowdown in productivity growth in the U.S. economy during the 1970's and finds that the two types of regulations that he studied, namely workers safety and health and environmental regulations, can explain up to 30 percent of the decline in the productivity of US manufacturing industries during 1970's. But he considers all manufacturing industries and does not study the specific effects of the cotton dust standard which is the subject of this study.

Two papers specifically focus on the effects of the 1978 cotton dust standards on the performance of the affected firms. Maloney and McCormick (1982) develop a theoretical model where they show that, under certain sufficient conditions (including restricted entry) and in contrast with the traditional view, regulations could actually raise the *profitability* of (a subset of) the industry by raising the prices. They use the stock market price of the cotton firms to estimate the effect of the regulation on the value of the firms and show that some firms experienced an increase in their market values. Thus, there could be an industry-wide effect as well as an intra-industry transfer of profits from smaller to larger firms due to the latter ones' lower unit cost of compliance. Hughes, Magat, and Ricks (1986) on the other hand, take the same approach but use a different data set (daily rather than monthly stock price data) and come to a contrasting conclusion, namely zero or negative effect on industry profitability as well as greater negative effects for larger firms.

In contrast to this paper, however, the focus of Maloney and McCormick (1982) and Hughes, Magat, and Ricks (1986), is on firm profitability rather than productivity or TFP. Profitability, however, is different from productivity in that it is also affected by the demand side of the market, and for example, a monopolist can be highly profitable while being low in productivity. Furthermore, their sample is restricted to firms with publicly traded stocks, but restriction of the sample to only large firms with publicly traded stocks can result in selection bias. For example, regulations maybe more costly to small firms that are not in the stock market in terms of making adjustments to comply with new regulation, but even beneficial to larger firms as a result of facing lower competition from smaller firms that are forced to exit the market.

### 3.1.2. A simple theoretical model

How can higher safety and health regulations affect firm productivity? One way to think about this problem is to consider the effect of compliance requirements on the capital and labor needs for production and the way that TFP is measured. This approach is laid out and used in Gray (1987) and Greenstone, List, and Syverson (2012). The idea is that in order to comply with the safety standards, firms would need to install extra equipment or hire higher extra labor which are not directly contributing to the production of output. For example, for the case of cotton dust standards, firms have to install or upgrade equipment to control the level of dust emitted in the environment which would appear as higher capital expenditure on the balance sheets, but not necessarily higher output. As for the labor, required medical surveillance or training programs will force the firm to hire extra labor to perform these tasks which have no ostensible direct contribution to production.

To make the idea more exact, I borrow from the model in Greenstone, List, and Syverson (2012) where they assume a production function in the following Cobb-Douglas form

$$Q = A\tilde{K}^{\alpha}\tilde{L}^{1-\alpha} \tag{3.1}$$

here $\tilde{K}$ and $\tilde{L}$ are the "production-effective" levels of capital and labor, that is levels of these inputs that are actually used in production. Now suppose that $K$ and $L$ are *measured* capital and labor which include, but are not limited to, the production-effective inputs. This means they can be expressed in the following form

$$\tilde{K} = \lambda_K K$$

$$\tilde{L} = \lambda_L L$$

where $0 < \lambda_K < 1$ and $0 < \lambda_L < 1$ are the proportion of capital and labor that are effectively used in production. By replacing in (3.1) we obtain

$$Q = A(\lambda_K K)^{\alpha}(\lambda_L L)^{1-\alpha} \tag{3.2}$$
$$= A\lambda_K^{\alpha}\lambda_L^{1-\alpha}K^{\alpha}L^{1-\alpha}$$

So the measured TFP can be expressed as

$$\text{TFP} = \frac{Q}{K^{\alpha}L^{1-\alpha}} = A\lambda_K^{\alpha}\lambda_L^{1-\alpha} \tag{3.3}$$

the higher is the standard requirements, the more of capital and/or labor needs to be dedicated to conforming with the standards; the lower will be $\lambda_L$ and $\lambda_L$ and the measured TFP will be lower. However, as noted by Gray (1987), in addition to the effects on measured productivity, regulations may also have real effect on productivity, that is on $A$ in this model, through putting constraints on the production processes that the firm can choose and on firm's use of new technology.

### 3.2. Background on cotton dust standards

Exposure to cotton dust may cause a respiratory illness known as byssinosis or "brown lung disease" to develop. Although this disease had been known for a long time, its effects on the workers of textile industries in the U.S. was recognized only during 1960's and 70's when several scientific studies established the link between exposure to cotton dust and byssinosis. The disease can be acute or chronic, and may be reversible in its early stages, but sustained exposure can eventually lead to disability or fatal loss of respiratory function.

Table 3.1. Limits on different processes involving cotton dust

| **Process** | **1978 standard** ($\mu g/m^3$) | **1986 standard** ($\mu g/m^3$) |
|---|---|---|
| opening and spinning | 200 | 200 |
| slashing and weaving | 750 | 750 |
| waste houses | 500 | 500 |
| waste processing | Not applicable | 1000 |
| knitting | | Not applicable |
| cottonseed processing | Not applicable | Not applicable |

Regulation of cotton dust exposure of industry workers was first introduced in 1968 which, as a federal standard, limited the cotton dust in the work environment to 1000 $\mu g/m^3$. The Occupational Safety and Health Administration was established in 1970 and they adopted the standard in 1971 as an OSHA standard. In June 1978 OSHA issued the final Cotton Dust Standard which included different permitted dust levels for different manufacturing processes involving cotton. These limits are reported in table 3.1 (OSHA 2000).

### 3.2.1. Controversy over standards

In 1975, before the standard was issued, worker unions pushed for even more stringent limits of as low as $100\mu g/m^3$. On the other side, textile industry challenged the new standard soon after it was issued and appealed against in different appeal courts. The industry argued that OSHA should have relied on a cost benefit analysis in setting the permission level. The issue was taken to the Supreme Court in 1981 where it was upheld by the court and maintained as law. Later in 1986 an amendment to the standard became effective where some segments like knitting were exempt from the standard because there were not enough evidence of high risks in those segments.

According to the studies later conducted by OSHA the standard was successful in the sense that the incidence of brown lung disease among textile worker dropped to very low levels and the costs of compliance for the firms turned out to be lower than expected. OSHA, in its reports, also claimed that the standard benefited the industry by inducing it to modernize and become more productive. Most of the firms in the industry were compliant before the 1984 deadline and the revisions to the standard in 1985, which made some of the requirements more stringent, did not face much challenge from the industry, which may be taken as a confirmation of OSHA's claim. Along the same lines *The Economist* magazine in 1980 wrote

> Tougher government regulations on workers' health have unexpectedly given the U.S. industry a leg up. Tighter dust control rules for cotton plants caused firms to throw out tons of old, inefficient machinery and to replace it with the latest available from the world's leading textile machinery firms in Switzerland and West Germany.

Although the controversy seemed to be settled at the time and the industry did not further pursue overturning of the standard after they were in compliance, the question of whether the introduction of cotton dust regulations made the textile industry more productive by inducing it to adopt new more efficient technology was not fully settled. This question is what I turn to in this paper and try to address the problem using the industry level data that is publicly available. In the following sections I lay out the empirical analysis and the results deriving from the analysis.

## 3.3. Empirical analysis

### 3.3.1. Data

The data for this paper comes from NBER productivity database which is publicly available on NBER website (Bartelsman and Gray 1996). The data is at industry level, that is, 4-digit SIC code sub-industries. The data set covers a long period of time (1958–2009) and contains information about labor use and costs, investment and capital stock, energy, material, value of shipment, value added and a few industry price indexes that are used to deflate revenue-based measurement of production and express it in real terms. Crucially, the data set also comes with estimations of total factor productivity which are expressed as indexes normalized to be equal to 1 in the year 1987. The productivity measure is calculated based on a five-factor Cobb-Douglas production function with capital, production worker hours, non-production workers, non-energy materials, and energy as inputs. Measured TFP is the residual from estimating this production function. Ideally the analysis in this paper should be performed using plant-level data from Census of Manufacturers or Annual Survey of Manufacturer conducted by Census Bureau rather than industry level data; however, that data is difficult to obtain and was not available for the current study, but could be used for future extension of this work.

### 3.3.2. Productivity growth in the textile industry

The textile industry experienced a high rate of growth in productivity during the years following the promulgation of the cotton dust standards in 1978. The average growth rate of productivity for textile industry (2-digit SIC code 22) for the 7-year period of 1978-1984 was 1.52 percent, while the average of all industries during the same period was equal to 0.31 percent. This high productivity growth rate in textile industry can be observed only in the late 1970s and early 1980s years, not earlier or later, as can be seen in the plots in figure 3.1.

This can also be demonstrated using a simple regression of average TFP growth during the 7-year periods for each industry on a dummy for being in the textile industry. The results, as presented in table 3.2, indicate that during 1978-84 period the textile industry experienced a productivity growth that was significantly higher than the average of all other industries. The textile industry continued to enjoy a high average growth in the following 7-year period, though not significantly higher than the average of other industries. In the periods prior to 1978 and following 1992, the average productivity growth of textile industry was not significantly different from the average of other industries.

As suggested earlier, taken at face value, this may confirm OSHA's claim that the textile industry actually became more productive during the years prior to enforcement of the new standard. However, the question remains whether the standards actually caused this to happen or some other factor was the driving force.

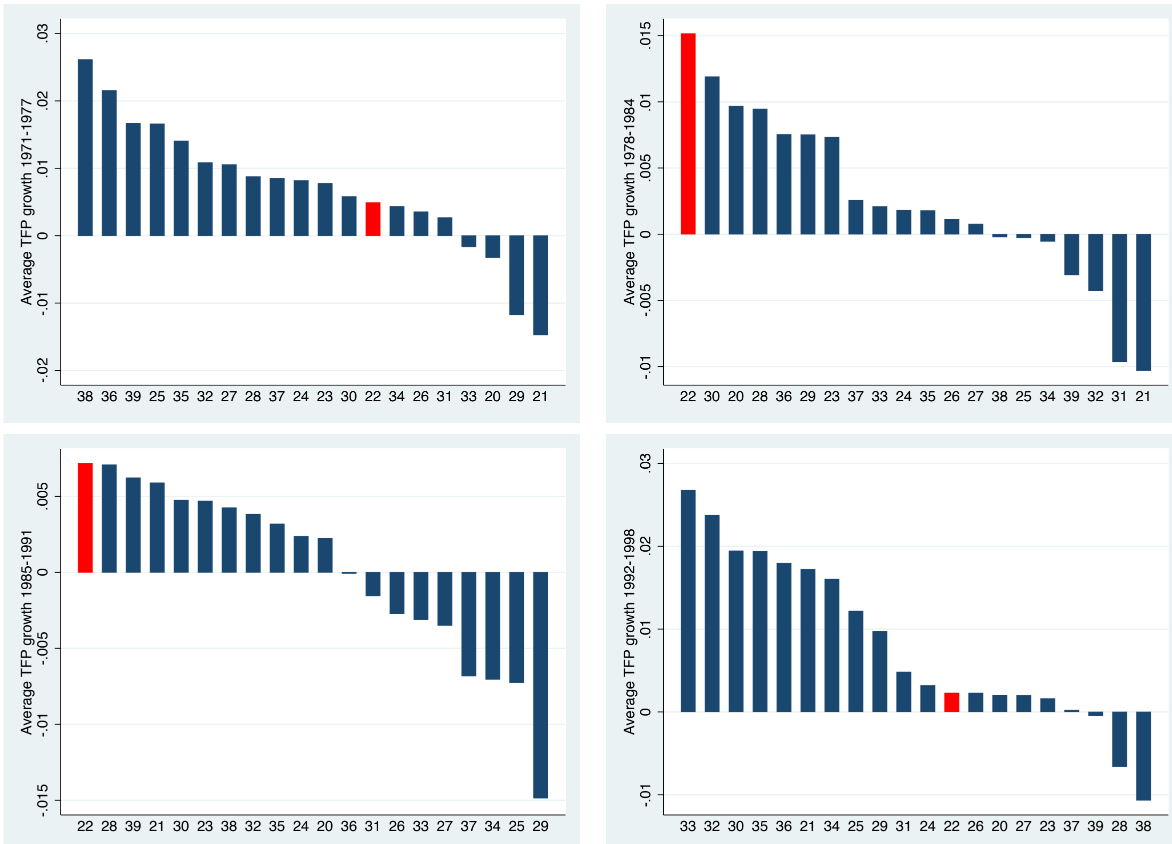


Figure 3.1. Average TFP growth rate of industries during 1971-1922

### 3.3.3. A closer look into the textile industry

The textile industry is classified under 2-digit SIC code 22 and consists of 23 4-digit SIC code sub-industries. The total capital stock in this industry grew until 1978 peaking at 1500 million dollars. After that year, the total capital in the textile industry started to shrink gradually. This can be seen in figure 3.2 where the value of total real capital stock has been plotted separately for the textile industry and for the other industries. It can be observed that while the non-textile industries (dotted line) continued to grow in capital stock, the textile industry essentially stagnated. A similar pattern can be seen in the trend

Table 3.2. High productivity growth periods in textile industry

| | *Dependent variable:* | | | |
|---|---|---|---|---|
| | Five factor productivity | | | |
| | 1971-1977 | 1978-1984 | 1985-1991 | 1992-1998 |
| | (1) | (2) | (3) | (4) |
| Textile dummy | −0.004 | 0.012*** | 0.007** | −0.007* |
| | (0.005) | (0.004) | (0.003) | (0.004) |
| Constant | 0.008*** | 0.003** | 0.001 | 0.009*** |
| | (0.001) | (0.001) | (0.001) | (0.001) |
| Observations | 459 | 459 | 459 | 458 |
| $R^2$ | 0.001 | 0.009 | 0.006 | 0.004 |
| *Note:* | | *p<0.1; **p<0.05; ***p<0.01 | | |

of total employment in the textile industry compared to average of the other industries in figure 3.3. A downward trend in employment level of the textile industry started in 1974 and continued until at least early 1990s. These facts point to a general decline in the U.S. textile industry in that period which started in mid 1970's and happens to be around the same period that the new standards were proposed. The comparison of TFP levels of textile and the other industries is drawn in figure 3.4. In terms of the trends in total factor productivity, the textile industry experienced lower TFP levels compared to the average of the other industries until 1974, after which it suffered a major negative shock to productivity, but later caught up with industry average in a matter of only ten years. The negative shock happened before the cotton standards went into effect (year 1978) and their implementation deadline (year 1984). This may suggest that the textile industry was undergoing a large scale transformation before the standards were promulgated and the standards may not have been the cause of the changes, contrary to what OSHA claimed.

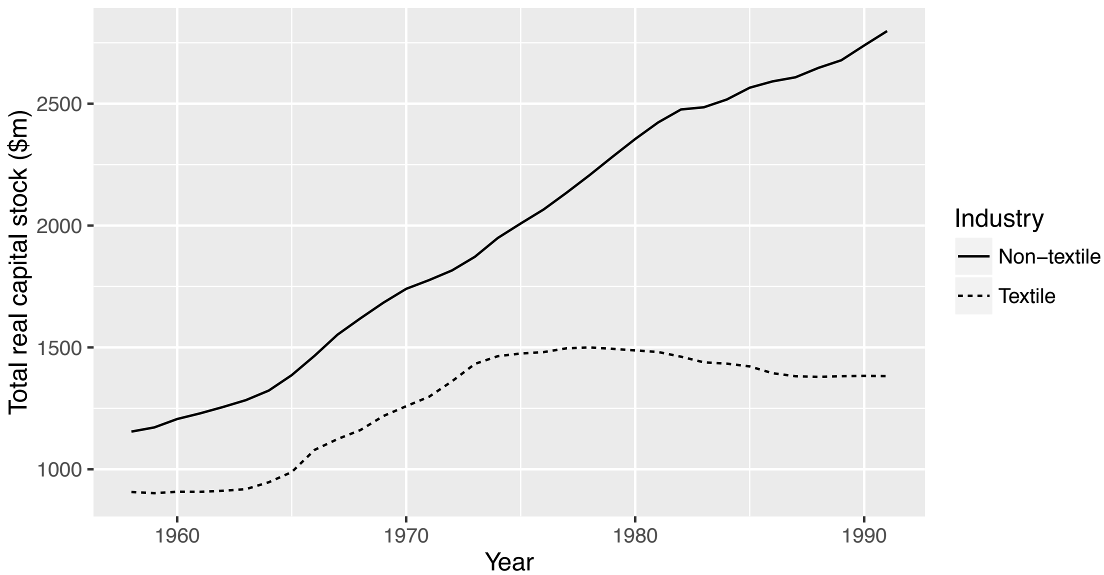


Figure 3.2. Total capital stock, textile vs other industries

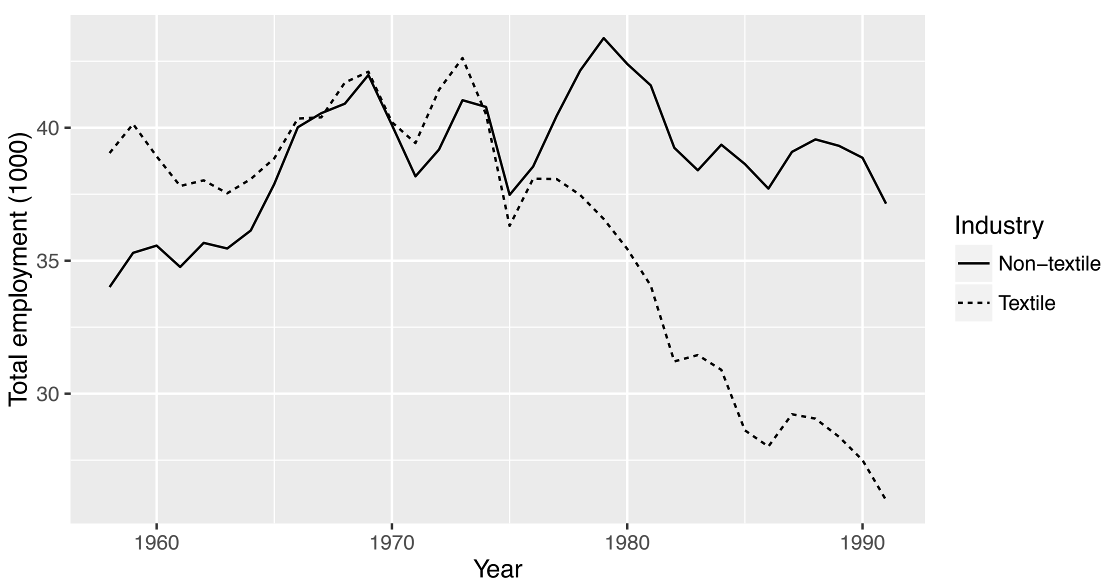


Figure 3.3. Total employment, textile vs other industries

But which sub-industries drove the stagnation in the textile industry? I have plotted the capital stock and employment at sub-industry (3-digit SIC code) level in figures 3.5

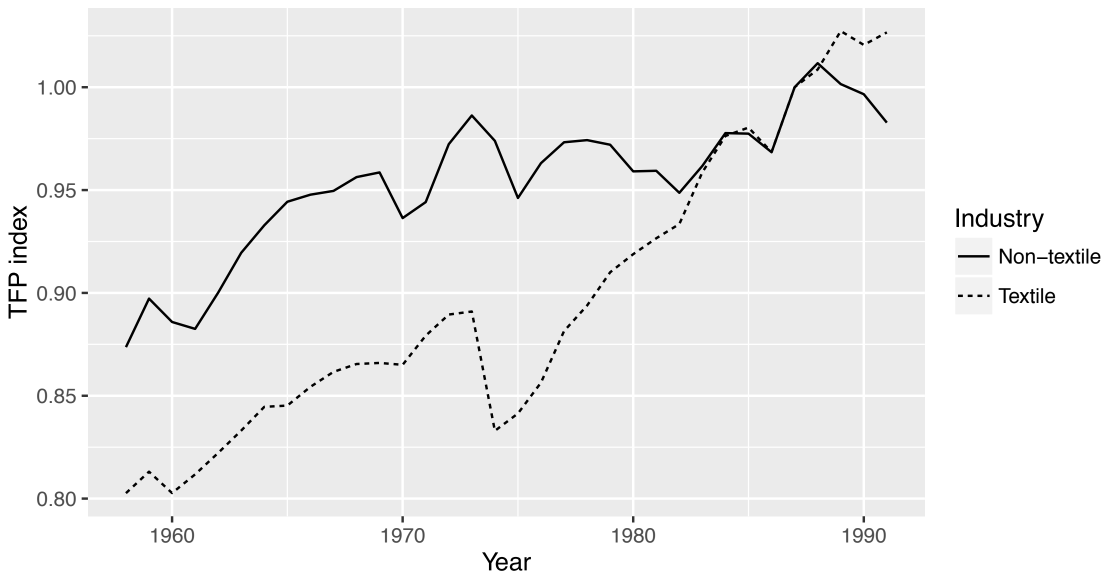


Figure 3.4. TFP index (five factor), textile vs other industries

and 3.6. It is evident from both figures that the sub-industry with 3-digit SIC code of 221 both constitutes a large portion of labor and capital use and has experienced the largest shrink in the value of capital stock and labor employment. The 3-digit code 221 corresponds to industry group “Broadwoven Fabric Mills, Cotton”, a sub-industry that has a high usage of cotton in its production process. Another important sub-industry (SIC code 222 for industry group of “Broadwoven Fabric Mills, Manmade Fiber and Silk”) also relies on cotton though to a lesser extent.

This may be taken as an indication that the stagnation in some industries in which cotton is an important material input had started much earlier than the proposed standards were announced and that the spike in the productivity of textile industry in late

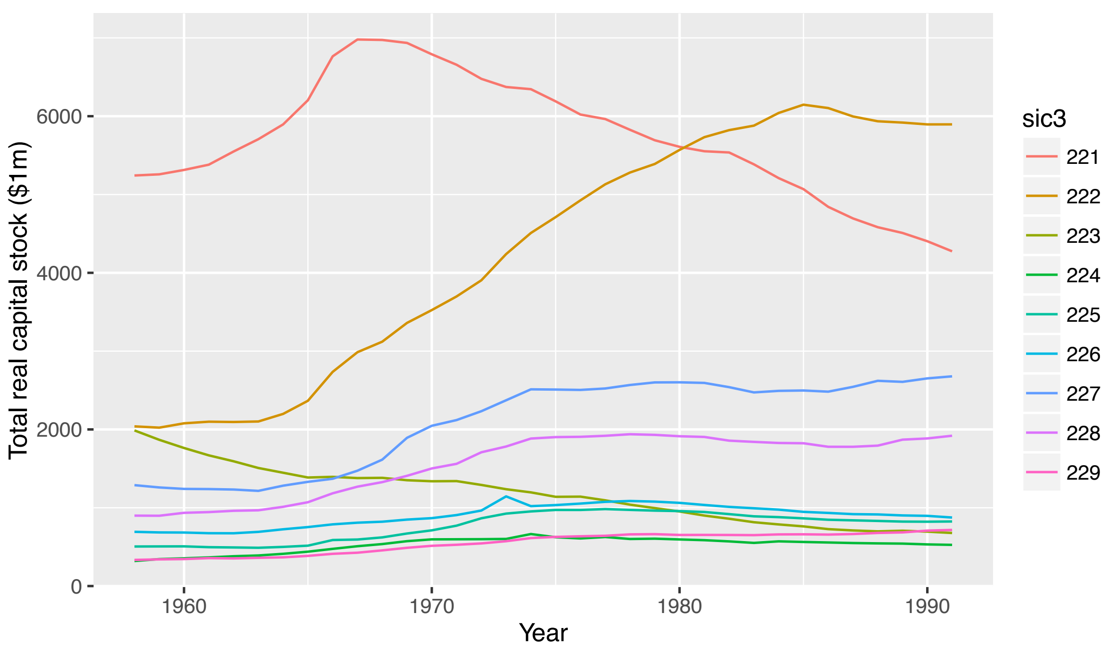


Figure 3.5. Capital stock by sub-industries in textile industry

1970 was something to be expected from an ailing industry that tried to regenerate itself, but still it cannot be ruled out that the standards may actually have accelerated an otherwise overdue process of technological modernization.

Let's take a closer look into which sub-industries were the ones with the highest usage of cotton in their production process. The firm level data on cotton usage was not available for this study; however, OSHA (2000) identifies industries using cotton in yarn preparation and weaving sectors. A summary of the information in Table 4 of that report is reproduced in table 3.3. The sub-industries with the highest percentage of establishments using cotton in 1977 fall under 221, 222 and 228 3-digit SIC codes. Broadwoven Fabric Mills, Cotton, happen to be the industry group with the highest proportion of establishments using cotton and also experiencing the most sever decline.

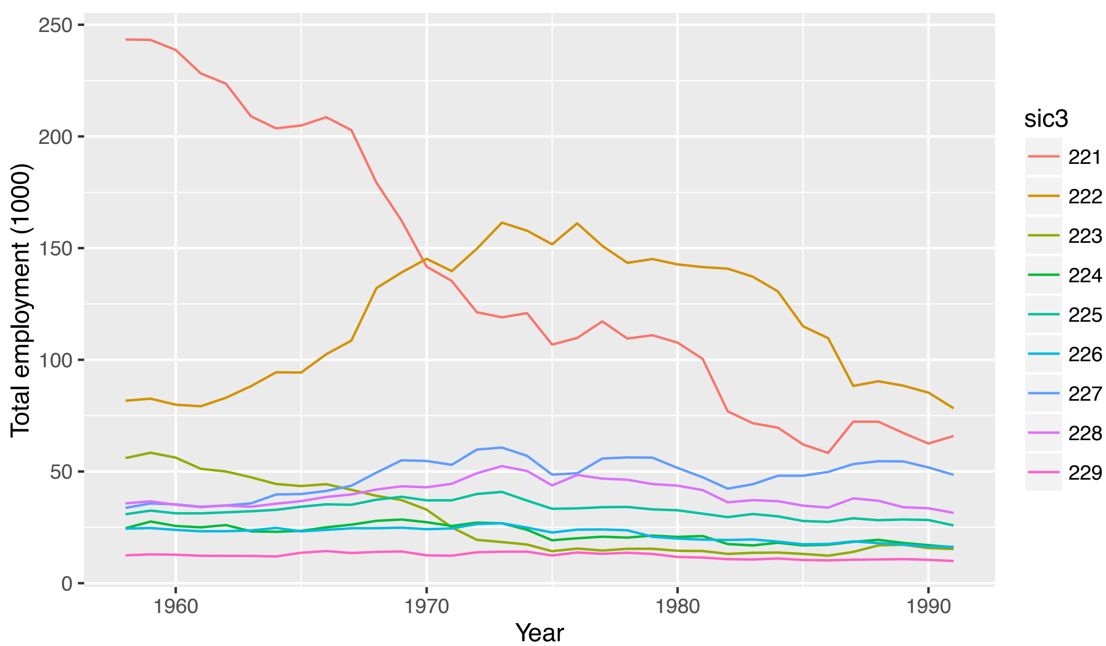


Figure 3.6. Employment by sub-industries in textile industry

| SIC | Description | Percentage |
|---|---|---|
| 2211 | Broadwoven Cotton Weaving | 69.8 % |
| 2221 | Broadwoven Synthetic Weaving | 21.1 % |
| 2241 | Narrow Fabrics Weaving | 13.3 % |
| 2281 | Yarn Spinning | 17.9 % |
| 2282 | Winding and Throwing | 5.3 % |
| 2284 | Thread Mills | 61.1 % |

Table 3.3. Establishments using cotton in 1977

### 3.3.4. Identifying affected industries

Even though the textile industry experienced a high rate of productivity growth after the cotton dust standards were issued, not all industries within this industry were affected in the same way by the standard. So I try to estimate the differential effects of the standard on different sectors of the textile industry (4-digit SIC code) based on a measure of whether a sector was affected by the standard.

The standard specifies permitted emission levels (PEL) of cotton dust in the work environments. Also different PELs are imposed on different processes. So one reasonable measure of the extent to which an establishment is affected by the standards would involve determining whether it uses cotton in its manufacturing process. Ideally firm-level data on cotton use as input should be used to identify affected versus unaffected firms and to what extent they were affected; however, since firm-level data is not available for this study, I rely on industry aggregates to construct the treatment variable.

For the matter of this paper I define an affected industry to be one with more than 50 percents of its establishments using cotton in 1977. Using this criteria and noting the degree of cotton use in sub-industries reported in table 3.3, Broadwoven Cotton Weaving (2211) and Thread Mills (2284) will be the ones "treated" by the standard. This condition for identifying affected industries is justified based on the fact that the proportion of establishments that used cotton in other industries is much lower (the highest being Broadwoven Synthetic Weaving with 21.1 percent of its establishments using cotton). I also try using the percentages as the treatment variable instead of 0-1 dummies, but that will not change the results while only making the interpretation of the model harder.

### 3.3.5. Difference in differences estimation

I estimate the effect of the standards on the productivity of textile sub-industries using difference-in-differences approach were the treatment variable is whether an industry is affected by the standard as defined in 3.3.4. The following regression is used for estimation

$$tfp_{ist} = \beta_0 + \beta_1 affected_s + \beta_2 after_t + \delta(affected_s \times after_t) + \varepsilon_{ist} \tag{3.4}$$

where $affected_s$ is the dummy variable that is equal to one for the sub-industries affected and $after_t$ is the dummy variable that indicates the period after the treatment. The parameter of interest in this equation is $\delta$ which denotes the size of the effect of the standard on the affected sub-industries compared to the control group. The size of the sample is $N = 23$ (the number of 4-digit SIC code sub-industries) in each period. There are two periods: one before the standards went into effect and one after. The dependent variable $tfp_{ist}$ is the average TFP index of the industry $i$ during period $t$ (before or after treatment) and treatment group $s$.

We can distinguish the periods at least in two different ways: either the year 1978 when the standards took effect or the year 1984, by which the standard required compliance. The former case ($\tau = 1978$) is justified based on the fact that standard would alter the behavior of the affected establishments once they took effect, and the latter case ($\tau = 1984$) is justified based on the fact that most of the firms may not start to react to the standards until the compliance deadline of 1984. The models based on both of these assumptions are estimated and reported in table 3.4 below (further investigation of the role of picking the "treatment year" $\tau$ is done in section 3.4).

Table 3.4 consists of four columns. The first two are the results of the regressions discussed above, that is a DID model where the dependent variable is the TFP index. Column 1 lists the estimated coefficient for a model in which the treatment year is taken to be 1978, and column 2 does the same for year 1984. Columns 3 and 4 are related to models in which the dependent variable is the TFP growth rather than TFP level and correspond to treatment years of 1978 and 1984 respectively. All of the estimated coefficients in model 3.4 are reported, namely the coefficients of the dummies for treatment, period and for their interaction.

In models 1 and 2, the dummies that indicate the second period (the "After" dummy) have positive signs and are statistically significant. This is in line with the long-term productivity growth of this industry seen earlier in figure 3.4. The "Affected" dummy also has a positive and significant coefficient which indicates a higher TFP level of this subset of the industry compared to the others throughout the sampling period. The treatment effect of the standards is captured by the interaction term After $\times$ Affected. In both models 1 and 2 this dummy has the expected negative sign, that is, the standards negatively affected the productivity level of the affected sub-industries, but only in model 2 it is significantly different from zero. Textile sub-industries with higher cotton use among active establishments experienced a larger decline in productivity compared to the ones with little or no cotton use, which is consistent with the hypothesis that regulations negatively affected the productivity of the firms in those industries.

The same effect is not observed when I use the TFP *growth rate* rather than its level. In columns 3 and 4 the coefficients of the treatment effect are not significantly different from zero. It may be concluded from this finding that the standard may have had only a level effect on productivity but did not affect the rate of growth of productivity significantly, which means the effect was a shock to the level but not to the rate of growth.

How can this conclusion be reconciled with the evidence presented earlier that the textile industry was undergoing a general decline and transformation before the standards were issued? The likely explanation is that the textile industry was performing poorly and in order to remain competitive internationally it needed to overhaul its technology. The process of adopting new technology is costly and may accompany capital and labor loss in order to transmute into a leaner and more efficient industry. The standards may have only accelerated this adoption process but otherwise have been costly to the productivity of the firms affected by them. This explanation is consistent with the theory which asserts that higher regulations lead to lower productivity, and the boom in productivity of the textile industry in 1980s was not the effect of the standards but the outcome of a separate transformation process.

Table 3.4. DID estimation results for effects of standards

| | *Dependent variable:* | | | |
|---|---|---|---|---|
| | TFP level | | TFP growth | |
| | $\tau = 1978$ | $\tau = 1984$ | $\tau = 1978$ | $\tau = 1984$ |
| | (1) | (2) | (3) | (4) |
| After | 0.144*** | 0.154*** | 0.244 | −0.397 |
| | (0.040) | (0.033) | (0.406) | (0.417) |
| Affected | 0.248** | 0.200** | −1.538 | −1.669 |
| | (0.095) | (0.078) | (0.973) | (1.001) |
| After × Aftfected | −0.242* | −0.213* | 0.684 | 1.890 |
| | (0.135) | (0.110) | (1.375) | (1.416) |
| Constant | 0.829*** | 0.852*** | 0.918*** | 1.098*** |
| | (0.028) | (0.023) | (0.287) | (0.295) |
| Observations | 46 | 46 | 46 | 46 |
| $R^2$ | 0.293 | 0.377 | 0.085 | 0.070 |
| *Note:* | | | | *p<0.1; **p<0.05; ***p<0.01 |

## 3.4. Robustness checks

In this section I perform checks to analyze the sensitivity of the results to choice of the "treated" group and treatment year.

### 3.4.1. Choice of treated group

The criterion used in this paper for being affected by the standards is that a sub-industry is affected if at least 50 percent of the firms in that sub-industry used cotton in their production process. Among the six textile sub-industries that used cotton two of them meet this criteria, namely industries with SIC codes 2211 and 2284. But is it possible that only one, and not both, of these industries are driving the result? To check this, I redo the estimation but with separate effects for the affected industries. The results are presented in table 3.5. Columns 1 and 2 of this table show the results of the regression when the dependent variable is TFP level while columns 3 and 4 are for models with TFP growth as the dependent variable.

In table 3.5 "After" is the period dummy as before, but now the "Affected" dummy is broken up into two separate fixed effects for sub-industries 2211 and 2284. The interaction effects After $\times$ SIC2211 and After $\times$ SIC2284 are the effects of interest here. This effect is negative and significant only for SIC2284 (Thread Mills) and for both treatment years of 1978 and 1984. The effect is not significant though for SIC2211 (Broadwoven Cotton Weaving). This implies that SIC2284 is driving the results, even though the percentage of the firms using cotton in this industry is lower compared to that of SIC2221 (61.1 percent vs 69.8 percent). The estimation results in table 3.5 imply that among the sub-industries of the textile industry which use cotton, Thread Mills were hit hardest by the standards, and that for the other sub-industries, even if there was an effect, it was too small to be detected using the current data. The effects in columns 3 and 4 pertaining to TFP growth are not significant, which is in agreement with the previous regression results in table 3.4.

Table 3.5. Robustness checks for the choice of affected sub-industries

| | *Dependent variable:* | | | |
|---|---|---|---|---|
| | TFP level | | TFP growth | |
| | $\tau = 1978$ | $\tau = 1984$ | $\tau = 1978$ | $\tau = 1984$ |
| | (1) | (2) | (3) | (4) |
| After | 0.144*** | 0.154*** | 0.244 | −0.397 |
| | (0.038) | (0.031) | (0.404) | (0.412) |
| SIC2284 | 0.427*** | 0.370*** | −1.828 | −2.163 |
| | (0.128) | (0.104) | (1.339) | (1.365) |
| SIC2211 | 0.070 | 0.029 | −1.248 | −1.175 |
| | (0.128) | (0.104) | (1.339) | (1.365) |
| After × SIC2284 | −0.347* | −0.368** | −0.434 | 0.777 |
| | (0.180) | (0.146) | (1.893) | (1.931) |
| After × SIC2211 | −0.138 | −0.058 | 1.801 | 3.003 |
| | (0.180) | (0.146) | (1.893) | (1.931) |
| Constant | 0.829*** | 0.852*** | 0.918*** | 1.098*** |
| | (0.027) | (0.022) | (0.285) | (0.291) |
| Observations | 46 | 46 | 46 | 46 |
| $R^2$ | 0.368 | 0.455 | 0.137 | 0.139 |
| *Note:* | | | | *p<0.1; **p<0.05; ***p<0.01 |

To further investigate how the choice of the affected industries might drive the results I repeat the estimations above once with each of the 23 textile sub-industries taken to be "affected" in each round. The estimated coefficients of the treatment effect $\delta$ along with their 90 percent confidence intervals are plotted in figure 3.7. On the horizontal axis are the 4-digit SIC codes of the "affected" industry in each round and the vertical

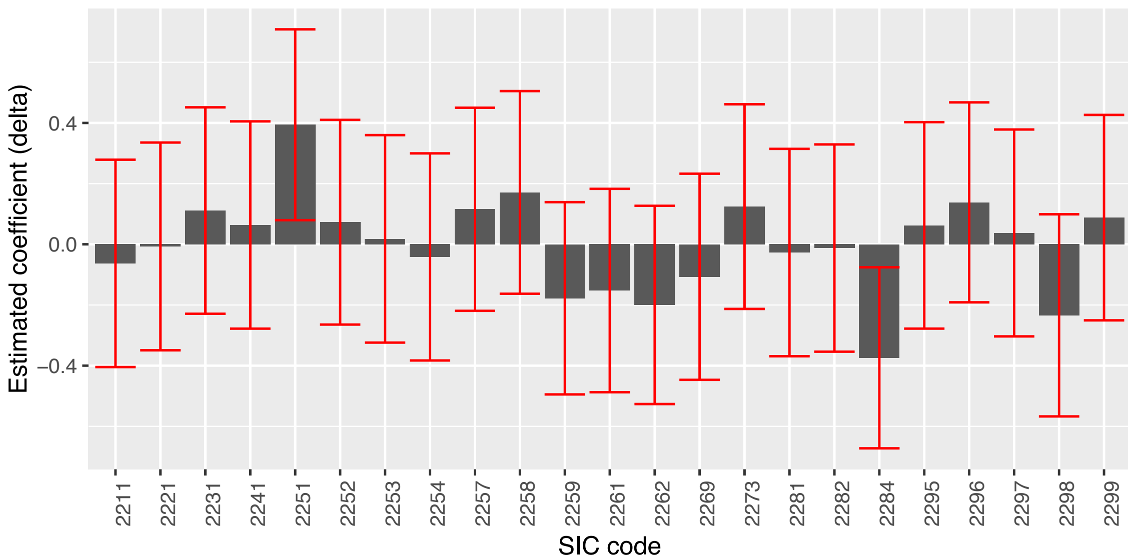


Figure 3.7. Coefficients of DID estimation with different sub-industries as affected

axis represents the value of the estimated coefficient. It is evident from the figure that the Thread Mills (SIC 2284) was the only sub-industry that was negatively affected by the standard using a 90 percent confidence interval. This shows that less confidence should be put into the criteria of being affected used here since there does not seem to be clear relationship between industries' use of cotton and being adversely affected by the standards.

### 3.4.2. Choice of the treatment year

Are the results of the DID model sensitive to choice the treatment year? I test this by repeating the estimation with different years as the treatment year, from 1970 to 1990. The resulting estimated coefficients along with their 90 percent confidence intervals are plotted in figure 3.8. It is evident from the figure that the negative effect is not specific to the selected treatment years of 1978 or 1984. The effect starts to appear in 1976, two years before the time of issuance of standard in 1978, and remains negative and significantly different from zero until the end of the sampling period, 1990, though the point estimates grow smaller in magnitude gradually after 1976. The (negative) effect is largest in 1976, but the largest upper bound of the 90 percent confidence intervals belongs to 1983, the year before the compliance deadline. After that the effect gradually becomes smaller until 1990. One conclusion from this analysis is that the effects do seem to appear around the time of the issuance of standard and are most distinguishable as we get close to the compliance deadline, but also that the effects were persistent as the affected industries did not catch up for a few years after the standards were implemented.

The number of firms in each industry, although available in OSHA documents is not a concern here since the productivity measure used here is an industry-wide index and normalized to be comparable across industries. Also the textile industry is geographically concentrated with 95 percent of establishment in four states, thus geographical position should not be an important confounding factor either.

## 3.5. Conclusion

Using industry level data and a difference in differences estimation approach, I find a negative effect for issuance of cotton dust standards on industries being affected by them. The effect become stronger and more significant when only the thread mills (2284) are considered as affected, which may reflect higher capital costs of this industry in order to comply with the standard. However the analysis here does not provide a definitive answer for this claim; it may also be that the thread mills sub-industry declined in productivity

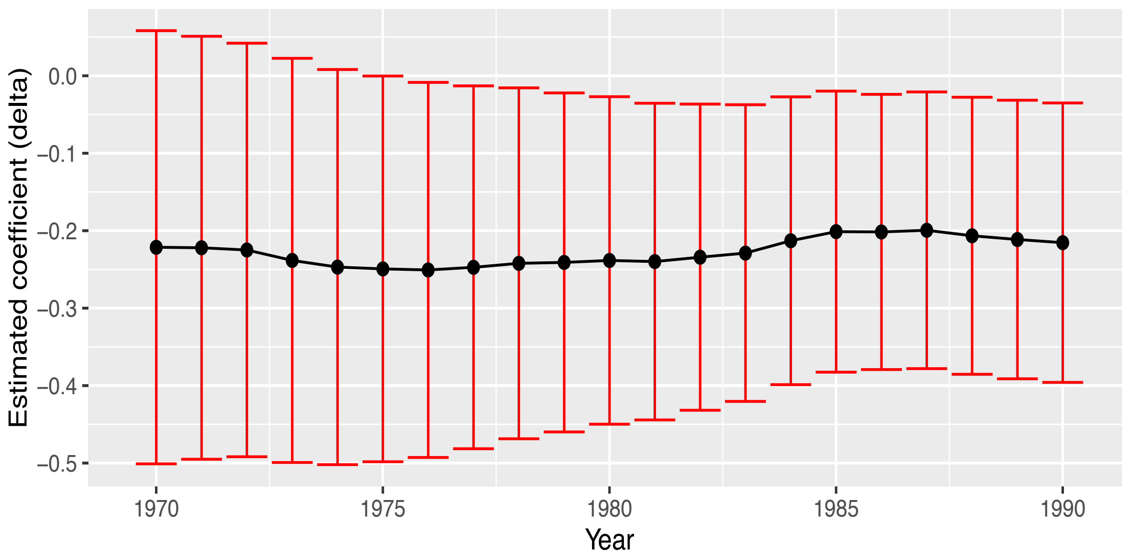


Figure 3.8. Coefficients of DID estimation for different years as post-regulation year

for some other cause. Also the result is not sensitive to the choice of treatment year and the effect seems to be persistent for many years after the standards were issued.

The small size of the sample may reduce the power of the tests and introduce biases as much information is lost due to aggregation at industry level. Nevertheless, the results in this paper do not contradict the predictions of the theory and the results found in other empirical works on the effects of regulation on productivity. However, it can still be argued that the standards did actually have the effect of inducing the textile industries to adopt the new technology sooner rather than later, as OSHA also claimed at the time.

The current work can be extended if detailed plant or firm level data from the textile industry is available. This could help exactly identify which firms were affected by the standards to avoid the imprecision resulting from aggregation. Because of their narrow target and quick introduction, cotton dust standards may also serve as a "natural experiment" for testing other theories in industrial organization. One candidate would be testing theories of technology adoption and the welfare impacts of government intervention in technology adoption.

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