2022

# Three essays on automation, trade, and inequality

BOSTON UNIVERSITY

GRADUATE SCHOOL OF ARTS AND SCIENCES

Dissertation

# THREE ESSAYS ON AUTOMATION, TRADE, AND INEQUALITY

by

**MD. DEEN ISLAM**

B.S.S., University of Dhaka, 2008
M.S., Western Illinois University, 2014
M.A., Boston University, 2019

Submitted in partial fulfillment of the

requirements for the degree of

Doctor of Philosophy

2022

Approved by

First Reader

Stefania Garetto, PhD
Associate Professor of Economics

Second Reader

Pascual Restrepo, PhD
Assistant Professor of Economics

Third Reader

Yuhei Miyauchi, PhD
Assistant Professor of Economics

## Acknowledgments

I am indebted to my advisors Stefania Garetto, Pascual Restrepo, and Yuhei Miyauchi for their guidance and support throughout my PhD journey. Their guidance, support, and encouragement during my PhD studies has been truly invaluable. I would like to thank my mother and siblings for their unconditional support. Knowing that you are there for me is what gives me energy and motivation to reach my goals. Thank you for always encouraging me to follow my dreams. Thanks to my friends, I am so grateful for having you and that you were part of this magical and surreal journey. You are all in my heart.

With regards to chapter one, I am also grateful to Joaquin Blaum, Siddharth George, Adam Guren, Tarek Hassan, Nyr Indictor, David Lagakos, Esteban Rossi-Hansberg, Stephen Terry, and seminar participants at the BU Macro Lunch Seminar and BU Macro Reading Group for helpful comments and suggestions. With regards to chapter two, I am indebted to participants at the BU Macro Lunch Seminars. For chapter three, I am grateful to my three coauthors: Kevin Gallagher, Warren Kaplan, and Veronika Wirtz, for their kind support and advice. I have been fortunate to work with and learn from them.

# THREE ESSAYS ON AUTOMATION, TRADE, AND INEQUALITY

**MD. DEEN ISLAM**

Boston University, Graduate School of Arts and Sciences, 2022

Major Professor: Stefania Garetto, PhD
Associate Professor of Economics

ABSTRACT

This dissertation investigates the effects of changes in technologies and trade-related policies on income inequality. The first chapter shows that an advancement in labor saving technologies, known as automation, raises the agglomeration of economic activity in large cities and increases wage inequality across regions. I show novel stylized facts about the relationship between city size and the routineness of tasks performed by workers. I develop a general equilibrium model of a spatial economy where automation affects the type of tasks performed by workers and is related to a firm's choice of production location. The model generates several predictions that are consistent with stylized facts and existing empirical evidence: larger cities have greater agglomerations of firms and grow larger when firms can automate more tasks in the production process. The model predicts that an increase in automation raises wage dispersion between larger and smaller cities. A 20% rise in automation increases wages in the top decile of largest cities by about 8% and lowers wages in smaller cities by about 2-8% and hence widens the wage gap by about 10 to 16%.

The second chapter investigates the effect of exchange rate volatility on the intensive and extensive margin of trade, and on income inequality within a country. It finds that the greater volatility in exchange rates lowers trade margins and income inequality. I derive testable predictions regarding the impact of exchange rate volatility on trade margins at the firm level and on income distribution at the industry level. I empirically test these

predictions using firm-level microdata. Empirical results provide clear support in favor of the model's predictions about the effects of volatility on trade margins.

Finally, in the third chapter, my coauthors and I investigate the effect of Bangladesh's graduation from Least Developed Country (LDC) status on the price of insulin, an essential medicine for diabetes, and on households' welfare and poverty. We find that upon Bangladesh's graduation from LDC status, the price of insulin could rise as much as 11 times the current price for patented insulin if an unregulated monopoly is allowed. This would significantly reduce welfare and increase the incidence of poverty for households with members suffering from diabetes.

# Contents

# List of Figures

# List of Abbreviations

| | | |
|---|---|---|
| ARCH | ............. | Autoregressive Conditional Heteroskedasticity |
| API | ............. | Active Pharmaceuticals Ingredients |
| BBS | ............. | Bangladesh Bureau of Statistics |
| BCG | ............. | Boston Consulting Group |
| BIS | ............. | The Bank of International Settlement |
| BLS | ............. | Bureau of Labor Statistics |
| CDP | ............. | Committee for Development Policy |
| CPS | ............. | Current Population Survey |
| CS | ............. | Consumer Surplus |
| CV | ............. | Compensating Variation |
| DGDA | ............. | Directorate General of Drug Administration |
| EV | ............. | Equivalent Variation |
| FDI | ............. | Foreign Direct Investment |
| FTA | ............. | Free Trade Agreement |
| GARCH | ............. | Generalized Autoregressive Conditional Heteroskedasticity |
| GDP | ............. | Gross Domstic Product |
| GMM | ............. | Generalized Method of Moments |
| HIES | ............. | Household Income and Expenditure Survey |
| IPUMS | ............. | Integrated Public Use Microdata Series |
| LDC | ............. | Least Developed Country |
| LV | ............. | Laspeyers Variation |
| NIC | ............. | Newly Industralized Country |
| OECD | ............. | Organisation for Economic Co-operation and Development |
| OLS | ............. | Ordinary Least Square |
| PV | ............. | Paasche Variation |
| PPP | ............. | Purchasing Power Parity |
| QUAIDS | ............. | Quadratic Almost Ideal Demand System |
| RTI | ............. | Routine Task Index |
| TRIPS | ............. | Trade Related Intellectual Property Rights |
| VAR | ............. | Vector Autoregression |
| VECM | ............. | Vector Error Correction Model |
| WHO | ............. | World Health Organization |
| WTO | ............. | The World Trade Organization |

# Chapter 1

# The Geography of Automation

## 1.1 Introduction

Over the last few decades, automation has driven rapid changes in firms' production structures. The pace of automation is increasing as artificial intelligence and machine learning techniques are becoming more efficient and sophisticated, and machines are now able to perform a wide range of routine-type tasks. The United Nations Conference on Trade and Development reported that around 1.6 million industrial robots were in use world-wide in 2017 (UNCTAD, 2017). Boston Consulting Group (BCG) predicted that the use of industrial robots will reach 2.5 million in 2019 and to 4 to 6 million in 2025 (BCG, 2015). A rise in the level of automation can displace many workers, especially workers performing mostly routine-type tasks. It can also increase incentives for firms to locate in more productive larger cities to take advantage of greater agglomeration externalities. Hence, small and less productive cities suffer a loss in employment in two dimensions: On one hand, a greater level of automation reduces labor demand everywhere; on the other hand, it increases the agglomeration of firms in large cities and lowers the labor demand in smaller and less productive places.

In this paper, I study the effect of automation on the spatial distribution of economic activity. An established fact in urban and spatial economics is that larger cities offer greater productivity advantages (Combes et al., 2012). So, firms have a higher incentive to locate in larger cities. However, the costs of locating in larger cities, especially labor costs, are also higher and hence not every firm can afford to locate in a large city. Nevertheless, with the increasing pace of automation, firms can adopt labor-saving technologies so that locating in larger cities becomes less costly. Thus, automation can lead to a spatial redistribution of production, employment, and income, affecting regional inequality.

Using an individual level data set, I show several stylized facts about the relationship between routineness of tasks and city size. First, I show that task-routineness is decreasing in city size; that is, workers in larger and more productive cities perform less routine-type tasks. Second, overtime, the fall in task-routineness is greater in larger cities. Specifically, larger cities have experienced a greater fall in the routineness of tasks in the last two decades. Third, growth in task-routineness is negatively associated with the growth rate of city size. This implies that faster growing cities have confronted a greater fall in workers' task-routineness.

To investigate the effects of automation on spatial distribution of economic activity and its effects on wage and welfare across cities, one needs to understand how heterogeneous firms respond to an increase in automation technology. I develop a model that is suitable to study this issue. In my model, heterogeneous firms choose a production location based on their location-specific productivity, on a location's exogenous characteristics as well as on the level of automation. City sizes are endogenously determined by firms' location choice. The model incorporates three factors in determining aggregate city productivity: exogenous city productivity, a city-specific firm's productivity, and agglomeration benefits originating from the city size. The model generates well-known facts in the literature that larger cities are more productive, and wages are higher in larger cities. Moreover, it predicts that a greater level of automation amplifies the agglomeration of firms in larger cities. In addition, it shows that larger cities have become more automated following an increase in the level of automation. Importantly, the equilibrium analysis of the model indicates that an increase in automation leads to a higher wage differential between smaller and larger cities.

Spatial redistribution of economic activities following an increase in automation leads to spatial inequality in wages. Small cities suffer greater losses in employment if firms relocate to large cities following an increase in automation. Large urban areas may not suffer significant losses in employment if the job displacement created by the increased level automation is smaller than the new jobs created by firms relocating in those urban areas. In addition, a greater proportion of jobs in smaller cities are generally simple and routine-type, which can easily be automated, whereas jobs in larger cities are complex and abstract-type, which cannot be easily replaced by machines. Frank et al. (2018) provide a comparative analysis of the effect of automation across the US urban areas and show that smaller cities face greater worker displacement and job content substitutions. Thus, this asymmetric impact of automation can potentially increase wage differential across cities.

I quantify the model by calibrating its parameters using data from Integrated Public Use Microdata Series (IPUMS) Current Population Survey (CPS), Compustat, and the US Bureau of Labor Statistics' (BLS) consumer expenditure survey 2019. I use the calibrated model to conduct a counterfactual analysis to assess the quantitative effects of the rise in automation on the spatial distribution of firms and on wage dispersion across cities. In this counterfactual analysis, I allow for a 20% uniform increase in automation frontiers for all firms, which is equivalent to a fall in task-routineness in the last 25 years. The results of the counterfactual analysis show that a 20% uniform increase in automation frontier boosts the mass of firms in larger cities and shrinks it in smaller cities. Largest 10% cities gain more than 7% in number of firms, while some smaller cities lose as much as 95% of the mass of firms. Inequality in city-level wages also rises following the uniform increase in automation frontiers. Average wage in larger cities increases by about 8% and decreases in smaller cities by about 2-8% and hence widens the wage gap by about 10 to 16 %.

The main contribution of the paper is to propose a spatial equilibrium model that can be used to explain the effects of automation on firms' sorting into more productive larger cities leading to geographic redistribution of economic activity and on spatial wage inequality.

Traditionally, spatial differences are ignored in studies of wage inequality and most studies are carried out at national level comparing wage dispersion among different groups of workers (Krusell and Smith, 1998; Castaneda et al., 2003; Kaymak and Poschke, 2016; Humber et al., 2017; Straub, 2019) and earnings difference between capital owners and workers (Moll et al., 2021). Recent literature in this area has focused on interregional variation in the distribution of income and has attempted to identify the determinants of spatial wage inequality (Donegan and Lowe, 2008; Glaeser et al., 2009; Bolton and Breau, 2012; Breau et al., 2014; Breau, 2015; Florida and Mellander, 2016; Lee et al., 2016; Liu et al., 2020). My paper contributes to this literature by introducing automation as a determinant of spatial dispersion in wages. The paper offers an additional channel of interregional differences in earnings through the re-organization of economic activity across urban areas.

The paper is naturally related to a growing body of literature on technological change and automation. I follow recent trends in literature and use a task-based production structure to model automation (Zeira, 1998; Acemoglu and Autor, 2011; Acemoglu and Restrepo, 2018a). Other studies in this area also investigate the effects of automation on wage inequality (Autor et al., 2003, 2006; Hémous and Olsen, 2014; Acemoglu and Restrepo, 2020). Some of these studies use a representative household framework (Acemoglu and Restrepo, 2018b; Caselli and Manning, 2019). I instead consider heterogeneity in agents' locational preferences and explore the implications of a higher level of automation on the wage of individuals living in different cities.

Finally, this paper advances the literature on the agglomeration of firms in large urban areas. Several studies propose different forces to explain the remarkable clustering of human activity in a few urban areas. Many stipulate that a large city would emerge if it were more convenient to live in a large city because of its amenities. However, if this was the case, then real wages in a large city would be lower than those in a smaller one. Though there has been convergence in the wage premium between large and small cities between 1940 and 1980, the wage premium in large cities has been increasing after 1980 (Giannone, 2017). A few studies have found empirical evidence of a productivity advantage of large cities. Ciccone and Hall (1993) find a powerful connection between density and productivity across states in the USA, and a similar finding is confirmed by Combes et al. (2010) for France. Ellison and Glaeser (1999) show that even after controlling for the natural and innate advantages of local areas, there is a significant geographical concentration suggesting agglomeration economies of different forms. An important source of advantage of large cities is that they bring firms and input suppliers in proximity, reducing transport and time costs, allowing them to benefit from knowledge spillover. I contribute to this branch of literature by proposing that automation can lower the cost of locating in large urban areas for firms and increase the incentive for firms to locate in larger cities. Thus, automation can potentially increase the clustering of firms in large cities generating greater agglomeration benefits for firms locating in these cities and rising wage premiums of large cities.

The paper is organized as follows. Section 2 presents novel stylized facts about the relationship between city size and automation in the US. Section 3 develops the model and illustrates its predictions. Section 4 explains the calibration and estimation of the model's parameters, describes the numerical results, and compares them with the existing literature. Section 5 contains the results of a quantitative analysis of an increase in automation on the spatial equilibrium. Section 6 concludes.

## 1.2 Stylized facts

In this section, I present novel stylized facts on the relationship between city size, measured as employment, and the extent of routine tasks performed in a city [1]. I provide three

[1] Here I use employment size, instead of population size, as a measure of a city because my focus is on agglomeration benefits from the production side. Thus, employment size provides a better measure for identifying production externalities, whereas population size may absorb both production and market size externalities.

facts about the association between city size and task-routineness: (1) In the cross-section, city size and task-routineness are negatively correlated; (2) Larger cities have experienced a larger decline in task-routineness; (3) Growth in city size is negatively associated with growth in routineness of tasks.

### 1.2.1 Data

To analyze the correlation between the routineness of tasks and the share of economic activity concentrated in cities of different sizes, I need a large sample of individual-level data on economic activity at a detailed geographic level. I use the Census Integrated Public Use Micro Samples (IPUMS) for the years 2000 to 2019 (Flood et al., 2020). IPUMS data include individuals' occupational information, such as industry of occupation, hourly wage rate, etc., and characteristics of individuals, such as race, level of education, geographic location, etc. I merge individuals' occupational information with task score data constructed by Autor and Dorn (2013) to determine the routineness of each occupation. The merged data are then aggregated at the county level.[2]

Autor and Dorn (2013) estimate each occupation's task score in three dimensions: routine, manual, and abstract. [3] I use data on each occupation's score for routine, manual, and abstract tasks to estimate mean scores for routine tasks ($RS_n$), manual tasks ($MS_n$), and abstract tasks ($AS_n$) for agents living in a given geographical unit. These scores are defined as follows:

$$RS_n = \frac{\sum_i routine\_score_{i,n}}{\sum_i Emp_{i,n}}$$

[2]The stylized facts in this section are shown at county level, but the patterns are similar at the Metropolitan Statistical Area (MSA) level.

[3]Autor and Dorn (2013) used the methodology of Autor et al. (2003) and merged job task requirements from the fourth edition of the US Department of Labor's Dictionary of Occupational Titles (DOT, US Department of Labor, 1977) to their corresponding Census occupation classifications to measure routine, abstract, and manual task content by occupation. To compare occupations and industries across different census years, Dorn (2009) constructed a crosswalk of occupational and industrial codes, which can be used to compare the different census data consistently.

$$AS_n = \frac{\sum_i abstract\_score_{i,n}}{\sum_i Emp_{i,n}}$$

$$MS_n = \frac{\sum_i manual\_score_{i,n}}{\sum_i Emp_{i,n}}$$

where $n$ denotes a county, and $i$ an individual. $Emp_n$ denotes the number of employees in county $n$. Using these three scores, one can calculate a routine task index (RTI) for each county:

$$RTI_n = lnRS_n - lnAS_n - lnMS_n \tag{1.1}$$

Thus, the higher the value of the RTI, the greater the level of routine tasks performed by workers in a county.

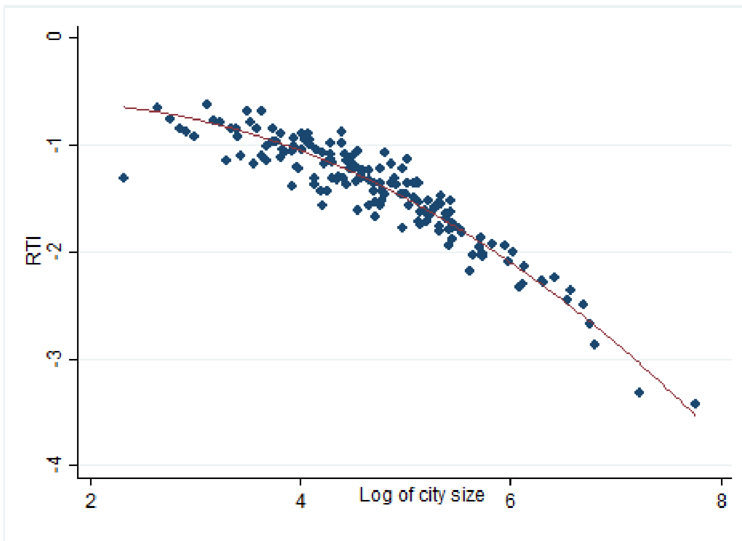
### 1.2.2 Summary statistics

The data set spans years from 2000 to 2019, and it includes about 400 counties. The main variables of interest are RTI and city size. RTI values range from -4.421 to 0.988, where the county with -4.421 RTI has workers performing the least routine-type tasks, while the county with 0.988 RTI has workers carrying out the most routine-type tasks than the other counties in the sample. RTI has a mean -1.616 indicating that average counties employ individuals who perform more abstract and manual-type tasks than routine-type tasks. City size, measured by the number of employed individuals living in the county, ranges from a minimum of 1 to a maximum of 3184; the average city size is 138. Summary statistics for these and other variables are shown in Appendix Table A.1.

**Fact 1: Workers in larger cities perform less routine-type task**

Figure 1·1 shows a negative relationship between city size and RTI.[4] This implies that workers in larger cities perform less routine-type tasks. I interpret these findings as showing that routine-type tasks are performed less by the human labor force and more by some automated technologies in large urban areas.

**Figure 1·1:** Workers in larger cities perform less routine-type tasks




Note: Figure 1·1 plots the average RTI at each percentile of city size for the year 2019. The average RTI is negative across all percentiles of city size in 2019. The decreasing relationship are similar holds any other year in the last two decades.

To establish the relationship in Figure 1·1 in a more robust way, I estimate the following fixed effect panel regression.

$$RTI_{nt} = \alpha_n + \tau_t + \beta_0 lnCS_{nt} + \beta X_{nt} + u_{nt} \tag{1.2}$$

[4]Figure 1·1 shows a bin scatter plot of city size (total employment) and the RTI values in 2019. In Figure 1·1, I control for industrial compositions and workers years of education. Additionally, I generate this bin scatter plots for three broad industry categories: Manufacturing, Services, and Trade, and plots for two levels of education: less than college and at least college. These plots are in Appendix Figure A·1 and A·2, respectively.

where $RTI_{nt}$ is the RTI in the city $n$ in year $t$, $lnCS_{it}$ is the log of city size[5], defined as the total employment in the city $n$ at time $t$, and $X_{nt}$ is a vector of other controls.[6] I also include city fixed effects $\alpha_i$ and time fixed effects $\tau_t$.

The results of regression Equation (1.2) are reported in Table A.2. The coefficient of $lnCS_{nt}$ implies that a 1% increase in city size is associated with about 0.42 lower RTI value. This effect is highly statistically and economically significant as the mean value of RTI is -1.616. This implies that for a city with initial RTI value equal to the sample mean, if the city size rises by 1%, then the RTI falls by about 25%.[7]

**Fact 2: Larger cities experienced a greater fall in routine-type tasks.**

Larger cities have experienced a greater fall in RTI in the last two decades. Figure 1·2 shows a negative relationship between the change in RTI and log of city size in 2000.[8]

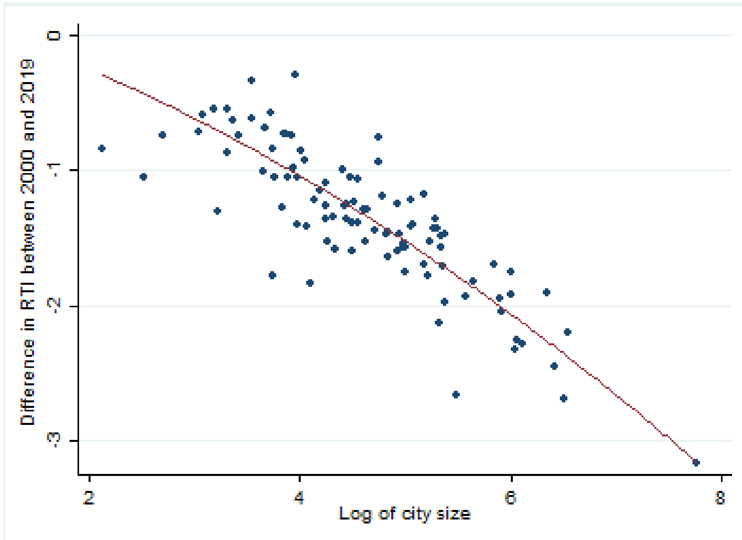
[5]City size is in logarithmic form to incorporate the non-linear relationship between RTI and city size.

[6]$X_{nt}$ includes log of median age of workers in city $n$ at time $t$ ($lnMA_{it}$), log of the median number of years of education of workers in city $n$ at time $t$ ($lnME_{it}$), the fraction of workers in city $n$ at time $t$ who are white ($WF_{it}$), and the wage rate in city $n$ at time $t$ ($lnWR$).

[7]I also studied the year fixed effects from regression 1.2, which is are shown in Appendix as **??**. **??** shows that all the time effects are negative, implying a gradual fall in the RTI, which I interpret an increase in the level of automation. In addition, time effects are getting larger in absolute value, especially since 2012, suggesting an accelerated rate of fall of RTI in larger cities.

[8]Figure 1·2 shows a bin scatter plot of city size (total employment) in 2000 and the change in RTI between 2000 and 2019. In Figure 1·2, I control for industrial compositions and workers years of education. Additionally, I generate this bin scatter plots for three broad industry categories: Manufacturing, Services, and Trade, and plots for two levels of education: less than college and at least college. These plots are in Appendix Figure A·3 and A·4, respectively.

**Figure 1·2:** Larger cities in 2000 experienced a greater fall in RTI




Note: Figure 1·2 shows that the change in RTI in the last two decades is decreasing in initial city size. This is true for any cross-section of city size.

Figure 1·2 implies that larger cities experienced a greater fall in the routineness of tasks performed by workers. To assess the robustness of this result, I estimate the following cross-sectional regressions:

$$\Delta RTI_n = \alpha_n + \beta_0 lnCS_{nt} + \beta X_n + u_n \tag{1.3}$$

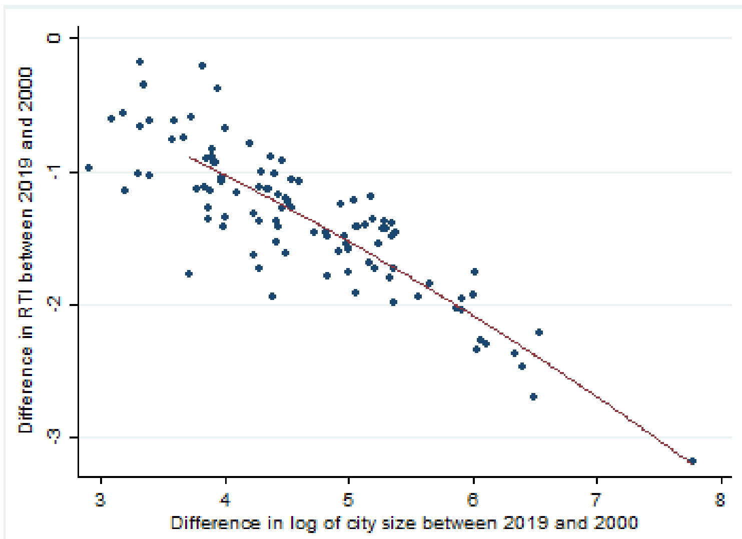
where $\Delta RTI_n$ is the change in RTI between 2000 and 2019 in city $n$. Appendix Table A.4 reports the results [9]. City size in the year 2000 and the change in RTI have a negative correlation is about -0.124. This effect is highly statistically significant and indicate that a city with 1% larger in 2000 has experienced a 0.124 percentage fall in RTI . Thus, cities that were larger in the year 2000 experienced greater change in the level of routineness of tasks performed. The results are similar when regressing the change in RTI on city characteristics in the year 2019 ( Table A.4).

[9] I also estimate Equation (1.3) for city size in 2019. The results are shown in Table A.3. I estimate the regression Equation (1.3) by weighting observations by the employment size in each city.

**Fact 3: Faster growing cities experienced a rapid fall in routine-type tasks.**

Cities that have had greater expansion in employment in the last two decades, experienced a larger fall in RTI. This is shown in the bin scatter plot in Figure 1·3 . Figure 1·3 shows the relationship between change in log of city size and change in RTI between year 2000 and 2019 [10] .

**Figure 1·3:** Relationship between growth in city size and growth in automation




Note: Figure 1·3 shows that faster growing cities have experienced greater decline in RTI in the last two decades.

Figure 1·3 clearly indicates a negative correlation between the growth in city size and the growth in RTI. To verify the robustness of this positive correlation between the growth of automation and city size growth, I estimate regression Equation (1.4):

$$\Delta RTI_n = \alpha_n + \beta_0 \Delta lnCS_n + \beta \Delta X_{nt} + u_n \tag{1.4}$$

Regressors in Equation (1.4) are in log difference form to measure the growth rates. Thus, $\beta_1$ measures the association of growth in city size and the growth of RTI. The results

[10]Similar bin scatter plots are generated for different industry categories and levels of education and given in appendix C in Figure A·5 and Figure A·6

are shown in Table A.5, which shows a robust negative correlation between the growth of RTI and the growth of city size. In addition, growth in the median years of education in the city is also significantly correlated with the negative growth of RTI. Thus, faster-growing cities with high education levels have experienced a more rapid fall in RTI.

In this section, I have shown the existence of a strong empirical relationship between city size and RTI, both in level and in growth rates. Firms and industries located in large urban areas perform less routine-type tasks compared to firms and industries located in small cities. In addition, Routine-type tasks fall at a faster rate in larger cities. In the next section, I develop a spatial general equilibrium model that generates predictions consistent with these stylized facts. The model can be used to analyze the effects of the fall in routineness of tasks on the distribution of economic activity over space and on wage inequality across cities.

## 1.3 Model

I develop a model to study the impact of automation on the geography of economic activity and of wage inequality. To this end, I combine a standard spatial model of firm sorting (Gaubert, 2018) with a task-based production technology á la Acemoglu and Restrepo (2018b). Heterogeneous firms produce a variety of goods using labor and capital as inputs and choose the location that minimizes their unit cost of production. Firms are heterogeneous in their productivity levels, which are also location-specific, and in their ability to substitute labor and capital in the production process ("automation"). Since wages are higher in bigger cities, those firms that need labor to perform routine-type tasks choose to locate in smaller cities, where wages are lower. On the contrary, firms that are able to automate more tasks can locate in larger cities. As a consequence, the spatial distribution of economic activity will be characterized by more automation in larger cities. To establish a link between the predictions of the model and the stylized facts, I interpret the decline in routine tasks in the data as indicating that routine activities are increasingly being performed by machines ("automation"). The model predicts that more automated production processes are more prevalent in larger cities lowering the RTI in those cities.

### 1.3.1 The environment

The economy is composed by a collection of locations, which I call cities. Cities are the places where production takes place and workers reside. I assume there are $N$ numbers of cities indexed by $n$ [11]. Each city is a cluster of housing units which are supplied by absentee landlords and assumed to be perfectly elastic.[12] In my model, the optimal city size is determined endogenously. The individuals choosing to reside in the city determine the demand for housing. [13] The economy has a total population L distributed over the N cities: $\sum_{n=1}^{N} L_n = L$. Agents are homogeneous and can freely move across cities, and I assume that there is no cost associated with migration. Given cities' wages, and individuals' idiosyncratic preferences for each city, individuals select a city to live in. Each individual supplies one unit of labor inelastically. Thus, the residents of a city constitute the workforce for firms in the city.

### 1.3.2 Consumer's problem

Agents rent housing (H) from absentee landlords and consume a composite good X. The preferences of an agent $i$ living in city $n$ are:

$$u_n^i(H_{ni}, X_{ni}) = a_n^i H_{ni}^{\beta} X_{ni}^{(1-\beta)} \tag{1.5}$$

[11]The main results of my model remain unchanged if I assume a continuum of cities instead of a finite set of cities.

[12]Model's predictions and quantitative results hold if housing supply is assumed to be fixed and exogenous. One implication of perfectly elastic housing supply is that rents are equalized across cities.

[13]The distance between cities has no role in determining the equilibrium quantities because I assume that varieties produced in a city can freely be traded across cities. In addition, I assume there is no central planner or local authority determining the size of the city. Many studies following Henderson (1974) exclusively model the problem of city planners in determining the city size. But here I abstract from this in my benchmark model, as my main objective is to investigate the impact of an increase in automation, ceteris paribus.

where $0 < \beta < 1$ is the expenditure share on housing and $a_n^i$ is the individual's idiosyncratic preference for city $n$ which is distributed Fréchet with shape parameter $\nu$: $Pr\left(a_n^i \leq a\right) = e^{-a^{-\nu}}$. The composite good $X$ is a CES aggregate of varieties:

$$X_{ni} = \left[ \int_{\omega \in \Omega} x_{ni}(\omega)^{\frac{\sigma-1}{\sigma}} d\omega \right]^{\frac{\sigma-1}{\sigma}} \tag{1.6}$$

where $\omega$ indexes individual varieties and $\sigma$ is the elasticity of substitution between varieties. The price index, P, is then given by:

$$P = \left( \int_{\omega \in \Omega} p(\omega)^{1-\sigma} d\omega \right)^{\frac{1}{1-\sigma}} \tag{1.7}$$

Plugging the solutions of $X_{ni}$ and $H_{ni}$ into the utility function and taking logs, gives the log Indirect Utility function:

$$\begin{aligned} V_n^i &= ln(\frac{W_n}{P}) - \beta ln(\frac{R}{P}) + lna_n^i \\ &= w_n - \beta r + ln(a_n^i) \equiv \delta_n + ln(a_n^i) \end{aligned} \tag{1.8}$$

Where $W_n$ is the wage in city $n$, $R$ is the housing rent, and $\delta_n$ is the mean utility in city $n$. Agents choose the city to live in to maximize their indirect utility function taking wage and rent as given. Thus, the agents optimal city choice is the solution to the following problem:

$$\underset{n}{max} \quad v_n^i \equiv \delta_n + ln(a_n^i) \tag{1.9}$$

Since $a_n^i$ is drawn from a Fréchet distribution, the share of workers in city $n$, i.e., the labor supply of the city $n$ is: [14]

$$L_n = \frac{W_n^{\nu}}{\sum_{n=1}^{N} W_n^{\nu}} L \tag{1.10}$$

Hence the labor supply of a city depends on the city-level wage only. Cities with higher wages attract more workers.

### 1.3.3 Firm's problem

There is a continuum of firms of mass 1, each producing a variety by combining a continuum of tasks. A firm in city $n$ produces a good $\omega \in [0, 1]$ using a task-based production function, according to which labor or capital are used to produce a certain task. I assume wages $W_n$ vary with city sizes, but the price of capital, $P_k$, does not vary with city size. A fraction of output is converted into capital, according to a technology where one unit of capital is produced using $\iota$ units of output. Thus, the price of capital is: $P_k = \iota P$, where $P$ is the price index. To produce $q_n(\omega)$ units of $\omega$ in city $n$, a firm combines the output of tasks $\tau$, $y(\omega, \tau)$, [15] where $\tau \in [0, 1]$ is the index of tasks. [16] The production function is given by:

$$q_n(\omega) = Z_n(\omega) \underset{\tau}{min} \left\{ y(\omega, \tau) \right\} \tag{1.11}$$

where $Z_n(\omega)$ is the firm and city-specific productivity: $Z_n(\omega) = z_n(\omega) A_n L_n^{\theta}$. $Z_n(\omega)$ is a function of three factors: (1) city-specific firm productivity $z_n(\omega)$, (2) city-level exogenous productivity $A_n$, and (3) city size $L_N$. The city-specific firm productivity $z_n(\omega)$ is different for different firms and I assume it is drawn from a log-normal distribution. A firm's productivity for a certain city is different from other firms' productivity for the same

[14] $\Pr\left( v_n \geq v_{n'} \forall n' \in N \right) = \frac{\delta_n^{-\nu}}{\sum_n^N \delta_n^{-\nu}} = \frac{W_n^{\nu} R^{-\beta\nu}}{\sum_{n=1}^{N} W_n^{\nu} R^{-\beta\nu}}$, which implies $\frac{L_n}{L} = \frac{W_n^{\nu}}{\sum_{n=1}^{N} W_n^{\nu}}$

[15] Grossman and Rossi-Hansberg (2008) and Grossman and Rossi-Hansberg (2012) introduced a task-based production function and use this structure to analyze the trade between cities or countries. Furthermore, Acemoglu and Restrepo (2018a) use a similar structure to show the impact of automation on local economic growth and employment.

[16] Each task is important in production process and there is a unit continuum of tasks.

city. For example, firms producing automobiles are more productive in Detroit, Michigan, whereas firms producing software or computer applications are more productive in Silicon Valley, California. $A_n$ captures the effect of city characteristics on firms' productivity like geographical and climatic features of cities. I assume $A_n$ has a log-normal distribution. The city size $L_n$ is the endogenous component of $Z_n(\omega)$ and the parameter $\theta$ measures the strength of agglomeration benefits with respect to $L_n$. [17]

Firms produce differentiated varieties and engage in monopolistic competition. There are no trade costs, and varieties produced in a city are freely tradable across cities. Firms choose a production location based on its production externalities and labor costs. More productive and larger cities have higher wages but also offer greater external benefits. Thus, each firm weighs the costs and benefits of a production location and chooses the one that minimizes its costs of production.

The production function in equation (1.11) is Leontief. That is, tasks are perfect complements, and each task is essential in the production process. Therefore, the quantity of output depends on the quantity of each task. So, the optimal quantities of tasks $\tau$ and $\tau'$ required to produce variety $\omega$ must be the same:

$$y(\omega, \tau) \equiv y(\omega, \tau') = y(\omega), \quad \forall \tau, \tau' \in [0, 1] \tag{1.12}$$

Using equation (1.12), I can write the production function for variety $\omega$ as:

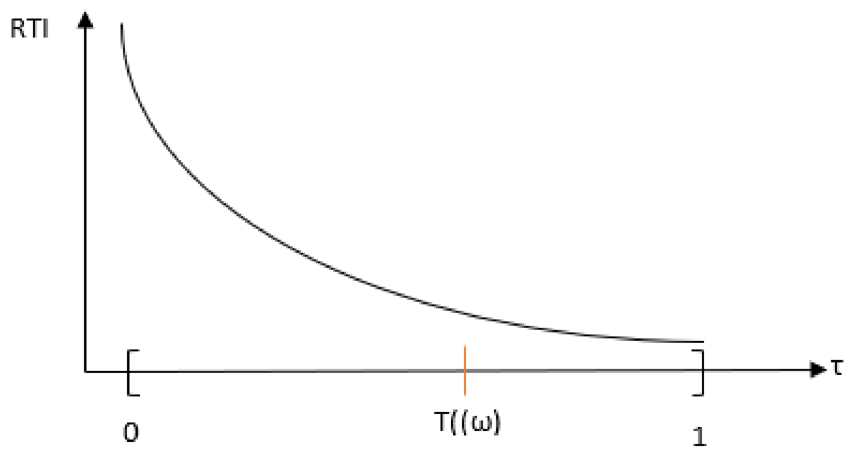
$$q_n(\omega) = Z_n(\omega) y(\omega) \tag{1.13}$$

Thus, the quantity of output is a function of the optimal quantity of tasks and of the

[17]The structure of agglomeration benefits in the model is different from the traditional ways. The problem with the traditional approach of modeling the agglomeration benefits of large cities is that it gives rise to some extreme distributions of firms, such as all firms being optimally clustered in a single city to maximize profits. This degenerate distribution is not very intuitive and realistic, and it implies that a firm's optimal choice of a production location is independent of its exogenous productivity. Thus, the traditional approach requires additional assumptions to rule out the degenerate distribution of firms across cities. Hence, I incorporate city-level exogenous productivity as well as the firm's idiosyncratic draws of productivity for each city.

firm-specific productivity shifter. I assume that tasks are ranked by the extent of their routine components, where $\tau = 0$ for the most routine-type tasks, and $\tau = 1$ for the least routine-type tasks. Thus, the RTI is inversely related to the task index $\tau$ in $\omega$:

**Figure 1·4:** Task index $\tau$ ranked from most to least RTI




Since routine-type tasks are easier to automate, I assume that they can also be performed by capital. Each firm is characterized by an exogenous cutoff $T(\omega)$ such that all tasks $\tau \in [0, T()\omega]$ can be automated. I refer to $T(\omega)$ as the "automation frontier" for firm producing $\omega$, and I assume that $T(\omega)$ is uniformly distributed between 0 and 1. Each task $y(\omega, \tau)$ such that $\tau \leq T(\omega)$ can be produced using either labor ($l$) or capital ($k$), and each task $\tau > T(\omega)$, $y(\omega, \tau)$ can only be produced using labor. Thus, lower $\tau$ tasks can be automated and produced by capital whereas higher $\tau$ tasks cannot be automated. The production function for tasks is given by:

$$y(\omega, \tau) = \begin{cases} \gamma l(\tau) + \eta k(\tau), & \tau \leq T(\omega) \\ \gamma l(\tau), & \tau > T(\omega) \end{cases}$$

where $\gamma$ and $\eta$ denote labor and capital productivity, respectively. Since capital is produced and determined in equilibrium, I assume that the price of capital ($P_k$) does not exceed the price of labor ($W_n$). [18] In addition, I assume that the cost of capital does not

[18] Acemoglu and Restrepo (2018b) argue that labor has a strict comparative advantage in tasks with a higher

vary across cities. Thus, the optimal demands for labor and capital do not depend on the city size $L_n$, but only on the level of automation. The cost of performing a task $\tau$ in city $n$, $p_n(\tau)$, is:

$$p_n(\tau) = p(\tau) = \frac{P_k}{\eta} \quad \tau \leq T(\omega) \tag{1.14}$$

$$p_n(\tau) = \frac{W_n}{\gamma} \quad \tau > T(\omega) \tag{1.15}$$

The optimal production location for a firm is influenced by two forces: a dispersion force and an agglomeration force. The dispersion force is $W_n$, which is higher in larger cities and acts as a barrier for all firms locating in larger cities. However, the agglomeration force, which is the external benefits emanating from proximity among firms, encourages the bunching of firms in a single place. Thus, I solve the firm's locational choice problem in two steps. First, I find the labor demand function of a firm by minimizing the labor costs subject to the production constraint.[19] I do not include the cost of capital in the objective function as capital cost does not vary across cities and hence it does not affect the spatial cost minimization. Secondly, after finding a firm's labor demand functions for different cities, I minimize the unit cost of production to determine the optimal location choice for the firm.

The unit cost of production varies across cities as wages and agglomeration benefits are different for different cities. This is given by:

$$c_n(T(\omega)) = \frac{1}{Z_n^{\omega}}\left(\frac{T(\omega)P_k}{\eta} + \frac{(1 - T(\omega))W_n}{\gamma}\right) \tag{1.16}$$

A firm chooses a city size that minimizes its unit cost. The optimal city size is then

index. Consequently, there is a unique threshold of task index below which it is cheaper to produce these tasks using only capital and vice-versa.

[19]detail derivation is given in Appendix A.

determined as:

$$n^*(T(\omega)) = \underset{n}{argmin}\left\{\frac{1}{Z_n^\omega}\left(\frac{T(\omega)P_k}{\eta} + \frac{(1-T(\omega))W_n}{\gamma}\right)\right\} \tag{1.17}$$

The minimized unit cost is:

$$c^*(T(\omega)) = \left\{\frac{1}{Z_n^\omega}\left(\frac{T(\omega)\iota P}{\eta} + \frac{(1-T(\omega))W_n}{\gamma}\right)\right\} \tag{1.18}$$

As $p(\omega) = c^*(T(\omega))$, so the price index becomes:

$$P = \left(\int_{\omega\in\Omega} c^*(T(\omega))^{1-\sigma} d\omega\right)^{\frac{1}{1-\sigma}}$$

The mass of firms in city $n$, $\Omega_n$, is defined as:

$$\Omega_n = \left\{\omega : \frac{(1-T(\omega))W_n}{\gamma Z_n^\omega} = min\left\{\frac{(1-T(\omega))W_n}{\gamma Z_{n'}^\omega}\right\}, n' = 1, 2, \ldots, N\right\} \tag{1.19}$$

The expected level of automation in city $n$, $T_n$, is:

$$T_n = E\{T(\omega)|A_n\}$$

### 1.3.4 Housing market

There is an exogenous number of cities in the economy. The sizes of these cities are endogenously determined, based on the cities' characteristics and the benefits offered to workers and firms. Housing supply is perfectly elastic, which implies that housing rent is equalized across cities. The housing market equilibrium is characterized by:

$$L_n\frac{\beta W_n}{R} = H_n \tag{1.20}$$

### 1.3.5 Spatial equilibrium

**Definition:**The equilibrium in this spatial economy is a menu of city level wages $W_n$, allocation of labor $L_n$, and a distribution of firms across cities, as functions of $A_n$, $H_n$, and $\iota$ that satisfies the following conditions:

1. Individuals choose a city to maximize the indirect utility given in Equation (1.8):

2. Firms choose a production location to minimize their unit costs of production given in Equation (1.17).

3. The local labor markets and the capital market clear: the city-level labor demand equals the labor supply, and the capital stock satisfies the aggregate resource constraint:

$$L_n^d = L_n \tag{1.21}$$

$$K = \frac{(1 - \int_\omega p(\omega)^{-\sigma} P^{1-\sigma} d\omega) \sum_n W_n L_n}{(1 - P_k \int_\omega p(\omega)^{-\sigma} P^{1-\sigma} d\omega)} \tag{1.22}$$

   Where equation (1.22) for capital stock is derived from the conditions: $Y = \sum_n W_n L_n + P_k K$ and $Y = X + K$.

4. Capital prices are equalized across cities.

5. The housing market clears.

I can prove the existence and uniqueness of the equilibrium. Here I have an integer number of cities; however, the proof can be generalized for a non-integer number of cities as is standard in the literature (Behrens et al., 2014).

**Proposition 1:** *The spatial equilibrium defined in this section exists and the equilibrium is unique.*

The proof is contained in Appendix A. In my model, two fundamentals provide a non-degenerate distribution of firms across space: the city's exogenous productivity and the firm's heterogeneous productivity across cities. Exogenous city productivities rank cities in terms of their relative attractiveness, and firms' city-specific productivity ensures not all firms choose the most productive city to locate in. However, if a firm draws similar productivity for two cities, then it chooses the city with the largest exogenous productivity. Here, firms' heterogeneous city-specific productivities are necessary to guarantee a non-degenerate firm distribution, but exogenous city productivity is not crucial in this regard. Nevertheless, exogenous city productivity is needed to connect city size and expected city-level automation, as I summarize in Proposition 2 below.

### 1.3.6 Characterization of the equilibrium

In this section, I derive the implications of the model regarding the effect of changes in the automation frontier $T(\omega)$ for the equilibrium.

**Proposition 2:** *$L_n$ and $T_n = E\{T(\omega)|A_n\}$ are increasing in $A_n$. Therefore, larger cities have lower RTI.*

The formal proof of proposition 2 is in Appendix A. When a firm draws a large value of $T(\omega)$, it performs a greater fraction of tasks using capital, and since the price of capital is the same across cities, it can lower the total cost of production by locating in a large city which will offer greater agglomeration benefits. On the other hand, when the firm chooses a large city as a production location, it also faces a higher wage rate. Since the labor requirements are lower for larger $T(\omega)$, labor costs do not increase significantly unless the firm chooses a highly productive location . This implies that a firm chooses the production location with larger $A_n$ for higher values of $T(\omega)$, i.e., more automated firms sort into most productive cities. Hence, city level expected value of $T(\omega)$ at different $A_n$, $T_n = E\{T(\omega)|A_n\}$, is increasing in $A_n$. Similarly, more productive cities are also larger in size as endogenous agglomeration benefits are larger in cities with greater $A_n$. This implies that city size, $L_n$, and the city-level $T_n$ are positively correlated. If we assume that a higher level of automation coincides with less routine tasks performed by workers, this implies that the RTI is lower in larger cities, which is consistent with the stylized fact 1.

**Proposition 3:** *A uniform increase in the level of the automation frontier for all firms,* $T'(\omega) > T(\omega)\ \forall\ \omega$*,*

*(i) Increases the number of firms in cities with larger* $A_n$*.*

*(ii) Increases the city-wide automation level* $T_n$ *in cities with larger* $A_n$*.*

*(iii) Increases wage dispersion across cities.*

The formal proof of proposition 3 is in Appendix A. Proposition 3$(i)$ states us that when all firms have greater automation possibilities, it is optimal for some firms to relocate to more productive locations. So there is an increase in the automation frontier if the mass of firms increases in cities with greater $A_n$. To illustrate the intuition of this proposition, suppose for a given value of automation frontier $T(\omega)$, a firm chooses a production location that minimizes its effective cost of labor, i.e., $\frac{(1-T(\omega))W_n}{\gamma Z_n^{\omega}}$. Here the chosen production location is optimal, and it balances the opposite effects of wage and agglomeration benefits with respect to city size. Now, if this firm has a higher automation possibility, $T'(\omega) > T(\omega)$, because of improvement in technology, the firm can lower its total cost of labor by utilizing the increased automation potential. As a result, the effective total cost of labor is likely to be lower in a more productive location compared to the initial location because moving to a more productive city will allow the firm to exploit the full agglomeration benefits as before, but the firm does not have to incur the same labor cost as the labor requirement is lower now. Thus, if all firms have a higher level of automation potential than before, many firms would optimally choose more productive cities. Consequently, the number of firms will increase in the most productive cities, cities with a higher $A_n$, and decrease in less productive cities.

The intuition behind $3(ii)$ follows. The firms with the largest $T(\omega)$ are the most likely to move to a more productive location, so $T_n$ is increasing in $A_n$, as less productive places will lose the most automated firms when the automation frontier increases across firms.

To understand Proposition $3(iii)$, note that when the automation frontier increases uniformly for all firms, there are two effects on the spatial labor demand. First, all firms require less labor in their production processes, which lowers the demand for labor across cities. Second, following the increase in the automation frontier, some firms optimally choose more productive cities, which causes the labor demand to decrease in less productive cities and increase in cities with greater $A_n$. Thus, less productive cities face lower labor demand both because of technological change and of emigration of firms, whereas cities with larger $A_n$ suffer a loss in labor demand only because of the use of more automated technologies but significantly gain in labor demand from the immigration of firms attracted to their greater productivity advantages. Thus, more productive cities will face a net increase in labor demand following a uniform increase in the automation frontier. Consequently, the equilibrium wage will increase in cities with greater $A_n$ but decrease in cities with smaller $A_n$. Thus, this will increase the range of wages paid across different cities and hence, the standard deviation of city-level wages will also increase.

To summarize, this section presents a simple model that generates predictions consistent with the stylized facts. The model predicts that more automation will lead to a greater agglomeration of firms in more productive cities. More productive cities increase in size, while less productive cities shrink. Most importantly, the model provides predictions about the effect of increased automation on wage inequality across cities.

## 1.4 Quantitative analysis

In this section, I quantitatively estimate the magnitude of the effects predicted in Propositions 2 and 3. To estimate the model, I need to assign values to the expenditure share on housing $\beta$, the shape parameter of the fričhet distribution of agents' idiosyncratic preferences for cities $\nu$, agglomeration elasticity with respect to city size $\theta$, capital production technology $\iota$, capital productivity $\eta$, labor productivity $\gamma$, and elasticity of substitution between varieties $\sigma$, to the parameters of the firms' automation frontier distribution $T(\omega)$, to the firm's city-specific productivity distribution $z_n^{\omega}$, and to the city specific exogenous productivity distribution $A_n$. I take some of these parameter values from the literature and estimate the others.

### 1.4.1 Direct calibration

I calibrate the following parameters using values from the existing literature: $\beta$, $\theta$, $\iota$, $\eta$, $\gamma$, and $\sigma$. Table 1.1 reports the calibrated parameter values and their sources. The value of expenditure share on housing, $\beta$, is taken from the Bureau of Labor Statistics' 2019 report of consumer expenditures on major expenditure categories (BLS, 2019). The report provides the share of housing expenditure for different types of households, which varies from a minimum value of 30.7% for a married couple with children to a maximum of 35.9% for a single person. Since my model considers a single individual as a household, I fix the value of $\beta$ to 0.35. The literature provides a wide range of values for the agglomeration elasticity parameter $\theta$. I choose the most recent estimate provided by Redding and Turner (2015), $\theta = 0.1$. Similarly, the elasticity of the substitution parameter $\sigma$ has also a broad range of estimates. The widely used estimate of $\sigma$ is provided by Broda and Weinstein (2006). This study estimates the elasticity of substitution for different industries and for different aggregations of product varieties. They find a smaller value for $\sigma$ for less disaggregated varieties. Since I use only industry-level data instead of firm level data, I use a lower value for $\sigma$. Brynjolfsson and Hitt (2003) estimate the labor productivity parameter $\gamma$ using micro data from Compustat and International Data Group (IDG). They also compute the combined productivity, $\eta$, of physical capital and computers using the same data set. I use their estimates to fix the values of $\gamma$ and $\eta$.

**Table 1.1:** Calibration of parameter values

| Name | Definition | Value | Source |
|---|---|---|---|
| $\beta$ | Expenditure share on housing | 0.35 | consumer expenditure–2019, 2019 BLS |
| $\theta$ | Agglomeration elasticity | 0.1 | Redding and Turner (2015) |
| $\sigma$ | Elasticity of substitution | 4.0 | Broda and Weinstein (2006) |
| $\gamma$ | Labor productivity | 0.75 | Brynjolfsson and Hitt (2003) |
| $\eta$ | Capital productivity | 0.22 | Brynjolfsson and Hitt (2003) |

### 1.4.2 Estimation: $\nu$ and $\iota$

I estimate the shape parameter of the frićhet distribution of agents' idiosyncratic preferences for cities $\nu$ and capital production technology $\iota$ by using data from several sources. First, the shape parameter of Frećhet distribution ($\nu$) is estimated using a panel fixed effect regression as follows. The model provides a relationship between labor supply and wage at the city level as in equation (1.10), where is the only unknown parameter. So, using the data on observable quantities such as city size, city-level average wage, and other city characteristics, I can estimate the parameter $\nu$. Taking log on both sides of equation (1.10):

$$lnL_n = lnL - ln\sum_{n=1}^{N} W_n^{\nu} + \nu lnW_n + \psi X_n + e_n \tag{1.23}$$

Here the vector $X_n$ includes characteristics: city-level median age and the education of workers, and the fraction of white employees to estimate. In equation (1.23), $lnL - ln\sum_{n=1}^{N} W_n^{\nu}$ does not vary across cities; hence this is the constant term of the regression. To estimate the equation (1.23), I need data on city level population, wages, and the vector of city-specific characteristics, X. IPUMS data provides information on wages, average wage of all individuals living in the city, and the controls in X. I use county-level data from the US census to measure city-level population. The results of the estimation of Equation (1.23) are shown in Appendix Table A.6. The estimates of $\nu$ range from 1.26 to 1.75 for different specifications. Thus, I set the value of $\nu$ to 1.5, which falls in the middle of the range.

The other parameter that I estimate is the capital production parameter ($\iota$), which represents the amount of output needed to get one unit of capital. I obtain firm's revenue, capital invested, and expenses on wages and salaries from Compustat. I then estimate the following regression:

$$lnR_i = \alpha_0 + \alpha_1 lnK_i + \alpha_2 lnL_i + e_i \tag{1.24}$$

Equation (1.24) provides revenue (R) elasticities with respect to capital expenditure ($\alpha_1$) and labor expenditure ($\alpha_2$) [20]. However, I need to estimate $\frac{dK}{dR}$. Thus, using the estimate of $\alpha_1$ from regression Equation (1.24), I can write:

$$\alpha_1 = \frac{d(R)}{d(K)}\frac{K}{R} = \frac{d(pq)}{d(p_k k)}\frac{p_k k}{pq} = \frac{dq}{dk}\frac{k}{q} \tag{1.25}$$

where revenue ($R$) is price ($p$) times output ($q$) and capital expenditure ($K$) is price of capital ($p_k$) times the quantity of capital ($k$). Also, the price of capital, $p_k$, can be written as $p_k = \iota P$, where $p$ and $p_k$ are assumed to be constant determined by the market and technological constraint. Thus, I fix the value of $\iota$ as follows:

$$\iota = \frac{1}{\alpha_1}\frac{k}{q} = \frac{1}{\alpha_1}\frac{K/p_k}{R/p} = \frac{1}{\alpha_1}\frac{K}{R}\frac{p}{\iota p} \tag{1.26}$$

where I use the relationship $p_k = \iota \times p$. Hence, the value of $\iota$ is finally determined by all observable quantities as follows:

$$\iota = \sqrt{\frac{1}{\alpha_1}\frac{K}{R}} \tag{1.27}$$

[20] I use variables in logarithmic form instead of level form because there is significant non-linearity in the relationship between $R$ and $K$.

The results of regression 1.24 are shown in Appendix Table A.7. The estimate of $\alpha_1$ is 0.92 without controlling for labor expenses and 0.85 after controlling for labor expenses. Considering the value of $\alpha_1$ to be 0.85 and using the mean value of $R$ and $K$, I obtain

$$\iota = \sqrt{\frac{1}{\alpha_1}\frac{K}{R}} = \sqrt{\frac{1}{0.85}\frac{6875.88}{3907.89}} = 1.44.$$

### 1.4.3 Estimation: Distributions

To compute the model numerically, I need to specify the parameters of the distributions of T($\omega$), $z_n^\omega$ and $A_n$. First, I assume that the automation frontier $T(\omega)$ follows a uniform distribution: [21] $T(\omega) \sim U(0, b)$. I use the IPUMS data to compute the RTI score of workers in 2019. The standard deviation of the average RTI at the city-level is around 0.13 and the mean is about -1.6. I choose the parameter $b$ to match the mean and the standard deviation of city-level, RTI[22] and get $b = 0.50$. [23]

Second, I assume that the city-specific exogenous productivity $A_n$ is log-normally distributed. [24] I use a specification similar to Diamond (2016) to decompose city-level productivity into its endogenous and exogenous components as follows:

$$lnW_n = \beta_0 + \beta_1 lneduc_n + \beta_2 RTI_n + lnA_n \tag{1.28}$$

where $lnW_n$ is the log of city level average wage, $educ_n$ is the log of city level average education level, $RTI_n$ is the city level measure of automation, and $A_n$ is the city level exogenous productivity. Here $lneduc_n$ and $RTI_n$ determine the city level endogenous

[21] I estimate the distribution of $T(\omega)$ directly from the IPUMS data, where parameter $b$ in the distribution of $T(\omega)$ matches the standard deviation of RTI. The distribution of RTI approximately follows a uniform distribution when normalized between 0 and 1. This empirical distribution of $RTI$ is given in the appendix in Figure A·7

[22] Matching parameter $b$ with the standard deviation of RTI allows to link observable quantity $RTI$ with model's measure of automation.

[23] b is between $0.13 \times \sqrt{12} = 0.45$ and $\frac{1}{|-1.6|} = 0.62$.

[24] I assume that $An$ follows a log-normal distribution, which is a result of the Zipf's law and Gibrat's law, and many studies show that the city size distribution follows Zipf's and Gibrat's laws (Rosen and Resnick, 1980; Dobkins and Ioannides, 2001; Ioannides and Overman, 2003; Gabaix and Ioannides, 2004).

productivity. I estimate equation (1.28) treating $A_n$ as the error term. I then use the $exp(A)$ as a measure of city-level exogenous productivity, $A_n$. Appendix Table A.8 provides the fixed effect panel estimates of regression Equation (1.28). Estimates of these different specifications of regression Equation (1.28) provide a similar distribution of residuals, which I treat as the measure of $lnA_n$. This distribution is shown in Appendix Figure A·8. The estimated distribution of $lnA_n$ has mean 1.032 and standard deviation 0.277.

Third, I need to estimate the parameters of the distribution of city-specific productivity, $z_n^\omega$. I assume this distribution is log-normal: $z_n^\omega \sim lognormal(\mu, \sigma^2)$. To estimate the $\mu$ and $\sigma^2$, I follow two steps: first, I estimate the city-specific industry's overall agglomeration benefits, $Z_n^\omega = z_n^\omega A_n L_n^\theta$, as the share of industry's employment in city's total employment: $Z_n^\omega = \frac{E_n^\omega}{E_n}$ , where $E_n^\omega$ is the employment in $\omega$ and $E_n$ is the total employment in city n. I then estimate the equation (1.29):

$$Z_n^\omega = \alpha_0 + \alpha_1 lnA_n + \theta lnL_n + lnz_n^\omega \tag{1.29}$$

where I can observe all the variables except $z_n^\omega$, so I treat it as an error term in the regression. I then use the residuals of this regression as the measure of $z_n^\omega$. The results are shown in Appendix Table A.9. This distribution is shown in Appendix Figure A·9. The distribution has a mean of 1 and standard deviation of 0.02.

### 1.4.4 Simulation results

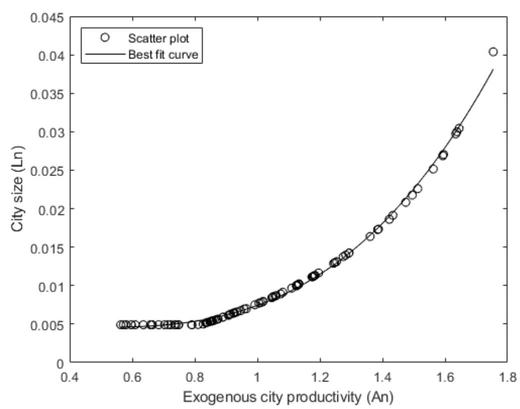
In this section, I describe the simulation results of the equilibrium for the parameter values specified in the previous. The objective of this simulation is to numerically estimate the relationship between city size and city-level automation as summarized in Proposition 2. I use these simulation results as baseline estimates and conduct a counterfactual analysis by increasing the automation frontier of firms and then compute the effects of this increase in the level of automation on the spatial distribution of firms and the wage inequality across cities. The details of the counterfactual analysis are presented in the next section.

**City productivity, city size, and automation**

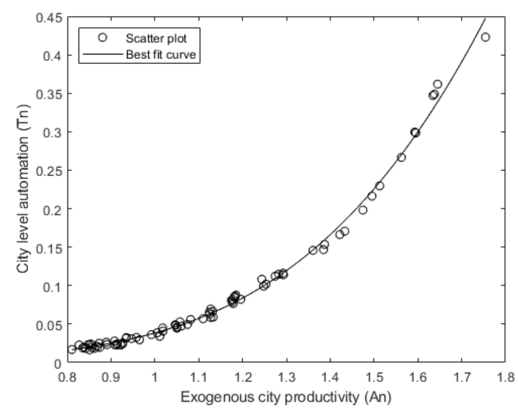
I first present the model's numerical results about the relationships between exogenous city productivity, city size, city-level automation and RTI. Figure 1·5a shows that city size $L_n$ is an increasing and convex function of city's exogenous productivity $A_n$. Many studies identify several reasons for the existence of large urban areas. Rappaport (2008) shows that differences in city sizes can be attributed to cities' total factor productivity. In addition, Lee and Li (2013) identify exogenous factors such as climate, geographic features, and industrial composition as important drivers of city size. The average effect of these exogenous factors is captured in my model by the exogenous city productivity variable, $A_n$.

**Figure 1·5:** City size and city-level automation are increasing in city's exogenous productivity

**(a)** Cities with greater exogenous productivity are larger in size




**(b)** Cities with greater exogenous productivity have higher average automation




Note: Figure 1·5aplots the exogenous city productivity $A_n$ and the equilibrium city size $L_n$, and figure 1·5b plots the city-level automation $T_n$, the average of all firms' level of automation locating in the city, and exogenous city productivity $A_n$.

The most important and novel result of my model is the relationship between city productivity, city size, and the expected level of automation of all firms residing in the city, $T_n$. The relationship between $A_n$ and expected city-level automation $T_n$, as shown in

Figure 1·5b, is very similar to the relationship between $A_n$ and $L_n$.

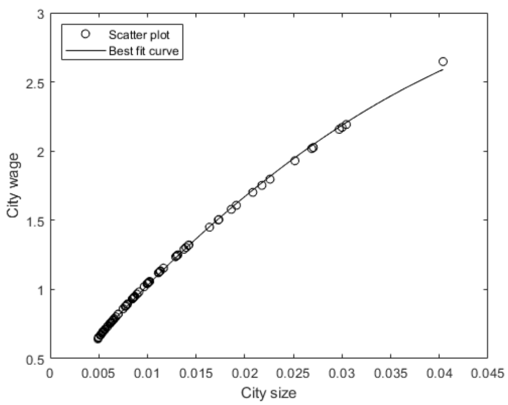
Automation in my model is defined by the level of capital/labor ratio and increase in automation means a higher magnitude for capital/labor ratio. Thus, a positive relationship between average city level automation and city size suggests a larger capital/labor ratio in larger cities. Many previous empirical studies document this relationship. Segal (1976) argues that one of the important determinants of observed higher output per worker in larger cities is a larger capital/labor ratio. He indicates that the capital/labor ratio may increase with city size, and higher ratios of money wages to profit rates in larger cities would imply higher capital/labor ratios. Broersma and Oosterhaven (2009) find a positive relationship between city size, productivity, and capital/labor ratio. They find about half of the explained variation in the labor productivity within the Netherlands in the 1990s is because of urbanization. Farazmand et al. (2015) use the US Census of Manufacturing 2007 to estimate the elasticity of substitution between capital and labor. They find a significant impact of city size on the elasticity of substitution between capital and labor.

**City size, wages, and number of firms**

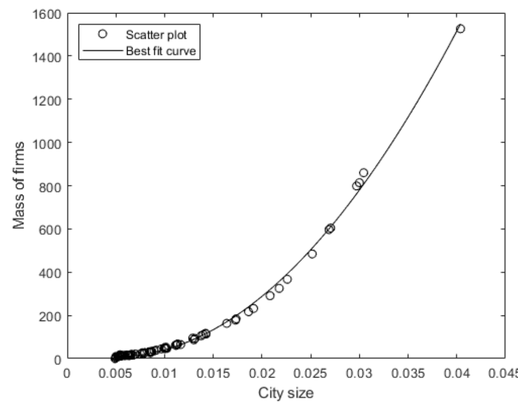
Numerical results of the model show a positive correlation between city size and city-level wage (Figure 1·6a). That is, large cities have higher wages (urban wage premium).

**Figure 1·6:** Wages and number of firms are increasing in city size

**(a)** Wages are higher in larger cities




**(b)** Number of firms is larger in bigger cities




Note: Figure 1·6a plots the city-level equilibrium wage $W_n$ and city size $L_n$, and figure 1·6b plots the equilibrium number of firms $\Omega_n$ and city size $L_n$.

A large and growing empirical literature provides evidence supporting the urban wage premium. Glaeser and Mare (2001) find that US cities with a population of at least 1 million have about 36 percent higher average wages, and smaller cities have about 21 percent lower wages as compared to surrounding areas. Rosenthal and Strange (2004) find that a doubling of the urban population drives a 3-8 percent increase in productivity, and hence wages. Similar results are also reported for different countries, other than the US. For example, Combes et al. (2008) report that wages in Paris are on average 15% higher compared to other large cities, and up to 35 and 60 percent higher than in midsize cities and rural areas, respectively. In a meta-analysis, Melo et al. (2009) use results from 34 studies and estimate the elasticity between city size and productivity/wage. They found that the elasticity between urban agglomeration and wage is about 6 percent. Recent studies have also found evidence of a positive correlation between city size and wage (Baum-Snow and Pavan, 2012a,b; Pan et al., 2016; Korpi and Clark, 2019).

The model produces a positive and convex relationship between city size and the number of firms (Figure 1·6b). Several studies confirm this relationship empirically. Using data on

22 Danish towns, Kristensen (1991) shows that larger city size leads to greater concentration of firms in the city. Similar results have been obtained by many other papers (Black and Henderson, 1999; Henderson et al., 2001; Mascarilla and Yegorov, 2005).

## 1.5 Counterfactual analysis

In this section, I use the calibrated model to investigate the effects of further increases in the level of automation on the spatial distribution of firms and on wage inequality across cities. The model provides precise predictions about these effects. Proposition 3 states that a uniform increase in the level of automation frontiers raises the agglomeration of firms in larger cities and lowers it in smaller cities. In addition, it predicts that a similar change in the level of automation increases wage dispersion. Here I give a quantitative context to these predictions. For this purpose, I compute the equilibrium of the model under a counterfactual scenario where firms' automation potential is higher than in the calibrated model, and compare the results with the baseline equilibrium.

The baseline automation frontier has a uniform distribution between 0 and 0.5, $T(\omega) \sim U(0, b)$, where $b$ is 0.5 and is estimated by matching the mean and standard deviation of city-level RTI values in 2019. To determine the counterfactual value of $b$, I first compute the change in city-level RTI over the last two decades. Thus, using the values of RTI in 2000, I estimate the corresponding value of parameter $b$, which is about 0.42. This implies that over the last two decades the parameter $b$ in the automation frontier distribution increases from 0.412 to 0.5, which is about 20% increase. So, I fix the counterfactual value of $b$ to 0.6, which is also about 20% increase in the level of automation from its baseline value of 0.5 in 2019.

Proposition 3 states that an increase in automation potential drives an increase in the agglomeration of firms in large cities. To show this, I estimate the percentage change in the equilibrium number of firms at each decile of the spatial distribution of firms. The results are shown in Figure 1·7.

**Figure 1·7:** Midsize cities suffer greater loss in the mass of firms than other cities when the automation potential increases uniformly across firms

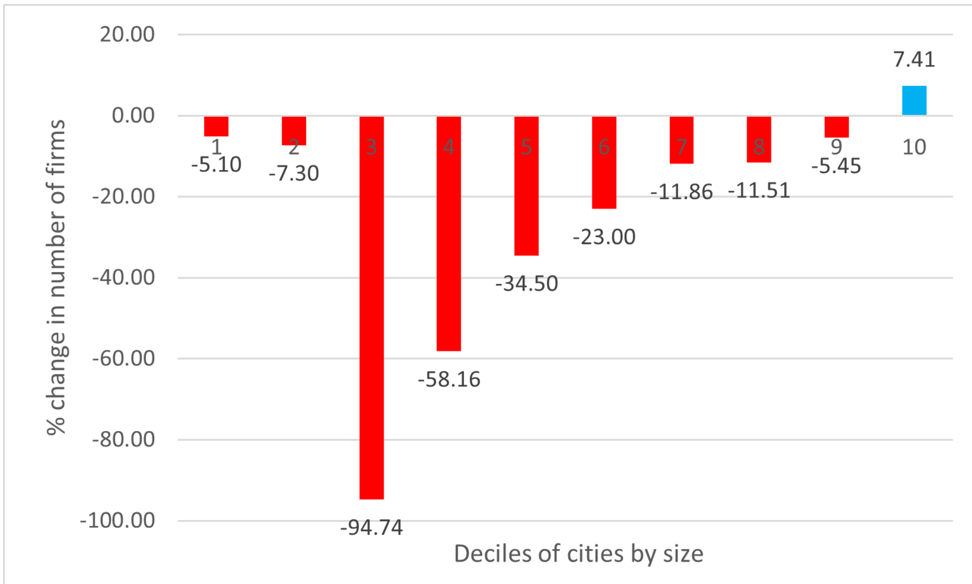


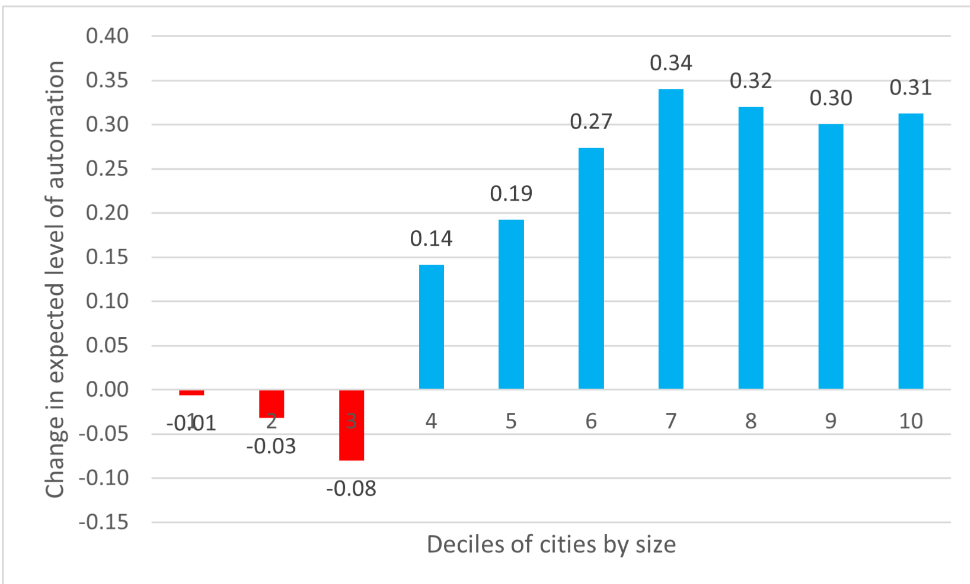

Figure 1·7 shows that, when automation potential increases uniformly across firms, the number of firms in midsize cities drops while it rises in larger cities. [25] It illustrates that automated firms move to the largest decile of city sizes. This gives rise to a few superstar cities with more firms.

Many recent studies find similar empirical evidence across the world. Kemeny and Storper (2020) analyze the US data and find empirical evidence in support of this result. They argue that recurrent waves of major technological shocks change the demand for skilled workers performing complex tasks and help create superstar cities offering significantly higher wages and standards of living. Similarly, Manyika et al. (2018) analyze 3,000 of the world's largest cities, each with a population of at least 150,000 and $125 million GDP. They find that the 50 superstar cities are among the most innovative and digitally smart cities.

[25] In the first two deciles of city-size distribution, the change is small because these cities are tiny in size in the baseline calibration. Changes in the absolute number of firms are shown in Appendix Figure A·10.

Proposition $3(ii)$ states that the expected value of city-level automation $T_n$ increases in larger cities following a uniform increase in automation frontier. To illustrate this, I compute the change in average city-level automation at each decile of city size. The results are shown in Figure 1·8, which shows that cities in the lowest size deciles experience a fall in average city-level automation, $T_n$, whereas cities in upper deciles have a greater average level of automation when the automation frontier increases uniformly.

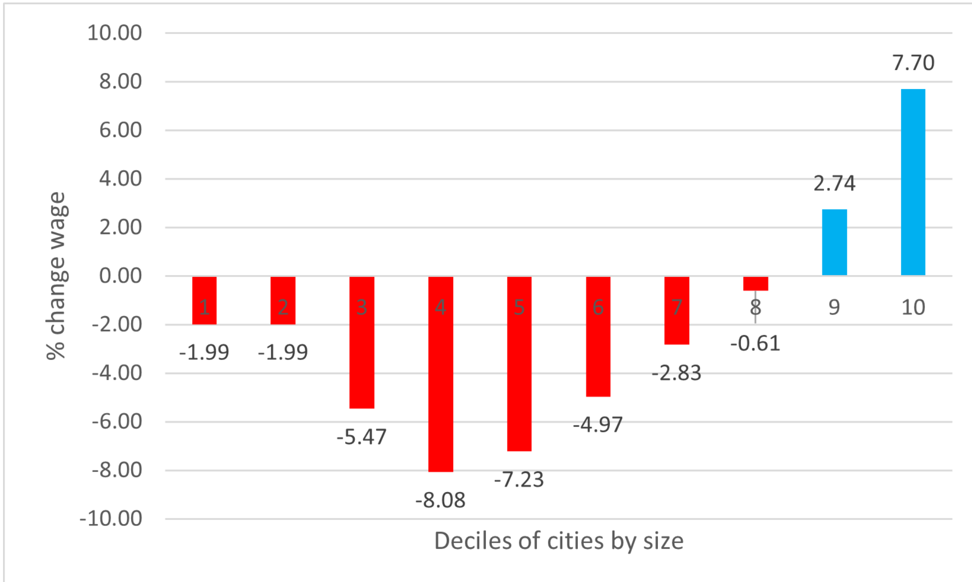
**Figure 1·8:** Larger cities have positive change in the level of Expected automation




The reason for these differential effects of a uniform increase in the automation frontier on average city-level automation is that most automated firms sort into larger and more productive cities leading to an increase in average automation in larger cities and decrease in smaller cities.

Proposition $3(iii)$ predicts that a uniform increase in the automation frontier will lead to a greater dispersion in wages. Figure 1·9 shows the percentage change in average wages cross deciles of city sizes. Here, 20% increase in the automation frontier widens the wage gap by more than 15%, thus, raising regional wage inequality significantly.

**Figure 1·9:** Wage dispersion rises following an uniform increase in automation potential




Many recent studies have investigated the effect of an increase in automation on wage inequality between high-skilled and low-skilled workers. Hémous and Olsen (2014) introduce the use of machines that replace low-skilled labor and complement high-skilled labor in an endogenous growth model and find that an increase in automation investment reduces the future growth rate of low-skilled wages, even turning the growth rate to negative, and the total labor share of low-skilled workers. Lankisch et al. (2019) analyze the effects of automation on wages of high-skilled and low-skilled workers. Their simulated model shows that the increase in automation leads to a decline in real wages of low-skilled workers and increases the skill premium.

Zhang (2019) argues that an acceleration in automation generates the displacement effect and the capital reallocation effect, and generally the displacement effect is larger than the capital reallocation effect, which widens the wage gap between skilled and unskilled labor. Acemoglu and Restrepo (2021) find that about 50% to 70% of changes in the US wage structure over the last four decades are due to a decline in wages of workers performing routine tasks in sectors with rapid growth in automation. The model in this paper provides a different but complementary angle to look at wage inequality emanating from increasing adoption of automation. It brings spatial insights into the picture and illustrates that the rise in automation can also geographically separate high-paid and low-paid workers.

## 1.6 Concluding remark

In this paper, I provided new stylized facts about the relationship between the size of a city and the intensity of routine-tasks performed in it. I interpret a decline in the presence of routine tasks as an increase in automation in a location and developed a general equilibrium spatial model to investigate the effects of an increase in automation (or a fall in routineness of tasks) on the distribution of economic activity and on regional wage inequality. Equilibrium analysis of the model provides several predictions about the impact of increased automation on wage dispersion across cities, which are consistent with stylized facts and with existing empirical evidence. I examine the effects of a counterfactual uniform increase in automation and show that a greater automation potential can lead to a greater agglomeration of firms, higher wages, and a greater expected level of automation in larger cities, while the effects are reversed in smaller cities. Precisely, the model predicts that wage dispersion across cities could increase more than 15% when the level of automation increases uniformly by 20% from the current level.

The model in this paper can be used to study the effects of changes in other forces of agglomeration, such as face-to-face learning, knowledge spillover, specialized skill requirements, availability of input suppliers, etc., on regional wage dispersion. Another avenue of future work is to investigate the effect of a pandemic, such as the Covid-19 that limits the scope of in-person work, on the adoption of the automation technology and on regional wage inequality. Exploring the effects of the interaction between automation technology and work-from-home technology on the spatial distribution of economic activity is particularly interesting.

# Chapter 2

# Exchange Rate Uncertainty, Margins of Trade and Income Distribution

## 2.1 Introduction

One of the longstanding questions in international economics is "how does the volatility in exchange rate affect the volume of trade?" The question is crucial since if there were a channel through which exchange rate volatility could affect the volume of trade and the number of firms involved in trade, then the choice of exchange rate regime could be used as a valuable tool for trade policy. Notwithstanding that the choice of exchange rate regime may depend on many other factors and may cause various economic effects, this study provides new results on the impact of exchange rate volatility on trade margins, which helps to correctly estimate the costs and benefits of any exchange rate regime. Under the assumption that agents are risk-averse, the economic reasoning suggests that when agents face uncertainty about prices, they contract their economic activities. Analogously, in an open economy, when a risk-averse firm faces uncertainty about the exchange rates with its trading partners, she would reduce the volume of trade.

In this paper, I explore this age-old issue. However, rather than focusing on the volume of trade, I attempt to entangle the effect of exchange rate volatility on the intensive and extensive margin of trade separately. This enables us to investigate the effect of exchange rate volatility not only on the volume of trade, but also on the income distribution in a given sector or industry. For example, if uncertainty in the exchange rate allows only a few firms to be able to export, then the income distribution may become more skewed. The reason for this is that workers are generally paid higher wages in exporting firms (Bernard et al., 2007) and lowering the number of exporting firms will make the income distribution more skewed. To investigate the effect of exchange rate volatility on the intensive and extensive margin of trade, we need to solve the problem of a trading firm about whether to enter into an export market, and if enters then how much to export, given the uncertainty in the exchange rate. For this purpose, I use the Helpman, Itskhoki, and Redding (HIR) (2010) framework and add the exchange rate friction to it.

The HIR framework combines the Melitz (2003) model with Diamond-Mortensen-Pissarides search and matching frictions. The HIR framework also introduces an *ex post* match-specific heterogeneity in a worker's ability. Here firms cannot directly observe the ability of the matched workers, so they screen workers to increase the average ability of their hires; for this purpose, they need to bear some screening costs. This *ex post* match specific screening provides some bargaining power to workers and so instead of a fixed wage, workers receive some share of revenue which is determined by Nash bargaining between the firm and its workers. I introduce a real exchange rate variable into the HIR framework and assume that firm owners are risk averse and maximize their expected payoff.

The model in this paper suggests that both the intensive margin of export and the number of exporting firms are decreasing in exchange rate volatility. The model also shows that firm's size determined by the productivity cutoff is positively related to exchange rate volatility. This implies that the income distribution will be more positively skewed under a more volatile exchange rate regime, leading to higher income inequality. In the final part of the paper, I use firm level data to test these predictions empirically. I find robust empirical evidence that exchange rate volatility does indeed depress the intensive and extensive margin of trade, i.e., higher exchange rate volatility leads to a lower fraction of firms' output being exported and a smaller fraction of firms being able to participate in the export market. This implies that overall trade volume will also be negatively affected by exchange rate volatility. However, empirical evidence about the effect of exchange rate volatility on income distribution is not clear and requires further investigations.

The dominant result of previous empirical studies is that the trade volume is relatively lower under floating exchange rate regime, which indicates that the exchange rate volatility has an adverse effect on trade (Cushman, 1983; Akhtar & Hilton, 1984; Koray & Lastrapes, 1989; Caballero & Corbo, 1989; Lastrapes & Koray; 1990; Asseery & Oeel, 1991; Kumar and Dhawan' 1991; Bini-Smaghi,1991; Chowdhury, 1993; Kroner & Lastrapes, 1993; Caporale & Doroodian; Hook & Boon, 2000; Doganlar, 2002; Arize, Malindretos & Kasibhatla,2003; Baak, 2004; Lee & Shin, 2004; Arize, Osang & Slottje, 2005;Lee and Saucier, 2007). This empirical result provides support to initial theoretical models that predict the possible negative impact of exchange rate volatility on the volume of trade (Ethier, 1973; Clark, 1973; Baron, 1976; Cushman, 1986; Peree & Steinherr, 1989; Viane & Vries, 1992).

However, many of these studies are prone to problems of the definition and classification of exchange rate pegging (direct or indirect) and used multilateral trade in which indirect pegging[1] may not be very effective. Hence, some studies focused only on bilateral trade and the degree of bilateral exchange rate fluctuations. These studies find no or a weak relationship between exchange rate volatility and trade, and only significant impact in some specific sector such as agriculture (Gotur, 1985; Bailey, Tavlas & Ulan, 1986; Bailey & Tavlas, 1988; Mann, 1989; Medhora, 1990; Feenstra & Kendall, 1991; Wang & Barrett, 2002; Hwang & Lee, 2005). Furthermore, some other papers even find positive correlation between the exchange rate volatility and the trade volume (McKenzie & Brooks, 1997; McKenzie, 1998; Kasman & Kasman, 2005). Theoretical models are also proposed to explain this counter-intuitive empirical results (Hooper & Kohlhagen, 1978; De Grauwe

[1]In indirect pegging, the domestic currency is used as base currency and foreign currency is quoted per domestic currency.

1988; Franke, 1991; Secru & Vanhulle 1992; Gagnon, 1993; Bacchetta and Wincoop, 1998; Sercu and Uppal, 2003).

A new trend in empirical research of exchange rate volatility and trade is the use of the gravity model. However, this new development in empirical research has also failed to establish unanimity on this issue. Different researchers find contrasting empirical results. Nevertheless, most of the studies finds a negative relationship between the exchange rate volatility and trade volume (Dell'Ariccia, 1999; Frankel & Rose, 2000; Aristotelous, 2001; Klein & Shambaugh, 2006; Adam & Cobham, 2007; Hayakawa & Kimura, 2009; Nuroglu & Kunst, 2012). The main finding of these papers is that any exchange rate regime which leads to lower exchange rate volatility reduces the transaction cost of trade and hence is significantly more pro-trade than any exchange rate regime with higher exchange rate fluctuations.

Some studies argue that the empirical estimation of the gravity equation are incorrectly performed and the statistical significant effect of the exchange rate volatility on the volume of trade is only the outcome of poor econometric specification of the gravity equation (Clark, Tamirisa, & Wei, 2004; Tenreyro, 2007; Baum & Caglayan, 2009). In response to these criticisms, Tenreyro (2007) estimates the gravity model using an instrumental-variable version of the pseudo-maximum likelihood estimator. After estimating the model using a broad sample of countries from 1970 to 1997, she finds that exchange rate variability has no significant impact on trade once the effect of currency union is controlled. She rationalizes the results by noting that the availability of forward contracts, currency options, and other alternatives for risk diversification provide sufficient hedging to reduce the potential negative impacts of exchange rate volatility on trade. Similarly, in this paper, I estimate a gravity type equation for intensive margin of trade using Generalized Method of Moments (GMM) as well as the log version of that equation using Ordinary Least Squares (OLS). I use the GMM estimation to handle the endogeneity problem arising from the serially correlated demand shifters (GDP of trading partners) along with inherent measurement errors in survey data.

Previous empirical and theoretical studies that attempt to find the impact of exchange rate volatility on trade use aggregate variables and data; that is, they consider the aggregate trade of the country. However, the aggregate trade of a country may not be significantly affected by exchange rate volatility if there are only a few highly productive firms which have larger shares of trade so that they can absorb any risk posed by the volatile exchange rate. In such situations, exchange rate volatility may cause some small and less productive firms to stop participating in trade, but the overall volume of trade for that country may not fall that much. Hence, from the policy perspective, this indicates that we should investigate the impact of exchange rate volatility separately for the intensive margin (share of each firm's output that is traded internationally) and extensive margin (number of firms involve in international trade) of trade. This paper bridges this gap in exiting literature and contributes in two important ways: it provides separate testable predictions for the effects of exchange rate volatility on the intensive and extensive margin of trade; and it uses the firm level disaggregate data to test these predictions empirically. In addition, it investigates the implications of exchange rate volatility for income inequality within a country.

The rest of this paper is organized as follows: Section 2 provides the model setup and results from the solution of the model. In Section 3, I test the model's predictions using different econometric models. Discussion and conclusion are given in Section 4.

## 2.2 The Model

The basic structure of the model in this paper is similar to the HIR (2010) framework with the additional friction of exchange rate volatility. The HIR combines the framework of Melitz (2003) and Diamond-Mortensen-Pissarides search and matching frictions within this framework. Furthermore, the HIR model introduces *ex post* match-specific heterogeneity in workers ability. A general Cobb-Douglas production function is specified as production technology, which includes both the workers' average ability and the firm specific productivity. This means that firm's specific productivity and workers' average ability are complements. Hence, a highly productive firm has an incentive to hire high ability workers. However, employers cannot directly observe the workers' ability and thus, spend resources on screening the pool of matched workers in order to improve the average ability of the hired workers.

The screening technology is the same for all firms within an economy, so larger firms have greater returns from investment in screening and employing only highly productive workers. This enables more productive firms to have workers of higher average ability than less productive firms. Consequently, it is difficult for highly productive and larger firms to replace their hired workers, and this provides greater bargaining power to workers employed in those firms. As a result, workers in larger and more productive firms get higher wages compared to workers employed in less productive and smaller firms. In an open economy, larger and more productive firms have even higher incentives to screen their workers more intensively to become more competitive in export markets. This causes a natural selection: more productive firms enter into the export market and this makes them become even larger and more productive. Thus, workers in the exporting firms receive significantly higher wages than workers employed in the non-exporting firms.

I introduce the exchange rate into the HIR framework to show the role of exchange rate volatility in firms' decisions regarding hiring and minimum level of worker's ability to screen the matched workers. In addition, I derive predictions regarding the effects of exchange rate volatility on the intensive and extensive margin of export. Deriving the solutions for firm specific variables then allows to define the wage distributions of workers employed by domestic and exporting firms, and hence the impact of exchange rate volatility on the income distribution.

### 2.2.1 Model Setup

Consider a world composed by two countries, Home and Foreign, where foreign variables are denoted by an asterisk. The demand and supply side of the model are described below. Agents consume a continuum of horizontally differentiated varieties with Dixit-Stiglitz preferences. So, the real consumption index for the sector (Q) is given by:

$$Q = [\int_{j \in J} q(j)^{\beta} dj]^{1/\beta}, \quad 0 < \beta < 1$$

Here $\beta = \frac{\epsilon - 1}{\epsilon}$ and $\epsilon$ is the elasticity of substitution. $\beta$ is between 0 and 1 to ensure that varieties are close substitutes. The demand for each variety with the given expenditure in the sector $E = PQ$ is given by:

$$q(j) = A^{\frac{1}{1-\beta}} p(j)^{-\frac{1}{1-\beta}}$$

where $A = E^{1-\beta} P^{\beta}$, p(j) is the price of variety j and P is the general price index given by;

$$P = [\int_{j \in J} p(j)^{-\frac{\beta}{1-\beta}} dj]^{-\frac{1-\beta}{\beta}}$$

Thus, the equilibrium revenue of a firm producing variety j is:

$$r(j) = p(j)q(j) = Aq(j)^{\beta}$$

There is a continuum of workers who are *ex ante* identical. Let y be the output produced be the firm, production function is assumed to have Cobb-Douglas form:

$$y(\theta) = \theta h^{\gamma} \bar{a}, \quad 0 < \gamma < 1$$

where $\theta$ is the firm's productivity parameter, $h$ is the measure of workers hired by the firm and $\bar{a}$ is the average ability of the hired workers. Firms' productivity ($\theta$) and workers' ability follow Pareto distributions given by, respectively;

$$G_\theta(\theta) = 1 - (\theta_{min}/\theta)^z$$

$$G_a(a) = 1 - (a_{min}/a)^k$$

where $\theta \geq \theta_{min} > 0$, $z > 1$, $a \geq a_{min} > 0$ and $k > 1$. Here $z$ is the shape parameter of productivity distribution, and $k$ is the shape parameter of the distribution of workers' ability. Thus, the revenue function can be written as:

$$r(j) = Ay(\theta)^\beta \tag{2.1}$$

The above basic setup of the model is same as in HIR (2010), however, unlike HIR, I introduce the exchange rate into the price equation of HIR. Let $\tau$ be the iceberg trade cost and $\epsilon$ be the exchange rate between domestic currency and foreign currency, i.e., amount of domestic currency per foreign currency. Here $\tau$ is symmetric between country but $\epsilon$ is not. So, we can write:

$$\epsilon p * (j) = \tau p(j) \tag{2.2}$$

where $p$ is the domestic price of the product produced by the firm, and $p*$ is the price of the same product in the export market of the firm. Thus, the left hand side measures the sale revenue from one of the product in export market in domestic currency, and the right hand side is the cost of shipping $\tau$ amount of the product so that the export market receives one unit of the product and the cost is quoted in domestic currency. So, $\tau \geq 1$. Rearranging equation (2) we get:

$$p * (j) = \frac{\tau p(j)}{\epsilon} \tag{2.3}$$

The revenues from domestic sales $(r_d(j))$ and export $(r_x(j))$ can be written as follows:

$$r_d(\theta) = Ay_d(\theta)^\beta \tag{2.4}$$

$$r_x(\theta) = p*(\theta)q*(\theta) = A*\epsilon^\beta \tau^{-\beta} y_x(\theta)^\beta \tag{2.5}$$

In the labor market, workers are assumed to be *exante* homogeneous and wage inequality is within group inequality as in HIR. The labor market is characterized by search and matching frictions. A firm has to pay $bn$ in search costs to have a match with a measure of $n$ workers. In addition, firms spend on screening potential $n$ workers to employ those who satisfy a minimum ability threshold. So, in HIR the screening cost is assumed to have the form: $\frac{c}{\delta}a_c\delta$, where $c > 0$ and $\delta > 0$. Incurring this screening costs, firms can identify workers with an ability below $a_c$. Screening costs are increasing in the ability threshold $a_c$ chosen by the firm as more complex and costlier tests are required for higher ability cutoffs. The cost function of the firm is denoted by C, which takes the following form:

$$C = bn + \frac{c}{a}a_c^\delta - f_d - f_x I_x \tag{2.6}$$

where $b$ is the per worker search cost, $n$ is the number of matches, so $bn$ is the total search costs, $a_c$ is the ability cutoff for *expost* screening by the firm, so $ca_c^\delta/\delta$ is screening cost for cutoff ability $a_c$, $f_d$ is fixed cost of production; $f_x$ is the fixed cost of entering into the export market, and $I_x$ is an indicator variable taking value 1 if the firm exports and 0 otherwise.

Here workers do not receive any fixed wage, rather firm and its employee bargain over the revenue and the solution of this bargaining game as given in HIR (2010) is that the firm receives the fraction $1/(1+\beta\gamma)$ of revenue and each worker receive the fraction $\beta\gamma/(1+\beta\gamma)$ of average revenue per worker.

### 2.2.2 Firm's Problem

Firms are assumed to be risk averse. The optimal decision for a firm to serve only the domestic market or serve both the domestic and export market can be characterized by a condition that equates the marginal revenues from these two markets. The reason is that the marginal cost of production is the same for the domestic and export markets, and there is only some additional fixed cost of export. Hence, the optimality condition is given by;

$$r'_d(\theta) = E[r'_x(\theta)]$$

$$\beta A Y_d(\theta)^{\beta-1} = \beta A * \tau^{-\beta} y_x(\theta)^{\beta-1} E[\epsilon^{\beta}]$$

$$[\frac{y_x(\theta)}{y_d(\theta)}]^{1-\beta} = \frac{A^*}{A}\tau^{-\beta} E[\epsilon^{\beta}] \tag{2.7}$$

Equation (2.7) implies that a firm's export-to-domestic sales ratio is increases as the foreign demand rises or domestic demand falls; expected exchange rate depreciates (larger value of $\epsilon$), and iceberg trade cost falls (lower value of $\tau$). Here the export-to-domestic sales ratio is a measure of intensive margin of trade. Here, a firm's export-to-domestic sales ratio depends on the expected value of a concave function of the exchange rate. So, in this case not only the level but also the volatility of the exchange rate affects the intensive margin of trade. Here, the exchange rate volatility is given by the standard deviation of exchange rates[2].

**Proposition 1:** *For each firm, the ratio of the export-to-domestic sale is decreasing in exchange rate volatility.*

[2]Suppose that $F(\epsilon)$ is some default distribution of $\epsilon$. Now add a noise to $\epsilon$, i.e., $\epsilon' = \epsilon + x$ where $x$ follows a mean zero distribution. Here the distribution of $\epsilon$ and $\epsilon'$, which is denoted by $G(\epsilon)$, have the same mean but the distribution of $\epsilon'$ has a larger variance than the distribution of $\epsilon$. Thus, Second Order Stochastic Dominance implies that for any concave function $u(\dot{})$, we have $U(F) = \int u(\epsilon)dF(\epsilon) \geq \int u(\epsilon')dG(\epsilon') = U(G)$.

Proof of Proposition 1 is given in the Appendix. Proposition 1 shows that any exchange rate regime that lowers the fluctuation in exchange rates will induce each firm to export a larger fraction of total output compared to the fraction of total output exported in a more volatile exchange rate regime. The total output of a firm catering both domestic and foreign market is;

$$y(\theta) = y_d(\theta) + y_x(\theta)$$

Using Equation (2.7), we can write:

$$\begin{aligned} y_d(\theta) =& y(\theta) - \left(\frac{A^*}{A}\tau^{-\beta}E[\epsilon^{\beta}]\right)^{\frac{1}{1-\beta}} y_d(\theta) \\ \Rightarrow y(\theta) =& y(\theta)\left[1 + \left(\frac{A^*}{A}\tau^{-\beta}E[\epsilon^{\beta}]\right)^{\frac{1}{1-\beta}}\right] \end{aligned}$$

Define the following function:

$$\Upsilon(\theta) = 1 + I_x(\theta)(\frac{A^*}{A}\epsilon^{\beta}\tau^{-\beta})^{\frac{1}{1-\beta}} \tag{2.8}$$

Here $\Upsilon(\theta)$ is 1 if the firm is selling only in domestic market, and is greater than 1 if it sells in both markets. $\Upsilon(\theta)$ is concave in $\epsilon$ if $0 < \beta < \frac{1}{2}$, otherwise it is convex in $\epsilon$. Here $0 < \beta < \frac{1}{2}$ implies that the sector in which firm operates does not produce very close substitute varieties. Thus, when $\epsilon$ increases, that is domestic currency depreciates, export increases but less than in proportion and so the $\Upsilon$ rises at a decreasing rate. Now Using Equation (2.8) we can write:

$$y_d(\theta) = \frac{y(\theta)}{\Upsilon(\theta)} \tag{2.9}$$

Similarly, we can write;

$$y_x(\theta) = y(\theta)[\frac{\Upsilon(\theta) - 1}{\Upsilon(\theta)}] \tag{2.10}$$

**Corollary 1:** *The output share of each firm that is sold domestically will increase and the output share of export will decrease as exchange rate volatility rises.*

Proof of Corollary 1 is given in Appendix. Corollary 1 is another statement of the effect of exchange rate volatility on the intensive margin of trade. Corollary 1 implies that even the absolute level of export is decreasing in exchange rate volatility. Combining Equation (2.7), Equation (2.9), and Equation (2.10), the total revenue of the firm can be written as:

$$r(\theta) = Ay(\theta)^{\beta}\Upsilon(\theta)^{1-\beta} \tag{2.11}$$

Here $r(\theta)$ is a concave function of $\Upsilon$ and for $0 < \beta < \frac{1}{2}$, $\Upsilon$ is a concave function of $\epsilon$. Thus, when $0 < \beta < \frac{1}{2}$, $r(\theta)$ will be a concave function of $\epsilon$. The intuition is similar that when firm's product is not very close substitutes, then any increase in $\epsilon$, i.e., a depreciation of domestic currency, would increase $r(\theta)$ but at a decreasing rate. If $\frac{1}{2} < \beta < 1$, then $\Upsilon$ will be a convex function of $\epsilon$ and $r(\theta)$ will be a concave transformation of a convex function of $\epsilon$, so it is not clear whether $r(\theta)$ would be concave or convex in $\epsilon$ for $\frac{1}{2} < \beta < 1$.

since $n$ is the number of firm specific match and $a_c$ is the firm's chosen cutoff of ability screening, so the measure of hired workers, $h$, can be written as $h = n(a_{min}/a_c)^k$ and the average ability of the hired workers is given by $\bar{a} = ka_c/(k-1)$. So, the production function can be written as:

$$y = \kappa_y \theta n^{\gamma} a_c^{1-\gamma k}, \qquad \kappa_y \equiv \frac{k}{k-1} a_{min}^{\gamma k}$$

Here we need $0 < \gamma k < 1$ for a firm to have an incentive to screen. Now, assume that the firm is risk averse so that the utility function of the firm u(.) satisfies $u'(.) > 0$ and $u''(.) < 0$. Thus, firm's objective is to maximize the expected utility from the profit it makes by selling it's product in home and foreign countries. Therefore, following Sandmo (1971) firm's problem can be written as follows:

$$\underset{n\geq 0, a_c > a_{min}, I_x \in \{0,1\}}{\text{Max}} \qquad E[u(\pi(\theta))]$$

Where $\pi(\theta) = \frac{1}{1+\beta\gamma} r(\theta) - C$. Here $\pi(\theta)$ is the profit defined as the difference between firm's share of revenue and costs, where $\frac{1}{1-\beta\gamma}$ is the Nash bargaining share of revenue received by the firm, and $r(\theta)$ and C are revenue and cost functions, which are given by (13) and (6), respectively. In this maximization problem firm chooses $n$ and $a_c$ to maximize it's profit and hence the expected utility. So, first order conditions for the firm's problem is given by:

$$n : \frac{\beta\gamma}{1+\beta\gamma} E[u'(\pi) r(\theta)] = bnE[u'(pi)] \tag{2.12}$$

$$a_c : \frac{\beta(1-\gamma k)}{1+\beta\gamma} E[u'(pi) r(\theta)] = ca_c^{\delta} E[u(\pi)] \tag{2.13}$$

The right hand side of Equation (2.12) shows the increase in expected revenue from choosing a larger value of n. When a firm chooses a larger value of $n$, it can employ higher ability, which increases the firm's productivity and hence the revenue. The left hand side of the Equation (2.12) shows the cost of choosing a larger value of $n$, that is, a firm needs to pay higher search cost if it chooses larger value of $n$. Equation (2.13) shows that if the firm decides to increase the screening cutoff of workers' ability ($a_c$), then the average ability of workers employed by the firm will increase, which will increase the firm's output and associated revenue. However, the firm needs to pay higher screening costs to increase the screening cutoff. Optimality requires equating these two contrasting effects of changing in screening cutoff. Under a fixed exchange rate regime, the solutions for n and ac are very similar to solutions as in HIR (2010) except that here $\Upsilon(\theta)$ is differently defined.

**Proposition 2:** *The optimal choice of n and $a_c$ are decreasing in exchange rate volatility.*

Proof of Proposition 2 is given in Appendix. Proposition 2 says that when the firm faces a more volatile exchange rate, its expected revenue is lower compared to no uncertainty in exchange rates. This is because the revenue function is decreasing in exchange rate volatility. Hence, it is optimal for the firm to choose a lower ability cutoff for screening, which will enable the firm to reduce its screening costs on one hand and lower the bargaining power of the hired workers on the other hand so that if there is any unanticipated negative shock in exchange rates; i.e., if the exchange rate appreciates unexpectedly, then it can replace workers more easily and also save on screening costs. As a result of choosing a lower cutoff for screening, the firm will also select a lower value for n (number of matched workers). This will further reduce search costs paid by the firm.

**Proposition 3:** *For each exporting firm, total output is decreasing in exchange rate volatility.*

Proof of Proposition 3 is given in Appendix.

### 2.2.3 Productivity cutoffs

### 2.2.4 Productivity cutoffs

Combining the equation (17), (18), Frim revenue in (13), and Production technology, the revenue function under the fixed exchange rate as given in the HIR is:

$$r(\theta) = \kappa_r [c^{\frac{\beta(1-\gamma k)}{\delta}} b^{-\beta\gamma} \Upsilon(\theta)^{(1-\beta)} A\theta^{\beta}]^{1/\Gamma} \tag{2.14}$$

Where $\kappa_r$ as given in HIR. Thus, the productivity cutoff for the firm to enter into domestic market (or equivalently exit cutoff, denoted by $\theta_d$) is given by the zero profit condition:

$$\frac{\Gamma}{1+\beta\gamma} \kappa_r [c^{\frac{\beta(1-\gamma k)}{\delta}} b^{-\beta\gamma} \Upsilon(\theta)^{(1-\beta)} A\theta^{\beta}]^{1/\Gamma} = f_d \tag{2.15}$$

Here $\Upsilon(\theta) = 1$ for the exit cutoff. Productivity cutoff of export ($\theta_x$) is given by the firm's indifference between selling only in the domestic market or serving both domestic and foreign market:

$$\frac{\Gamma}{1+\beta\gamma}\kappa_r[c^{\frac{\beta(1-\gamma k)}{\delta}}b^{-\beta\gamma}\Upsilon(\theta)^{(1-\beta)}A\theta^{\beta}]^{1/\Gamma}[\Upsilon(\theta)^{(1-\beta)\Gamma}-1] = f_x \tag{2.16}$$

Under the floating exchange rates, the revenue function is:

$$r(\theta) = \kappa_r[c^{\frac{\beta(1-\gamma k)}{\delta}}b^{-\beta\gamma}E[\Upsilon(\theta)^{(1-\beta)}]A\theta^{\beta}]^{1/\Gamma} \tag{2.17}$$

The exit productivity cutoff ($\theta_d$) under floating exchange rate regime is same as that of under fixed exchange rate regime, given by equation (24), since exchange rate volatility does not affect the firm's decision to enter into the domestic market and this is reflected in condition that $\Upsilon(\theta) = 1$ for the domestic market. However, the export productivity cutoff ($\theta_x$) in floating exchange rate regime is now given by the following equation:

$$\frac{\Gamma}{1+\beta\gamma}\kappa_r[c^{\frac{\beta(1-\gamma k)}{\delta}}b^{-\beta\gamma}\Upsilon(\theta)^{(1-\beta)}A\theta^{\beta}]^{1/\Gamma}[E(\Upsilon(\theta)^{(1-\beta)\Gamma})-1] = f_x \tag{2.18}$$

**Proposition 4**: Export productivity cutoff ($\theta_x$) is lower under fixed exchange rate regime (similarly, for any other type of peg) than under flexible exchange rate regime given that $\beta < \delta\Gamma$.

Proposition 4 implies that under the given conditions, some firms close to the export productivity cutoff under fixed exchange rates will stop exporting if we introduce exchange rate volatility. The economic intuition for this result is that the firms with productivity close to export cutoff under fixed exchange rate will have lower expected revenue if exchange rate volatility is introduced as revenue function is concave in $\epsilon$ under the given conditions and so it will no longer be optimal for them to continue to export.

### 2.2.5 Income Inequality

Exchange rate volatility also affects the wages paid by exporting firms. The effect of exchange rate volatility on the total wage payment in an exporting firm is summarized in the following proposition:

**Proposition 5**: Revenue share of workers (total wage payment) and the average wage are a decreasing function of exchange rate volatility.

To see the impact of exchange rate volatility on income inequality, we need to solve firm specific variables in terms of $\Upsilon$. Under the fixed exchange rate regime, solutions are same as in HIR except the difference in $\Upsilon(\theta)$;

$$r(\theta) = \Upsilon(\theta)^{(1-\beta)/\Gamma} r_d(\frac{\theta}{\theta_d})^{\beta/\Gamma}, \quad r_d \equiv \frac{1+\beta\gamma}{\Gamma} f_d \tag{2.19}$$

$$n(\theta) = \Upsilon(\theta)^{(1-\beta)/\Gamma} n_d(\frac{\theta}{\theta_d})^{\beta/\Gamma}, \quad n_d \equiv \frac{\beta\gamma}{\Gamma}\frac{f_d}{b} \tag{2.20}$$

$$a_c(\theta) = \Upsilon(\theta)^{(1-\beta)/\delta\Gamma} a_d(\frac{\theta}{\theta_d})^{\beta/\delta\Gamma}, \quad a_d \equiv [\frac{\beta(1-\gamma k)}{\Gamma}\frac{f_d}{c}]^{1/\delta} \tag{2.21}$$

$$w(\theta) = \Upsilon(\theta)^{k(1-\beta)/\delta\Gamma} w_d(\frac{\theta}{\theta_d})^{\beta k/\delta\Gamma}, \quad w_d \equiv b[\frac{\beta(1-\gamma k)}{\Gamma}\frac{f_d}{ca_{min}^{\delta}}]^{k/\delta} \tag{2.22}$$

Corresponding solutions of firm specific variables under the floating exchange rate regime are as follows:

$$E[r(\theta)] = E[\Upsilon(\theta)^{(1-\beta)/\Gamma}] r_d(\frac{\theta}{\theta_d})^{\beta/\Gamma}, \quad r_d \equiv \frac{1+\beta\gamma}{\Gamma} f_d \tag{2.23}$$

$$E[n(\theta)] = E[\Upsilon(\theta)^{(1-\beta)/\Gamma}] n_d(\frac{\theta}{\theta_d})^{\beta/\Gamma}, \quad n_d \equiv \frac{\beta\gamma}{\Gamma}\frac{f_d}{b} \tag{2.24}$$

$$E[a_c(\theta)] = E[\Upsilon(\theta)^{(1-\beta)/\delta\Gamma}] a_d(\frac{\theta}{\theta_d})^{\beta/\delta\Gamma}, \quad a_d \equiv [\frac{\beta(1-\gamma k)}{\Gamma}\frac{f_d}{c}]^{1/\delta} \tag{2.25}$$

$$E[w(\theta)] = E[\Upsilon(\theta)^{k(1-\beta)/\delta\Gamma}]w_d(\frac{\theta}{\theta_d})^{\beta k/\delta\Gamma}, \quad w_d \equiv b[\frac{\beta(1-\gamma k)}{\Gamma}\frac{f_d}{ca_{min}^{\delta}}]^{k/\delta} \qquad (2.26)$$

Comparing the set of equations in (33)-(36) and (37)-(40), we can see that the firm's revenue is decreasing in exchange rate volatility for $\beta < \delta\Gamma$. However, we have already shown that the revenue is decreasing for the entire range of $\beta$ ($0 < \beta < 1$), and so this is a non-restrictive condition. For wage, the exponent on $\Upsilon(\theta)$ is $\frac{k(1-\beta)}{\delta\Gamma}$. Now, if the assumption $\beta < \delta\Gamma$ holds as in proposition 5, the wage will be concave in $\Upsilon(\theta)$ as $k > 1$, where $\delta$ is the parameter in screening cost function (screening cost function is $ca_c^{\delta}/\delta$). Thus, wage is also decreasing in exchange rate volatility. In addition, the exporting firms pay higher wages due to higher average ability of workers, which makes it harder to replace employed workers and this gives greater bargaining power to the workers. Consequently, under any exchange rate regime, workers will get higher wages employed in firms serving both domestic and foreign markets compared to their counterparts employed in firms that serve only the domestic market.

The difference in wages between workers employed in firms catering both domestic and export markets and workers employed in firms catering only domestic market will be higher if there is no exchange rate uncertainty compared to a more volatile exchange rate regime. The reason is screening cutoff ($a_c(\theta, \epsilon)$) is decreasing in exchange rate volatility (proposition 3), which means that average ability of workers is decreasing in exchange rate volatility as well. Consequently, an exporting firm pays a higher wage to its workers if there is no exchange rate volatility. This is true as long as not all firms operating in the sector are also exporting or only serving the domestic market, that is, the conclusion regarding wage difference in less and more volatile exchange rate regime will be valid only if some firms in the sector have productivity higher than the export cutoff productivity (so $\frac{\theta_d}{\theta_x}$ is between 0 and 1). Distribution of wages of workers employed in firms serving only domestic market and firms serving both the domestic market and foreign market under no exchange rate uncertainty are again same as given in HIR, except here $\Upsilon(\theta)$ is defined differently:

$$\begin{aligned} G_{w,d}(w) &= \frac{1-(\frac{w_d}{w})^{1+1/\mu}}{1-\rho^{z-\frac{\beta(1-k)}{\delta\Gamma}}} \\ G_{w,x}(w) &= 1-[\frac{w_d}{w}\Upsilon_x^{\frac{\beta(1-k)}{\delta\Gamma}}\rho^{-\frac{k\beta}{\delta\Gamma}}]^{1+1/\mu} \end{aligned} \tag{2.27}$$

Similarly, the corresponding wage distributions under the floating exchange rate regime are given by:

$$G_{w,d}(w) = \frac{1-(\frac{w_d}{w})^{1+1/\mu}}{1-\rho^{z-\frac{\beta(1-k)}{\delta\Gamma}}} \tag{2.28}$$

$$G_{w,x}(w) = 1-[\frac{w_d}{w}E[\Upsilon_x^{\frac{k(1-\beta)}{\delta\Gamma}}]\rho^{-\frac{k\beta}{\delta\Gamma}}]^{1+1/\mu} \tag{2.29}$$

Where $\rho \equiv \frac{\theta_d}{\theta_x}$ is a measure of extensive margin of trade openness, and $\Upsilon_x$ is given in equation (10) and is a measure of intensive margin of trade openness as defined in HIR. $G_{w,d}(w)$ is the distribution of wages across workers employed by the domestic firms, and it is a truncated Pareto distribution, and $G_{w,x}(w)$ is the distribution of wages across workers employed by the exporting firms, and it is an untruncated Pareto distribution. $\mu \equiv \frac{\beta k/\delta}{z\Gamma-\beta}$, $z$ and $k$ are the shape parameter of the Pareto distribution of productivity of firms ($\theta$) and workers' ability (a), respectively.

Here wage distributions for workers employed by domestic firms is not influenced by exchange rate volatility. The intuition is that exchange rate volatility has no effect on optimal choice of $n(\theta)$ and $a_c(\theta)$ by the firms serving only domestic market. But the wage distributions of workers employed by exporters will be affected by exchange rate volatility. Now, if assumption $\beta < \delta\Gamma$ continues to hold, then the mean and the variance of the wage distribution of workers employed by exporters will be higher under no exchange rate uncertainty compared to the mean and the variance of the wage distribution under a volatile exchange rate regime. This implies that the choice of exchange rate regime may change the first and second moments of the wage distribution and so cause a higher income inequality within the sector. In addition, under less volatile exchange rate regime the mean of the wage distribution is higher for exporting firms than that of under a more volatile exchange rate regime, so worker employed in exporting firms gets on an average higher wage when there is no or less volatility in the exchange rate and this will cause larger difference in wages received by workers employed in domestic firms (serve only domestic market) and workers employed in exporting firms (serve both domestic and export market).

## 2.3 Empirical Evidence

In this section I empirically test some predictions of the model presented in section 3. One distinctive feature of this study is its use of firm level trade data rather than aggregate trade data at the country-level or industry-level. Thus, here I can estimate the effect of exchange rate volatility on intensive and extensive margins of firm level trade, and the impact of exchange rate volatility on wage and income distributions.

### 2.3.1 Data Source

For firm level trade data, I use the World Bank Enterprise Survey, which is conducted in different countries in different years. The oldest survey year is 2006 and the most recent survey year is 2016. I treat firm level data from these different surveys as pooled cross-sectional data. This data set is downloaded on September 8, 2017 from the World Bank Web-portal.[3] I construct different firm level trade variables using this data. Detail of the variable definition and construction is given in appendix. In addition to firm level trade data, Enterprise Survey includes information on a firm's total annual sales and the average monthly compensation to a full time worker. Enterprise Survey also provides information on some characteristics of workers employed in the firm, such as average year of education and proportion workers who received training.

For the measure of exchange rate volatility, I use the monthly trade-weighted real exchange rates. The reason that I use a trade-weighted measure of exchange rates rather

[3] https://www.enterprisesurveys.org/portal/index.aspx#/library?dataset=Enterprise%20Survey

than bilateral exchange rates is that in the enterprise survey I don't have any information about the destination of the origin. One benefit of using trade-weighted exchange rates is that it captures the essential fluctuations in the exchange rates which are more important to exporting firms. In addition, by using the trade-weighted real exchange rates, I can mitigate the effect of indirect pegging. I use real rather than nominal trade-weighted exchange rates so that I can control the relative difference in general price levels in origin and destination countries. Trade-weighted real exchange rates data can be obtained from Bank of International Settlement (BIS) website. I downloaded the data on trade-weighted real exchange rates on September 22, 2017 (the link is http://www.bis.org/statistics/eer.htm). I construct a measure of exchange rate volatility using this trade-weighted real exchange rates, which is the standard deviation of monthly exchange rates for a given year. The detail of the definition and construction of the measure of exchange rate volatility is given in the appendix.

Enterprise Survey provides firm level data for more than 110 countries, and almost all of these countries are developing countries. However, trade-weighted real exchange rate data from BIS is available for at most 61 countries, and of these 61 countries some are developed/industrialized economy and some are developing economy. In these two data sets, there are 28 countries that are common and most of these are developing countries. Thus, the final data set includes information from 28 countries on 50,213 firm units in 30 different industries. The lists of countries and industries are given in appendix.

### 2.3.2 Descriptive Statistics

Before I discuss the results of econometric estimation, I provide descriptive statistics on different characteristics of the firms and the workers in the sample. Proportion of firms with various firm characteristics are shown in the following table 1:

In Table 2.1, the percentage of firms with different characteristics serving only the domestic market (Domestic Firms) or both the domestic and export market (Exporting

**Table 2.1:** Proportion of Firms with Different Characteristics

| | | Domestic Firms | Exporting Firms |
|---|---|---|---|
| Proportion of Firms | | 79.26 | 20.74 |
| Firm Size | Micro | 0.72 | 0.35 |
| | Small | 44.99 | 16.38 |
| | Medium | 36.69 | 35.69 |
| | Large | 17.59 | 47.59 |
| Ownership | Female | 33.51 | 35.99 |
| | Male | 63.69 | 60.33 |
| Legal Status | Shareholding Company (Shares Trade) | 4.28 | 7.33 |
| | Shareholding Company (Non-traded Shares) | 49.10 | 66.45 |
| | Sole Proprietorship | 27.90 | 9.76 |
| | Partnership | 7.76 | 6.40 |
| | Limited Partnership | 7.59 | 7.02 |
| | Other | 1.99 | 2.16 |

Source: World Bank Enterprise Survey.

firms) are reported. The first row shows the proportion of firms serving only the domestic market and firms serving both the domestic and foreign market. In the sample, 79.26 percent of firms serve only the domestic market and 20.74 percent of firms serve both the domestic and foreign market. This satisfy the prior expectation that the proportion of firms serving both the domestic and export markets is usually lower than the proportion of firms serving only the domestic market. In terms of the size of the firm, there are four groups: Micro (total number workers less than 5), Small (total number of workers between 5 and 19), Medium (total number of workers between 20 and 99), and Large (total number of workers greater than or equal to 100). A very small fraction of firms are classified as micro firms; only 0.72 percent of domestic and 0.35 percent of exporting firms are micro firms.

The proportion of small firms is larger for domestic firms than that of exporting firms. 44.99 percent of domestic firms are small, whereas only 16.38 percent of exporting firms are categorized as small. The proportion of medium size firms is similar for both domestic and exporting firms; 36.69 percent of domestic firms are grouped as medium firms and the corresponding figure for exporting firms is 35.69. However, the proportion of large firms is almost three times larger for exporting firms compared to domestic firms: only 17.59 percent of domestic firms are designated as large firms, whereas 47.59 percent of exporting firms are identified as large firms. This is in line with the expectation that exporting firms are generally larger than domestic firms.

In terms of ownership of firms, both domestic and exporting firms show a similar pattern. In the case of domestic firms, 33.51 percent of firms have at least one female shareholder in the ownership of firms and the rest 63.69 are solely owned by male entrepreneurs. The corresponding figures for exporting firms are 35.99 percent and 60.33 percent, respectively. Here proportion of female ownership of firms is slightly larger for exporting firms. I also look into the nature of the legal status of the firms. Almost half of the domestic firms are shareholding companies with non-traded shares for domestic firms and about two-thirds of exporting firms are shareholding companies with non-traded shares. Sole proprietorship is the second largest group for domestic firms, whereas the proportion of firms with other legal status are more or less the same for exporting firms. As descriptive statistics, I also present some characteristics of employees employed in both domestic and exporting firms. These statistics are shown in Table 2.2.

The first row of Table 2.2 shows mean number of two types of permanent employees: production workers and non-production workers. The mean number of production and non-production employees in domestic firms is 62.12 and 20.54, respectively. The corresponding figures for exporting firms are 221.42 and 64.54, respectively. Here, non-production employees are managers, administrative and sales personnel. One interesting point is that the ratio of production to non-production employees is about 3:1 for domestic firms and close to 4:1 for exporting firms. This shows that the average level of productivity will be higher for exporting firms than that of for domestic firms. This iterates empirical

**Table 2.2:** Composition and Characteristics of Employees

| | | Domestic Firms | Exporting Firms |
|---|---|---|---|
| Average Number of Permanent Employees | Production | 62.12 | 221.42 |
| | Non-production | 20.54 | 64.54 |
| Composition of production Employees | Skill | 39.99 | 149.28 |
| | Unskilled | 20.35 | 66.03 |
| Proportion of Employees with Average Educational Attainment | 0-3 years | 6.31 | 2.28 |
| | 4-6 years | 23.80 | 12.15 |
| | 7-9 years | 42.80 | 47.30 |
| | 10-12 years | 20.30 | 26.35 |
| | 13 years and above | 4.12 | 7.00 |

Source: World Bank Enterprise Survey.

fact that exporting firms are more productive than domestic firms.

The second row of Table 2.2 shows the average number of skilled and unskilled production workers in domestic and exporting firms. The mean number of skilled production workers in domestic firms is 39.99, whereas the mean number of unskilled production workers in domestic firms is 20.35. For domestic firms, on average 2 skilled production workers are mixed with one unskilled production worker. The average numbers of skilled and unskilled production workers in exporting firms are 149.28 and 66.03, respectively. In the exporting firms, more than 2 skilled production workers are mixed with one unskilled production workers. Thus, the average level of workers' skill or ability will be higher in exporting firms compared to domestic firms.

Proportion of employees with different average educational attainment is shown in the third row of Table 2.2. In domestic firms, more than 70 percent of workers have an average schooling of less than 10 years, whereas around 60 percent of employees in exporting firms have less than 10 years of average schooling. Only around 4 percent of employees in domestic firms have average educational attainment of 13 years or more than 13 years. For exporting firms. Though, this figure is not very high, but almost twice as large as that of domestic firms, that is, 7 percent of employees in exporting firms have average schooling years equal to or greater than 13 years. Thus, it can be concluded that on average employees in exporting firms have higher average educational attainment than employees in domestic firms.

### 2.3.3 Incentive Margin of Trade

In this section, I empirically test the model's predictions regarding the effect of exchange rate volatility on the intensive margin of trade (Propositions 1 and 2).. Rewriting equation (8), we get:

$$\frac{y_x(\theta)}{y_d(\theta)} = (\frac{A^*}{A})^{1-\beta} \tau^{\frac{-\beta}{1-\beta}} (E[\epsilon^{\beta}])^{1-\beta} \tag{2.30}$$

Hence, the ratio of export to domestic sale is a function of home and foreign demand shifters ($A, A^*$), iceberg trade costs ($\tau$), and exchange rate volatility (some function od $\epsilon$). So, we can write;

$$ETD = f(A, A^*, \tau, \epsilon) \tag{2.31}$$

Where ETD stands for export to domestic sale. I use two different measures of ETD: (1) Diving the direct export by the sum of domestic sales and indirect export (Denoted by ETD1), and (2) diving the sum of direct and indirect export by the domestic sales. Here, indirect export is a fraction of output that a firm sales to other domestic firms which then export it or use it in production of export (denoted by ETD2). The ETD1 measure of intensive margin of trade may suffer from the problem of double counting. Nevertheless, for the sake of comparison, I obtain estimates using both of these measures of intensive margin of firm level trade. Here, I take Gross Domestic Product per capita of home country(DP) and World (World_GDP) as a measure of $A$ and $A^*$, respectively. I take GDP per capita rather than GDP in order to avoid country and population size. GDP data is collected from World Bank Development Indicator.[4] As a measure of iceberg trade costs, I control for size, country, industry (sector), and year fixed effects. For the measure of exchange rate volatility, I use the sample standard deviation of monthly exchange rate data, where the sample period is 1 year or 12 months. In addition, I also include the lag of exchange rate volatility, which is the standard deviation of the immediate previous year. This is to capture the lag effect of exchange rate volatility on intensive margin of trade as in most cases exporters may not observe entire range of exchange rate fluctuations for the current year, and in which case they may put higher weight on last year's exchange rate volatility in making their export decision.

Let X be the set of controls; X=Exchange_Vol, Lag_exchange_Vol GDP, World_GDP, Size, Country, Sector, Year. Now, I estimate three types of models: OLS, Linear GMM, and Exponential GMM. Specifying the regression equations:

$$y = X'\beta + u \tag{2.32}$$

$$y = exp(X'\beta) + u \tag{2.33}$$

Where y is ETD1 or ETD2, X is the vector of controls defined above, $\beta$ is the vector of parameters, and u is assumed to be iid errors. I assume u to be iid as most of the firms that are surveyed in different years are not the same firms and survey years are not consecutive, so no or very small serial correlation. In addition, I expect no or less spatial correlation among firms across countries. I also expect there is no or very small degree of reverse causality of firms' export on exchange rate volatility as only a small fraction of firms were surveyed and there is less chance of having a single firm with a majority of export share. So, exchange rates are assumed to be exogenous. Hence, I estimate the regression equation (46) by OLS and linear GMM models and regression equation (47) by non-linear(exponential)

[4] http://databank.worldbank.org/data/reports.aspx?source=world-development-indicators

GMM model. In GMM estimation I also include lags of GDP and World_GDP as extra instruments as GDP and World_GDP can be highly serially correlated and lags of these variables may correlated with the error. Thus, in GMM estimation we have 11 moment conditions to estimate 9 parameters. The results are reported in following Table 2.3.

**Table 2.3:** Effects of Exchange Rates Volatility on the Intensive Margin of Trade

| | Dependent Variable: ETD1 | | | Dependent Variable: ETD2 | | |
|---|---|---|---|---|---|---|
| | OLS | Linear GMM | Non-linear GMM | OLS | Linear GMM | Non-linear GMM |
| Exchnage_Vol | -0.03562 | -0.03876 | -0.16928 | -0.01879 | -0.02136 | -0.11161 |
| | (0.01414) | (0.01272) | (0.03899) | (0.01624) | (0.01449) | (0.03254) |
| Lag_Exchange_Vol | -0.09816 | -0.09227 | -0.24178 | -0.13369 | -0.12454 | -0.25152 |
| | (0.01303) | (0.01093) | (0.03245) | (0.01493) | (0.01264) | (0.02868) |
| GDP | 0.00003 | 0.00002 | 0.00003 | 0.00004 | 0.00003 | 0.00003 |
| | (0.000003) | (0.000004) | (0.00004) | (0.000003) | (0.000005) | (0.000003) |
| World_GDP | -0.000013 | -0.00016 | 0.00008 | 0.00002 | 0.00006 | 0.00019 |
| | (0.00018) | (0.00022) | (0.00041) | (0.0002) | (0.0002) | (0.00036) |
| Size | 0.48503 | 0.45806 | 0.96571 | 0.59380 | 0.55209 | 0.87930 |
| | (0.02652) | (0.03129) | (0.05971) | (0.03042) | (0.03519) | (0.05097) |
| Sector | Yes | Yes | Yes | Yes | Yes | Yes |
| Country | Yes | Yes | Yes | Yes | Yes | Yes |
| Year | Yes | Yes | Yes | Yes | Yes | Yes |
| N | 49167 | 49167 | 49167 | 48620 | 48620 | 48620 |
| $Adjusted R^2$ | 0.0121 | | | 0.0148 | | |

[1] Standard Deviation is in the parenthesis..
[2] GMM standard deviations are heteroskedastic robust estimated by two step procedure.
Source: Estimated Using World Bank Enterprise Survey and BIS Exchange Rates Data.

Columns (2)-(4) in Table 2.3 show the results of different models when dependent variable is ETD1. The OLS estimates in column (2) have expected signs except the estimate of World_GDP. The estimate of Exchange_Vol shows that if the standard deviation increases by 1, then the ratio of export to domestic sales goes down by 0.03562, or approximately 3.6 percent. This estimate is statistically significant at 5 percent level (p-value of the estimate is 0.012). The estimate of Lag_Exchange_Vol is also highly statistically significant (p-value is 0.000) and shows that if the previous years standard deviation rises by 1, then the ratio of export to domestic sales falls by 0.09816 or approximately 9.8 percent. This reflects the fact that firms put higher weight on the recent history of exchange rate volatility rather than the current exchange rate volatility. This may be due to the fact that owners of the firms form their expectation adaptively, or the information on current volatility may not be widely and reliably available.

The estimate of GDP is positive and highly statistically significant (p-value is 0.000), which shows that if the GDP per capita increases by 1 US Dollar, the ratio of exports to domestic sales increases by 0.00003. This may seem counter-intuitive, as if domestic income goes up, domestic demand increases and this should cause a fall in the export-to-domestic sales ratio. However, this may not be true for several reasons. Firstly, a rise in GDP does not necessarily imply a rise in domestic income if there is large foreign direct investment (FDI) in the country and the productions from this FDI are only exported or a major part of the productions are exported. Secondly, most of the countries in the sample are developing countries and for such countries where people spend significant fraction of their income on foods and other basic necessities, an increase in income in those countries may not increase the demand for manufacturing that much and may have slight increase in the ratio of export to domestic sales. Thirdly, the positive estimate may be due to reverse causality; that is, rather than an increase in GDP causing a rise in export to domestic sales, it is quite possible that the increase in export to domestic sales causes a rise in GDP, which is not very counter-intuitive. Nonetheless, I do not explore this issue further, as the main purpose of this paper is to entangle the effect of exchange rate volatility on firm level trade, especially firm-level exports.

The estimate of World_GDP does not have the expected sign. One may expect that a rise in the world's income will increase the demand for various goods, and this may lead to an increase in the export-to-domestic sales ratio. However, if the increase in domestic income is larger than the increase in world's income, then we may see a negative relationship between world's income and export to domestic sales. Since, I also control for GDP, a measure of domestic income, this may not be the reason of this negative estimate. In addition, this estimate of World_GDP is neither economically (1 US dollar increase in World's GDP will lead to a 0.001 percent fall in the export to domestic sales) nor statistically significant(p-value of the estimate is 0.460). The estimate of the size of the firms is highly economically and statistically significant(p-value is 0.000). However, there is no natural interpretation of this estimate; the only thing that we can say about this estimate is that larger firms have very high export-to-domestic sales ratios. In this OLS regression, I also control for country, sector, and year. Estimates of these variables are not reported as there is no natural interpretation of these estimates.

The linear GMM estimates are in column (3). I get almost same results in linear GMM as in OLS except there is slight increase in the absolute value of the estimate of Exchange_Vol variable (0.0356 to 0.0387) and this now becomes statistically significant even at 1 percent level of significance (p-value is 0.002). The most interesting estimates are the estimates of non-linear GMM, which are reported in column (4). Absolute values of all of the controls have been significantly increased in non-linear GMM estimates. Now, a one standard deviation increase in current and lag exchange rate volatility will lead to a 16.93 percent and 24.18 percent decrease in the export-to-domestic sales ratio, respectively. These increases are highly economically significant and emphasize the impact of exchange rate volatility on the intensive margin of export. Here, the statistical significance of the estimate of Exchange_Vol has also increased markedly (p-value is now 0.000). In addition, now the estimate of World_GDP has expected positive sign, but still not statistically significant, p-value is larger than 0.9. Thus, comparing the estimates from the three models, we can conclude that non-linear GMM fits data better than other models and matches closely to the structural equation of intensive margin of export. Hence, the best econometric model provides the strongest support in favor of predictions regarding the effect of exchange rate volatility on the intensive margin of export.

Columns (5)-(7) show the estimates of different models when the dependent variable is ETD2. Here, we have similar patterns in results for most of the variables. The estimates of Exchange_Vol have expected signs in all three models, but are not statistically significant at 5 percent level in OLS and linear GMM models, p-values are 0.247 and 0.140, respectively. However, the estimate of Exchange_Vol is still highly statistically significant in the non-linear GMM; the p-value the estimate is less than 0.001. The estimates of Lag_Exchange_Vol are very similar in terms of magnitude and significance to the estimates of Lag_Exchange_Vol reported in column (2)-(4). Now the World_GDP has positive coefficients in all these three models, but still not statistically significant. Estimates of the coefficients of other variables also do not vary much whether we use ETD1 or ETD2 as a dependent variable. Thus, no matter how we define the ratio of the export-to-domestic sales, we obtain robust empirical evidence supporting the prediction of the model presented in this paper regarding the effect of exchange rate volatility on intensive margin of trade.

Proposition 2 provides very similar prediction regarding the effect of exchange rate volatility on the intensive margin of export as the prediction of proposition 1 except the fact that proposition 2 uses fraction of total output exported or sold domestically separately rather than taking the ratio of these two and it requires stricter parametric restriction ($0 < \beta < \frac{1}{2}$). I also tests this prediction empirically. I obtain the non-linear GMM estimates where I use fractions of total output that are sold domestically and exported as separate dependent variables. Here, we can also define export as only direct export (denoted as Export1) or sum of direct and indirect export (denoted as Export2). Analogously, domestic sale can be defined as total output less direct export (denoted as Domestic1) or total output less the sum of direct and indirect export (denoted as Domestic2). Using all these four dependent variables, I estimate the non-linear GMM model; the results are shown in Table 2.4.

From Table 2.4, we can see that Exchange_Vol and Lag_Exchange_Vol have expected signs when dependent variables are Export1 or Domestic1, that is when we define export as

**Table 2.4:** Effects of Exchange Rates Volatility on the Intensive Margin of Export and Domestic Sales

| | Dep Var is Export1 | Dep Var is Export2 | Dep Var is Domestic1 | Dep Var is Domestic2 |
|---|---|---|---|---|
| Exchnage_Vol | -0.01504 | 0.02608 | 0.000595 | -0.00211 |
| | (0.00935) | (0.0081) | (0.00056) | (0.00067) |
| Lag_Exchange_Vol | -0.13969 | -0.15669 | 0.00645 | 0.00931 |
| | (0.00899) | (0.00799) | (0.00052) | (0.00059) |
| GDP | 0.00002 | 0.00002 | -0.00003 | -0.000004 |
| | (0.000001) | (0.000002) | (0.00001) | (0.000002) |
| World_GDP | 0.00063 | 0.00078 | -0.00004 | -0.00006 |
| | (0.00012) | (0.0001) | (0.000008) | (0.00001) |
| Size | 0.86212 | 0.73246 | -057789 | -0.06848 |
| | (0.01744) | (0.01440) | (0.00125) | (0.00142) |
| Sector | Yes | Yes | Yes | Yes |
| Country | Yes | Yes | Yes | Yes |
| Year | Yes | Yes | Yes | Yes |
| N | 50213 | 50213 | 49167 | 48620 |

[1] Standard Deviation is in the parenthesis.. [2] GMM standard deviations are heteroskedastic robust estimated by two step procedure. Source: Estimated Using World Bank Enterprise Survey and BIS Exchange Rates Data.

only direct export and rest of the output as domestic sales. However, now the estimate of the coefficient of Exchange_Vol is no longer statistical significant. This may be due to the fact that exporters may have a lag in processing exchange rate volatility or more importantly, the exchange rate volatility does not affect all the sectors in the same way according to proposition 2. Industries with $0 < \beta < \frac{1}{2}$ are negatively affected by the exchange rate volatility, whereas some industries with $\frac{1}{2} < \beta < 1$ may be positively affected by the exchange rate volatility. Hence, pooling all these industries together may result in statistical insignificance estimate od Exchange_Vol.

To investigate this issue further, I estimate the effects of exchange rate volatility on the intensive margin of export at industry level. Since the measure of exchange rate volatility is at country level, I could not estimate the industry-level effects for all the industries due to the lack of enough variation in the exchange rate volatility. Furthermore, because of lack of enough variation in exchange rate volatility, I could not estimate the linear or non-linear

GMM models as the initial weighting matrix is not positive definite. Nevertheless, I estimate the regression equation (46) by OLS and only the estimates of coefficients of Exchange_Vol and Lag_Exchange_Vol are reported in Table 2.5. From Table 2.5 we can see that the estimates of Lag_Exchange_Vol when dependent variable is the fraction of total output that is directly exported (Export1) are mostly negative and statistically significant, which satisfy our prior expectation. The estimates of coefficient of Exchange_Vol ranges from statistically significant negative effects to insignificant and positive effects. This may reflect the fact that in some given industries where varieties are not close substitutes, exporting firms may be able to absorb a large part of the shock in exchange rate volatility, and so there may no effect of exchange rate volatility on exports. We can a see a similar pattern of results when the dependent variable is fraction of total output less direct export (Domestic1), where the estimates of Lag_Exchange_Vol are mostly positive as expected and there are mix of estimates for Exchange_Vol. These OLS estimates may not be the perfect measures of exchange rate volatility on intensive margins of export and domestic sales; however, these results provide some evidence in favor of the prediction given in proposition 2.

**Table 2.5:** Effects of Exchange Rates Volatility on the Sectoral Intensive Margin of Export and Domestic Sales

| | Dep Var: Export1 | | De Var: Domestic1 | |
|---|---|---|---|---|
| Sector | Exch_Vol | Lag_Exch_Vol | Exch_Vol | Lag_Exch_Vol |
| Chemicals & Chemical Products | 1.06265 | -0.99188 | -0.93306 | 0.99922 |
| | (0.29892) | (0.35373) | (0.25859) | (0.30629) |
| Chemicals, Plastics & Rubber | | 2.060429 | | -2.53678 |
| | | (0.61107) | | (0.58369) |
| Fabricated Metal Products | 1.10474 | -6.56229 | -1.73163 | 4.95811 |
| | (0.65987) | (1.54418) | (0.50217) | (1.15826) |
| Food | -0.74647 | 0.44322 | 0.86656 | -0.49821 |
| | (0.21752) | (0.21154) | (0.18779) | (0.18249) |
| Garments | 1.96338 | -1.25679 | -1.40157 | 0.44246 |
| | (0.41111) | (0.44818) | (0.29779) | (0.32192) |
| IT & IT Services | 3.44171 | -2.15391 | -2.31178 | 2.09208 |
| | (0.4651) | (0.69219) | (0.38857) | (0.48687) |
| Machinery & Equipment | 1.98555 | -3.96852 | -1.65864 | 3.52595 |
| | (0.65293) | (0.85595) | (0.89766) | (0.78228) |
| Manufacturing | -0.22192 | -1.97946 | -0.20832 | 1.62160 |
| | (0.87678) | (0.84863) | (0.79807) | (0.77455) |
| Non-Metallic Mineral Products | 0.35153 | -1.42452 | -0.99869 | 0.84213 |
| | (0.45078) | (0.68238) | (0.35983) | (0.54253) |
| Other Manufacturing | 0.35479 | -1.41929 | -0.21283 | 0.88973 |
| | (0.27724) | (0.30876) | (0.20605) | (0.22805) |
| Other Services | 0.09195 | -0.65114 | 0.23679 | 0.21831 |
| | (0.18972) | (0.18089) | (0.14837) | (0.14089) |
| Rest of Universe | -1.99338 | -1.11333 | 2.00686 | 1.23586 |
| | (0.52673) | (0.35019) | (0.48117) | (0.31941) |
| Retail | 0.27288 | -0.21924 | -0.15379 | 0.13613 |
| | (0.07992) | (0.06699) | (0.06097) | (0.05101) |
| Rubber & Plastics Products | -3.02627 | 3.15674 | 2.41762 | -3.80013 |
| | (0.89783) | (1.76594) | (0.73561) | (1.44661) |
| Textiles | 1.04182 | -0.66561 | -0.51934 | 0.63302 |
| | (0.73392) | (0.64423) | (0.59838) | (0.52587) |

[1] Standard Deviation is in the parenthesis..
Source: Estimated Using World Bank Enterprise Survey and BIS Exchange Rates Data.

### 2.3.4 Extensive Margin of Export

To test the model's prediction (Proposition 5) regarding the extensive margin of export, I estimate regression equation (46) by OLS and linear GMM, and equation (47) by non-linear GMM. Proposition 5 requires a parametric assumption to be true, here I ignore this parametric restriction and estimate the unconstrained model. If I get empirical evidence in favor of the unconstrained model, then I can claim that the prediction of proposition 5 will hold under any parametric restriction. Here my dependent variable is the fraction of firms that participates in export market along with domestic sale (denoted as Export_Frac). I use the same set of controls as in the test of intensive margin of trade. Thus, I obtain a table similar to Table 2.3.

**Table 2.6:** Effects of Exchange Rates Volatility on the Extensive Margin of Trade

| | Dependent Variable: Export_Frac | | |
|---|---|---|---|
| | OLS | Linear GMM | Non-linear GMM |
| Exchange_Vol | 0.00090 | 0.00099 | 0.00212 |
| | (0.00042) | (0.00047) | (0.00221) |
| Lag_Exchange_Vol | -0.00646 | -0.00646 | -0.02725 |
| | (0.00039) | (0.00045) | (0.00206) |
| GDP | 0.00001 | 0.00001 | 0.00003 |
| | (0.000001) | (0.000001) | (0.000001) |
| World_GDP | 0.00012 | 0.00013 | 0.00056 |
| | (0.00001) | (0.000006) | (0.00003) |
| Size | 0.02286 | 0.02286 | 0.11162 |
| | (0.00079) | (0.000081) | (0.00392) |
| Sector | Yes | Yes | Yes |
| Country | Yes | Yes | Yes |
| Year | Yes | Yes | Yes |
| N | 47739 | 47739 | 47739 |
| Adjusted $R^2$ | 0.1622 | | |

[1] Standard Deviation is in the parenthesis..
[2] GMM standard deviations are heteroskedastic robust estimated by two step procedure.
Source: Estimated Using World Bank Enterprise Survey and BIS Exchange Rates Data.

In Table 2.6, the results of regression for extensive margin of trade are reported. The estimates of the coefficient of Exchange_Vol are positive in all three models, which is counter-intuitive. This may be due to greater noise in the volatility of current exchange rates and so firms place low weight on the information of current exchange rate volatility when making the export decision. As a result, the estimated coefficient of Exchange_Vol is not statistically significant in non-linear GMM model. The estimates of coefficient Lag_Exchange_Vol are all negative and statistically significant in these three models. This satisfies our prior expectation that higher volatility in the exchange rate will cause a decrease in the proportion of firms who participate in the export market.

Estimates for GDP and World_GDP are also positive in all these three models. This makes intuitive sense: as output of a country goes up, which is the combined production of all firms, then on average more firms will be able to enter into the export market. This is a positive production shock. Similarly, when the world's GDP increases, demand for different products also increases, causing a higher price than before, and this will enable many marginal firms to enter into the export market, who otherwise may not find it profitable to participate in the export market. All these estimates of GDP and World_GDP are highly statistically significant, p-values are less than 0.001. The estimates of the coefficient of Size have also expected signs in these three models, which implies that if in a country the average size of the firms rises then more firms will participate in the export market. These estimates are also highly statistically and economically significant. In all these three regressions, I also control for country, industry and year fixed effects and since the estimated coefficients of these variables have no natural interpretation, so these estimates are not reported.

Empirical results of the unconstrained version of proposition 5 provide some evidence in favor of the prediction of the model. Specially, the results from non-linear GMM estimation can be rationalized by the model's prediction. In non-linear GMM estimation, we get the expected negative effect of lag exchange rate volatility on the extensive margin of export. The effect of contemporaneous exchange rate volatility is not statistically significant and the possible reason for this, as mentioned above, could be the adaptive behavior on the part of firms, which may place lower weight on the current volatility due to lack of availability of reliable current information on exchange rate volatility. Estimates of the coefficients of all other variables also make sense and do not contradict the model's intuition. Thus, on the basis of these results of the unrestricted model, we can conclude that under certain parametric assumptions as required by proposition 5, we will be able to obtain more robust estimates that would provide the validity of proposition 5. Hence, overall we can conclude that exchange rate volatility has an adverse effect on the extensive margin of export as well.

### 2.3.5 Effects of Exchange Rates Volatility on Wage and Income Inequality

The model's prediction regarding the effect of exchange rate volatility on the wage is summarized in proposition 5, which says that average wage or total wage payment to workers is decreasing in the exchange rate volatility in exporting firms. To test this prediction, I estimate the regression equation (25) by OLS, where the dependent variable is the log average monthly payment to production workers measured in US Dollars (lwageUSD) and the same set of controls in log form with an additional variable, which is the log of average level of education of workers, as education and wage are expected to be correlated. Since the information on wages is not available for all of the countries in the sample and the variation in exchange rate volatility is only at the country level, I could not obtain the estimates using the GMM method. Even though the results of OLS may not be unbiased and efficient due to small sample size and measurement errors, the OLS results may provide some direction of the effect of exchange rate volatility on wage payments in exporting firms. However, to minimize the impact of measurement errors and outliers, I plot the density of the dependent variable lwageUSD and use the observations $0 < lwageUSD < 10$. The results are given Table 2.7.

**Table 2.7:** Effects of Exchange Rates Volatility on the Average Wage Payment

| | Coefficient | Std. Err. | P-value |
|---|---|---|---|
| Exchnage_Vol | -458549.7 | 1006663 | 0.649 |
| Lag_Exchange_Vol | -156685 | 486122.1 | 0.842 |
| GDP | -2666.25 | 440.01 | 0.000 |
| World_GDP | -15593.88 | 14221.01 | 0.273 |
| Size | 5308729 | 1952061 | 0.007 |
| Sector | Yes | Yes | Yes |
| Country | Yes | Yes | Yes |
| Year | Yes | Yes | Yes |
| N | 9965 | | |
| $Adjusted R^2$ | 0.0052 | | |

Source: Estimated Using World Bank Enterprise Survey and BIS Exchange Rates Data.

In Table 2.7, the estimates of the coefficients of Exchange Vol in both IMF and BIS sample are highly statistically significant and have expected signs. This fulfills the model's prediction. But the estimates of Lag1 Exchange Vol do not have expected signs in any of these samples. However, other lag measures of exchange rate volatility have expected negative signs in both samples except Lag2 Exchange Vol in BIS sample. These estimates are not statistically significant at the 5 per cent level except the estimate for Lag3 Exchange Vol. Nonetheless, the null hypothesis that the joint effect of exchange rate volatility on wage is negative cannot be rejected. These estimates show that if exchange rate volatility increases, then average wage payments in exporting firms decrease.

The model also offers a prediction (Proposition 6) about the effect of exchange rate volatility on mean of the wage distributions in domestic and exporting firms in a sector. The model predicts that the optimal choices of n and ac are larger for exporting firms than those of domestic firms. Hence, for a given sector, the mean of the wage distribution of exporting firms will be higher than the mean of the wage distribution of the domestic firms, and the difference in means between the exporting and domestic firms falls as the volatility in the exchange rate increases. Thus, I obtain OLS estimates of the regression equation

(25), where the dependent variable is the log of mean difference, and usual control vector in log form except the regressors size, as here observations are aggregated at the industry level, so we can no longer utilize the variation in firm's size. The results of OLS regression for both IMF and BIS samples are shown in Table 2.8.

Columns (2) and (3) in Table 2.8 reports the OLS estimate of regressions where the dependent variable is the log of difference in means for IMF and BIS sample, respectively. Here only the estimates of contemporaneous exchange rate volatility have expected negative sign and are statistically significant, which support the model's prediction. However, the other measures of exchange rate volatility, i.e., the lags of standard deviation in exchange rates, are neither statistically significant nor have expected signs. Results in Table 2.8 offer a mix empirical evidence in favor of model's prediction regarding the effects of exchange rate volatility on the mean of wage distributions of exporting and domestic firms. The reason for insignificant estimates of lag measures of exchange rate volatility may be due to a very small sample size; wage information is available only for a few countries and wage data may also suffer from significant measurement errors.

**Table 2.8:** Mean and Std. Dev, of Wages Paid in Domestic and Export Firms (Local currency)

| | Only Domestic | | Domestic and Export | | | |
|---|---|---|---|---|---|---|
| Country | Mean | Std. Dev | Mean | Std. Dev | Mean Difference | Std. Dev. Difference |
| Argentina | 975.89 | 429.01 | 1176.72 | 620.42 | 200.82 | 191.41 |
| Brazil | 43851.11 | 69797.24 | 72967.99 | 77744.89 | 29116.88 | 7947.66 |
| Bulgaria | 353.97 | 898.67 | 422.51 | 705.09 | 68.54 | -193.58 |
| Chile | 262904.24 | 271322.98 | 320500.68 | 334059.59 | 57596.44 | 62736.61 |
| Colombia | 461795.06 | 205967.52 | 520404.37 | 319139.52 | 58609.31 | 113172.00 |
| Croatia | 4996.38 | 6317.65 | 4668.45 | 3075.77 | -327.92 | -3241.87 |
| Czech | 20738.47 | 34477.193 | 15212.57 | 8395.6937 | -5525.90 | -26081.49 |
| Estonia | 7746.44 | 5018.73 | 9053.5 | 3742.1966 | 1307.06 | -1276.54 |
| Hungary | 113906.33 | 70328.79 | 124359.96 | 68912.39 | 10453.63 | -1416.40 |
| Indonesia | 34112238 | 380100000 | 95131879 | 667000000 | 61019641 | 286900000 |
| Latvia | 246.83 | 161.37 | 319.37 | 225.69 | 72.54 | 64.32661 |
| Lithuania | 1081.13 | 576.25 | 1381.70 | 914.13 | 300.58 | 337.88 |
| Mexico | 5169.49 | 23110.74 | 3918.11 | 2953.78 | -1251.38 | -20156.96 |
| Peru | 778.35 | 433.46 | 1049.47 | 823.46 | 271.11 | 390.01 |
| Poland | 1519.05 | 834.85 | 1619.92 | 804.36 | 100.87 | -30.49 |
| Romania | 6955.90 | 19530.48 | 4172.94 | 5634.06 | -2782.96 | -13896.42 |
| Russia | 13659.93 | 10346.68 | 16149.18 | 14836.32 | 2489.26 | 4489.64 |
| South Africa | 2980.21 | 2597.59 | 4637.88 | 3147.54 | 1657.67 | 549.94 |
| Turkey | 1870.22 | 13143.81 | 5579.57 | 59411.1 | 3709.35 | 46267.29 |
| Slovenia | 609.72 | 468.11 | 862.55 | 672.17 | 252.83 | 204.06 |

Source: World Bank Enterprise Survey.

## 2.4 Concluding Remark

The partial equilibrium model and some of its results described in section 3 do not provide the full picture, and the predictions of the model are also based on some specific assumptions on parameters. However, this partial equilibrium model with these parametric assumptions can generate the empirical findings of many previous studies. The predictions of this partial equilibrium model are also similar to Bacchetta and Wincoop (2000) that predicts, depending on the degree of complementarity or substitution between consumption and leisure, the volume of trade can increase or decrease in fixed or floating exchange rate regimes. Analogously, our partial equilibrium also predicts that depending on the degree of complementarity or substitution among the varieties that are produced in the sector, we can see that the trade can increase under fixed exchange rate regime (that is when $0 < \beta < 1/2$), and otherwise it could fall under fixed exchange rate regime, which implies higher trade in floating exchange rate regime.

Regarding employment and income distributions, prediction of our partial equilibrium model is also dependent on some parametric assumptions. Nevertheless, those parametric assumptions are plausible; when the workers' ability distribution is less sparse and the screening cost is relatively high, firms choose lower values for number of workers it expects to be matched with ($n$) and lower level of cutoff for $expost$ matched specific screening the workers' ability ($a_c$) in floating exchange rate regime than in fixed exchange rate regime. This implies a dampening effect of the floating exchange rate on the level of employment.

Under the same parametric assumptions, our model suggests that the each worker in exporting firms gets higher wage in fixed exchange rate regime than in floating exchange rate regime, while the wages received by the workers in domestic firms stay same in these two exchange rate regimes. This implies that the difference in wage between workers employed by domestic firms and workers employed by exporting firms would be larger under the fixed exchange rate regime than that of under the floating exchange rate regime. The choice of exchange rate regime also has an impact on the dispersion of wage distribution of exporting firms, a fixed exchange rate regime causes larger dispersion in wages compared to flexible exchange rate regime. Dispersion in wage distribution of domestic firms is the same in either of the two exchange rate regimes.

Even though our partial equilibrium model has some interesting predictions, there are several practical phenomena that it does not incorporate. Two such cases are the existence of forward market for foreign exchange and the possibility of uncertainty regarding domestic price levels (also the foreign price level). Incorporating the forward market for foreign currency and allowing the price uncertainty in our partial equilibrium model, we expect to find an even richer set of predictions that match the empirical findings more closely obtained by numerous studies. Nonetheless, the partial equilibrium approach may not give the broader picture, as the choice of exchange rate regime also depends on other concerns, such as autonomy of monetary policy, incentives to FDI or remittance, etc. Thus, a general equilibrium approach would be a better framework to address the other questions related to the choice of exchange rate regime and it's impact on the income distribution.

The next step of this research proposal would be to incorporate above-mentioned extensions in our partial equilibrium model and construct the general equilibrium model to disentangle the effect(if there is any) of exchange rate regime on trade volume and the within country income distribution. We also plan to do counterfactual analysis and calibration of these partial equilibrium and general equilibrium models. We expect we can find many interesting predictions from our model regarding this one of the age-old questions in international economics.

The model proposed in this paper offers several testable predictions about the direction of effects of exchange rate volatility on intensive and extensive margins of export at the firm level. In addition, the model links exchange rate volatility and wage distributions of domestic and exporting firms in a way that can be verified by available survey data. I use the World Bank Enterprise Survey that provides comprehensive

rm level data on a number of dimensions, including the firm's degree of domestic and export market participation and the average wage and quality of workers. I empirically test the predictions of the model that are presented as propositions in the paper.

Regarding the intensive margin of trade, the model predicts that higher exchange rate volatility lowers the ratio of export-to-domestic sales. Similarly, the fraction of total output that is exported is decreasing in exchange rate volatility and the fraction of output sold domestically is increasing in exchange rate volatility. Several econometric models are estimated with different definitions of the intensive margin of trade and measures exchange rate volatility. The results of these models under different specifications do not contradict the findings of each other and provide consistent support in favor of the model's prediction about the direction of the effects of exchange rate volatility on the intensive margin of the trade.

In Case of the extensive margin of trade, the model predicts that there is positive relationship between export productivity cutoff and exchange rate volatility; that is, higher exchange rate volatility requires a larger critical value of productivity for the firms to enter into export markets. Thus, on average, under a more volatile exchange rate regime, a lower fraction of firms will be able to survive in the export markets. I test this prediction empirically by regressing the fraction of exporting firms on a set of regressors including the measures of exchange rate volatility. Overall, regression results provide support in favor of the model's prediction about the effect of exchange rate volatility on the extensive margin of export.

The model suggests that workers' wages are decreasing in exchange rate volatility for exporting firms. On the other hand, workers' wages in domestic firms are not affected by exchange rate volatility. This implies that the difference in wage between workers employed by domestic firms and workers employed by exporting firms would be lower under a more volatile exchange rate regime. Empirical results support the model's prediction about the effect of contemporaneous exchange rate volatility on the mean difference of wage distributions. However, lag measures of exchange rate volatility are neither statistically significant nor have expected signs.

This paper has one important limitation that instead of using bilateral exchange rate volatility, it uses the volatility of trade-weighted exchange rates. This measure of exchange rate volatility could be very different from the actual exchange rate volatility that each firm faces in its export markets. Since in the Enterprise Survey information on the export destination is not available, I cannot construct a measure of exchange rate volatility based on bilateral exchange rates between a firm's local currency and the currencies used in its export markets. Hence, in future research it would be interesting to test the different predictions of the proposed model using the firm level data and a measure of exchange rate volatility constructed by using bilateral exchange rates between firms' local and export market's currencies. In addition, the firm-level data in the World Bank Enterprise Survey are not of high quality. So, using high quality firm level data could provide more robust empirical evidence supporting the model's predictions.

# Chapter 3

# The Social Costs of Graduating from Least Developed Country Status: Analyzing the Impact of Increased Protection on Insulin Prices in Bangladesh

## 3.1 Introduction

Least developed countries (LDCs) are exempt from granting pharmaceutical patents until 1 January 2033 (World Trade Organization [WTO] 2015). In addition, LDC members of the WTO also have the option of not filing patent mailbox applications and obtaining exclusive marketing rights until January 2033 (WTO 2015). This implies that LDC member countries have freedom to reject a pharmaceutical patent application if the exemption is active. This temporary exemption is important to ensure access to essential medicines in LDCs. The temporary exemption may facilitate local production of generic versions of many essential medicines among those LDC members who are capable, while allowing others to import generic medicines.

However, once this temporary exemption is over, LDC members must ensure patent protection and provide exclusive marketing rights for any patented medicines. This change may greatly restrict access to essential medicines in low-income countries. We use the case of Bangladesh's LDC graduation to carry out an ex-ante analysis of the impact of such graduation on access to insulin, a lifesaving medicine for individuals with diabetes.

As an LDC, Bangladesh does not presently need to comply with global commitments under the WTO's Trade Related Intellectual Property Rights (TRIPS) provisions, commonly referred to as the TRIPS Agreement. Currently, Bangladesh can produce the generic version of any medicine and patent protection for pharmaceuticals is not allowed. In 2021, if certain conditions are met, the United Nations will recommend Bangladesh for graduation from the LDC category in 2024. Consequently, firms will no longer be able to produce copies of medicines that are on patent in Bangladesh after the country's graduation from LDC status. Household out-of-pocket expenditure as a percentage of total health expenditure in Bangladesh was more than 67% in 2015, of which more than 75% was on pharmaceuticals (Ministry of Health and Family Welfare 2016). This implies that prices of some medicines may increase significantly after 2024, which will place an even larger burden of health expenditure on households.

Higher prices can affect access to medicines in several ways. First, higher prices of medicines may force some households to stop taking medicines or take less than the recommended dose. Second, households may also reduce other forms of consumption, such as food or spending on children's education, to cope with the additional expenditure on medicines. Thus, higher prices of medicines not only affect their usage, but may also reduce consumption of foods, education, and other essential amenities that are necessary to lead a healthy life. This paper estimates the impact of these different types of expenditure substitution. We estimate the changes in household welfare following the implementation of pharmaceutical patenting and stricter intellectual property rights (IPRs) that would potentially increase the prices of some medicines. For this purpose, we choose the market for insulin to estimate these effects.

Insulin is a good tracer medicine to measure the effects of stronger IPR on access to medicines for several reasons. First, some types of insulin would still be under patent (in other countries) after Bangladesh's LDC graduation, which implies that IPR provisions will be a binding constraint on the insulin market. Second, the burden of diabetes is increasing in Bangladesh. More than 10% of adults have diabetes (mostly type 2), and more than 70,000 deaths per year are attributable to diabetes or high blood glucose (World Health Organization [WHO] 2016). This means that insulin is widely required to satisfy the health needs of the population. Finally, expenditure on insulin is mostly out of pocket (WHO 2016). Thus, after Bangladesh's LDC graduation, the price of insulin may significantly increase as patented versions are imported.

In this paper, we use household income and expenditure (HIES) data (Bangladesh Bureau of Statistics [BBS] 2016) and the quadratic almost ideal demand system (QUAIDS) to estimate household substitution patterns among food, medicines, and education for households with potential expenditure on insulin. In addition, we estimate the loss in household welfare and increase in household poverty resulting from the higher prices of insulins. Unlike other ex-ante studies that investigate a similar question for different medicines in other LDCs or developing countries, we use household-level data to estimate elasticities of medicine demand and perform welfare analysis.

There are several advantages of using household data rather than the market share data of different brand and generic medicines, or aggregate sales and average prices data. First, household data allows us to control many characteristics of a household and individuals living in the household, which are important determinants of demand for medicines along with the price of medicine. Thus, controlling for those characteristics will enable us to estimate the demand parameters consistently and efficiently. Second, household data enables us to estimate the different types of substitution between medicines and other important expenditure items, such as food and education. Third, sales data of different brand or generic medicines are often proprietary, and it can be very hard and expensive to get access to that data. Moreover, sales data may not be very representative, especially for LDCs. On the other hand, HIES data is available for most LDCs, which is the best representative sample of the population. In addition, HIES data is often publicly available.

Thus, our paper provides an effective way to estimate demand parameters of insulin and perform household welfare analysis with household data for Bangladesh, which could also be applied for any other medicine and HIES data of any other LDC to carry out the similar analysis.

The paper finds that household demand for insulin is highly price inelastic, even more inelastic than household demand for food. The price elasticity of insulin is less than 1 in absolute value, and the price of insulin could increase more than 11 times its current price if a stronger IP regime facilitates an unregulated monopoly for insulin; this would have a significant welfare effect for households with members who need insulin. We find that the aggregate annual expenditure of those households goes up by \$336 million, which can be as low as \$148 million and as high as \$656 million. The welfare cost of the unregulated monopoly of insulin would vary from \$71 million to \$408 million under various estimation methods and measures of welfare. Moreover, the increase in the price of insulin would have a serious impact on household poverty: poverty rates for households needing insulin could increase between 3 and 40 percentage points.

The rest of the paper is organized as follows. Section II provides some background on Bangladesh's LDC graduation and the current status of IP regulation and the pharmaceutical industry in Bangladesh. Section III is a discussion of relevant studies. Section IV details the methodology and estimation techniques with a description of the data and its sources. Section V shows the estimation results along with household welfare and poverty analysis. Section VI discusses some policy implications, the limitations of our analysis, and our conclusions.

## 3.2 Background

Bangladesh is in the process of making its transition out from the group of LDCs (United Nations [UN] 2020). This involves a country meeting a graduation threshold under at least two of the following three pre-defined criteria: per capita income, human assets, and economic vulnerability.[1] Decisions on inclusion into, and graduation from, the list of LDCs is made by the United Nations General Assembly based on recommendations by the Committee for Development Policy (CDP), a subsidiary body of the UN Economic and Social Council. The CDP, is among other things, mandated to review the category of LDCs every 3 years and to monitor their progress after graduation from the category (Bhattacharya 2009). In March 2018, the CDP found that Bangladesh met the criteria for graduation for the first time by satisfying all three criteria. If Bangladesh meets the graduation criteria for a second time at the next triennial review in 2021, the CDP may recommend Bangladesh for graduation from the LDC category in 2024 (WTO 2018).

LDC classification accords a country duty-free access to the richer economies of the world, exemption from IP rights enforcement, and other economic benefits (UN 2020). The loss of LDC privileges for Bangladesh would carry with it a 3-year grace period from 2024 to 2027, during which time Bangladesh must prepare itself for graduation. The most visible trade-related implication of LDC graduation is the loss of preferential market access, such as the loss of concessions granted to LDCs under the global system of trade preferences among the developing countries (UN 2019). Since LDCs are also exempt from the trade-related aspects of the TRIPS Agreement, graduation out of LDC status may have significant implications for IP rights enforcement in Bangladesh, which will have to be addressed by the pharmaceutical and software industries, among others (UN 2019).

Bangladesh has a burgeoning manufacturing capability and a relatively self-sufficient pharmaceutical sector. Companies generally manufacture finished medicine formulations by

---

[1]Income criterion is based on a 3-year average estimate of gross national income per capita for 2011–2013, based on the World Bank Atlas method (under $1,025 \mathit{forinclusion}, \mathit{above}$1,230 for graduation, as applied in the 2018 triennial review). The Human Assets Index is based on indicators of (i) nutrition: percentage of population undernourished; (ii) health: mortality rate for children aged 5 years or under; (iii) education: the gross secondary school enrollment ratio; and (iv) adult literacy rate. The Economic Vulnerability Index is based on indicators of: (i) population size; (ii) remoteness; (iii) merchandise export concentration; (iv) share of agriculture, forestry, and fisheries; (v) share of population in low elevated coastal zones; (vi) instability of exports of goods and services; (vii) victims of natural disasters; and (viii) instability of agricultural production.

assembling known generic and, in some cases, patented components. Since pharmaceutical patents in Bangladesh were suspended in 2008, this created opportunities for local generic production of medicines patented outside Bangladesh, with several generic companies supplying the same medicine. For example, local firms manufacturing medicines patented abroad include Incepta, Beximco, Beacon, Renata, Square, and Eskayef. Domestically produced medicines patented abroad include sofosbuvir, sitagliptin, linagliptin, vildagliptin, rivaroxaban, and emphagliflozin (Islam et al. 2017). Some firms have been engaged in producing active pharmaceuticals ingredients (APIs), excipients and solvents that are used as raw material in producing the final medicine formulations. Innovative R&D activity is, however, virtually nonexistent in the Bangladesh pharmaceutical industry as it is a generics market and generic formulations represent the main business of the Bangladesh pharmaceutical industry. Presently, the market consists of approximately 8,000 generic products and 258 firms with manufacturing capability, in addition to imported already-patented products (Islam, Rahman, and Al-Mahmood 2018). This local production supplies over 95% of Bangladesh's pharmaceutical needs, and about 80% of these medicines are generics. The top 30–40 companies by value dominate almost the entire market in which the top 10 hold a 70% domestic market share, and the top two—Beximco and Square Pharma—capture over 25% of the market (Islam, Rahman, and Al-Mahmood 2018). In brief, the Bangladesh pharmaceutical market can be divided as follows:

- high-end products (e.g., anti-cancer, insulin, and vaccines) produced by multinationals—if on patent, they are not patented yet in Bangladesh;
- branded generics (antibiotics, GI medicines);
- low-end generics; and
- contract manufacturing (domestic and export).

The dynamic nature of the Bangladesh pharmaceutical industry contrasts with its long-standing IP system. Patent rules and procedures are governed by the original Patents and Designs Acts of 1911. Bangladesh has not replaced or amended the 1911 Act. It only issued a Notification in 2008 that applications for pharmaceutical and agrochemical product patents were to be suspended since LDC members of the WTO could exempt pharmaceutical products from patent protection. This waiver has been extended until 2033 by the TRIPS Council. Bangladesh can benefit from these transition periods but only if it retains LDC status (Chowdhury 2018). Some companies in Bangladesh can make high-end products like insulin to compete with multinationals (Mohuiddin 2018). This is important as Bangladesh ranks as one of the 10 countries with the highest number of people with diabetes globally (IHME 2019).

A recent scoping review for Bangladesh (Biswas et al. 2016) found that a final estimate of diabetes prevalence, obtained after pooling data from individual studies among 51,252 participants, was 7.4%, somewhat less than the estimated overall global prevalence of 9.3% . For Bangladesh, with 165 million inhabitants in 2020 (World Bank 2020), this means there are 11.6 million people with diabetes, about half of them undiagnosed. Undiagnosed diabetes is more likely among people of lower socioeconomic status (Hasan et al. 2019). The prevalence of diabetes is higher in males compared to females in urban areas and vice versa in rural areas. Analyses revealed an increasing trend of diabetes prevalence among both the urban and rural populations.

Type 2 diabetes is the most common form of diabetes worldwide, comprising over 90% of all cases (WHO 2019). Management of type 2 diabetes includes diet, physical exercise, and weight management (NIDDK 2020). Some patients with type 2 diabetes require medication such as oral anti-diabetes medicines and, in some cases, insulin (NIDDK 2020). Patients with type 1 diabetes require insulin. Since patients with diabetes have a higher risk of developing cardiovascular diseases, they may also require additional medicines (NIDDK

2020). Generally, insulin is more expensive than several commonly used oral anti-diabetes medicines that have been marketed for many decades and are available at a low price; these generics are recommended as a first-line pharmacological treatment for diabetes (WHO 2015).

Diabetes has emerged as a major public health problem worldwide, especially in low-and-middle income countries, where more than 80% of all people with diabetes are living. The International Diabetes Federation estimated that the global prevalence of diabetes among adults in 2013 was 8.3%, or roughly 382 million people living with diabetes, and this is projected to increase to more than 592 million in less than 25 years, which might be a conservative estimate. Southeast Asia accounts for close to one-fifth of all diabetes cases worldwide and the prevalence of diabetes is projected to increase by 71% in this region by 2035. The International Diabetes Federation Diabetes Atlas, 4th edition in 2009 projected that diabetes prevalence in Bangladesh would increase more than 50% by 2017, ranking Bangladesh 8th in the number of people with diabetes globally. The economic and human costs provoked by diabetes in a large population such as in Bangladesh will continue to be substantial. This study estimates the effect of graduation out of LDC status and the attendant changes in IP protection for pharmaceuticals on the price of insulin price and the subsequent impacts on welfare and poverty in Bangladesh.

## 3.3 Literature Review

This paper builds on an emerging body of literature on the impacts of trade and investment treaties on access to medicines. A full assessment of this literature can be found in Islam et al. (2019). This literature is commonly grouped into two categories—ex-ante analyses that examine the extent to which proposed policies might impact access to medicines, and ex-post analyses that examine the impact of trade and investment treaties that have already occurred. This paper falls in the ex-ante category, attempting to estimate the extent to which access to insulin will be jeopardized in Bangladesh under a scenario where it loses its exemption from the TRIPs Agreement under the WTO if it graduates from the LDC status in the coming years.

Most ex-post studies find that trade and investment treaties adversely impact access to medicines in developing countries but to a lesser degree than do ex-ante studies. With respect to ex-post studies, some analyses look at the impacts of WTO-related provisions and others look at free trade agreements (FTAs). Of the WTO studies, Kyle, and Qian (2014) examined the impact of intellectual property rights (IPRs) in the TRIPS Agreement on the launch of new medicines, prices, and sales using data from 59 countries at varying levels of development. They found that patented medicines have higher prices and quantities sold, and that new medicine launches were unlikely without patent protection. Other studies examine impacts from FTAs that have more stringent provisions than the TRIPS Agreement, particularly those of the United States (US). Examples of this literature are studies that examine the US–Jordan FTA and find that the FTA increased prices of essential medicines and delayed market entry of generics (Abbot et al. 2012). Shaffer and Brenner (2009) examined the Central American Free Trade Agreement and found that it reduced access to generics already on the market and delayed entry of other generics. Most recently, Trachtenberg et al. (2020) found that the US–Chile trade agreement increased both the price and sale volume of biologics.

This present study builds on a set of ex-ante studies which predictably estimate adverse impacts given the underlying assumptions they deploy from economic theory. The outcomes that ex-ante studies predict reflect the models' underlying assumptions, which are rooted in economic theory. When a firm is granted a patent, economic theory predicts the firm will supply a restricted quantity at a higher price because the patent grants the producing firm a temporary monopoly over the product (Baker 2016).

Akaleephana et al. (2009) used a trade liberalization framework and attempted to find effects on prices and quantities following a reduction in tariffs or other trade barriers to estimate the potential cost savings in Thailand resulting from an absence of TRIPS-plus provisions and increased price competition between innovative and generic producers of 74 international non-proprietary name imported medicines. These authors found that a proposed US–Thailand treaty would increase medical expenses and reduce the entry of generic medicines.

Chaves et al. (2017) used the IPR impact aggregate model to project the impact of TRIPS-plus provisions of the Mercosur–European Union FTA on the public expenditures and domestic sales of antiretroviral medicines (ARVs) and hepatitis C medicines in Brazil and reckoned that the treaty would increase medicine expenditures and decrease sales by domestic producers.

This paper is like the work of Chaudhuri, Goldberg, and Jia (2006) and Dutta (2011) in terms of the nature of the research question being investigated. Chaudhuri, Goldberg, and Jia (2006) used a two-stage budgeting framework (using data from 1999 to 2000) to investigate the effects on prices and welfare when one or more domestic generics are withdrawn from the quinolone market in India due to the TRIPS Agreement of the WTO.[2] That study found considerable consumer welfare losses from a reduction in the variety of products available on the market after TRIPS. We used household survey data to estimate the effects of stronger IP laws in the market for insulin in Bangladesh and obtained similar results of welfare loss as in Chaudhuri, Goldberg, and Jia (2006) and Dutta (2011).

## 3.4 Methodology, Estimation Framework, and Data

To estimate the effect of graduating from LDC status on the prices of essential medicines such as insulin, we analyze the effect of introducing patent protection for pharmaceuticals in Bangladesh. This introduction will potentially reduce competition in the pharmaceutical

[2]Quinolones are a subsegment of systematic antibacterials.

market, and even the market of innovative medicines might be monopolized by the patent holder if there is no further regulation of medicine prices. Hence, analyzing the effects of Bangladesh's LDC graduation on medicine prices is akin to estimating the effects on medicine prices due to the pharmaceutical market becoming more monopolized through new patent protection and a withdrawal of generic versions of innovative medicines from the local market.

In this paper, we estimate the demand for insulin in Bangladesh as the burden of Type 2 diabetes is increasing in Bangladesh and the price of insulin affects many persons with Type 2 diabetes. We combine a variety of data sources for this purpose. To estimate the demand elasticities for pharmaceutical products and/or medicines, previous studies used market share data. For example, Chaudhuri, Goldberg, and Jia (2006) and Dutta (2011) used IQVIA market share data of different brands or generics of quinolones in the Indian market to examine the impact of the WTO agreement. The IQVIA market sales data of quinolones was representative of the Indian market. However, IQVIA market share data only covers 2% of total sales of medicines in Bangladesh, which is not representative enough to carry out a rigorous demand parameter estimation. Hence, we use the household-level expenditure data on medicine and other items instead of market share data. The household-level data have the advantage of reporting the cost of medicines faced by households rather than the price reported by manufacturers, but the drawback of using household-level data is that it does not provide the quantity or price of medicines but rather the total cost of medicines per person monthly or annually.

Accordingly, for our estimation purpose we use Bangladesh's Household Income Expenditure Survey (HIES) (2016) data for information on different categories of expenditures (e.g., food, medicines, and education), household characteristics (e.g., income, number of members, and geography of residence) and household head's characteristics (e.g., age, gender, religion, employment status, and employment sector). The summary statistics of these variables are provided in Tables A1.1 and A1.2 in Appendix 1. From HIES, we select the households with at least one member with diabetes. The 2016 HIES was conducted by BBS from April 2016 to March 2017 (BBS 2019). This newest HIES is the most extensive household survey in Bangladesh.

The HIES data provide the most granular information on a wide range of individual and household characteristics. The survey is conducted at three levels (urban and rural breakdown, district level, and household level) and is designed to represent different socioeconomic groups in every part of the country. A sample design was adopted for the 2016 HIES with 2,304 primary sampling units in eight administrative and geographical divisions (Barisal, Chittagong, Dhaka, Khulna, Mymensingh, Rajshahi, Rangpur, and Sylhet) and 64 districts, selected from the last Housing and Population Census in 2011. Within each primary sampling unit, 20 households were selected for interviews. The final sample size was 46,080 households. The sample was stratified at the district level and included a total of 132 substrata: 64 urban, 64 rural, and 4 main city corporations (BBS 2019). Details of the survey design of HIES can be found in International Household Survey Network (2020).

From the 2016 HIES, we construct our sample consisting of all households with at least one member suffering from diabetes. We excluded individuals who are suffering from multiple chronic diseases as there is no breakdown of medicine expenditure in HIES. Finally, we have a sample of 1,125 households with at least one member suffering from only chronic disease which is diabetes. The summary statistics of the sample is provided in Table A.12 and Table A.13 We complement the HIES data with insulin prices from the Directorate General of Drug Administration (DGDA) of Bangladesh, where prices of all approved insulins and their respective strengths are reported.

To measure the effects of stronger IPR on the use of insulin and consumption of other essential items, we model a household's decision problem of allocating income in broad expenditure categories such as food, medicine, and education. We estimate the parameters at this stage using a version of QUAIDS. Traditionally, elasticities of demand are estimated using a nested logit model of demand or full random coefficient logit model of demand (Dutta 2011; Chatterjee, Kubo, Pingali 2015). One potential issue of these demand models is that the demand for any medicine such as insulin generally depends on the physicians' prescription, especially if patients are not very well informed. So, taste for a particular brand of insulin is unlikely to be independent across consumers, which violates the key assumption in those demand modeling strategy. Moreover, to estimate a nested logit model of demand or a full random coefficient logit model of demand, we need data on sales of different brand and generic types of insulin, which are not available in the case of Bangladesh. IQVIA does have some sales data for Bangladesh, but the coverage is very limited and are not representative. Hence, we choose the QUAIDS framework, which allows us to estimate the price elasticity of insulin using the household's expenditure on insulin. One advantage of using the household data to estimate the elasticities is that we can control many household characteristics, which are important in estimating the elasticities more consistently. The QUAIDS framework requires expenditure shares on these expenditure categories, price or price index, total household income, and other household level controls, all of which are available in the HIES (2016). Here, we use the Poi (2012) specification of QUAIDS, which incorporates the demographic variables.

### 3.4.1 Demand

The QUAIDS model in our estimation framework is based on the following indirect utility function used in Banks, Blundell, and Lewbel (1997):

$$lnV(\mathbf{p}, m) = \left\{ \frac{lnm - lna(\mathrm{p})}{b(\mathbf{p})}^{-1} + \lambda(\mathrm{p}) \right\} \tag{3.1}$$

where $lna(\mathbf{p})$ is the transcendental logarithm function of prices or costs of individual expenditure items, $p_i$:

$$lna(\mathbf{p}) = \alpha_0 + \sum_{i=1}^{3} \alpha_i lnp_i + \frac{1}{2} \sum_{i=1}^{3} \sum_{j=1}^{3} \gamma_{ij} lnp_i lnp_j \tag{3.2}$$

and $b(\mathbf{p})$, is the Cobb–Douglas price aggregator, and $\lambda$(p) are defined as follows:

$$b(\mathbf{p}) = \prod_{i=1}^{3} \lambda_i lnp_i$$

$$\gamma(\mathrm{p}) = \sum_{i=1}^{3} \lambda_i lnp_i$$

Here, we need to estimate parameters $\{\alpha_i, \beta_i, \gamma_i, \lambda_i\}$ except $\alpha_0$, which is generally set to some value lower than the lowest value of $lnm$ in the sample (Deaton and Muellbauer 1980; Banks, Blundell, and Lewbel 1997). The set of parameters satisfy some conditions: Adding up $\sum_{i=1}^{3} \alpha_i = 1$, homogeneity $\sum_{i=1}^{3} \beta_i = 0$, Slustsky symmetry $\sum_{j=1}^{3} \gamma_{ij} = 0$, $\sum_{i=1}^{3} \lambda_i = 0$, and $\gamma_{ij} = \gamma_{ji}$. Now, we specify the expenditure share equation of expenditure item i by applying the Roy's identity to equation (1):

$$\omega_i = \alpha_i + \sum_{j=1} \gamma_{ij} lnp_j + \beta_i ln\left(\frac{m}{a(\mathbf{p})}\right) + \frac{\lambda_i}{b(\mathbf{p})} \left[ ln\left\{\frac{m}{a(\mathbf{p})}\right\}\right]^2, \qquad j \in \{1,2,3\} \tag{3.3}$$

where $\omega_i$ is the household's budget share for expenditure category $i$; and here we only consider expenditure on three items: food (1), medicine (2), and education (3), $\omega_i$ is defined as follows:

$$\omega_i \equiv \frac{p_i q_i}{\sum_j p_j q_j} = \frac{p_i q_i}{m}, \qquad j \in \{1,2,3\}$$

Here $q_i$ is the quantity of item $i$ and $p_i$ is the price or cost of expenditure category $j$, m is the household income spent on food, medicine, and education.

### 3.4.2 Demographics

Household and household head characteristics can be incorporated into the QUAIDS framework using the scaling techniques first used by Ray (1983). Poi (2002), using this scaling technique, introduces the demographic variables into the QUAIDS model. Suppose $\mathbf{Z}$ is the vector of demographic variables and $e(\mathbf{p}, u)$ is the expenditure function. Ray's scaling method decomposes the expenditure function into a scaling function, which depends on prices, level of utility, and demographics, and an expenditure function, which depends on prices and level of utility only. Specifically,

$$e(\mathbf{p}, u, \mathbf{Z}) = m_0(\mathbf{p}, u, \mathbf{Z}) \times e(\mathbf{p}, u)$$

Here, the scaling function $m_0(\mathbf{p}, u, \mathbf{Z})$ takes the following form:

$$m_0(\mathbf{p}, u, \mathbf{Z}) = \bar{m}_0(\mathbf{Z}) \times \phi(\mathbf{p}, u, \mathbf{Z})$$

where $\bar{m}_0(\mathbf{Z})$ is the part of the scaling function that depends on demographics only; that is, a larger family will have a larger expenditure on food compared to a smaller family, and a family with more school-aged children is likely to have higher educational expenditure than a family with no school-aged children. The second part $\phi(\mathbf{p}, u, \mathbf{Z})$ accounts for the interaction between the consumption pattern and demographics; that is, a family with a member with diabetes may consume a different type of food compared to a family with no such member. Ray (1983) parameterizes $\bar{m}_0(\mathbf{Z})$ and $\phi(\mathbf{p}, u, \mathbf{Z})$ as follows:

$$\bar{m}_0(\mathbf{Z}) = 1 + \rho'\mathbf{Z}$$

$$\phi(\mathbf{p}, u, \mathbf{Z}) = \frac{u \prod_{j=1}^{3} p_j^{\beta_j} \left( \prod_{j=1}^{3} p_j^{\eta_j' Z} - 1 \right)}{\frac{1}{u} - \sum_{j=1}^{3} \lambda_j lnp_j}$$

where $\rho$ and $\eta$ are vectors of parameters to be estimated. The expenditure share equations specified in Equation (3.3) become:

$$\omega_i = \alpha_i + \sum_{j=1} \gamma_{ij} lnp_j + (\beta_i + \eta_j^{'}\mathbf{X}) ln\left(\frac{m}{\bar{m}_0(\mathbf{Z})a(\mathbf{p})}\right) \tag{3.4}$$
$$+ \frac{\lambda_i}{b(\mathbf{p})c(\mathbf{p},\mathbf{Z})}\left[ln\left\{\frac{m}{\bar{m}_0(\mathbf{Z})a(\mathbf{p})}\right\}\right]^2, \qquad j \in \{1,2,3\}$$

where $c(\mathbf{p},\mathbf{Z}) = \prod_{i=1}^{3} p_i^{\eta_j^{'}\mathbf{Z}}$ and the additional adding-up condition $\sum_{i=1}^{3} \eta_j = 0$

### 3.4.3 Elasticities

The uncompensated price elasticity of demand for good i with respect to the price of good $j(\epsilon_{ij})$ is derived in Poi (2012) and given as follows:

$$\epsilon_{ij}^h = \frac{dlnq_i}{dlnp_j} = -\delta_{ij} + \frac{1}{\omega_i}\left(\gamma_{ij} - \left[\beta_i + \eta_i^{'}\mathbf{Z} + \frac{2\lambda_i}{b(\mathbf{p})c(\mathbf{p},\mathbf{Z})} ln\left\{\frac{m}{\bar{m}_0(\mathbf{Z})a(\mathbf{Z})}\right\}\right]\right.$$
$$\left.\times\left(\alpha_j + \sum_k \gamma_{ik} lnp_k\right) - \frac{(\beta_j + \eta_j^{'}\mathbf{Z})\lambda_i}{b(\mathbf{p})c(\mathbf{pZ})}\left[ln\left\{\frac{m}{\bar{m}_0(\mathbf{Z})a(\mathbf{p})}\right\}\right]^2\right)$$

where $\delta_{ij} = 1$ if $i = j$ and 0 otherwise, and $h$ is the index for households. The expenditure or income elasticity for good $i(\mu_i)$ is derived as follows:

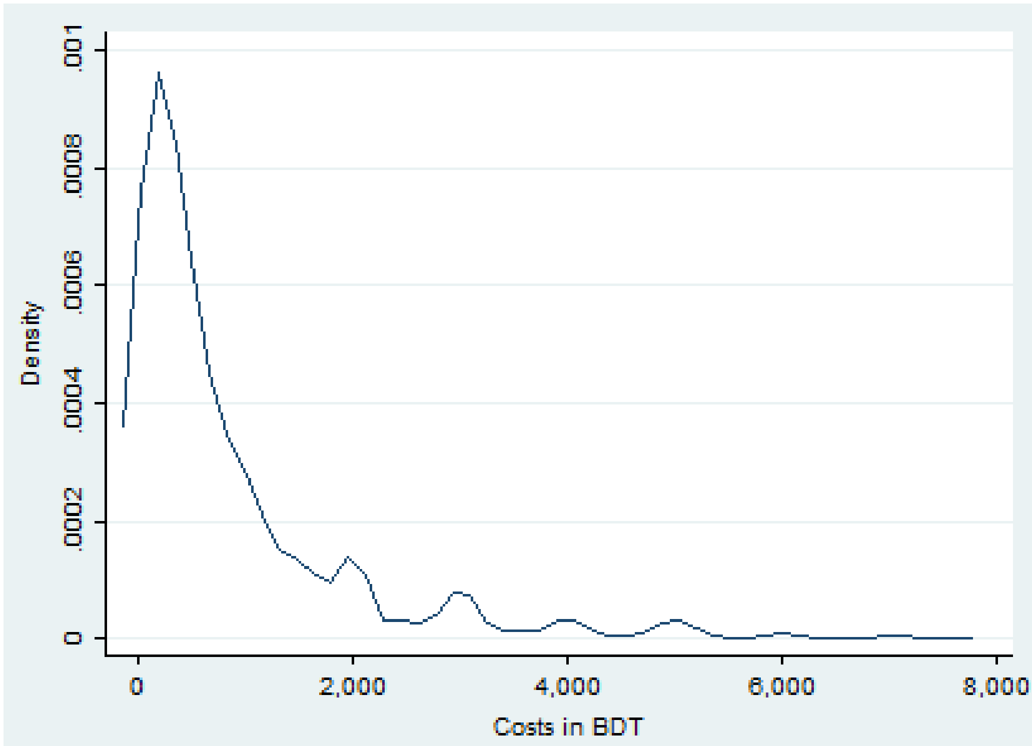
$$\mu_i^h = \frac{dlnq_i}{dlnm} = 1 + \frac{1}{\omega_i}\left[\beta_i + \eta_i^{'}\mathbf{Z} + \frac{2\lambda_i}{b(\mathbf{p})c(\mathbf{p},\mathbf{Z})} ln\left\{\frac{m}{\bar{m}_0(\mathbf{Z})a(\mathbf{p})}\right\}\right]$$

The formula for price elasticities here is at the household level. The price elasticities at the market level are then the average of the household-level price elasticities.

### 3.4.4 Econometric issues

The HIES (2016) does not provide any information on whether a household with a person who is living with diabetes needs to purchase insulin for that member, so to estimate the demand parameters and elasticities for insulin demand, we construct a sample that has the highest probability of including the households that purchase insulin. For this purpose, we use the maximum retail price of each registered insulin to estimate the cost per daily dose as defined by WHO, and then calculate the monthly cost of insulin for an individual. Firstly, we estimate the bounds on insulin cost per month for an individual and our calculation shows that the monthly cost of using only insulin lies between Tk436 and 1925 BDT. Secondly, for the purpose of this study we assume that the individuals who use only non-insulin diabetes medicines are in the lower bound of the abovementioned price range of insulins. That is, individuals whose monthly cost of diabetes medicines is below Tk436 are assumed to use only non-insulin diabetes medicines. The distribution of the costs of diabetes medicines is shown in Figure 1. From the distribution of costs of diabetes medicines, we obtain that around 47% of observations (534 out of 1,125) are below the lower bound of Tk436. Thus, the proportion of households using only insulin, insulin plus non-insulin, or expensive non-insulin medicines is about 53%. Hence, our sample for the analysis is the 38% of households with at least one member with diabetes in which per person costs of medicines are between Tk436 and Tk1925 (424 out of 1,125).

**Figure 3·1:** Distribution of Monthly per Person Costs of Diabetic Medicines




Note: Figure 3·1 plots the distribution of monthly per person costs of diabetic medicine in Bangladesh as reported in HIES 2016. The costs are measured in Bangladeshi currency (BDT) and it ranges from 0 to about 8000 BDT.

Here, we do not include households with members suffering from diabetes along with other chronic illnesses. Our assumptions seem plausible given that Mohiuddin (2019) found that about 15% of patients with diabetes use only insulin, whereas Islam et al. (2017) found that about 41% of patients with diabetes use insulin in Bangladesh.

Since our sample includes only those households that have at least one member with diabetes and the per person costs of medicines is between Tk436 and Tk1,925, the bounds on the cost of medicines ensure that our sample includes almost all households spending on insulin; however, this does not ensure the exclusion of households whose expenditures on medicine fall within the bounds, but these expenditures are not on insulin. This may introduce a sample selection bias into our estimation. To minimize this bias, we perform a

Heckman type correction for selection bias. This correction is performed in two stages. In the first stage, we estimate the following Probit model:

$$Prob(D = 1|X) = \Phi(X\theta) \tag{3.5}$$

where $X$ is the vector of explanatory variables that includes different individual characteristics such as age, gender, education, and ethnicity, as well as individual household characteristics such as household income, location, religion, household head's education, age, and gender. $\theta$ is a vector of unknown parameters, and $\Phi$ is the cumulative distribution function of the standard normal distribution. Here, vector $X$ could be the same as $Z$ or different than $Z$; that is, we can use the variable vector $Z$ in place $X$, or we could use a subset of $Z$ with some other control variables to construct $X$. The indicator variable D is defined as follows:

$$D = \begin{cases} 1, & \text{if monthly cost of diabetic medicine is less thab 436 BDT} \\ 0, & \text{Otherwise} \end{cases}$$

Estimation of this Probit model yields results that can be used to predict the probability for everyone with diabetes that uses only non-insulin diabetes medicines given the various individual and household characteristics. We use this estimated Probit model to predict the probability that an individual uses only non-insulin diabetes medicines for our sample, individuals with diabetes with monthly costs more than Tk436. These predictions will be unbiased and consistent if the error terms in the Probit model are uncorrelated with control variables and are normally distributed. After estimating this Probit model, we obtain the correlation between the predicted values and the residuals of the model and this correlation is almost 0 (–0.0004). So, we can maintain the assumption that the error terms of the Probit model and the set of control variables are uncorrelated. Assuming that these assumptions are satisfied, we estimate the probabilities that the individuals using only insulin or insulin with other non-insulin medicines in our sample using the estimated Probit model:

$$Prob(D = 0|X) = 1 - \Phi(X\theta) \tag{3.6}$$

Using these estimated probabilities, we estimate the inverse Mills' ratio as follows:

$$\zeta(X\hat{\theta}) = \frac{\phi(X\hat{\theta})}{1 - \Phi(X\hat{\theta})} \tag{3.7}$$

where $\phi$ is the probability density function. After estimating the inverse Mills' ratio, we estimate the QUAIDS model, where now $Z$ includes $\zeta(X\hat{\theta})$ as an additional control along with the other control variables described above. Assuming that the error terms are jointly normal, we estimate the QUAIDS model including Mills' ratio as an additional demographic variable.

A second issue in the estimation of the QUAIDS model is that the costs of diabetes medicines might be correlated with other unobserved individual or household characteristics (Islam et al. 2019). To overcome this problem, we construct an instrumental variable (IV) for the cost of diabetes medicines. To construct this IV, we argue that the cost of diabetes medicines of an individual might be correlated with unobserved individual and household characteristics, but these unobserved characteristics are orthogonal to cost of medicines of individuals residing in the same geographic area. Thus, we use the average cost of medicines in the smallest geographic unit of HIES as the IV for cost of diabetes medicines, as the price or cost of diabetes medicines is correlated within the same geographic region, but orthogonal to a specific individual's or household's characteristics, where the average is calculated by a leave-one-out method. That is, the IV for the cost of medicines for individuals in household $h$ residing in region $r$ is the average cost of medicines for all individuals residing in the same region $r$ except members of household $h$. Let us refer to this IV as $IV_1$, so $IV_1$ is given as follows:

$$IV_{ihr} = \frac{\sum_{h \in r \setminus h} p_{dhr}}{N_r} \tag{3.8}$$

where $IV_{1hr}$ is the $IV$ for the cost of medicines of individuals in household $h$ in region $r$, $p_{dhr}$ is the cost or price of diabetes medicines of an individual in household $h$ in region $r$, $\sum_{h \in r \setminus h} p_{dhr}$ is the sum of the cost of diabetes medicines of all individuals in region r except for individuals living in household $h$, and $N_r$ is the total number of individuals with diabetes living in region $r$ and incurring a cost of medicines between 436 BDT and 930 BDT. Similarly, we construct an $IV$ for the prices of food and education.

Another issue in estimating the demand parameters is that error terms $u$ may be spatially correlated as costs of diabetes medicines are generally correlated with the types of health care provider such as public hospitals, private hospitals, and pharmacies, and we have certain types of health care providers in each region (Islam et al. 2019). This may introduce heteroscedasticity in the QUAIDS model and hence reduce the efficiency of the estimators. To eliminate the heteroscedasticity due to spatial correlation in error terms $u$, we cluster the standard errors at the union or ward level, which is the lowest administrative unit in Bangladesh.

### 3.4.5 Computing Counterfactual Price Changes

To determine the range of potential increases in the prices of insulin following Bangladesh's graduation from LDC, we use estimated demand elasticities to compute the ranges of markups and marginal costs based on the current prices of insulin and insulin market structure. Since the expenditure items in our QUAIDS model is defined broadly (i.e., food, medicine, and education), it is expected that the price elasticities of demand would be very low. Hence, it would be impossible to determine the insulin prices under the monopoly market structure ensured by stronger IP laws as a monopoly's equilibrium output is always at the elastic part of the market demand curve. Hence, to compute the counterfactual prices of insulin under monopoly market structure, we need to estimate the slope of the demand function of insulin so that we can use this slope to estimate the price elasticities of demand at different points on the demand curve. This estimated elasticity is then used to derive the optimal monopoly markup. Here, we assume that the market demand for insulin is linear in insulin prices and estimate this linear demand function by estimating the following regression equation:

$$\omega_2 = \varphi_0 + \varphi_1 p_2 + \varphi_2 \bar{\omega} + Z'\Omega + u \tag{3.9}$$

where $\omega_2$ is the household expenditure on insulin, $p_2$ is the price of insulin faced by the household, $\bar{\omega}$ is the minimum level of income necessary to ensure a subsistence level of food consumption for the household. $\bar{\omega}$ is calculated by multiplying the household size and the national lower poverty level income as reported in the final report of the 2016 HIES (BBS 2019); $Z^{'}$ is the vector of household and household head's characteristics; $u$ is the error term; and $\varphi_0, \varphi_1, \varphi_2, \Omega$ are parameters to be estimated. Here, the main parameter of interest is $\varphi_1$, which then is used to calculate the slope of the insulin demand curve with respect to insulin price as follows:

$$\frac{d\omega_2}{dp_2} = \frac{d(p_2 q_2)}{dp_2} = q_2 + p_2 \frac{dq_2}{dp_2} = \hat{\varphi}_1$$

$$\bar{b} = \frac{dq_2}{dp_2} = \frac{\hat{\varphi}_1}{\bar{p}_2} - \frac{\bar{q}_2}{\bar{p}_2} \tag{3.10}$$

where $\bar{b}$ is the slope of the demand curve evaluated at the average price and quantity of the insulin. We also verify the estimated slope of the inverse demand curve using the own price elasticity of insulin demand obtained from our QUAIDS model as follows:

$$0 = p_2 + q_2 \frac{dp_2}{dq_2} = 1 + \frac{1}{E_{22}} \tag{3.11}$$

$$\frac{dp_2}{dq_2} = 1 + \frac{1}{E_{22}} - \frac{\bar{p}_2}{\bar{q}_2} = \frac{1}{\bar{b}} \tag{3.12}$$

where we use the fact that at the midpoint of the demand curve, marginal revenue is 0. Once we have the estimated slope of the insulin demand curve, we can estimate the price elasticities of the insulin demand curve:

$$E_{22} = \bar{b}\frac{p_2}{q_2} \tag{3.13}$$

Now, we can find the elasticities at different points of the demand curve. With these estimated elasticities, we can find the optimal markup for the monopoly. In addition to simulating the counterfactual markup and price under monopoly market structure, we also use the average insulin price in Pakistan, where the pharmaceutical market is less regulated and strong IP laws govern the market (Basant 2007). Nevertheless, most types of insulin are very affordable in Pakistan compared to other South Asian countries. The main reason that a stronger IPR regime did not lead to exorbitant price increases for insulin in Pakistan is the provision of the insulin supply by the public sector (Ewen et al. 2019). The reasons that we choose current insulin prices in Pakistan as another counterfactual price are: (i) this provides an interesting scenario where strong IP laws coexist with public sector participation, which enables greater access to insulins, and (ii) the size and characteristics of the economy of Pakistan are comparable to those of Bangladesh.

### 3.4.6 Welfare Analysis

To have insights into the welfare effects of a stronger IPR regime in post-LDC Bangladesh under two counterfactual prices: simulated prices under monopoly market structure and prices in a less regulated neighboring country (Pakistan), we use several measures of welfare as elaborated by Araar and Verme (2016). Our first measure is the consumer surplus (CS), defined as the difference between willingness to pay and the market price of insulin. The measure of CS is given as follows:

$$CS = \int_{p_2}^{p_{2'}} D(p_2)dp_2 \tag{3.14}$$

where $p_2$ and $p_{2'}$ are the current and counterfactual prices of insulin, $D(p_2)$ is the demand function of insulin. Here, to estimate the CS we need to know the Marshallian demand function $D(p_2)$. For a linear demand system and moderate change in prices, CS can be estimated using the following equation:

$$CS = -x_2 \Delta p_2 (1 + 0.5 E_{22} \Delta p_2) \tag{3.15}$$

For the problem concerned in this paper, the price changes could be significantly higher and so the above formula will provide a highly overstated estimate for CS. Araar and Verme (2016) derived an approximation CS formula for a large price change:

$$CS = -x_2 \Delta p_2 (1 - \frac{0.5 \Delta p_{22}}{1 + \Delta p_2} \tag{3.16}$$

CS as a measure of welfare is somewhat restrictive as it assumes that the marginal utility of real income is constant and there is no distributional effect of price changes. It also captures only the partial equilibrium effect and does not perfectly measure the change in welfare if the changes in prices are large. However, CS is a straightforward and easy-to-estimate welfare measure, which would be a good standard to compare with other measures of welfare. The next two welfare measures that we estimate are compensating variation (CV) and equivalent variation (EV). These measures are defined as follows:

$$CV = e(p_2, v^0) - e(p_{2'}, v^0) = \int_{p_2}^{p_{2'}} h(p_2, v^0) dp_2 \tag{3.17}$$

$$EV = e(p_2, v^1) - e(p_{2'}, v^1) = \int_{p_2}^{p_{2'}} h(p_2, v^1) dp_2 \tag{3.18}$$

Where $v^0$ and $v^1$ are levels of generic indirect utility before and after the implementation of a stronger IPR regime, respectively, $e(\dot{})$ is the generic expenditure function, and $h(dot)$ is the Hicksian demand function. Here, CV is the monetary compensation required to bring the consumer back to the original utility level after the price change, and EV is the monetary change required to obtain the same level of utility after the price change (Araar and Verme 2016). One computational problem in calculating CV and EV is that we need to know the indirect utility level before or after the changes in prices. One solution to this computational problem is to derive CV and EV from CS as given in Chipman and Moore (1980):

$$CV = (1 - e^{\frac{CS}{m}})m \tag{3.19}$$

$$EV = (e^{\frac{CS}{m}} - 1)m \tag{3.20}$$

where $m$ is the income level. In addition to these measures of welfare, there are two simple straightforward measures of welfare: Laspeyers Variation (LV), which is defined as the exact change in income necessary to purchase the initial bundle of goods at prices after and before the change in the IPR regime LV is defined as follows:

$$LV = e(p_{2'}, v^0) - e(p_2, v^0) \tag{3.21}$$

where $X^0$ is the initial bundle of goods purchased before the change in prices. The second measure is the Paasche Variation (PV), which is defined as the exact change in income required to purchase the final bundle of goods at prices after and before the change in the IPR regime. PV is given as follows:

$$PV = e(p_{2'}, v^1) - e(p_2, v^1) \tag{3.22}$$

where $X^1$ is the final bundle of goods purchased after the change in prices due to a change in the IPR regime. To estimate LV or PV, we just need the information of quantity purchased before or after the change in the policy regimes and the associated changes in prices, whereas to estimate the other measures of welfare requires some knowledge or assumptions on the demand function or the utility function.

## 3.5 Results

### 3.5.1 Price and Expenditure Elasticities

Table A.14 in Appendix reports the parameter estimates of our QUAIDS model. The estimated uncompensated price elasticities and expenditure elasticities are reported in Table 3.1. Here, all elasticities are the average elasticities across all households in the sample. The price elasticities are reported in panel A and denoted as Eij, where subscript i denotes the expenditure on item i, and j denotes the price of item j. The estimate of price elasticity of food, E11, is consistently estimated across different models; E11 ranges from 93.7% to 99.0% under different specifications. The price elasticities of insulin have expected negative signs only under IV specification, and these vary from 92.7% to 94.3%, whereas the price elasticities of education vary from 14.5% to 25.5% under various specifications but are not statistically significant.

**Table 3.1:** Uncompensated Price and Expenditure Elasticities of Major Expenditure Items in Bangladesh

| | Not corrected | | Corrected | |
|---|---|---|---|---|
| | OLS | IV | OLS | IV |
| Price elasticities | | | | |
| $E_{11}$ | $-0.988^{***}$ | $-0.945^{***}$ | $-0.990^{***}$ | $-0.990^{***}$ |
| $E_{12}$ | $-0.103^{***}$ | $-0.004^{***}$ | $-0.106^{***}$ | $-0.004^{***}$ |
| $E_{13}$ | $-0.071^{***}$ | $-0.054^{***}$ | $-0.072^{***}$ | $-0.060^{***}$ |
| $E_{21}$ | $-0.0433^{***}$ | $-0.621^{***}$ | $-0.042^{***}$ | $-0.563^{***}$ |
| $E_{22}$ | $-0.377^{***}$ | $-0.927^{***}$ | $-0.413^{***}$ | $-0.943^{***}$ |
| $E_{23}$ | $-0.120^{***}$ | $-0.107^{***}$ | $-0.125^{***}$ | $-0.090^{***}$ |
| $E_{31}$ | $0.062^{***}$ | $-2.011^{***}$ | $0.082^{***}$ | $-2.124^{***}$ |
| $E_{32}$ | $-0.010$ | $0.013$ | $-0.010$ | $0.003$ |
| $E_{33}$ | $-0.180$ | $-0.255$ | $-0.180$ | $-0.143$ |
| Expenditure elasticities | | | | |
| $E_1$ | $1.162^{***}$ | $1.003^{***}$ | $1.168^{***}$ | $1.001^{***}$ |
| $E_2$ | $-0.454^{***}$ | $0.203^{***}$ | $-0.495^{***}$ | $0.289^{***}$ |
| $E_3$ | $0.133$ | $2.251^{***}$ | $0.111$ | $2.258^{***}$ |

[1] OLS=Ordinary least squares estimates, IV=Instrumental variable estimates.
[2] $***p < 0.01$, $**p < 0.05$, and $*p < 0.1$.
Source: QUAIDS model estimates based on data from the Bangladesh Bureau of Statistics. 2019. Report on the Household Income and Expenditure Survey 2016. Dhaka: Statistics and Information Division, Ministry of Planning, Government of Bangladesh.

The cross-price elasticities show interesting demand patterns as well. The cross-price elasticities between food and insulin ($E12$) or education ($E13$) are always negative under all specifications and statistically different from zero. This indicates that expenditure on food falls in response to an increase in the price of insulin or education. However, the cross-price elasticities between insulin and food ($E21$) or education ($E23$) are positive under IV specifications, which indicates that an increase in the price of food or education may not lead to a decrease in demand for insulin.

### 3.5.2 Marginal Costs and Markups

Currently, the market for insulin in Bangladesh is oligopolistic. To find the markups in this market, we assume that marginal cost of producing insulin is constant and the same for all producers. If there are n firms in the market with the same marginal cost, c, the markup is defined as follows: $\frac{P-c}{p} = -\frac{1}{n}\frac{Q}{P}\frac{dP}{dQ}$. The current insulin market in Bangladesh is to some extent competitive. There are seven domestic producers of insulin supplying 50 different insulin products in Bangladesh (DGDA 2019). The differences in these products are in terms of dosages size and the producers. In addition, there are six foreign producers, who have registered a combined 65 insulin products in Bangladesh (DGDA 2019). The licenses of products of two foreign producers expired in 2015 and early 2016.[3] Hence, there are now 11 suppliers of insulin in Bangladesh.[4] Thus, the markup is given by the following formula: $\left(\frac{1}{1+\frac{1}{11\times|E_{22}|}}\right)$. The marginal costs are calculated using the bounds of insulin prices, which is the amount paid by a household for 1 month of insulin supply. We use the maximum retail prices reported by DGDA to estimate this monthly expenditure on insulin, which is found to be between 436 BDT and 925 BDT. The estimated markups and bounds of marginal cost of a 1-month insulin supply are reported in the Table 3.2.

**Table 3.2:** Implied Markups and Marginal Costs under Current Market Structure of Insulin

| | Not corrected | | Corrected | |
|---|---|---|---|---|
| | Lower bound | Upper bound | Lower bound | Upper bound |
| Price elasticities | -0.93 | -0.93 | -0.94 | -0.94 |
| Markups | 1.11 | 1.109 | 1.107 | 1.107 |
| Marginal costs | 393.24 | 1740.73 | 393.97 | 1743.94 |

[1] Marginal costs are in BDT.
Source: Authors' calculations based on data from the Bangladesh Bureau of Statistics. 2019. Report on the Household Income and Expenditure Survey 2016. Dhaka: Statistics and Information Division, Ministry of Planning, Government of Bangladesh; and Directorate General of Drug Administration. "Registered Products." Government of Bangladesh. http://www.dgda.gov.bd/index.php/manufacturers/allopathic (accessed October 14, 2019).

From the Table 3.2, we can see that the current markups range from 1.107 to 1.109,

[3]Eli Lilly & Company's license in the US expired in May 2016. Lilly's license in France expired in May 2015. https://www.dgda.gov.bd/index.php/2013-03-31-05-16-29/registered-imported-drugs.

[4]The list of insulin suppliers in Bangladesh is given in Table A.15

reflecting the fact that the current market is characterized by some competitive forces as the markups are around 10% over the marginal cost (MC). The lower and upper bound of MC ranges from 393.24 BDT to 1,740.73 BDT and from BDT 393.97 to 1,743.94 BDT, respectively. These bounds reflect end user MCs rather than MCs at the production level. Thus, these are the MCs of all value added of insulin production: from production to final purchase by households.

### 3.5.3 Demand Function of Insulin and Counterfactual Prices

We estimate the insulin demand function as specified in Equation (3.9) using the IV for insulin prices. The result of the regression equation (9) is reported in the Table A.16 in Appendix. The estimates of the coefficient of insulin price (p2IV) are negative under the estimation strategies of not correcting and correcting for sample selection bias. We use the estimate of the coefficient of p2IV in a regression corrected for sample selection bias, and this estimate is $var\hat{p}hi_1 = -0.11$. Then the estimated slope coefficient, $\bar{b} = -0.00137$b, is given as follows:

$$\bar{b} = \frac{dq_2}{dp_2} = \frac{\hat{\varphi}_1}{p_2} - \frac{\bar{q}_2}{\bar{p}_2} = \frac{\hat{\varphi}_1}{p_2} - \frac{\bar{p}_2\bar{q}_2}{\bar{p}_2^2} = \frac{-0.11}{884.16}\frac{973.33}{884.16^2} = -0.00137$$

where Tk973.33 is the average monthly household expenditure on insulin and 884.16 BDT is the average of monthly price of insulin. Now, the elasticity of insulin demand at the average price and quantity of insulin are given as follows:

$$E_{22} = \bar{b}\frac{\bar{p}}{\bar{q}} = \bar{b}\frac{\bar{p}^2}{\bar{p}\bar{q}} = -0.00137 \times \frac{884.16^2}{973.33} = -1.10$$

Using this elasticity of insulin demand measured approximately at the midpoint of the insulin demand curve, we can find the maximum markups:

$$\frac{1}{1 + \frac{1}{|E_{22}|}} = \frac{|E_{22}|}{1 + |E_{22}|} = 11.01$$

This markup shows that under an unregulated monopoly, the insulin price could be more than 11 times higher than current insulin prices, where the current markup of insulin in Bangladesh is about 1.1. Using the estimated markup under an unregulated monopoly and the upper and lower bounds of MC as reported in Table 3.2, we estimate maximum possible counterfactual prices of insulin, which are reported in Table 3.3. These counterfactual prices show the most extreme situations of an increase in insulin prices in Bangladesh following its graduation from LDC status and the enforcement of strong IP laws. Thus, these provide some bounds on the prices of insulin in a worst-case scenario.

**Table 3.3:** Counterfactual Markups and Prices of Insulin under an Unregulated Monopoly in BDT

| | Not corrected | | Corrected | |
|---|---|---|---|---|
| | Lower bound | Upper bound | Lower bound | Upper bound |
| Marginal costs | 393.24 | 1740.73 | 393.97 | 1743.94 |
| Counterfactual markups | 11.01 | 11.01 | 11.01 | 11.01 |
| Counterfactual prices | 4329.59 | 19165.43 | 4337.59 | 19200.78 |
| Change in prices | 3893.59 | 17235.43 | 3901.59 | 17270.78 |

[1] Marginal costs are in BDT.

Source: Authors' calculations based on data from the Bangladesh Bureau of Statistics. 2019. Report on the Household Income and Expenditure Survey 2016. Dhaka: Statistics and Information Division, Ministry of Planning, Government of Bangladesh; and Directorate General of Drug Administration. "Registered Products." Government of Bangladesh. http://www.dgda.gov.bd/index.php/manufacturers/allopathic (accessed October 14, 2019).

For the Pakistan price counterfactual, we use the average insulin prices reported in Ewen et al. (2019), where the insulin prices for several low- and middle-income countries including Pakistan were surveyed in 2016. Since our sample is from the 2016 HIES, we use the insulin prices in Pakistan as reported in Ewen et al. (2019). These prices are shown in Table 3.4, where we only show the average insulin prices in the private sector (private pharmacies, hospitals, and clinics), as reported in Ewen et al. (2019), since the public sector insulin price is very similar to the private sector price for any specific type of insulin. However, the Glargine analogue insulins are only available in the private sector, particularly at private retail pharmacies.

**Table 3.4:** Insulin Prices in Pakistan in 2016 ($ per 1,000 IU)

| | Catridge | | | | Vial | |
|---|---|---|---|---|---|---|
| | Retail Pharmacies | | Hospitals/Clinics | | Retail Pharmacies | |
| | Brand | Bio-similar | Brand | Bio-similar | Brand | Bio-similar |
| Short-acting human | 5.81 | 4.50 | 5.81 | 4.72 | | |
| Intermediate-acting human | 5.81 | 4.67 | | | | |
| 30/70 human | 5.15 | 4.48 | | | 5.82 | 7.89 |
| Glargine analogue | 28.60 | 20.65 | | | | |

[1] IU = international unit.

Source: Authors' calculations using data from Table 2 in Ewen, Margaret, Huibert-Jan Joosse, David Beran, and Richard Laing. 2019. "Insulin Prices, Availability and Affordability in 13 Low-Income and Middle-Income Countries." BMJ Global Health 4 (3): e001410.

The average insulin price (1,000 IU) in Pakistan in 2016 ranged from about $4.50 to $7.89, except for the glargine analogue. Using the BDT–$ exchange rate in June 2016 from Bangladesh Bank,[5] the central bank of Bangladesh, these average prices correspond to between 352.8 BDT and 618.58 BDT, whereas the average monthly cost of insulin per person in Bangladesh is about 884.16 BDT. Since 1,000 IU of insulin is approximately the monthly supply of insulin for an individual, the average monthly insulin cost for most types of insulin is significantly higher in Bangladesh than in Pakistan. However, average prices for long-acting insulins such as glargine analogues range from $20.65 to $28.65, which corresponds to between 1618.18 BDT and 2,246.16 BDT, which are higher than the average monthly insulin costs in Bangladesh. Here, we use the price of the original brand of glargine analogues in Pakistan as the counterfactual price of insulin in Bangladesh under stricter IP laws. To estimate the upper bound of price increases and loss in welfare, we take the difference between this price, 2,246.16 BDT and the current monthly average cost of insulin per person in Bangladesh, 8,84.16 BDT, which implies a potential 154% increase in the average monthly cost of insulin in Bangladesh.

[5] The Tk–$ exchange rate in June 2016 was 78.4. https://www.bb.org.bd/econdata/exchangerate.php.

### 3.5.4 Welfare Analysis

The welfare estimates are reported in Table 3.5. The welfare loss estimates in this table are aggregate national level estimates. The welfare losses in the "Upper bound" column correspond to upper bound price changes in columns 2 and 4 of Table 3.4. Similarly, the welfare losses in columns 3 and 4 in Table 3.5 correspond to lower bound price changes in columns 1 and 3 of Table 3.4. The welfare estimates in column 5 of Table 3.5 are calculated for the counterfactual price increase from the average price of 884.16 BDT. The welfare loss estimates in the last column, column 6, of Table 3.5 are calculated by using the originator's price of long-acting insulin glargine analogues in Pakistan. All these estimates of welfare loss show the worst-case scenario, which entails maximum welfare losses under an unregulated monopoly because of stronger IP laws after Bangladesh's graduation from LDC status.

The first row of Table 3.5 is the measure of aggregate increases in household expenditures due to an increase in insulin prices following Bangladesh's graduation from LDC status. Here LV and PV measures are the same, as we use the same composition of goods before and after changes in insulin prices. The upper bound of the aggregate increase in household expenditure under an unregulated monopoly is about $656 million per year, whereas the lower bound is about $148 million per year. The aggregate increase in household expenditure would be significantly lower, about $52 million per year if the insulin prices in Bangladesh stayed at a similar level to insulin prices in Pakistan.

**Table 3.5:** Annual Aggregate Welfare Losses under an Unregulated Monopoly and Neighbor Price ($ million)

| | Upper bound | | Lower bound | | Average Price | Pakistan Price |
|---|---|---|---|---|---|---|
| | Corrected | Not corrected | Corrected | Not corrected | | |
| LV=PV | 654.94 | 656.27 | 147.96 | 148.26 | 336.31 | 51.76 |
| CS | 327.49 | 328.15 | 74.00 | 74.15 | 168.18 | 25.90 |
| CV | 406.68 | 407.69 | 77.45 | 77.61 | 187.02 | 26.31 |
| EV | 272.78 | 273.23 | 70.82 | 70.96 | 152.57 | 25.50 |

[1] IU = international unit.
Source: Authors' calculations based on data from the Bangladesh Bureau of Statistics. 2019. Report on the Household Income and Expenditure Survey 2016. Dhaka: Statistics and Information Division, Ministry of Planning, Government of Bangladesh.

For an increase in price of insulin, the relationship among losses in CS, CV, and EV are as follows: CV > CS > EV. From Table 3.5, we can see that these relationships are satisfied. From the figures in third (CV) and fourth (EV) rows in Table 3.5, the annual aggregate loss in welfare under an unregulated monopoly will range from $71 millionto 407$ million. However, under the Pakistan price counterfactual, the annual loss in welfare would be around $26 million.

The welfare effect of an increase in insulin prices at the household level in Table 3.6, which reports the increase in household expenditure and the increase in expenditure as a percentage of household average income per year for three counterfactual scenarios: largest upper bound estimate (upper bound IV), smallest lower bound estimate (lower bound OLS), and the Pakistan price counterfactual.

**Table 3.6:** Household-Level Welfare Analysis of Insulin Increases in Bangladesh

| | Incidence of Diabetes (Range of Estimates) | | | |
|---|---|---|---|---|
| | Total | 4.5% | 7.4% | 35% |
| Population (2016) | 161,356,000 | 7,261,020 | 11,940,344 | 56,474,600 |
| Households (2016) | 39,742,855 | 1,788,429 | 2,940,971 | 13,910,000 |
| | Increase in Expenditure and Welfare Loss per Household | | | |
| | Aggregate Welfare Loss ($) | Dollar per Household per Year | | |
| Pakistan price | 51,760,000 | 28.9 | 17.6 | 3.7 |
| Lower bound OLS | 147,960,000 | 82.7 | 50.3 | 10.6 |
| Upper bound IV | 656,270,000 | 337.0 | 223.1 | 47.2 |
| | Impact per Affected Household (Average annual income per household: $2,447[6]) | | | |
| | | Welfare as % of average Income | | |
| Pakistan price | | 1.18% | 0.72% | 0.15% |
| Lower bound OLS | | 3.38% | 2.06% | 0.43% |
| Upper bound IV | | 15.00% | 9.12% | 1.93% |
| | Welfare as % of GDP (2016 Bangladesh GDP: $221 billion) | | | |
| Pakistan price | 0.02% | | | |
| Lower bound OLS | 0.06% | | | |
| Upper bound IV | 0.27% | | | |

[1] Ranges of estimates according to Mohiuddin, Abu Kholdun. 2018. "An A–Z of Pharma Industry Review: Bangladesh Perspectives." PahrmaTutal 6 (12): 64–78.
Source: Authors' calculations based on data from the Bangladesh Bureau of Statistics. 2019. Report on the Household Income and Expenditure Survey 2016. Dhaka: Statistics and Information Division, Ministry of Planning, Government of Bangladesh; and World Bank. "World Development Indicators." https://databank.worldbank.org/source/world-development-indicators (accessed June 1, 2020).

The annual welfare impacts of stronger IP laws could be from $51.6 million across impacted households (Pakistan price counterfactual) to an upper bound of $565.3 million under an unregulated monopoly (Table 3.6). According to a review of the literature (Biswas et al. 2016), the incidence of people with diabetes in Bangladesh is estimated to be between 4.5% and 35.0%, with the "pooled preference" being 7.4%. The average number of people in a household in Bangladesh is 4.06 (BBS 2019). The cost per impacted household per year would therefore range from $17.5 to $223.1, which implies a 0.72% to about a 9.12% decline in affected household incomes.

### 3.5.5 Poverty Impact

An increase in the price of insulin because of stricter IP laws would also have a significant impact on poverty incidence for households that require access to lifesaving insulins for the members with diabetes living in those households. To show the effect of a price rise in insulin on household poverty, we estimate the rate of poverty for the households with members with diabetes, especially with members needing insulin. Table 3.7 shows the absolute number of people and households and rates of poverty under the upper and lower poverty lines at the national level, households with persons having diabetes, and households with members requiring insulin.

**Table 3.7:** Initial Level of Poverty in Bangladesh

| | | Lower Poverty Line | | Upper Poverty Line | |
|---|---|---|---|---|---|
| | Total Households (million) | Households in Poverty (million) | Poverty Rate (%) | Households in Poverty (million) | Poverty Rate (%) |
| 1. National | 39.33 | 5.07 | 12.89 | 9.55 | 24.28 |
| 2. Households with diabetes | 1.05 | 0.27 | 25.36 | 0.35 | 33.57 |
| 3. Households needing insulin | 0.38 | 0.08 | 20.99 | 0.10 | 27.44 |

[1] Ranges of estimates according to Mohiuddin, Abu Kholdun. 2018. "An A–Z of Pharma Industry Review: Bangladesh Perspectives." PahrmaTutal 6 (12): 64–78.
Source: Authors' calculations based on data from the Bangladesh Bureau of Statistics. 2019. Report on the Household Income and Expenditure Survey 2016. Dhaka: Statistics and Information Division, Ministry of Planning, Government of Bangladesh.

Table 3.7 shows there are about 39.33 million households in Bangladesh, and out of them, 12.89% fall below the lower poverty line and 24.28% fall below upper poverty line.[7] The corresponding poverty rates for households with at least one member living with diabetes are 25.36% and 33.54%, respectively, and for households needing insulin they are 20.99% and 27.44%, respectively. The absolute number of households that would fall below the lower and upper poverty lines as result of an increased price in insulin along with

[7]Lower and upper poverty line incomes are defined in HIES (2016).

the percentage increase from the initial level are reported in Table 3.8.

**Table 3.8:** Poverty Rates in Bangladesh after an Increase in Insulin Prices

| | Households in Poverty Before a Price Increase (million) | Households in Poverty After a Price Increase (million) Upper Bound | Lower Bound | Pakistan Price | Increase in Household Poverty Rates (%) Upper Bound | Lower Bound | Pakistan Price |
|---|---|---|---|---|---|---|---|
| | | | | Lower Poverty Line | | | |
| National | 5.7 | 5.22 | 5.11 | 5.08 | 3.05 | 0.77 | 0.24 |
| Households with diabetes | 0.27 | 0.42 | 0.3 | 0.28 | 58.27 | 14.69 | 4.61 |
| Households needing insulin | 0.08 | 0.23 | 0.12 | 0.09 | 194.51 | 49.06 | 15.40 |
| | | | | Upper Poverty Line | | | |
| National | 9.55 | 9.69 | 9.58 | 9.57 | 1.45 | 0.36 | 0.18 |
| Households with diabetes | 0.35 | 0.49 | 0.39 | 0.37 | 39.45 | 9.8 | 4.92 |
| Households needing insulin | 0.1 | 0.24 | 0.14 | 0.12 | 133.23 | 33.11 | 16.62 |

Source: Authors' calculations based on data from the Bangladesh Bureau of Statistics. 2019. Report on the Household Income and Expenditure Survey 2016. Dhaka: Statistics and Information Division, Ministry of Planning, Government of Bangladesh.

Poverty estimates in Table 3.8 are reported only for the upper bound and lower bound of price change under an unregulated monopoly scenario, estimated using IVs for prices with correction for sample selection bias and the price change under the Pakistan counterfactual policy regime. The numbers of households that fall below the lower poverty line are 5.2 million and 5.1 million for the upper and lower bound of an unregulated monopoly counterfactual scenario, respectively, which are about 3.0% and 0.8% higher than the initial level. For the Pakistan price counterfactual, the increase is much smaller, with only about a 0.24% increase from the initial level of poverty.

Among all households with at least one member with diabetes, 0.27 million households are estimated to be below the lower poverty line, which increases to 0.42 million, 0.30 million, and 0.28 million under each of the three counterfactual scenarios, respectively. These increases represent a rise in poverty rates ranging from 4.61% to 58.27% from the current level of poverty for these households. Out of all households that require insulin for one or more than one member, 0.08 million fall below the lower poverty line, which increases by 194.51% to 0.23 million under the upper bound and 49.06% to 0.12 million under the lower bound of an unregulated monopoly counterfactual scenario. Under the Pakistan price counterfactual scenario, the number of households that fall below the lower poverty line is 0.09 million, which is 15.40% higher than the initial level. The pattern of increases in the poverty rates are similar under the upper poverty line.

Table 3.9 reports the numbers of households that are below the lower and upper poverty lines, and the percentage increase in poverty from the initial level of poverty under the various counterfactual price increase scenarios. We also estimated the poverty rates as a fraction of total households for three different aggregate levels.

After an increase in the insulin price under a stricter IPR policy regime, the fraction of total households that fall below the lower poverty line ranges from 12.92% to 13.28% under these three counterfactual scenarios, or an increase in poverty rates ranging from 0.03 percentage points to 0.39 percentage points. Similarly, among all the households with at least one person with diabetes, the share of households that will be under the lower poverty line increases from an initial 25.36% to between 26.53% and 40.14%, with the increase in poverty rates ranges from 1.17 percentage points to 14.78 percentage points. We can see a very substantial increase in household poverty among the households needing insulin. Here, under the three different counterfactual scenarios, the share of households that fall below the lower poverty line among all households needing insulin ranges from 24.22% to 61.81% from an initial poverty rate of 20.99%, which indicates an increase in poverty rates ranging from 3.23 percentage points to 40.82 percentage points for those households. We see a very similar pattern in increased poverty rates when we use the upper poverty line instead of the lower poverty line.

**Table 3.9:** Poverty Rates before and after an Increase in Insulin Prices and Percentage Change

| | Initial Household Poverty Rates | Household Poverty Rates after Price Increase | | | Percentage Point Increase in Poverty Rates | | |
|---|---|---|---|---|---|---|---|
| | | Upper Bound | Lower Bound | Pakistan Price | Upper Bound | Lower Bound | Pakistan Price |
| | | | | Lower Poverty Line | | | |
| National | 12.89 | 13.28 | 12.99 | 12.92 | 0.39 | 0.10 | 0.03 |
| Households with diabetes | 25.36 | 40.14 | 29.09 | 26.53 | 14.78 | 3.73 | 1.17 |
| Households needing insulin | 20.99 | 61.81 | 31.28 | 24.22 | 40.82 | 10.30 | 3.23 |
| | | | | Upper Poverty Line | | | |
| National | 24.28 | 24.63 | 24.37 | 24.33 | 0.35 | 0.09 | 0.04 |
| Households with diabetes | 33.54 | 46.78 | 36.83 | 35.20 | 13.23 | 3.29 | 1.65 |
| Households needing insulin | 27.44 | 64.01 | 36.53 | 32.01 | 36.56 | 9.09 | 4.56 |

Source: Authors' calculations based on data from the Bangladesh Bureau of Statistics. 2019. Report on the Household Income and Expenditure Survey 2016. Dhaka: Statistics and Information Division, Ministry of Planning, Government of Bangladesh.

## 3.6 Discussion and Conclusion

This paper built on previous theoretical and empirical insights to estimate the potential impact of Bangladesh's LDC graduation on its population living with diabetes in general and insulin users in particular. To date, few if any studies deploy an ex-ante partial equilibrium framework that estimates price changes due to trade policy change and then links those results to household behavior models and data. We model and then estimate the potential impact of LDC graduation on the price of insulin in Bangladesh and then link those price changes. Following those estimates, we calculate demand elasticities and relate them to Bangladeshi household data to determine the impacts of those potential price changes in household wealth.

Our findings have significant policy ramifications as well. Bangladesh has a high incidence of diabetes and insulin users, as well as a fairly thriving domestic industry that supplies those treatments to patients in need. We find that prices of insulin would increase significantly in Bangladesh due to LDC graduation and the subsequent requirement to comply with the intellectual property provisions of the WTO. What is more, such price changes would also have significant welfare impacts for the population. LDC graduation would trigger a significant jump in insulin prices that could cause a 1%–15% decline in the welfare, i.e., increase in expenditure, of households with diabetes, increasing the poverty rate of households with diabetes by 54%–58% and of those needing insulin by 15%–195% unless policy adjustments are carried out.

Our estimates of the impact of an increase in insulin price under a stronger IP regime on household welfare and poverty has some important data limitations. These limitations emanated from the lack of detailed expenditure information on medicines by individuals with diabetes. The 2016 HIES of Bangladesh does not provide disaggregated data on types of diabetic medicines, i.e., whether an individual with diabetes needs insulin or non-insulin medicines, and it contains no information on the quantity of medicines needed per day or per month. To construct the sample for our analysis, we needed to infer the households needing insulin from the expenditure on medicines for chronic disease reported in the 2016 HIES and compare this expenditure to an interval constructed using administrative data on monthly insulin costs. It was likely that there would be some households needing insulin but not included in our sample if the household's monthly expenditure on medicines fell below the lower bound of the cost of insulin constructed using administrative data. Similarly, there would be some households that do not need insulin but expenditure on medicines by those households fell within the interval. In the prior scenario, our household welfare and poverty estimates would be underestimated, and in latter scenario, these would be overestimated. Hence, without additional information on medicine expenditure by the households with members living with diabetes, we could not determine the direction of bias that our constructed sample may induce.

Another data limitation in the 2016 HIES is that it seems to underrepresent the fraction of the population suffering from diabetes. In the final report, 186,078 individuals were included in the survey, but only 2,238 individuals were reported to be living with diabetes, which is about 1.2% of the sample. However, it has been estimated that about 10% of the population of Bangladesh are suffering from diabetes, with half of them going undiagnosed (WHO 2016). Hence, we would expect about 5% of the individuals in our sample to report a diagnosis of diabetes. The underrepresentation of individuals with diabetes in the 2016 HIES would also cause a downward bias in estimation. Thus, in this case our estimated effects of an increase in insulin price on households' welfare and poverty are conservative estimates, which signifies that the true welfare cost of a stricter IP regime in Bangladesh after its graduation from LDC status would be significantly higher.

That said, this paper should not be the last word on this subject for Bangladesh, but rather it should start a discussion. As noted earlier, this analysis suffers from a lack of data availability in a transparent manner. Better data collection and dissemination will be paramount to achieving a better understanding of these issues in economics in general and in Bangladesh in particular.

# Appendix A

# Appendices

## A.1 Chapter 1: Additional Results, Tables and Figures

### A.1.1 Solution to the utility maximization problem

Individual $i$'s optimal quantities of housing ($H_i$) and the composite good ($X_i$) are solutions to the following problem:

$$\max_{H,X} \quad a_n^i H_{ni}^{\beta} X_{ni}^{(1-\beta)}$$

$$subject \ \ to \quad RH_{ni} + PX_{ni} \leq W_n^i$$

Since housing supply is perfectly elastic, housing rent is same across cities. Assuming individuals expend their entire wage income on these two expenditure categories, solutions to the utility maximization problem provide the demand functions for composite good $X_{ni}$ and housing $H_{ni}$:

$$X_{ni} = \frac{(1-\beta)W_n}{P} \tag{A.1}$$

$$H_{ni} = \frac{\beta W_n}{R} \tag{A.2}$$

**Solution to the firm's spatial labor cost minimization problem**

Let $l_n^d(\omega, \tau)$ denote the labor demand to produce task $\tau$ by the firm producing variety $\omega$ in city $n$. The labor cost minimization across cities for this firm is given by:

$$\min_{l_n^d(\omega,\tau)} \sum_n W_n l_n^d(\omega, \tau)$$

$$subject \quad to \quad q_n(\omega) = Z_n^\omega y(\omega),$$

$$l_n^d \geq 0$$

Here in the above labor cost minimization problem, a firm minimizes its labor cost to produce a certain quantity of output. The first order Karush-Kuhn-Tucker condition implies that:

$$l_n^d: \quad W_n = \lambda_n Z_n^\omega \gamma, \quad l_n^d \geq 0, \quad l_n^d(W_n - \lambda_n Z_n^\omega \gamma) = 0 \tag{A.3}$$

$$\lambda_n: \quad q(\omega) - Z_n^\omega \gamma l_n^d \leq 0, \quad \lambda_n \geq 0, \quad \lambda_n(q(\omega) - Z_n^\omega \gamma l_n^d) = 0 \tag{A.4}$$

For $q(\omega) > 0$, I must have $l_n^d > 0$, which implies $W_n - \lambda_n Z_n^\omega \gamma = 0$. Thus, I can write

$$\lambda_n = \frac{W_n}{\gamma Z_n^\omega} > 0$$

Analogously, it is true that $q(\omega) - Z_n^\omega \gamma l_n^d = 0$. This provide us the labor demand in city n:

$$l_n^d = \frac{q(\omega)}{\gamma Z_n^\omega} = \frac{y(\omega)}{\gamma} \tag{A.5}$$

Since workers are homogeneous, so the demand for labor by a firm across cities are perfect substitute. Hence the demand for labor to produce a task $\tau$ by the firm $\omega$ is given by:

$$l_n^d(\omega, \tau) = \begin{cases} \frac{y(\omega,\tau)}{\gamma} & \text{if } \frac{W_n}{\gamma Z_n^\omega} = min\{\frac{W_{n'}}{\gamma Z_{n'}^\omega}\}, n' = 1, 2, \ldots, N \\ 0, & otherwise \end{cases}$$

From the first order condition (Equation (A.3)) of the spatial labor cost minimization of the firm, I get $\gamma = \frac{W_n}{Z_n^\omega}$. Thus, the labor cost minimization across cities implies that the city-specific labor demand function for a task $\tau$ used to produce a variety $\omega$ is :

$$l_n^d(\omega, \tau) = \frac{y(\omega, \tau)}{\gamma}, \quad \tau > T(\omega) \tag{A.6}$$

The total labor demand by the firm producing variety $\omega$ is the sum of labor needed to produce tasks indexed greater than or equal to $T(\omega)$:

$$l_n^d(T(\omega)) = \int_{T(\omega)}^{1} \frac{y(\omega,\tau)}{\gamma} d\tau \qquad (A.7)$$
$$= \frac{(1-T(\omega))q(\omega)}{\gamma Z_n^{\omega}}$$

Where I use the fact that $y(\omega,\tau) = y(\omega)$ from Equation (1.12). Similarly, the total labor demand in city n is the sum of all the labor demand of firms located in the city:

$$l_n^d = \int_{\omega} \frac{(1-T(\omega))q(\omega)}{\gamma Z_n^{\omega}} d\omega, \quad \omega \in \Omega_n \qquad (A.8)$$

The aggregate labor demand is then sum of labor demand across cities:

$$l = \sum_n l_n^d = \sum_n \int_{\omega} \frac{(1-T(\omega))q(\omega)}{\gamma Z_n^{\omega}} d\omega \qquad (A.9)$$

### A.1.2 Proofs

**Proof of proposition 1.**

I construct the proof in 3 steps and statement of each step is proven as lemmas.

**Lemma 1:** *Each city has an unique labor market equilibrium.*

■ **Proof of lemma 1.**

To prove lemma 1, I first show that the labor demand is decreasing in city level wage and labor supply is increasing in city level wage. The city level labor demand is: $l_n^d = \int_{\omega} \frac{(1-T(\omega))q(\omega)}{\gamma Z_n^{\omega}}, \quad \omega \in Mf_n$. Now, for some $W_n > W_{n'}$, we must have $Mf_n \subset Mf_{n'}$. This implies that $l_n^d < l_n^{d'}$, that is, labor demand is decreasing in wages at city level. Analogously, the labor supply is: $l_n = \frac{W_n^{\nu} R_n^{-\beta\nu}}{\sum_{n=1}^{N} W_n^{\nu} R_n^{-\beta\nu}} L$. Since, rent does not vary across cities due to the endogenous housing supply, so the labor supply would be increasing in wages. Thus, a decreasing labor demand and an increasing labor supply in wages guarantees at least one wage level for each city where the labor demand equals the labor supply. To prove the uniqueness of this equilibrium, suppose there are two wage levels where the labor demand and supply are equal for city $n$. Without the loss if generality, let $W_n^{'} > W_n$ for some given values of fundamentals, $z_n^{\omega}$ and $A_n$. Since, $W_n^{'} > W_n$, so $l_n^{'} > l_n$ but $l_n^{d'} < l_n^d$. Now if $W_n$ is the equilibrium wage, then $l_n^d = l_n$. This implies that $l_n^{d'} < l_n^d = l_n < l_n^{'}$. Thus, $W_n^{'}$ cannot be an equilibrium wage as there is excess supply of labor at $W_n^{'}$. Hence, each city has an unique labor market equilibrium. ■

**Lemma 2:** *Equilibrium wage and city size are positively correlated, that is* $\frac{\delta W_n}{\delta l_n}$

**Proof of lemma 2.**

This is a fundamental lemma which is essential to rule out the degenerate distribution of city sizes. To prove this lemma, consider two cities with similar characteristics and the only difference between these two cities is the their sizes. Suppose $l_n > l_n^{'}$, which implies that $Z_n > Z_n^{'}$. Thus, if $W_n = W_n^{'}$, then $Mf_n \subset Mf_{n'}$. So, for the labor demand in these two cities satisfy the inequality: $;_n^d > l_n^{d'}$. However, if $W_n = W_n^{'}$, the labor supply in these two cities must be equal. Hence, if labor market is in equilibrium in city size $l_n^{'}$, that is $l_n^{d'} = l_n^{'}$, then we must have $l_n^d > l_n$. This implies that $W_n > W_n^{'}$. ■

**Lemma 3:** *Output of each variety $\omega$ and city size are positively correlated. That is, a firm producing a large quantity of variety $\omega$ chooses a large city to locate in.*

**Proof of lemma 3.**

The minimized unit cost is $c^*$, so the total cost can be written as $c^* q(\omega) = y(\omega)\left(\frac{T(\omega)\iota P_k}{\eta} + \frac{(1-T(\omega))W_n}{\gamma}\right)$. Differentiating both sides with respect to city size $l_n$, we have:

$$q(\omega)\frac{\delta c^*}{\delta l_n} + c^*\frac{\delta q(\omega)}{\delta l_n} = \frac{\delta y(\omega)}{\delta l_n}\left(\frac{T(\omega)\iota P_k}{\eta} + \frac{(1-T(\omega))W_n}{\gamma}\right) + \frac{y(\omega)(1-T(\omega))}{\gamma}\frac{\delta W_n}{\delta l_n}$$

From which I get the relationship between city size and output:

$$\frac{\delta q(\omega)}{\delta l_n} = \frac{\delta y(\omega)}{\delta l_n}\left(\frac{T(\omega)\iota P_k}{\eta} + \frac{(1-T(\omega))W_n}{\gamma}\right) + \frac{y(\omega)(1-T(\omega))}{\gamma}\frac{\delta W_n}{\delta l_n} - \frac{q(\omega)}{c^*}\frac{\delta c^*}{\delta l_n}$$

where $\frac{\delta y(\omega)}{\delta l_n} > 0$ if the firm producing variety $\omega$ decides to produce a larger quantity. Also, in lemma 2, I show that $\frac{\delta W_n}{\delta l_n} > 0$. Since, $c^*$ is the minimized unit cost with respect to $l_n$, so $\frac{\delta c^*}{\delta l_n} = 0$. Thus, by combining these results, we have $\frac{\delta y(\omega)}{\delta l_n} > 0$, that is, output of a firm and city size are positively correlated. Alternatively, it is also true that $\frac{\delta l_n}{\delta y(\omega)} > 0$. That is, a firm producing a large quantity of output chooses a larger city to locate in. ■

**Lemma 4:** *Each product market has an unique equilibrium.*

**Proof of lemma 4.**

The demand function for variety $\omega$ is $q^d(\omega) = p(\omega)^{-\sigma}P^{\sigma-1}E$, where $E$ is the amount of income spent on tradable composite good $X$. Here demand function is monotonically decreasing in own price, and increasing in price index and expenditure share $E$. In lemma 2 and 3, I show that a firm chooses a larger city to locate to supply greater quantity of output and larger cities have higher wages. This implies that a firm supplies a larger quantity of output if and only if it receives higher price for its variety. That is, supply of a variety is increasing in its price. In addition, the supply function is monotone as the city size and wage are positively correlated. Hence, there is an unique equilibrium for each product variety. ■

**Proof of Proposition 1.**

Lemmas 1-4 and Walras' law imply that the capital market is in equilibrium, and hence is optimally allocated. Thus, there is an unique spatial equilibrium exists for the economy defined in section 3.5. ■ Lemmas 1-4 and Walras' law imply that the capital market is in equilibrium, and hence is optimally allocated. Thus, there is an unique spatial equilibrium exists for the economy defined in section 3.5.

**Proof of proposition 2.**

The minimized unit cost is $c^*(T(\omega)) = \left\{\frac{1}{Z_n^{\omega}}\left(\frac{T(\omega)P_k}{\eta}+\frac{(1-T(\omega))W_n}{\gamma}\right)\right\}$. First order condition with respect to $A_n$:

$$\left(\frac{\delta c^*}{\delta A_n}\right) = \left[-\frac{1}{A_n} - L_n\theta\frac{dL_n}{dA_n}\right]c + \frac{1-T(\omega)}{z_n^{\omega}A_nL_n^{\theta}}\frac{dW_n}{dA_n} = 0$$

After rearranging, I get:

$$\frac{1}{A_n} + L_n\theta\frac{dL_n}{dA_n} = \frac{1-T(\omega)}{\left(\frac{T(\omega)P_k}{\eta}+\frac{(1-T(\omega))W_n}{\gamma}\right)}\frac{dW_n}{dA_n} \tag{A.10}$$

Differentiating with respect to $L_n$ and rearranging:

$$\frac{dL_n}{dA_n} = \frac{1-T(\omega)}{\theta\left(\frac{T(\omega)P_k}{\eta}+\frac{(1-T(\omega))W_n}{\gamma}\right)}\frac{d}{dL_n}\frac{dW_n}{dA_n}$$

where I use $Z_n^{\omega} = A_n z_n^{\omega} L_n^{\theta}$. Now, here we must have $\frac{d}{dL_n}\frac{dW_n}{dA_n} > 0$, otherwise distribution of firms will be degenerate where all firms locate in the most productive cities. Here $\frac{1-T(\omega)}{\theta\left(\frac{T(\omega)P_k}{\eta}+\frac{(1-T(\omega))W_n}{\gamma}\right)} > 0$ as $0 \leq T(\omega) \leq 1$. Thus, we have $\frac{dL_n}{dA_n} > 0$.

Now, $T_n = E\{T(\omega)|A_n\} = \int_{\omega\in\Omega_n} T(\omega)d\omega$. The first order condition of firms' locational choice problem in Equation (A.10) implies that a firm with larger $T(\omega)$ chooses a production location with larger $A_n$. Hence, $\frac{T_N}{A_n} > 0$. Thus, $\frac{T_n}{L_n} = \frac{T_N}{A_n}\frac{A_N}{L_n} > 0$. So, City-level automation in increasing in city size or city-level RTI is falling in city size. ■

**Proof of proposition 3(i).**

Consider $T'(\omega) > T(\omega)\ \forall\omega$. Since, $(1-T(\omega))W_n \geq (1-T'(\omega))W_n$, which holds for all firms locating in city $L_n$. Thus, for some firms:

$$\frac{(1-T'(\omega))W_n^{'}}{\gamma Z_n^{'\omega}} \leq \frac{(1-T'(\omega))W_n}{\gamma Z_n^{\omega}}$$

where $W_n^{'}$ and $Z_n^{'\omega}$ are the wage and aggregate agglomeration benefits of city $A_n^{'}$, and $A_n^{'} \geq A_n$. Thus, some firms will optimally choose a larger city size if these firms draw a larger value of $T(\omega)$. Hence, by the definition of $\Omega_n$ in the equation 1.24, we have $\Omega_n \subset \Omega_n'$. ■

**Proof of proposition 3(ii).**

From Equation (A.10), if $T'(\omega) > T(\omega)\ \forall\omega$, $T_n$ will be larger in most productive cities as every firm in those cities will have greater $T(\omega)$ and some firms with higher $T(\omega)$ will now choose more productive city. ■

**Proof of proposition 3(iii).**

Since I don't have an analytical solution for the equilibrium wage, so to prove the proposition 4, I utilize the fact that for most distribution, most of the observations clustered around the two standard deviations of mean. This fact provides us a simple relationship between the standard deviation and range of a distribution (Taylor, 2021), which is $Sd = \frac{Range}{4}$. That is, there is direct proportional relationship between standard deviation and range, and proving the increase in range is tantamount to proving the increase in standard deviation. Thus, I prove that the range of $W_n$ increases following an uniform increase in automation potential, $T(\omega)$. To prove this, consider two cities: $A_1$ and $A_N$ and without the loss of generality, suppose $A_1 = min\left\{A_n, n = 1, 2, \dots, N\right\}$ and $A_N = max\left\{A_n, n = 1, 2, \dots, N\right\}$. The city level total labor demand for these cities are $l_1^d = \int_{\omega} \frac{(1-T(\omega))q(\omega)}{\gamma Z_1^{\omega}} d\omega, \quad \omega \in \Omega_1$ and $l_N^d = \int_{\omega} \frac{(1-T(\omega))q(\omega)}{\gamma Z_N^{\omega}} d\omega, \quad \omega \in \Omega_N$. The corresponding equilibrium wages are $W_1$ and $W_N$, and thus the range of wages is: $Range(W_n) = W_N - W_1$ when the automation potential is $T(\omega)$. If the automation potential $T(\omega)$ increases to $T'(\omega)$, then $l_1^d$ decreases because

$T'(\omega) > T(\omega)$ and $Mf_1^{'} \subset Mf_1$. This implies $W_1^{'} < W_1$. However, $l_N^d$ increase under $T'(\omega)$ as $Mf_N^{'} \supset Mf_N$ and aggregate labor constraint. This implies that $W_N^{'} > W_N$. Thus, we have $W_1^{'} < W_1 < W_N < W_N^{'}$. Hence, we have $Range(W_n) = W_N - W_1 < Range(W_n^{'}) = W_N^{'} - W_1^{'}$.

■

### A.1.3 Algorithm to solve for the equilibrium

To solve for equilibrium objectives: $\{W_n, R_n, l_n^s, l_n^d, P, Y, K, T(\omega) \to n\}$, I use the following algorithm.

- Parameters:
  - Select parameter values for the set of parameters $\{\beta, \nu, \theta, \iota, \eta, \gamma, \sigma\}$ and pick N,
  - generate $A_n$, $H_n$, $\omega$, and $T(\omega)$ with some distribution
- Solving for equilibrium:
  - Guess $\{W_n, R_n, P, Y\}$
  - Compute $\{l_n^s, l_n^d, T(\omega) \to n, K\}$ using the following formulas:
    * Labor supply: $l_n^s = \frac{W_n^{\nu} R_n^{-\beta\nu}}{\sum_{n=1}^{N} W_n^{\nu} R_n^{-\beta\nu}} L$
    * Allocation of firms: $\min c^*(T(\omega)) = \left\{ \frac{1}{Z_n^{\omega}} \left( \frac{T(\omega)\iota P}{\eta} + \frac{(1-T(\omega))W_n}{\gamma} \right) \right\}$
    * Labor demand:

$$l_n^d = \int_{\omega \to n} \frac{(1-T(\omega))q(\omega)}{\gamma Z_n^{\omega}} d\omega = \int_{\omega \to n} \frac{(1-T(\omega))}{\gamma Z_n^{\omega}} c^*(T(\omega))^{-\sigma} P^{\sigma-1} Y d\omega$$

    * Aggregate capital: $K = \sum_n \int_{\omega} \frac{T(\omega)}{\eta Z_n^{\omega}} c^*(T(\omega))^{-\sigma} P^{\sigma-1} Y d\omega$
  - Update the initial guess for $\{W_n, R_n, P, Y\}$ using the following formulas:
    * $R_n' = L_n \frac{\beta W_n}{\bar{H}_n}$
    * $P' = \left( \int_{\omega \in \Omega} c^*(T(\omega))^{1-\sigma} d\omega \right)^{\frac{1}{1-\sigma}}$
    * $Y' = RK + wL = \iota K + \sum_n \frac{W_n}{P} l_n^s$
    * $W_n' = W_n + W_n \epsilon (l_n^d / l_n^s -)$

### A.1.4 Tables

**Table A.1:** Descriptive statistics

| Variable | | Mean | Std. Dev. | Min | Max | Observations |
|---|---|---|---|---|---|---|
| RTI | Overall | -1.616 | 0.617 | -4.421 | 0.988 | N = 5425 |
| | Between | | 0.528 | -4.045 | -0.602 | n = 408 |
| | Within | | 0.281 | -2.651 | 0.338 | $\bar{T}$= 13.297 |
| City size | Overall | 137.878 | 221.026 | 1 | 3184 | N = 5425 |
| | Between | | 186.353 | 11.545 | 2558 | n = 408 |
| | Within | | 44.633 | -503.872 | 763.878 | $\bar{T}$= 13.297 |
| Median age | Overall | 41.211 | 3.62 | 25 | 67 | N = 5425 |
| | Between | | 2.312 | 29.5 | 52.4 | n = 408 |
| | Within | | 3.013 | 26.078 | 66.666 | $\bar{T}$= 13.297 |
| Median education | Overall | 11 693 | 1.579 | 6 | 16 | N = 5425 |
| | Between | | 1.221 | 9.636 | 15 | n = 408 |
| | Within | | 1.045 | 3.46 | 16.755 | $\bar{T}$= 13.297 |
| White employee | Overall | 0.416 | 0.088 | 0 | 1 | N = 5425 |
| | Between | | 0.075 | 0.079 | 0.543 | n = 408 |
| | Within | | 0.041 | -0.028 | 0.934 | $\bar{T}$= 13.297 |
| Hourly wage | Overall | 6.505 | 8.703 | 0 | 154.48 | N = 5425 |
| | Between | | 6.568 | 0 | 78.963 | n = 408 |
| | Within | | 4.452 | -28.409 | 82.023 | $\bar{T}$= 13.297 |

[1] Note: This table shows the descriptive statistics for IPUMS and Autor and Dorn (2013) data. RTI is the routine task index computed using Autor and Dorn (2013) data. City size is the number of individuals employed in a county, Median age is the median age of employed individuals, Median education is the median years of education of employed individuals, White employee is the fraction of employees in a county who are white, Hourly wage is hourly wage rate of employees in US dollar in a county. All these variables are from IPUMS data.

**Table A.2:** Larger cities have lower RTI

| | Dep. Var.= $RTI$ | | |
|---|---|---|---|
| | (1) | (2) | (3) |
| $lnCS$ | $-0.422^{***}$ | $-0.421^{***}$ | $-0.421^{***}$ |
| | (0.021 ) | ( 0.021) | ( 0.022) |
| $lnMA$ | | $-0.096$ | $-0.02$ |
| | | (0.065) | (0.066) |
| $lnME$ | | $-0.523^{***}$ | $-0.429^{***}$ |
| | | (0.064) | (0.066) |
| $WF$ | | $-0.321^{**}$ | $-0.444^{***}$ |
| | | (0.157) | (0.158) |
| $lnWR$ | | $-0.048^{***}$ | $-0.049^{***}$ |
| | | (0.009) | (0.009) |
| $Constant$ | $0.254^{***}$ | $2.15^{***}$ | $1.793^{***}$ |
| | (0.093) | (0.318) | (0.32) |
| $Time\quad FE$ | No | No | Yes |
| $Overall\quad R^2$ | 0.7426 | 0.7535 | 0.7544 |
| Observations | 5425 | 5425 | 5425 |
| Groups | 408 | 408 | 408 |

[1] Note: Standard errors are in parentheses. Standard errors are clustered at county level.
[2] $^{***}p < 0.01$, $^{**}p < 0.05$, and $^{*}p < 0.1$.
[3] Source: Estimated using IPUMS and Autor and Dorn (2013) data.

**Table A.3:** Larger cities in the year 2019 experienced greater fall in RTI

| | Dep. Var.= $\Delta RTI$ | |
|---|---|---|
| | (1) | (2) |
| $lnCS2019$ | $-0.098^{***}$ | $-0.048^{***}$ |
| | ( 0.002) | (0.004) |
| $lnMA2019$ | | $0.665^{***}$ |
| | | (0.044) |
| $lnME2019$ | | $-1.113^{***}$ |
| | | (0.023) |
| $WF2019$ | | $1.012^{***}$ |
| | | (0.025) |
| $lnWR2019$ | | $-0.044^{***}$ |
| | | (0.005) |
| $Constant$ | $0.148^{***}$ | 0.016 |
| | (0.015) | (0.188) |
| $Overall \quad R^2$ | 0.0674 | 0.2472 |
| Observations | 23107 | 23107 |

[1] Robust standard errors are in parentheses. Employment in 2019 is used as weight.
[2] $***p < 0.01$, $**p < 0.05$, and $*p < 0.1$.
[3] Source: Estimated using IPUMS and Autor and Dorn (2013) data.

**Table A.4:** Larger cities in the year 2000 experienced greater fall in RTI

| | Dep. Var.= $\Delta RTI$ | |
|---|---|---|
| | (1) | (2) |
| $lnCS2000$ | $-0.124^{***}$ | $-0.124^{***}$ |
| | ( 0.005) | (0.005) |
| $lnMA2000$ | | 0.049 |
| | | (0.045) |
| $lnME2000$ | | $-0.298^{***}$ |
| | | (0.032) |
| $WF2000$ | | $2.154^{***}$ |
| | | (0.027) |
| $lnWR2000$ | | $0.162^{***}$ |
| | | (0.006) |
| $Constant$ | $-0.159^{***}$ | $-0.35^{***}$ |
| | (0.013) | (0.173) |
| $Overall \quad R^2$ | 0.0069 | 0.2517 |
| Observations | 19111 | 19111 |

[1] Robust standard errors are in parentheses. Employment in 2000 is used as weight.
[2] $^{***}p < 0.01$, $^{**}p < 0.05$, and $^{*}p < 0.1$.
[3] Source: Estimated using IPUMS and Autor and Dorn (2013) data.

**Table A.5:** Faster growing cities become more automated

| | Dep. Var.= $\Delta RTI$ | | | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| $\Delta lnCS$ | $-0.468^{***}$ | $-0.434^{***}$ | $-0.546^{***}$ | $-0.607^{***}$ |
| | (0.081 ) | (0.082 ) | ( 0.114) | (0.0124) |
| $\Delta lnMA$ | | $-0.409$ | 0.185 | 0.337 |
| | | (0.417) | (0.491) | (0.539) |
| $\Delta lnME$ | | $-0.975^{***}$ | $-1.024^{***}$ | $-1.165^{***}$ |
| | | (0.268) | (0.247) | (0.284) |
| $\Delta lnWF$ | | $-0.005$ | 0.003 | 0.002 |
| | | (0.015) | (0.014) | (0.016) |
| $\Delta lnWR$ | | $-0.094^{**}$ | $-0.129^{**}$ | $-0.118^{**}$ |
| | | (0.04) | (0.05) | (0.053 ) |
| $Constant$ | $-0.207^{***}$ | 0.158 | $-0.224$ | $-0.180$ |
| | (0.032) | (0.604) | (0.0575) | (0.668) |
| $Overall \quad R^2$ | 0.2497 | 0.3574 | 0.4414 | 0.4603 |
| Observations | 138 | 138 | 138 | 138 |

[1] Note: Robust standard errors are in parentheses. Columns (1) and (2) show unweighted regression estimates. Column (3) provides the weighted estimates, where the county-level employment in 2000 is used as weight. Similarly, column (4) show the weighted estimates, where the county-level employment in 2019 is used as weight.
[2] $^{***}p < 0.01$, $^{**}p < 0.05$, and $^{*}p < 0.1$.
[3] Source: Estimated using IPUMS and Autor and Dorn (2013) data.

**Table A.6:** Estimation of idiosyncratic city preferences, $\nu$

| | Dep. Var.= City level population, $L_n$ | | |
|---|---|---|---|
| | (1) | (2) | (3) |
| $WR$ | 1.76*** | 1.42*** | 1.26*** |
| | (0.000) | (0.016) | (0.014) |
| $MedAge$ | | −0.01** | −0.008** |
| | | (0.004) | (0.003) |
| $MedEduc$ | | −0.036*** | −0.029* |
| | | (0.008) | (0.007) |
| $WhiteFrac$ | | −0.951* | −0.029*** |
| | | (0.547) | (0.488) |
| $Constant$ | 9.07*** | 9.68*** | 8.999*** |
| | (0.530) | (0.570) | (0.869) |
| $TimeFE$ | No | No | Yes |
| $Overall\ R^2$ | 0.006 | 0.061 | 0.095 |
| N | 3888 | 3888 | 3888 |

Standard errors are in parentheses.
$^{***}p < 0.01$, $^{**}p < 0.05$, and $^{*}p < 0.1$.
Source: Own computation using IPUMS, AHS, and US census.

**Table A.7:** Estimation of capital production technology, $\iota$

| | Dep. Var.= Total revenue ($R$) | |
|---|---|---|
| | (1) | (2) |
| *Capital* | 0.921*** | 0.845*** |
| | (0.002) | (0.034) |
| *Labor* | | 0.269*** |
| | | (0.032) |
| *Constant* | −0.048*** | −0.976*** |
| | (0.011) | (0.242) |
| $R^2$ | 0.7756 | 0.7698 |
| N | 76637 | 339 |

Standard errors are in parentheses.
$^{***}p < 0.01$, $^{**}p < 0.05$, and $^{*}p < 0.1$.
Source: Estimated using Compustat data.

**Table A.8:** Estimation of city level exogenous productivity, $A_n$

| | Dep. Var.= wage rate $W_n$ | | |
|---|---|---|---|
| | (1) | (2) | (3) |
| *lneduc* | 1.7561*** | 1.761*** | 0.712*** |
| | (0.109) | (0.115) | (0.117) |
| *rti* | | 0.005 | 0.048 |
| | | (0.043) | (0.041) |
| *Constant* | −1.748*** | −1.757*** | 0.746*** |
| | (0.279) | (0.287) | (0.288) |
| *Time FE* | No | No | Yes |
| *Overall* $R^2$ | 0.118 | 0.118 | 0.227 |
| N | 5123 | 5123 | 5123 |

Standard errors are in parentheses.
$^{***}p < 0.01$, $^{**}p < 0.05$, and $^{*}p < 0.1$.
Source: Estimated using Compustat data.

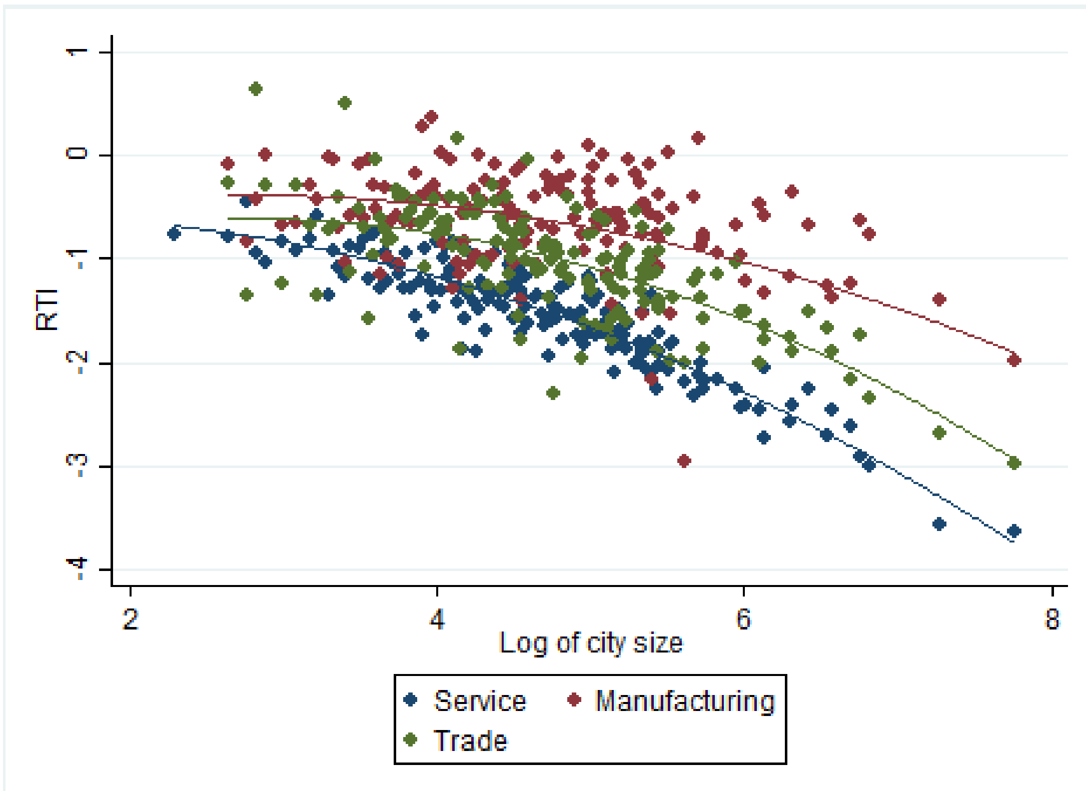
**Table A.9:** Estimation of industries' city specific productivity, $z_n^{\omega}$

| | Dep. Var.= $Z_n^{\omega}$ | |
|---|---|---|
| | (1) | (2) |
| $lnA_n$ | $0.0003^{*}$ | 0.0002 |
| | (0.0002) | (0.0002) |
| $lnL_n$ | $-0.0098^{***}$ | $0 - 0.01030^{***}$ |
| | (0.0002) | (0.0002) |
| $Constant$ | $0.076^{***}$ | $0.0776^{***}$ |
| | (0.0011) | (0.0012) |
| $Time \quad FE$ | No | Yes |
| $Overall \quad R^2$ | 0.1944 | 0.1945 |
| N | 254921 | 254921 |

Standard errors are in parentheses.
$^{***}p < 0.01$, $^{**}p < 0.05$, and $^{*}p < 0.1$.
Source: Estimated using Compustat data.

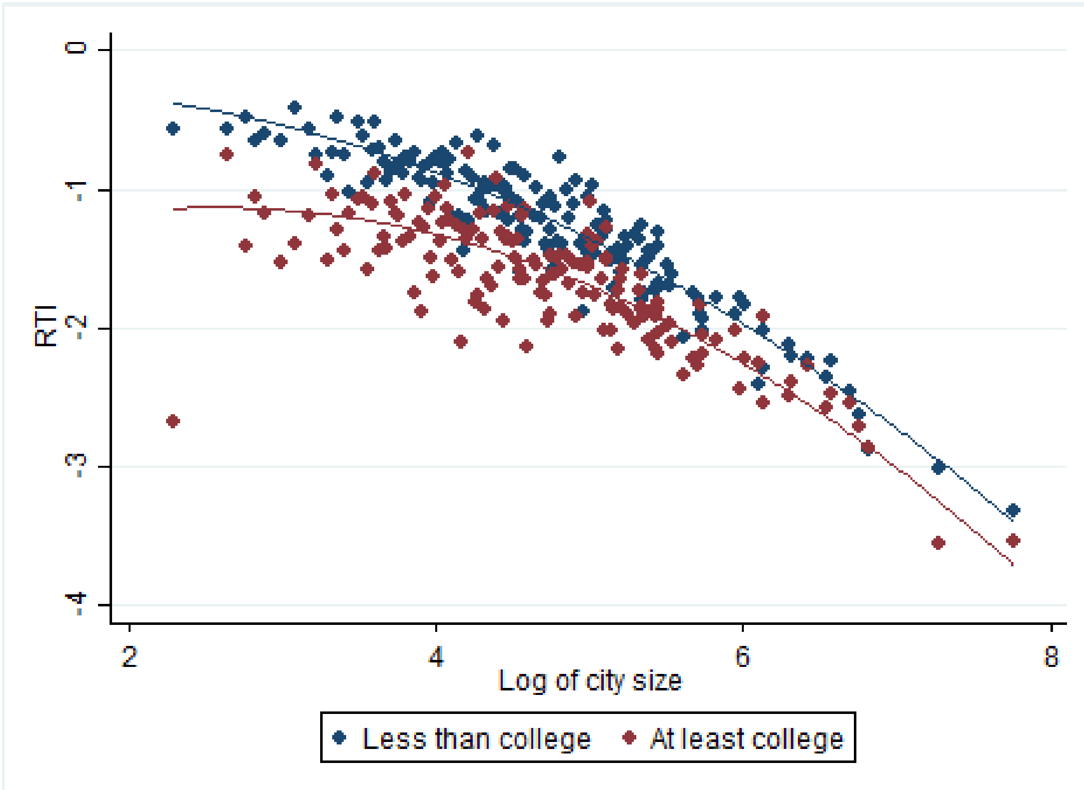
### A.1.5 Figures

**Figure A·1:** Lower routineness in larger cities holds across different industries



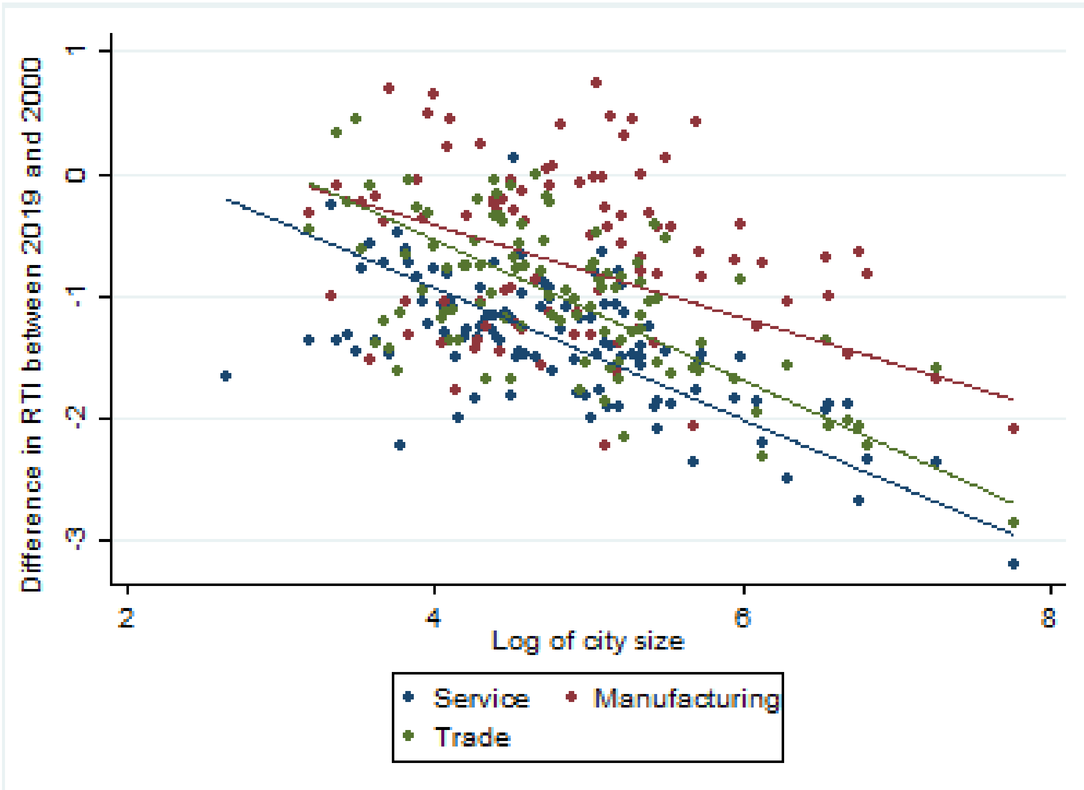

Note: Figure A·1 plots RTI values and the log of employment size at the county level (city size) at three aggregated sectors: Services, Manufacturing, and Trade for the year 2019. RTI values are falling in city size for all three sectors, but the negative relationship between RTI and city size is more pronounced for service sector. This implies that routine intensive tasks are automated at a greater extend in larger cities in service sector.

**Figure A·2:** Lower routineness in larger cities holds for both college and less than college education



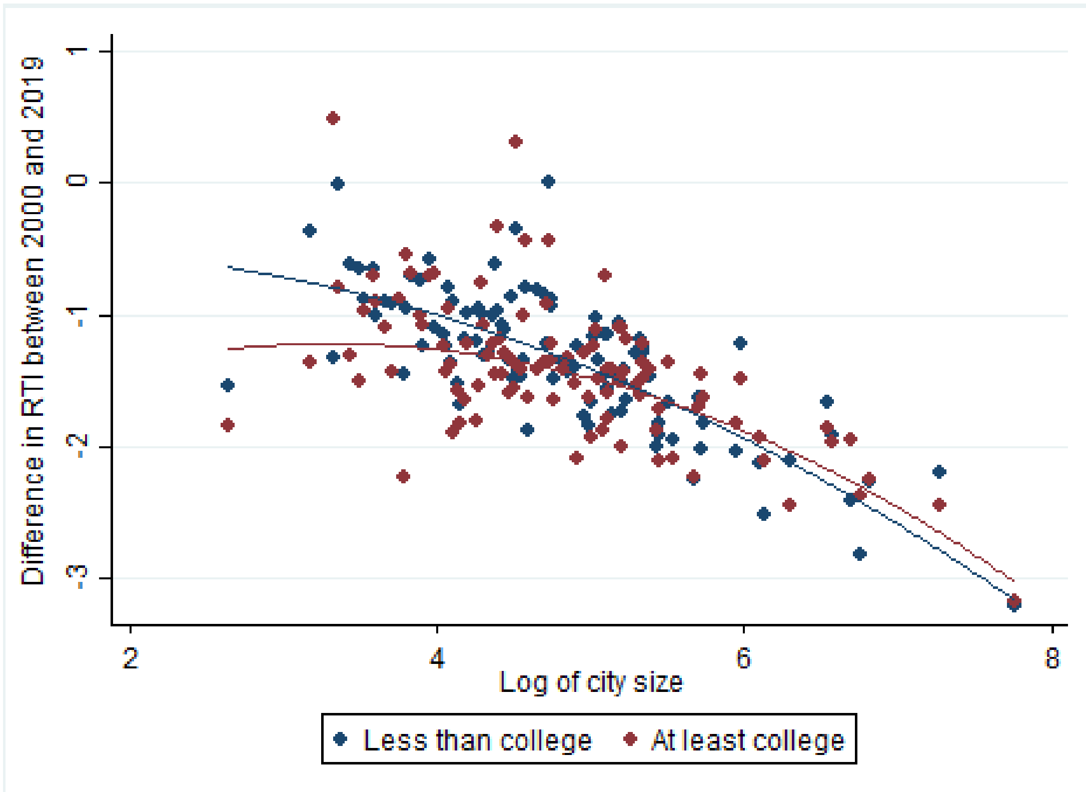

Note: Figure A·2 plots RTI values and the log of employment size at the county level (city size) for workers with college education and less-than-college education for the year 2019. RTI values are falling in city size for all levels of education. This implies that routine intensive tasks are performed significantly less in larger cities by workers with any level of educations.

**Figure A·3:** Larger cities experienced greater fall in RTI across different industries



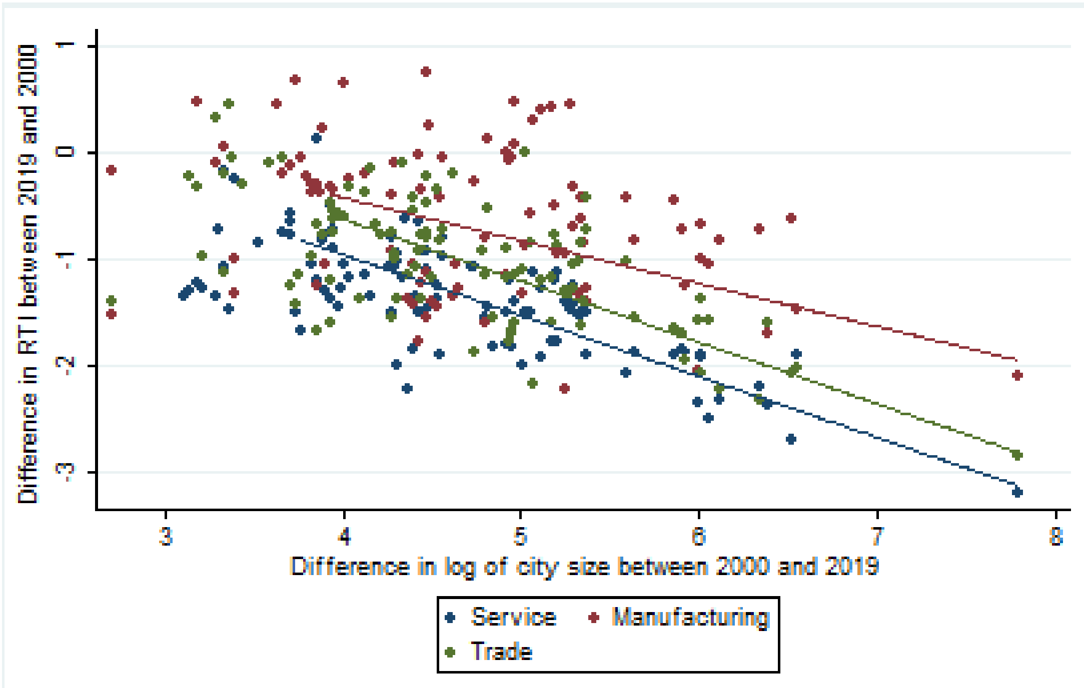

Note: Figure A·3 plots the change in RTI values between 2019 and 2000 and the log of employment size at the county level (city size) at three aggregated sectors: Services, Manufacturing, and Trade. Larger cities experience grater fall in RTI values are falling over the last 20 years in all three sectors, and like the levels of RTI, the negative relationship between the change in RTI and city size is stronger for service and trade sectors compared to manufacturing. This implies that routine intensive tasks are automated at a greater rate in larger cities in last two decades, specially in service and trade sectors.

**Figure A·4:** Larger cities experienced greater fall in RTI for both college and less-than-college education



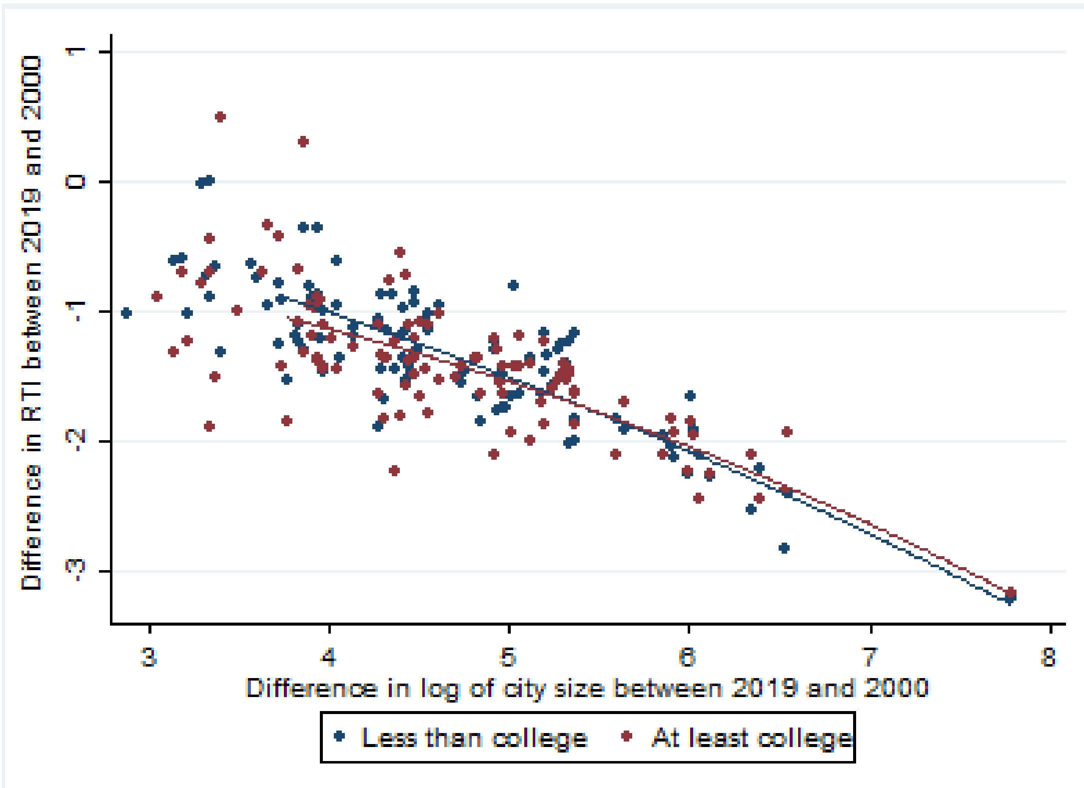

Note: Figure A·4 plots the change in RTI values between 2019 and 200 and the log of employment size at the county level (city size) for workers with college education and less-than-college education for the year 2019. Figure A·4 shows that the change in RTI values is greater in larger city size for all levels of education. This implies that routine intensive tasks performed by workers with different levels of education have been automated at a greater rate in larger cities.

**Figure A·5:** Faster growing cities experienced greater fall in RTI across different industries



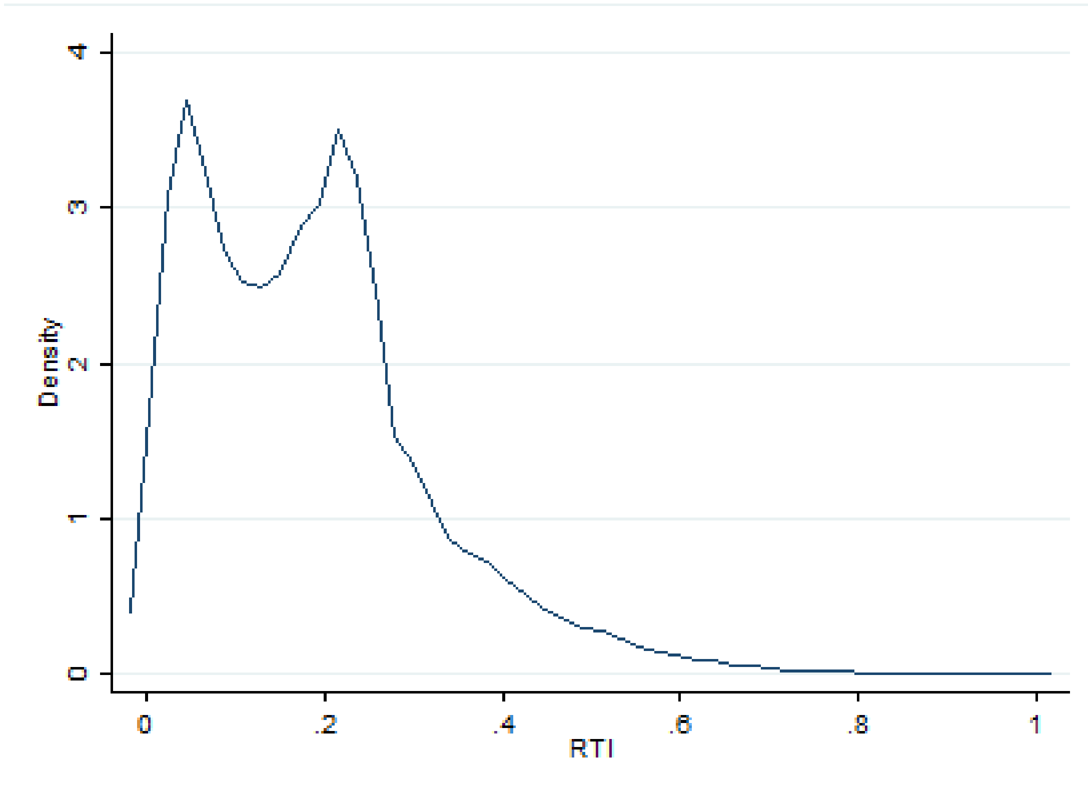

Note: Figure A·5 plots the change in RTI values and the change in log of employment size at the county level (city size) between 2019 and 2000 at three aggregated sectors: Services, Manufacturing, and Trade. Figure A·5 shows that cities experiencing faster growth over the last two decades also have the grater fall in RTI values in all three sectors, and like the levels of RTI and city size, the negative relationship between the change in RTI and the change in city size is stronger for service and trade sectors than that of for manufacturing. This implies that faster growing cities automated routine intensive tasks at a greater rate in last two decades, specially in service and trade sectors.

**Figure A·6:** Faster growing cities experienced greater fall in RTI for both college and less-than-college education



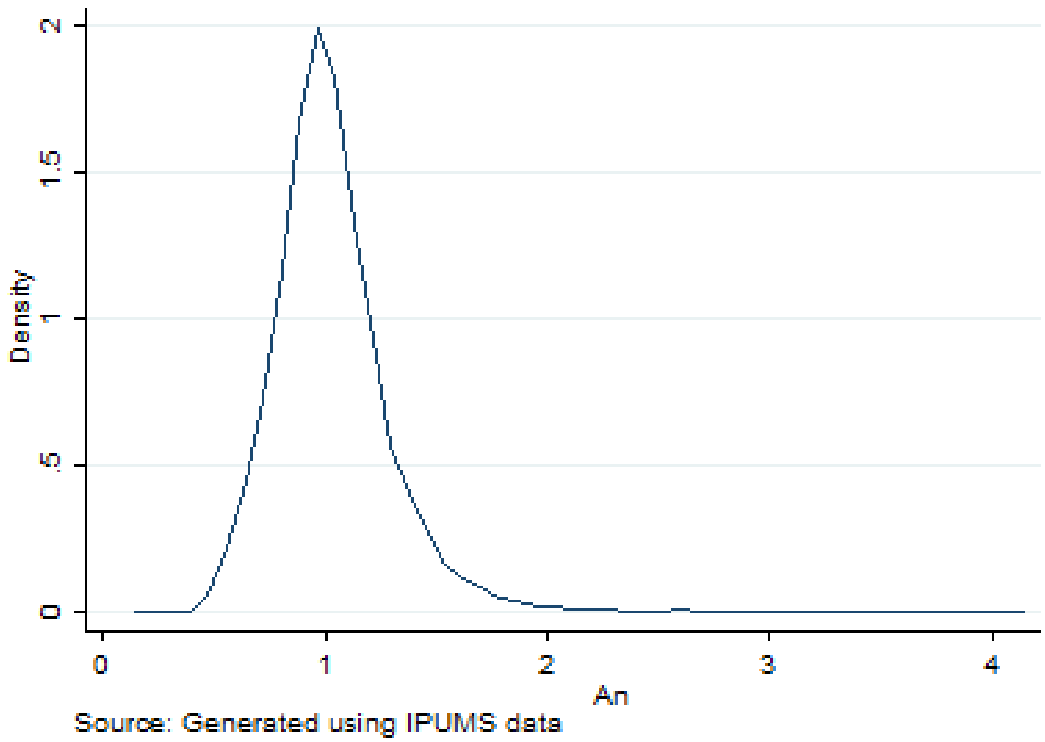

Note: Figure A·6 plots the change in RTI values and the change in log of employment size at the county level (city size) for workers with college education and less-than-college education between 2019 and 2000. Figure A·6 shows that the faster growing cities have experienced greater fall in RTI values for all levels of education. This implies that routine intensive tasks performed by workers with different levels of education have been automated at a greater rate in faster growing cities.

**Figure A·7:** Empirical distribution of Routine Task Index, $RTI$



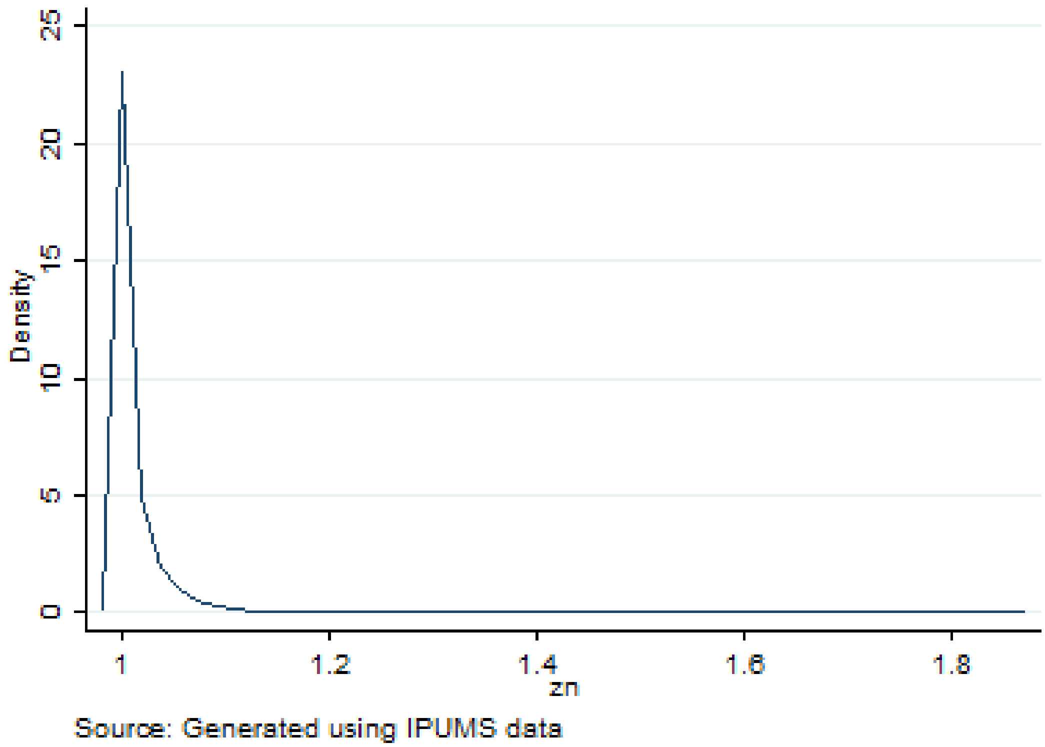

Note: Figure A·7 plots the distribution of scaled RTI values in 2019. The scaling in RTI values is done by dividing the county-level RTI values by the difference between maximum and minimum values of RTI for all counties in 2019. Figure A·7 shows that the most of the county-level scaled RTI are small and only a small fraction of counties employ the workers who have high levels of RTI.

**Figure A·8:** Distribution of city exogenous productivity, $lnA_n$



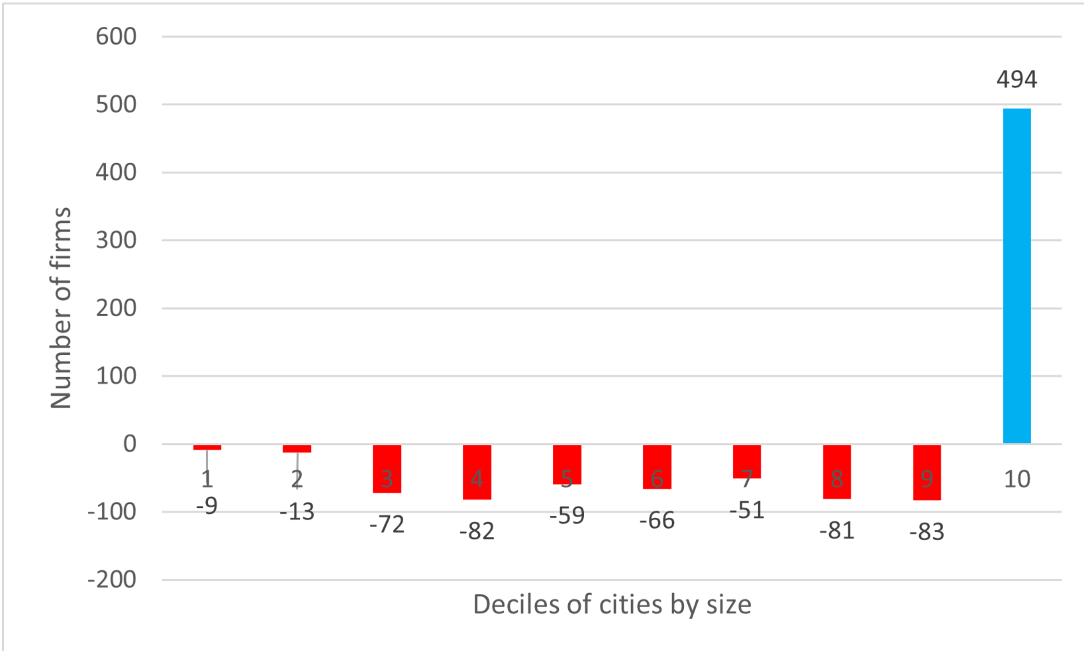

Note: Figure A·8 plots the distribution of exogenous city-level productivity $A_n$ estimated using the Equation (1.28). Figure A·8 shows that $A_n$ is approximately log normal with mean 1 and variance 0.28.

**Figure A·9:** Distribution of city-specific firm's exogenous productivity, $lnz_n^\omega$




Note: Figure A·9 plots the distribution of exogenous city-firm level productivity $lnz_n$ estimated using the Equation (1.29). Figure A·9 shows that $z_n$ is approximately log normal with mean 1 and variance 0.02.

**Figure A·10:** Midsize cities suffer greater loss when automation potential increases uniformly




Note: Figure A·10 shows the change in the number of firms at deciles of city size obtained counterfactual analysis. Figure A·10 highlights the loss in mass of firms in cities of all sizes except the cities in the largest city size decile.

## A.2 Chapter 2: Variable Description, Proofs, and Additional Tables

### A.2.1 Definition and Variable Construction

**Trade-weighted measure of exchange rate volatility**: The trade-weighted exchange rate, commonly known as Nominal Effective Exchange Rates (NEER), is the geometric weighted average of a basket of bilateral exchange rate (Klau and Fung 2006). Real EER (REER) is the nominal EER adjusted with the respective relative price index. Here the weights are based on manufacturing trade flows, including both bilateral trade and third-market competition by double-weighting. The BIS EER calculation is performed for the EER basket of economy. Suppose there are j number of countries in the BIS EER basket and the weight the BIS EER places on each economy is indexed by i. In addition, suppose there are k foreign markets and h foreign producers. Economy j trades bilaterally with i and js exports compete with is exports and all other exports of h in k markets. Hence, to capture the effect of the relative exchange rate changes between i and j, the weights in an EER basket incorporate import competition, direct export competition and third-market export competition. Algebraically, the weight of i ($w_i$ ) in the EER basket of j as given in Klau and Fung (2006) can be written as:

$$w_i^m = \frac{m_j^i}{m_j}$$

$$w_i^x = \left(\frac{x_j^i}{x_j}\right)\left(\frac{y_i}{y_i + \sum_h x_h^i}\right) + \sum_{k \neq i}\left(\frac{x_j^k}{x_j}\right)\left(\frac{\overset{k}{i}}{y_i + \sum_h x_h^i}\right)$$

$$w_i = \left(\frac{m_j}{x_j + m_j}\right)w_i^m + \left(\frac{x_j}{x_j + m_j}\right)w_i^x$$

where $w_i^m$, $w_i^x$ and $w_i$ are import weight, export weight, and overall weight, respectively, $x_j^i(m_j^i)$ = economy $j$'s export to (import from) economy $i$, $x_j(m_j)$ = economy $j$'s total exports (imports), $y_i$ = home supply of domestic gross manufacturing output of economy $i$, $\sum_h x_h^i$ =total eport from $h$ to $i$ excluding $j$. Using these bilateral trade weights $(w_i)$, BIS calculates monthly EER. The IMF REERs are calculated using following rule:

$$E_i = \prod_{j \neq i} \frac{P_i R_i}{P_j R_j} W_{ij}$$

where $j$ refers to trade partners. $P$'s are CPIs, and ${}_iR$ and $R_j$ are bilateral nominal exchange rates of country $i$ to $j$ against the US dollars (measured in US dollar per local currency). $W_{ij}$ is the weight defined as follows:

$$W_{ij} = (\alpha_M + \alpha_S) W_{ij}(M) + \alpha_c W_{ij}(C) + \alpha_T W_{ij}(T)$$

where $W_{ij}(M)$, $W_{ij}(C)$, and $W_{ij}(T)$ are country-weights for manufactures, commodities, and tourism; $\alpha_M$, $\alpha_S$, $\alpha_c$, and $\alpha_T$ denote the shares of manufactures, (non-tourism) services, commodities, and tourism in overall trade.

I use the monthly REER supplied by IMF and BIS, which is available in the respective websites. Using these monthly REER, I de

ne my trade-weighted measure of exchange rate volatility for a given year as the sample standard deviation of monthly REER in that year. Hence, the Exchange Vol is defined as follows;

$$Exch\_Vol_t = \sqrt{\frac{\sum_{i=1}^{12}(REER_{it} - RE\bar{E}R_t)^2}{11}}$$

where $Exch\_Vol_t$ is the exchange rate volatility measure for year t, i is the index for month, $REER_{it}$ is the REER of the month i in year t, $RE\bar{E}R_t$ is the average of monthly REER for year t, and 11 is coming from $n - 1 = 12 - 1 = 11$. Thus, the $Lag\_Exch\_Vol_t = Exch\_Vol_{t-1}$.

**ETD1 and ETD2**: ETD1 and ETD2 are two different measures of the intensive margin of trade and are defined as export to domestic sale ratio. The Enterprise Survey collects information on what per cent of establishment's sales were National sales, Indirect exports (sold domestically to third parties that export products), and Direct export. Here the problem is how we should treat the 'Indirect export,' should it be considered as export or as domestic sales. Thus, I de

ne two measures of export to domestic sales ratio. In ETD1, Indirect export is treated as domestic sales and so EDT1 is the ratio of Direct export to the sum of National sales and Indirect exports. On the other hand, Indirect exports are treated as exports in ETD2, and hence ETD2 is defined as the ratio of the sum of Direct and Indirect exports to National sales.

**Export1, Export2, Domestic1, and Domestic2**: Like EDT1 and ETD2, Export1 and Export2 are two different measures of the intensive margin of trade. These are also different to each on the basis of treatment of Indirect export. Here Export1 is defined as the fraction of total output that is directly exported, whereas Export2 is defined as the fraction of total output which directly or indirectly exported. Similarly, Domestic1 is defined as fraction output, which is sold domestically or sold to a third party that participates in the export market and Domestic2 is defined as the fraction of total output, which is only sold domestically/nationally.

**EXport_Frac**: Export_Frac is the measure of the extensive margin of trade. It is defined as the fraction of firms that participates both in domestic and export markets. To construct this variable, I identify exporting firms for each industry in a country and hence, I de

ne Export_Frac as the ratio of total exporting firms in any given industry to total firms in that industry in a given country.

**Wage**: Wage is approximately the average monthly compensation, including benefits when applicable, for each type of production full-time worker in a given year. It is measured in local currency units.

**Mean Diff. and Std. Dev. Diff.**: Mean Diff. is the difference in average wages paid in the firms serving both domestic and export markets and the firms serving only domestic market. To construct this variable, I first find the economy wide mean of the average wages paid in domestic firms and exporting firms, then I subtract the mean of average wages of domestic firms from the mean of average wages of exporting firms. Thus, a positive number of Mean Diff. indicates that the mean wage of all workers employed by exporting forms is higher than the mean wage of all firms employed in the firms serving only domestic markets, and vice-versa. Analogously, Std. Dev. Diff. is the difference of standard deviations of average wages of workers in exporting firms and workers in domestic firms. A positive value of Std. Dev. Diff. shows that the variation in wages of exporting firms is larger than the variation in wages of domestic firms, and vice-versa.

**GDP and World_GDP**: GDP is the Gross Domestic Product per capita of each country and World_GDP is the average of Gross Domestic Product per capita of the all countries for which data is available. These variables are measured in constant 2010 US dollars. Data on both of these variables and their lags are collected from the World Development Indicator database of World Bank.

**Sector**: Sector is the broadly classified industries. It comprises: all manufacturing sectors according to the group classi

cation of ISIC Revision 3.1: (group D), construction sector (group F), services sector (groups G and H), and transport, storage, and communications sector (group I), and all public or utilities-sectors.

**Size**: Size is the firm's size in terms of the number of workers. Firms are classified into four categories: Micro (less than 5 workers), Small (number of workers between 5 and 19), Medium (number of workers between 20 and 99), and Large (Number of workers greater than 99).

**Year**: Year is the survey year.

**Education**: Education is the average educational attainment of a typical production worker employed in the firm. There are

ve possible values of Education: 1 means 0-3 years of education, 2 means 4-6 years of education, 3 means 7-9 years of education, 4 means 10-12 years of education, and 5 means 13 or more years of education.

### A.2.2 Proofs

**Proof of proposition 1:.** Since $\epsilon^{\beta}$ is a concave function of $\beta$ $(0 < \beta < 1)$, so using Jensen's inequality we get;

$$[\frac{y_x(\theta)}{y_d(\theta)}]^{1-\beta} = \frac{A^*}{A}\tau^{-\beta}E[\epsilon^{\beta}] < \frac{A^*}{A}\tau^{-\beta}[E(\epsilon)]^{\beta} \tag{A.11}$$

This implies that simply fixing the floating exchange rate at its expected value would increase the ratio of export to domestic sale. ■

**Proof of corollary 1.** Since $\Upsilon(\theta)$ is a concave function of $\epsilon$ for $0 < \beta < \frac{1}{2}$, so, $\frac{1}{\Upsilon(\theta)}$ is increasing in exchange rate volatility and $\frac{\Upsilon(\theta)-1}{\Upsilon(\theta)}$ is decreasing in exchange rate volatility. Combining these results with equations (11) and (12), shows that $y_d(\theta)$ is increasing in exchange rate volatility and $y_x(\theta)$ is decreasing in exchange rate volatility. ■

**Proof of proposition 2.** Under the fixed exchange rate (no uncertainty regarding exchange rate), $\bar{n}$ and $\bar{a_c}$ are characterized by the following equations:

$$\frac{\beta\gamma}{1+\beta\gamma}r(\theta) = bn \tag{A.12}$$

$$\frac{\beta(1-\gamma k)}{1+\beta\gamma}r(\theta) = ca_c^{\delta} \tag{A.13}$$

$n$ and $a_c$ are characterized by equation (15) and (16), which can be written as:

$$\frac{\beta\gamma}{1+\beta\gamma}\frac{E[u'(\pi)r(\theta)]}{E[u'(\pi)]} = bn \tag{A.14}$$

$$\frac{\beta(1-\gamma k)}{1+\beta\gamma}\frac{E[u'(\pi)r(\theta)]}{E[u'(\pi)]} = ca_c^{\delta} \tag{A.15}$$

Here $\frac{E[u'(\pi)r(\theta)]}{E[u'(\pi)]} = \frac{Cov[u'(\pi)r(\theta)]}{E[u'(\pi)]} + E[r(\theta)] < E[r(\theta)] < r(\theta)$, as $Cov[u'(\pi)r(\theta)] < 0$ and since $r(\theta)$ is concave in $\epsilon$ for $0 < \beta < \frac{1}{2}$, so by Jensen's inequality we get $E[r(\theta)] < r(\theta)$, where $r(\theta)$ is revenue under the fixed exchange rate. Comparing equations (19) and (20) with equations (21) and (22), left hand side of (21) and (22) are smaller than the left hand side of (19) and (20). Thus, $n$ and $a_c$ are smaller than $\bar{n}$ and $\bar{a_c}$, respectively. ■

**Proof of proposition 3.** Under a fixed exchange rate, the total output of the firm is given by:

$$\bar{y} = \kappa_y \theta \bar{n}^\gamma \bar{a_c}^{1-\gamma k}, \quad \kappa_y \equiv \frac{k}{k-1} a_{min}^{\gamma k}$$

Under a fixed exchange rate, the total output of the firm is given by:

$$y = \kappa_y \theta n^\gamma a_c^{1-\gamma k}, \quad \kappa_y \equiv \frac{k}{k-1} a_{min}^{\gamma k}$$

Since $n$ and $a_c$ are smaller than $\bar{n}$ and $\bar{a_c}$, so $y < \bar{y}$. ■

**Proof of proposition 4.** Consider to cumulative density functions (CDF) of $\epsilon$; $F(\epsilon)$ and $G(\epsilon)$, where $F(\epsilon)$ second order stochastically dominates (SOSD) $G(\epsilon)$, that is $G(\epsilon)$ is a mean preserving spread of $F(\epsilon)$. Here $F(\epsilon)$ is under some form of currency pegging regime and when there is strong pegging or fixed exchange rate $F(\epsilon)$ would be a degenerate distribution, $G(\epsilon)$ is the CDF of $\epsilon$ under a floating exchange rate regime with same mean as under $F(\epsilon)$. let $\Upsilon(\theta, \epsilon)^{(1-\beta)/\Gamma} = \Psi(\epsilon)$. So, by the definition of SOSD, we have $E[\Psi(\epsilon)] = \int \Psi(\epsilon) dG(\epsilon) \leq \int \Psi(\epsilon) dF(\epsilon) = \Psi(\epsilon) \int dF(\epsilon) = \Psi(\epsilon)$. Now comparing equations (25) and (27), we can see that $\theta_x^{fixed} \leq \theta_x^{floating}$. ■

**Proof of proposition 5.** Combining the Nash bargaining share of revenue received by workers, denoted by $W(\theta)$, and first order conditions we get:

$$W(\theta) = \frac{\beta\gamma}{1+\beta\gamma} r(\theta) = bn(\theta) \tag{A.16}$$

Or

$$W(\theta) = \frac{\beta\gamma}{1+\beta\gamma} r(\theta) = \frac{1}{1-\gamma k} \gamma c a_c(\theta)^\delta \tag{A.17}$$

Since $n(\theta)$ and $a_c(\theta)$ are decreasing function in exchange rate volatility, so equations (28) and (29) show that $W(\theta)$ is also a decreasing function in exchange rate volatility.

The average wage, denoted by $w(\theta)$, is given by;

$$w(\theta) = \frac{W(\theta)}{h(\theta)} \tag{A.18}$$

Where $h(\theta)$ is the measure of workers hired, which is given by $h(\theta) = n(a_{min}/a_c)^k$. So, rewriting $w(\theta)$ in terms of $n(\theta)$ and $a_c(\theta)$ we get;

$$w(\theta) = \frac{ba_c(\theta)^k}{a_{min}^k} \tag{A.19}$$

Or

$$w(\theta) = \frac{c\gamma}{(1-\gamma k)a_{min}^k} \frac{a_c(\theta)^{\delta+k}}{n(\theta)} \tag{A.20}$$

Here $k > 1$ and $\delta > 0$. So, equation (31) shows that $w(\theta)$ is a decreasing function of exchange rate volatility as $a_c(\theta)$ is decreasing in exchange rate volatility. Equation (32) shows the same result as $\delta + k > 1$. Hence, even though both $n(\theta)$ and $a_c(\theta)$ are decreasing in exchange rate volatility and $n(\theta)$ now appears in denominator, $w(\theta)$ would still be decreasing in exchange rate volatility due to $\delta + k > 1$. ■

## A.3 Chapter 2: Additional Tables

**Table A.10:** List of Countries and Survey Years

| Country | Year | Country | Year |
|---|---|---|---|
| Argentina | 2006 | Lithuania | 2009 |
| | 2010 | | 2013 |
| Brazil | 2009 | Malaysia | 2015 |
| Bulgaria | 2007 | Mexico | 2006 |
| | 2009 | | 2010 |
| | 2013 | | |
| Chile | 2006 | Peru | 2006 |
| | 2010 | | 2010 |
| China | 2012 | Philippines | 2009 |
| | | | 2015 |
| Colombia | 2006 | Poland | 2009 |
| | 2010 | | 2013 |
| Croatia | 2007 | Romania | 2009 |
| | 2013 | | 2013 |
| Czech Republic | 2009 | Russia | 2009 |
| | 2013 | | 2012 |
| Estonia | 2009 | Slovenia | 2009 |
| | | | 2013 |
| Hungary | 2009 | South Africa | 2007 |
| | 2013 | | |
| India | 2014 | Sweden | 2014 |
| Indonesia | 2009 | Thailand | 2016 |
| | 2015 | | |
| Israel | 2013 | Turkey | 2008 |
| | | | 2013 |
| Latvia | 2009 | Venezuela | 2006 |
| | 2013 | | 2010 |

Source: World Bank Enterprise Survey.

**Table A.11:** List of Industries

| | | |
|---|---|---|
| 1. Basic Metals & Metal Products | 11. Garments | 21. Rest of Universe |
| 2. Basic Metals/Fabricated Metals/Machinery & Equip. | 12. Hotels & Restaurants | 22. Retail |
| 3. Chemicals & Chemical Products | 13. IT & IT Services | 23. Rubber & Plastics Products |
| 4. Chemicals, Plastics & Rubber | 14. Leather Products | 24. Services |
| 5. Construction | 15. Machinery & Equipment | 25. Services of Motor Vehicles |
| 6. Electronics | 16. Manufacturing | 26. Textiles |
| 7. Electronics & Communications Equip. | 17. Motor Vehicles | 27. Textiles & Garments |
| 8. Fabricated Metal Products | 18. Non-Metallic Mineral Products | 28. Transport, Storage, & Communications |
| 9. Food | 19. Other Manufacturing | 29. Wholesale |
| 10. Furniture | 20. Other Services | 30. Wood Products & Furniture |

Source: World Bank Enterprise Survey.

## A.4 Chapter 3: Additional Tables

**Table A.12:** Mean and Standard Deviation of Household and Household Head's Characteristics

| | All households with at Least One Member with Diabetes | | | Households Needing Insulin | | |
|---|---|---|---|---|---|---|
| | Obs. | Mean | Std. Dev. | Obs. | Mean | Std. Dev. |
| Household size | 1124 | 6.38 | 3.34 | 424 | 6.44 | 3.35 |
| Average age (year) | 1124 | 35.03 | 12.24 | 424 | 35.15 | 11.59 |
| Head age (year) | 1124 | 51.48 | 13.17 | 424 | 51.49 | 12.80 |
| Monthly income (BDT) | 1125 | 28716.56 | 27074.13 | 424 | 30936.63 | 30831.34 |
| Monthly food spending (BDT) | 1124 | 9210.79 | 6610.99 | 424 | 9368.45 | 4855.21 |
| Monthly medicine spending (BDT) | 1125 | 1128.66 | 2680.49 | 424 | 973.33 | 545.03 |
| Monthly education spending (BDT) | 1015 | 1562.88 | 2673.55 | 383 | 1786.54 | 3034.72 |

Source: Authors' calculations based on data from the Bangladesh Bureau of Statistics. 2019. Report on the Household Income and Expenditure Survey 2016. Dhaka: Statistics and Information Division, Ministry of Planning, Government of Bangladesh.

**Table A.13:** Proportions of Household and Household Head's Characteristics

| | | All households with at Least One Member with Diabetes | | Households Needing Insulin | |
|---|---|---|---|---|---|
| | | Obs. | Proportion (%) | Obs. | Proportion (%) |
| Location | Rural | 618 | 51.07 | 202 | 47.64 |
| | Urban | 592 | 48.93 | 222 | 52.36 |
| House ownership | Does not own | 104 | 8.6 | 32 | 7.55 |
| | Own a house | 1106 | 91.4 | 392 | 92.45 |
| Religion | Non-Muslim | 143 | 11.82 | 48 | 11.32 |
| | Muslim | 1067 | 88.18 | 376 | 88.68 |
| School attending children | 0 | 392 | 32.37 | 134 | 31.6 |
| | 1 | 389 | 32.12 | 139 | 32.78 |
| | 2 | 297 | 24.53 | 106 | 25 |
| | 3 | 98 | 8.09 | 35 | 8.25 |
| | More than 3 | 35 | 2.9 | 10 | 2.36 |
| Members older than 60 years | 0 | 661 | 54.63 | 231 | 54.48 |
| | 1 | 418 | 24.55 | 146 | 34.43 |
| | 2 | 129 | 10.66 | 46 | 10.85 |
| | 3 | 2 | 0.17 | 1 | 0.24 |
| Members with noncommunicable diseases | 1 | 643 | 53.41 | 217 | 51.3 |
| | 2 | 449 | 37.29 | 168 | 39.72 |
| | 3 | 83 | 6.89 | 32 | 7.57 |
| | More than 3 | 29 | 2.41 | 6 | 1.42 |
| Household head's employment status | Unemployed | 269 | 22.25 | 96 | 22.64 |
| | employed | 940 | 77.25 | 328 | 77.36 |
| Household head's employment sector | Agriculture | 252 | 20.83 | 87 | 20.52 |
| | Industry | 129 | 10.66 | 51 | 12.03 |
| | Service | 829 | 69 | 286 | 67 |

Source: Authors' calculations based on data from the Bangladesh Bureau of Statistics. 2019. Report on the Household Income and Expenditure Survey 2016. Dhaka: Statistics and Information Division, Ministry of Planning, Government of Bangladesh.

**Table A.14:** Coefficients of QUAIDS Model

| | Not Corrected | | Corrected | |
|---|---|---|---|---|
| | OLS | IV | OLS | IV |
| $\alpha_1$ | 0.736*** | 0.884*** | 0.704*** | 0.917*** |
| $\alpha_2$ | 0.124*** | 0.259*** | 0.147*** | 0.240*** |
| $\alpha_3$ | 0.141*** | −143 | 0.149*** | −0.157** |
| $\beta_1$ | 0.164*** | 0.224*** | 0.111* | 0.174 |
| $\beta_2$ | −0.097*** | 0.184*** | −0.098*** | −0.245*** |
| $\beta_3$ | −0.067*** | −0.040 | −0.013 | 0.072 |
| $\gamma_{11}$ | 0.064*** | 0.034 | 0.062*** | 0.040 |
| $\gamma_{21}$ | −0.041*** | 0.012 | −0.040*** | 0.010 |
| $\gamma_{31}$ | −0.023*** | −0.046* | −0.022*** | −0.050** |
| $\gamma_{22}$ | 0.055*** | −0.023* | 0.055*** | −0.022* |
| $\gamma_{32}$ | −0.014*** | 0.012* | −0.015*** | 0.011* |
| $\gamma_{33}$ | 0.036*** | 0.034 | 0.036*** | 0.039 |
| $\lambda_1$ | 0.005*** | −0.030*** | 0.006*** | −0.030*** |
| $\lambda_2$ | −0.003*** | 0.029*** | −0.003*** | 0.030*** |
| $\lambda_3$ | −0.003* | 002 | −0.003** | 0.001 |
| $\eta_{Hsize\_1}$ | 0.001 | 0.018*** | 0.003 | 0.021** |
| $\eta_{Hsize\_2}$ | 0.001 | −0.007** | 0.000 | −0.006* |
| $\eta_{Hsize\_3}$ | −0.003 | −0.011** | −0.003* | −0.015** |
| $\eta_{AvgAge\_1}$ | −0.001** | 0.001 | −0.001* | 0.002 |
| $\eta_{AvgAge\_2}$ | 0.000 | −0.001 | 0.000 | −0.001 |
| $\eta_{AvgAge\_3}$ | 0.001* | −0.000 | 0.000** | −0.001 |
| $\eta_{NumSch\_1}$ | −0.011*** | −0.050*** | −0.012*** | −0.047*** |
| $\eta_{NumSch\_2}$ | −0.003** | 0.011** | −0.002 | 0.011*** |
| $\eta_{NumSch\_3}$ | 0.014*** | 0.039*** | 0.013*** | 0.036*** |
| $\eta_{Old60\_1}$ | −0.002 | −0.020** | −0.004 | −0.023** |
| $\eta_{Old60\_2}$ | −0.001 | −0.007* | −0.000 | 0.006 |
| $\eta_{Old60\_3}$ | 0.003 | 0.012** | 0.003 | 0.017** |
| $\eta_{NumNCD\_1}$ | 0.018*** | −0.002 | 0.017*** | −0.003 |
| $\eta_{NumNCD\_2}$ | −0.009*** | −0.005 | −0.008*** | 0.006 |
| $\eta_{NumNCD\_3}$ | −0.009*** | −0.00. | −0.008*** | −0.003 |
| $\eta_{HeadAge\_1}$ | −0.000 | −0.001 | 0.000 | −0.001 |
| $\eta_{HeadAge\_2}$ | −0.000 | 0.000 | −0.000 | 0.000 |
| $\eta_{HeadAge\_3}$ | 0.000 | 0.001 | 0.000 | 0.001 |
| $\eta_{HeadEmpl\_1}$ | −0.007 | −0.050*** | −0.004 | −0.055*** |
| $\eta_{HeadEmpl\_2}$ | 0.004 | 0.026*** | 0.002 | 0.029*** |
| $\eta_{HeadEmpl\_3}$ | 0.004 | 0.024*** | 0.003 | 0.027** |
| $\eta_{HeadSector\_1}$ | −0.008 | −0.017* | −0.009 | −0.019 |
| $\eta_{HeadSector\_2}$ | 0.005 | 0.010* | 0.005 | 0.013** |
| $\eta_{HeadSector\_3}$ | 0.003 | 0.007 | 0.004 | 0.006 |

**Table A.14:** Coefficients of QUAIDS Model (Cont.)

| | Not Corrected | | Corrected | |
|---|---|---|---|---|
| | OLS | IV | OLS | IV |
| $\eta_{HeadMuslim\_1}$ | −0.014 | 0.003 | −0.012 | 0.010 |
| $\eta_{HeadMuslim\_2}$ | 0.012** | −0.008 | 0.011** | −0.008 |
| $\eta_{HeadMuslim\_3}$ | 0.002 | 0.005 | 0.001 | −0.002 |
| $\eta_{House\_1}$ | −0.035*** | −0.019 | −0.032*** | −0.016 |
| $\eta_{House\_2}$ | 0.017** | 0.000 | 0.017** | 0.005 |
| $\eta_{House\_3}$ | 0.018*** | 0.019 | 0.015*** | 0.011 |
| $\eta_{Urban\_1}$ | −0.016*** | −0.035** | −0.015*** | −0.031 |
| $\eta_{Urban\_2}$ | −0.002 | −0.002 | 0.003 | 0.000 |
| $\eta_{IMR\_1}$ | | | 0.027 | 0.019 |
| $\eta_{IMR\_2}$ | | | 0.008 | 0.028 |
| $\eta_{IMR\_3}$ | | | −0.036 | −0.047 |
| $\rho_{Hsize}$ | −0.019 | 1.230 | 0.001 | 0.290 |
| $\rho_{AvgAge}$ | −0.006 | 0.298 | −0.003 | 0.177 |
| $\rho_{NumSch}$ | 0.035 | −1.266* | 0.011 | −1.752 |
| $\rho_{Old60}$ | 0.018 | −1.491 | −0.006 | −0.271 |
| $\rho_{NumNCD}$ | 0.190** | −0.531 | 0.126** | −0.613 |
| $\rho_{HeadAge}$ | −0.001 | −0.056 | 0.000 | −0.099 |
| $\rho_{HeadEmpl}$ | −0.052 | −0.393 | −0.016 | −1.958 |
| $\rho_{HeadSector}$ | −0.069 | −090 | −0.047 | −2.001 |
| $\rho_{HeadMuslim}$ | −0.163 | 7.168* | −0.107 | 7.748* |
| $\rho_{House}$ | −0.321** | 0.220 | −0.233 * * | −1.473 |
| $\rho_{Urban}$ | −0.037 | −1.653 | −0.052 | −1.832 |
| $\rho_{IMR}$ | | | −0.310* | 16.220* |

OLS = Ordinary Least Square, IV = Instrumental Variable.

***$p < 0.01$, **$p < 0.05$, and *$p < 0.1$.

Source: Authors' calculations based on data from the Bangladesh Bureau of Statistics. 2019. Report on the Household Income and Expenditure Survey 2016. Dhaka: Statistics and Information Division, Ministry of Planning, Government of Bangladesh.

**Table A.15:** Suppliers of Insulin in Bangladesh

| Domestic Producer (50 products) | Import (65 products) |
|---|---|
| 1. Advanced Chemical Industries Limited | 1. Eli Lilly & Company, USA (License expired as of 2016) |
| 2. Arsitopharma Limited | 2. Lilly France S.A.S |
| 3. Beximco Pharmaceuticals Ltd. | 3. Novo Nordisk A/S |
| 4. Drug International Ltd. | 4. Novo Noris Producao Pharmaceutica do Brasil Ltd. |
| 5. Incepta International Ltd. | 5. Novo Nordisk Production SAS (License expired in 2018) |
| 6. Popular Pharmaceutical Ltd. | 6. Sanofi Aventis Deutschland |
| 7. Square Pharmaceuticals Ltd. | |

Source: Government of Bangladesh, Directorate General of Drug Administration

**Table A.16:** Estimates of Insulin Demand Equation

| | Dep. Var. = Total Expenditure on Insulin | | | |
|---|---|---|---|---|
| | Not Corrected | | Corrected | |
| | Coefficient | SE | Coefficient | SE |
| p2IV | -0.11 | 0.22 | -0.112 | 0.22 |
| $\bar{\omega}$ | 0.03 | 0.02 | 0.027 | 0.02 |
| AvgAge | 7.85* | 4.29 | 7.803* | 4.38 |
| NumSch | *52.94* | 32.05 | -53.19 | 32.45 |
| Old60 | -48.42 | 36.22 | -47.942 | 37.36 |
| NumNCD | 74.04* | 38.54 | 74.45* | 39.34 |
| HeadAge | 0.65 | 3.01 | 0.49 | 4.32 |
| HeadGender | -172.7 | 109.9 | -169.0 | 130.0 |
| HeadEduc | 12.35 | 33.64 | 14.95 | 59.41 |
| HeadEmpl | 186.9** | 80.6 | 184.6** | 91.51 |
| HeadSector | 36.74 | 46.47 | 33.27 | 80.14 |
| Urban | 106.30 | 78.48 | 106.5 | 75.65 |
| HeadMuslim | 92.46 | 86.32 | 95.46 | 102.9 |
| House | -28.37 | 102.4 | -23.91 | 132.5 |
| IMR | | | 76.30 | 1436.7 |
| N | 421 | | 421 | |
| Adjusted $R^2$ | 0.066 | | 0.066 | |

Source: Authors' calculations based on data from the Bangladesh Bureau of Statistics. 2019. Report on the Household Income and Expenditure Survey 2016. Dhaka: Statistics and Information Division, Ministry of Planning, Government of Bangladesh.

# References


Abbott, R. B., Rania B., Lina B., Taher A. E., Thamer O., Hanan S., Mustafa S., & Ibrahim A. (2012). The Price of Medicines in Jordan: The Cost of Trade-Based Intellectual Property. *Journal of Generic Medicines*, 9 (2), 75–85.

Acemoglu, D. & Autor, D. (2011). Skills, tasks and technologies: Implications for employment and earnings. *In Handbook of labor economics*, Vol. 4, 1043-1171.

Acemoglu, D., Manera, A. & Restrepo, P. (2020). Does the US tax code favor automation? (No. w27052). National Bureau of Economic Research.

Acemoglu, D. & Restrepo, P. (2017). Robots and jobs: Evidence from US labor markets.

Acemoglu, D. & Restrepo, P. (2018a). The Race between Man and Machine: Implications of Technology for Growth, Factor Shares, and Employment. *American Economic Review*, 108(6), 1488-1542.

Acemoglu, D. & Restrepo, P. (2018b). Demographics and automation (No. w24421). National Bureau of Economic Research.

Acemoglu, D. & Restrepo, P. (2018c). Modeling Automation (No. w24321). National Bureau of Economic Research.

Acemoglu, D. & Restrepo, P. (2021). Tasks, Automation, and the Rise in US Wage Inequality (No. w28920). National Bureau of Economic Research.

Adam, C., & David C. (2007). Exchange rate regimes and trade. The Manchester School 75(1). 44-63.

Akaleephan, C., Suwit W., Rungpetch S., Paithip L., A., Achara A.U., Viroj, T., & Sripen, T. (2009). Extension of Market Exclusivity and Its Impact on the Accessibility to Essential Medicines, and Drug Expense in Thailand: Analysis of the Effect of TRIPs-Plus Proposal. *Health Policy*, 91 (2), 174–82.

Akhtar, A. M., & Richard, H.S. (1984) Exchange rate uncertainty and international trade: some conceptual issues and new estimates for Germany and the United States.

Araar, A., & Paolo, V. (2016). Prices and Welfare. Washington, DC: Poverty and Equity Global Practice Group, World Bank Group.

Aristotelous, K. (2001). Exchange-rate volatility, exchange-rate regime, and trade volume: evidence from the UK–US export function (1889–1999). *Economics Letters* 72(1), 87-94.

Arize, Augustine C., John M., & Krishna M. K. (2003). Does exchange-rate volatility depress export flows: The case of LDCs. *International Advances in Economic Research*, 9(1), 7-19.

Arize, C.A., Thomas O., & Daniel J. S. (2008). Exchange-rate volatility in Latin America and its impact on foreign trade. *International Review of Economics*, 17(1), 33-44.

Asseery, A., & David A. P. (1991). The effects of exchange rate volatility on exports: Some new estimates. *Economics Letters*, 37(2), 173-177.

Audretsch, D.B. & Feldman, M.P., 1996. R&D spillovers and the geography of innovation and production. *The American economic review*, 86(3), 630-640.

Autor, D., Katz, L.F. & Kearney, M.S., (2006). The polarization of the US labor market.

Autor, D.H., Levy, F. & Murnane, R.J., (2003). The skill content of recent technological change: An empirical exploration. *The Quarterly journal of economics*, 118(4), 1279-1333.

Autor, D. & Salomons, A., (2018). Automation Labor Share-Displacing? Productivity Growth, Employment, and the Labor Share. *Brookings Papers on Economic Activity*, 2018(1), 1-87.

Baak, S. (2004). Exchange rate volatility and trade among the Asia Pacific countries. In Econometric Society Far Eastern Meeting.

Bacchetta, P., & Eric, W.V. (1998). Does exchange rate stability increase trade and capital flows?. No. w6704. National bureau of economic research.

Bailey, M. J., George, S. T., & Michael, U. (1986) Exchange-rate variability and trade performance: evidence for the big seven industrial countries. *Review of World Economics*, 122(3), 466-477.

Bailey, M. J., George, S. T., & Michael U. (1987). The impact of exchange-rate volatility on export growth: some theoretical considerations and empirical results. *Journal of Policy Modeling*, 91, 225-243.

Bailey, M., & George S. T. (1988). Trade and investment under floating rates: the US experience dollars. *In Deficits and Trade, The CATO Journal*. Baker, B.K. (2016). Trans-Pacific Partnership Provisions in Intellectual Property, Transparency, and Investment Chapters Threaten Access to Medicines in the US and Elsewhere. *PLoS Medicine*, 13 (3), e1001970.

Bangladesh Bureau of Statistics. (2019). Report on the Household Income and Expenditure Survey 2016. Dhaka: Statistics and Information Division, Ministry of Planning, Government of Bangladesh.

Bank of International Settlement. (2017). Banks, J., R. B., & A. L. (1997). Quadratic Engel Curves and Consumer Demand. *Review of Economics and Statistics*, 79, 527–39. http://www.bis.org/statistics/eer.htm (accessed September 22, 2017)

Baron, D. P. (1976). Fluctuating exchange rates and the pricing of exports. *Economic Inquiry*, 14(3), 425-438.

Basant, R. (2007). Intellectual Property Rights Regimes: Comparison of Pharma Prices in India and Pakistan. *Economic and Political Weekly* 42 (39), 3969–77.

Baum, C. F., & Mustafa, C. (2009). The volatility of international trade flows and exchange rate uncertainty. Department of Economics, Boston College and Department of Economics, University of Sheffield, Working paper.

Baum-Snow, N. & Pavan, R. (2012). Understanding the City Wage Gap. *The Review of Economic Studies*, 79(1), 88-127.

Baum-Snow, N. & Pavan, R., (2012). Inequality and City Size. *The Review of Economic Studies*, 95(5), 1535-1548.

Behrens, K., Duranton, G. & Robert-Nicoud, F. (2014). Productive cities: Sorting, selection, and agglomeration. *Pournal of Political Economy*, 122(3), 507-553.

Bernard, A.B., Eaton, J., Jensen, J.B. & Kortum, S. (2003). Plants and productivity in international trade. *American economic review*, 93(4), 1268-1290.

Bessen, J.E. (2016). How computer automation affects occupations: Technology, jobs, and skills.

Bhattacharya, D. (2009). SABER. http://saber.eaber.org/node/23153 (accessed January 22, 2020).

Bini-Smaghi, L. (1991). Exchange rate variability and trade: why is it so difficult to find any empirical relationship?. *Applied economics*, 23(5), 927-936.

Biswas, T., Islam, A., Rawal, L. B. & Islam, S. M. S. (2016). Increasing Prevalence of Diabetes in Bangladesh: A Scoping Review. *Public Health* ,138, 4–11.

Black, D. & Henderson, V. (1999). Spatial evolution of population and industry in the United States. *American Economic Review*, 89(2), 321-327.

Bolton, K. & Breau, S. (2012). Growing unequal? Changes in the distribution of earnings across Canadian cities. *Urban Studies*, 49(6), 1377-1396.

Boston Consulting Group. (2015). The Robotics Revolution: The Next Great Leap in Manufacturing. https://www.bcg.com/perspectives/197062.

Breau, S. (2015). Rising inequality in Canada: A regional perspective. *Applied Geography*, 61, 58-69.

Breau, S., Kogler, D.F., & Bolton, K.C. (2014). On the Relationship between Innovation and Wage Inequality: New Evidence from Canadian Cities. *Economic Geography*, 90(4), 351-373.

Broersma, L. & Oosterhaven, J. (2009). Regional labor productivity in the Netherlands: Evidence of agglomeration and congestion effects. *Journal of Regional Science*, 49(3), 483-511.

Busso, M., Gregory, J., & Kline, P. (2013). Assessing the incidence and efficiency of a prominent place based policy. *American Economic Review*, 103(2), 897-947.

Caballero, R. J., & Vittorio C. (1989). The effect of real exchange rate uncertainty on exports: empirical evidence. *The World Bank Economic Review* 3(2), 263-278.

Caporale, T., & Khosrow D. (1994). Exchange rate variability and the flow of international trade. *Economics Letters*, 46(1), 49-54.

Chatterjee, C., Kensuke, K,, & Viswanath, P. (2015). The Consumer Welfare Implications of Governmental Policies and Firm Strategy in Markets for Medicines. *Journal of Health Economics*, 44,, 255–73.

Chaudhuri, S., Pinelopi G.K., & Panle J. (2006). Estimating the Effects of Global Patent Protection in Pharmaceuticals: A Case Study of Quinolones in India. *American Economic Review*, 96 (5), 1477–514.

Chaves, G,, Walter, G.B., & Marcela, V.F. (2017). Mercosur–EU Free Trade Agreement: Impact Analysis of TRIPS-Plus Measures Proposed by the EU on Public Purchases and Domestic Production of HIV and Hepatitis C Medicines in Brazil. Ministerio da Saúde, Brazil.

Chipman, J. S., & James, M. C. (1980). Compensating Variation, Consumer's Surplus, and Welfare.
textitThe American Economic Review, 70 (5), 933–49.

Chowdhury, A. R. (1993). Does exchange rate volatility depress trade flows? Evidence from error-correction models. *The Review of Economics and statistics*, 75(4), 700-706.

Chowdhury, A.M.A. (2018). Enforcement of Intellectual Property Rights in Bangladesh: To What Extent Is It TRIPS-Responsive? *Beijing Law Review* 9, 425–38.

Clark, P. B. (1973). Uncertainty, exchange risk, and the level of international trade. *Economic Inquiry*, 11(3), 302-313.

Clark, P., Natalia T., Shang-Jin W., Azim S., & Li Z. (2004). Exchange rate volatility and trade flows-some new evidence. IMF Occasional Paper 235.

Capello, R. (2002). Urban rent and urban dynamics: The determinants of urban development in Italy. *The Annals of Regional Science*, 36(4), 593-611.

Caselli, F. & Manning, A. (2019). Robot arithmetic: new technology and wages. *American Economic Review: Insights*, 1(1), 1-12.

Castaneda, A., Diaz-Gimenez, J. & Rios-Rull, J.V. (2003). Accounting for the US earnings and wealth inequality. *Journal of political economy*, 111(4), 818-857.

Ciccone, A. & Hall, R.E. (1993). Productivity and the density of economic activity. National Bureau of Economic Research, No. w4313

Combes, P.P., Duranton, G., Gobillon, L. & Roux, S. (2008). Spatial wage disparities: Sorting matters! *Journal of Urban Economics*, 63, 723-742.

Combes, P.P., Duranton, G., Gobillon, L. & Roux, S. (2010). Estimating agglomeration economies with history, geology, and worker effects. In Agglomeration economics (pp. 15-66). University of Chicago Press.

Combes, P.P., Duranton, G., Gobillon, L., Puga, D. & Roux, S. (2012). The productivity advantages of large cities: Distinguishing agglomeration from firm selection. *Econometrica*, 80(6), 2543-2594.

Criscuolo, C., Martin, R., Overman, H. & Van Reenen, J. (2012). The causal effects of an industrial policy. National Bureau of Economic Research, No. w17842

Cushman, D. O. (1983). The effects of real exchange rate risk on international trade. *Journal of international Economics*, 15(1), 45-63.

Cushman, D. O. (1986). Has exchange risk depressed international trade? The impact of third-country exchange risk. *Journal of international Money and Finance*, 5(3), 361-379.

Das, S. K. (2003). Effects of exchange rate volatility on international trade: An empirical Analysis. Vanderbilt University.

De Grauwe, P. (1988). Exchange rate variability and the slowdown in growth of international trade. *IMF Staff Papers*, 35(1), 63-84.

Deaton, A., & John, M. (1980). An Almost Ideal Demand System. *The American Economic Review*, 70 (3), 312–26.

Dell'Ariccia, G. (1999). Exchange rate fluctuations and trade flows: Evidence from the European Union. *IMF Staff papers*, 46(3), 315-334.

Desmet, K., Nagy, D.K. & Rossi-Hansberg, E. (2018). The geography of development. *Journal of Political Economy*, 126(3), 903-983.

Diamond, P. A. (1982). Aggregate demand management in search equilibrium. *The Journal of Political Economy*, 95(5), 881-894.

Diamond, P. A. (1982). Wage determination and efficiency in search equilibrium. *The Review of Economic Studies*, 49(2), 217-227.

Diamond, R. (2016). The determinants and welfare implications of us workers' diverging location choices by skill: 1980-2000. *American Economic Review*, 106(3), 479-524.

Directorate General of Drug Administration. (2019). Registered Products. Government of Bangladesh. http://www.dgda.gotav.bd/index.php/manufacturers/allopathic.

Dobkins, L.H. & Ioannides, Y.M. (2001). Spatial interactions among US cities: 1900–1990. *Regional science and urban Economics*, 31(6), 701-731.

Donegan, M. & Lowe, N. (2008). Inequality in the creative city: is there still a place for "old-fashioned" institutions?. *Economic Development Quarterly*, 22(1), 46-62.

Doğanlar, M. (2002). Estimating the impact of exchange rate volatility on exports: evidence from Asian countries. *Applied Economics Letters*, 9(13), 859-863.

Dutta, A. (2011). From Free Entry to Patent Protection: Welfare Implications for the Indian Pharmaceutical Industry. *The Review of Economics and Statistics*, 93 (1), 160–78.

Eaton, J. & Kortum, S. (2002). Technology, geography, and trade. *Econometrica*, 70(5), 1741-1779.

Ellison, G. & Glaeser, E.L. (1999). The geographic concentration of industry: does natural advantage explain agglomeration? *American Economic Review*, 89(2), 311-316.

Ellison, G., Glaeser, E.L. & Kerr, W.R. (2010). What causes industry agglomeration? Evidence from coagglomeration patterns. *American Economic Review*, 100(3), 1195-1213.

Ethier, W. (1973). International trade and the forward exchange market. *The American Economic Review*, 63(3), 494-503.

Ewen, M., Huibert-Jan, J., David, B., & Richard, L. (2019). Insulin Prices, Availability and Affordability in 13 Low-Income and Middle-Income Countries. *BMJ Global Health* 4 (3), e001410.

Fajgelbaum, P.D., Morales, E., Suárez Serrato, J.C. & Zidar, O. (2018). State taxes and spatial misallocation. *The Review of Economic Studies*, 86(1), 333-376.

Farazmand, F.A., Norcio, R. & Tu, Y.T. (2015). Manufacturing Location: Bigger vs Smaller Cities.

Feenstra, Robert C., & Jon D. K. (1991). Exchange rate volatility and international prices. National Bureau of Economic Research, No. w3644.

Florida, R. & Mellander, C. (2016). The geography of inequality: Difference and determinants of wage and income inequality across US metros. *Regional Studies*, 50(1), 79-92.

Frank, M.R., Sun, L., Cebrian, M., Youn, H. & Rahwan, I. (2018). Small cities face greater impact from automation. *Journal of The Royal Society Interface*, 15(139), 20170946.

Franke, G. (1991). Exchange rate volatility and international trading strategy. *Journal of International Money and Finance*, 10(2), 292-307.

Gabaix, X.& Ioannides, Y.M. (2004). The evolution of city size distributions. *In Handbook of regional and urban economics*, 4, 2341-2378.

Gagnon, J. E. (1993). Exchange rate variability and the level of international trade. *Journal of International economics*, 34(3), 269-287.

Gaubert, C. (2018). Firm sorting and agglomeration. National Bureau of Economic Research, No. w24478.

Giannone, E. (2017). Skilled-biased technical change and regional convergence. Technical report, University of Chicago Working Paper. http://home.uchicago.edu/elisagiannone/files/JMP ElisaG.pdf.

Glaeser, E. L. & Mare. D. C. (2001). Cities and Skills. *Journal of Urban Economics*, 19, 316-342.

Glaeser, E.L., Resseger, M. & Tobio, K. (2009). Inequality in cities. *Journal of Regional Science*, 49(4), 617-646.

Gotur, P. (1985). Effects of exchange rate volatility on trade: some further evidence. *Staff Papers*, 32(3), 475-512.

Government of Bangladesh, Ministry of Health and Family Welfare. (2016). Bangladesh National Health Accounts, 1997–2015. Dhaka: Health Economics Unit.

Graetz, G. & Michaels, G. (2015). Estimating the impact of robots on productivity and employment. Center for Economic Performance.

Graetz, G. & Michaels, G. (2017). Is modern technology responsible for jobless recoveries? *American Economic Review*, 107(5), 168-73.

Guerreiro, J., Rebelo, S. & Teles, P. (2017). Should robots be taxed? National Bureau of Economic Research, No. w23806.

Hasan, M. M., Fariha, T., Tariqujjaman, M., & Ahmed, S. (2019). Socioeconomic Inequalities of Undiagnosed Diabetes in a Resource-Poor Setting: Insights from the Cross-Sectional Bangladesh Demographic and Health Survey 2011. *International Journal of Environmental Research and Public Health*, 16 (1), 115.

Hayakawa, K, & Fukunari K. (2009). The effect of exchange rate volatility on international trade in East Asia. *Journal of the Japanese and International Economies*, 23(4), 395-406.

Helpman, E, Oleg, I, & Stephen, R. (2010). Inequality and unemployment in a global economy. *Econometrica*, 78(4), 1239-1283.

Hémous, D. & Olsen, M. (2014). The rise of the machines: Automation, horizontal innovation and income inequality. *American Economic Journal: Macroeconomics*, 14(1), 179-223.

Henderson, V. (1974). The Sizes and Types of Cities. *American Economic Review*, 64(4), 640-56.

Henderson, J.V., Shalizi, Z., & Venables, A.J. (2001). Geography and development. *Journal of Economic Geography*, 1(1), 81-105.

Hook, L. S. & Boon, T. H. (2000). Real exchange rate volatility and Malaysian exports to its major trading partners. Universty Putra Malaysia" Working Paper 6.

Hooper, P., & Steven K. W. (1978). The effect of exchange rate uncertainty on the prices and volume of international trade. *Journal of international Economics*, 8(4), 483-511.

Hubmer, J., Krusell, P., & Smith, A.A. (2016). The Historical Evolution of Wealth Distribution: A Quantitative-Theoretic Explanation. NBER Working Papers 23111.

Hwang, H., & Jin-woo L. (2005). Exchange rate volatility and trade flows of the UK in 1990s. *International Area Review*, 8(1), 173-182.

Ibanez, M.R., & Pennington-Cross, A. (2013). Commercial property rent dynamics in US metropolitan areas: an examination of office, industrial, flex and retail space. *The Journal of Real Estate Finance and Economics*, 46(2), 232-259.

IHME. (2019). Bangladesh. http://www.healthdata.org/bangladesh.

International Household Survey Network. (2020). Household Income and Expenditure Survey, 2016–2017. Bangladesh Bureau of Statistics. https://catalog.ihsn.org/index.php/catalog/.

Ioannides, Y.M., & Overman, H.G., 2003. Zipf's law for cities: an empirical examination. Regional science and urban economics, 33(2), pp.127-137.

Islam, M. D., Warren , K.A., Danielle, T., Rachel, T, Kevin, G. P., & Veronika, W. J. (2019). Impacts of Intellectual Property Provisions in Trade Treaties on Access to Medicine in Low and Middle Income Countries: A Systematic Review. *Globalization and Health*, 15 (1), 88.

Islam, S. S. M., Andreas, L., Uta, F., Michael, L., Jochen, S., Jonathan, B., Louis, W. N., & Rolf, H. (2017). Healthcare Use and Expenditure for Diabetes in Bangladesh. *BMJ Global Health*, 2 (1), e000023.

Islam, S., Aminur, R., & Abu, K. A. (2018). Bangladesh Pharmaceutical Industry: Perspective and the Prospects. *Bangladesh Journal of Medical Science* 17 (4):, 519–25.

Islam, S. M. S, Andreas, L., Uta, F., Michael, L., Jochen, S., Jonathan, B., Louise, W. N., & Rolf, H. (2017). Healthcare Use and Expenditure for Diabetes in Bangladesh. *BMJ Global Health*, 2 (1), e000033.

Jaffe, A.B., Trajtenberg, M., & Henderson, R. (1993). Geographic localization of knowledge spillovers as evidenced by patent citations. *The Quarterly journal of Economics*, 108(3), 577-598. bibitemBiS92 Kasman, A., & Saadet K. (2005). Exchange rate uncertainty in Turkey and its impact on export volume. *METU Studies in Development*, 32(1), 41.

Kaymak, B., & Poschke, M. (2016). The evolution of wealth inequality over half a century: The role of taxes, transfers and technology. *Journal of Monetary Economics*, 77, 1-25.

Kemeny, T., & Storper, M. (2020). Superstar cities and left-behind places: disruptive innovation, labor demand, and interregional inequality.

Klein, . W., & Jay C. S. (2006). Fixed exchange rates and trade. *Journal of international Economics*, 70(2), 359-383.

Kline, P. & Moretti, E. (2014). Local economic development, agglomeration economies, and the big push: 100 years of evidence from the Tennessee Valley Authority. *The Quarterly journal of economics*, 129(1), 275-331.

Koray, F., & William L.D. (1989). Real exchange rate volatility and US bilateral trade: a VAR approach. *The Review of Economics and Statistics*, 71(4), 708-712.

Korpi, M., & Clark, W.A.V. (2017) .Migration and occupational careers: The static and dynamic urban wage premium by education and city size. *Papers in Regional Science*, 98(1), 555-574.

Kotlikoff, L., & Sachs, J.D. (2012). Smart Machines and Long-Term Misery. NBER Working paper No. 18629.

Kristensen, G. (1991). Household and business firm densities in the Danish urban pattern. *In Geography Research Forum*, 11, 51-65.

Kroner, K. F., & William D. L. (1993). The impact of exchange rate volatility on international trade: reduced form estimates using the GARCH-in-mean model. *Journal of International Money and Finance*, 12(3), 298-318.

Krusell, P., & Smith, Jr, A.A. (1998). Income and wealth heterogeneity in the macroeconomy. *Journal of political Economy*, 106(5), 867-896.

Kumar, R., & Ravinder, D. (1991). Exchange rate volatility and Pakistan's exports to the developed world, 1974–85. *World development* 19(9), 1225-1240.

Kumar, V., & Joseph A. W. (1992). "Exchange rate variability and international trade. *Economic Review-Federal Reserve Bank of Atlanta*, 77(3), 17.

Kyle, M., & Yi, Q. (2014). Intellectual Property Rights and Access to Innovation: Evidence from TRIPS. NBER Working Paper No. 20799.

Lankisch, C., Prettner, K., & Prskawetz, A. (2019). How can robots affect wage inequality? *Economic Modelling*, 81, 161-169.

Lastrapes, W. D., & Faik K. (1990). Exchange rate volatility and US multilateral trade flows. *Journal of Macroeconomics*, 12(3), 341-362.

Lee, K., & Philippe S. (2007). "11. Exchange Rate Instability and Trade Integration: The Case of Asia. Corporate Strategies in the Age of Regional Integration, 219.

Lee, S., & Li, Q.(2013). Uneven landscapes and city size distributions. *Journal of Urban Economics*, 78, 19-29.

Lee, N., Sissons, P., & Jones, K. (2016). The geography of wage inequality in British cities. *Regional Studies*, 50(10), 1714-1727.

Lennert, M. (2015). The use of exhaustive micro-data firm databases for economic geography: The issues of geocoding and usability in the case of the amadeus database. *ISPRS International Journal of Geo-Information*, 4(1), 62-86.

Liu, T., & Cao, G. (2011). Determinants of city size of China: Development, government and location. *Resources Science*, 33(8), 1570-1577.

Liu, C.Y., Hu, F.Z. & Jeong, J. (2020). Towards inclusive urban development? New knowledge/creative economy and wage inequality in major Chinese cities. *Cities*, 105, 102385.

Manganelli, B., & Murgante, B. (2017). The dynamics of urban land rent in Italian regional capital cities. *Land*, 6(3), 54.

Marshall, A. (1890). Principles of Economics. London: Macmillan and Co.

Mann, C.L. (1989). The effects of exchange rate trends and volatility on export prices: Industry examples from Japan, Germany, and the United States. *Review of World Economics*, 125(3), 588-618.

Manyika, J., Ramaswamy, S., Bughin, J., Woetzel, J., Birshan, M. & Nagpal, Z. (2018). Superstars': The dynamics of firms, sectors, and cities leading the global economy. McKinsey Global Institute Discussion Paper.

Mascarilla, O., & Yegorov, Y. (2005). Spatial Agglomeration of Firms: Theory and Application for Industrial District 22 of Barcelona.

Mayer, T., Mayneris, F. & Py, L. (2012). The impact of urban enterprise zones on establishments' location decisions: Evidence from French ZFUs.

McCredie, B., Sadiq, K., & Chapple, L. (2019). Navigating the fourth industrial revolution: Taxing automation for fiscal sustainability. *Australian Journal of Management*, 44(4), 648-664.

McKenzie, M. D., & Robert D. B. (1997). The impact of exchange rate volatility on German-US trade flows. *Journal of International Financial Markets, Institutions and Money* 7(1), 73-87.

McKenzie, M. D. (1998). The impact of exchange rate volatility on Australian trade flows. *Journal of International Financial Markets, Institutions and Money*, 8(1), 21-38.

Medhora, R. (1990). The effect of exchange rate variability on trade: The case of the West African Monetary Union's imports. *World Development*, 18(2), 313-324.

Melitz, M. J. (2003). The impact of trade on intraindustry reallocations and aggregate industry productivity. *Econometrica*, 71(6), 1695-1725.

Melo, P.C., Graham, D.J., & Noland, R.B. (2009). A meta-analysis of estimates of urban agglomeration economies. *Regional Science and Urban Economics*, 39, 332– 342.

Mohiuddin, A. K. (2018). An A–Z of Pharma Industry Review: Bangladesh Perspectives. *PahrmaTutal*, 6 (12), 64–78.

Mohiuddin, A, K. (2019). Diabetes Fact: Bangladesh Perspective. *International Journal of Diabetes Research*, 2 (1), 14–20.

Moll, B., Rachel, L., & Restrepo, P. (2021). Uneven Growth: Automation's Impact on Income and Wealth Inequality. NBER Working Paper No. w28440.

Monte, F., Redding, S.J., & Rossi-Hansberg, E. (2018). Commuting, migration, and local employment elasticities. *American Economic Review*, 108(12), 3855-90.

Mortensen, D. T. (1970). A theory of wage and employment dynamics. *Microeconomic foundations of employment and inflation theory*, 167-211.

Mortensen, D. T., & Christopher P.A. (1994). Job creation and job destruction in the theory of unemployment. *The review of economic studies*, 61(3), 397-415.

National Institute of Diabetes and Digestive and Kidney Disease. Diabetes. https://www.niddk.nih.gov/health-information/diabetes (accessed June 1, 2020).

Nordhaus, W.D. (2015). Are we approaching an economic singularity? Information technology and the future of economic growth. NBER Working Paper No. w21547.

Nuroglu, E., & Robert K.M. (2012). The effects of exchange rate volatility on international trade flows: evidence from panel data analysis and fuzzy approach.

Overman, H.G., & Puga, D. (2010). Labor pooling as a source of agglomeration: An empirical investigation. In Agglomeration economics, 133-150.

Pan, L., Mukhopadhaya, P., & Li, J. (2016). City Size and Wage Disparity in Segmented Labour Market in China. *Australian Economic Papers*, 55(2), 128-148.

Perée, E., & Alfred S. (1989). Exchange rate uncertainty and foreign trade. *European Economic Review*, 33(6), 1241-1264.

Pesaran, M.H. (2006). Estimation and inference in large heterogeneous panels with a multifactor error structure. *Econometrica*, 74(4), 967-1012.

Pissarides, C. A. (1974). Risk, job search, and income distribution. *Journal of Political Economy*, 82(6), 1255-1267.

Poi, B. P. (2002). Dairy Policy and Consumer Welfare. In Three Essays in Applied Econometrics. Chapter II. Ann Arbor: Department of Economics, University of Michigan.

Poi, B. P. (2012). Easy Demand-System Estimation with QUAIDS. *The Stata Journal*, 12 (3), 433– 46.

Prettner, K., & Strulik, H. (2020). Innovation, automation, and inequality: Policy challenges in the race against the machine. *Journal of Monetary Economics*, 116, 249-265.

Rappaport, J. (2008). A productivity model of city crowdedness. *Journal of Urban Economics*, 63(2), 715-722.

Ray, R. (1983). Measuring the Costs of Children: An Alternative Approach. *Journal of Public Economics*, 22 (1), 89–102.

Rodríguez-Caballero, C.V. (2016). Panel Data with Cross-Sectional Dependence Characterized by a Multi-Level Factor Structure. On Factor Analysis with Long-Range Dependence, p.1967.

Rosen, K.T., & Resnick, M. (1980). The size distribution of cities: an examination of the Pareto law and primacy. *Journal of urban economics*, 8(2), 165-186.

Rosenthal, S.S., & Strange W.C. (2004). Evidence on the nature and sources of agglomeration economies. *Handbook of Regional and Urban Economics*, 4, 2119– 2171.

Saeedi, P., Inga, P., Paraskevi, S., Belma, M., Suvi, K., Nigel, U., Stephen, C., Leonor, G., Ayesha, A. M., Katherine, O., Jonathan, E. S., Dominic, B., & Rhys, W. (2019). Global and Regional Diabetes Prevalence Estimates for 2019 and Projections for 2030 and 2045: Results from the International Diabetes Federation Diabetes Atlas, 9th edition. *Diabetes Research and Clinical Practice*, 157, 107843.

Sandmo, Ag. (1971). On the theory of the competitive firm under price uncertainty. *The American Economic Review*, 61(1), 65-73.

Segal, D. (1976). Are there returns to scale in city size? *The Review of Economics and Statistics*, 58(3), 339-350.

Sercu, P., & Cynthia V. (1992). Exchange rate volatility, international trade, and the value of exporting firms. *Journal of banking & finance*, 16(1), 155-182.

Sercu, P., & Raman U. (2003). Exchange rate volatility and international trade: A general-equilibrium analysis. *European Economic Review*, 47(3), 429-441.

Shaffer, E. R., & Joseph, E. B. (2009). A Trade Agreement's Impact on Access to Generic drugs. *Health Affairs*, 28 (5), w957–w968.

Shambaugh, J. C. (2004). The effect of fixed exchange rates on monetary policy. *The Quarterly Journal of Economics*, 119(1), 301-352.

Simonovska, I., & Waugh, M.E. (2014). Trade models, trade elasticities, and the gains from trade. NBER Working Paper No. w20495.

Shin, K., & Jong-Wha L. (2004). Exchange rate regimes and economic linkages in East Asia. In Paper presented a International Workshop on Monetary and Exchange Rate Arrangements in East Asia organized by Claremont Mckenna College and Kore Institute for International Economic Policy, 26-27.

Straub, L. (2019). Consumption, savings, and the distribution of permanent income. Unpublished manuscript, Harvard University.

Susskind, D. (2017). A model of technological unemployment. University of Oxford, Department of Economics Discussion Paper. https://www.economics.ox.ac.uk/materials/papers/15126/819-susskind-a-model-of-technological-unemploymentjuly-2017.pdf.

Taylor, C. (2021). Range Rule for Standard Deviation. Retrieved from https://www.thoughtco.com/range-rule-for-standard-deviation-3126231.

Trachtenberg, D., Warren,K. A., Veronika, W. J., & Kevin, G. P. (2020). The Effects of Trade Agreements on Imports of Biologics: Evidence from Chile. *Globalization and Development*. doi: https://doi.org/10.1515/jgd-2019-0030.

von Thunen, Johan. (1826). The Isolated State. Hamburg: F. Perthes

Trullen, J. (1999). La Catalunya - Ciutats. - Revista econ‘omica de Catalunya, Generalitat de Catalonia, Barcelona.

Tenreyro, Silvana. (2007). On the trade impact of nominal exchange rate volatility. *Journal of Development Economics*, 82(2), 485-508.

Tinner, Flavia. (2015). Income Inequality-Do Exchange Rate Regimes Matter?: A Literature Review. PhD dissertation.

Tyers, R., & Zhou, Y. (2017). Automation and inequality with taxes and transfers.

UNCTAD. (2017). Trade and Development Report. United Nations, Geneva.

United Nations. (2019). Ex Ante Assessment of the Possible Impacts of the Graduation of Bangladesh from the Category of Least Developed Countries (LDCs). https://www.un.org /development/desa/dpad/wp-content/uploads/sites/45/IA-Bangladesh-2019.pdf.

United Nations. (2020). UN Office of the High Representative for the Least Developed Countries, Landlocked Developing Countries and Small Island Developing States. http://unohrlls.org/about-ldcs/criteria-for-ldcs/

United Nations. (2021). Graduation of Bangladesh, Lao People's Democratic Republic and Nepal from the LDC category. CDP News. https://www.un.org/development/desa/dpad/ 2021/graduation-of-bangladesh-lao-peoples-democratic-republic-and-nepal-from-the- ldccategory/

Viaene, J., & Casper G. D. (1992). International trade and exchange rate volatility. *European Economic Review*, 36(6), 1311-1321.

von Thunen, J. (1826). The Isolated State. Hamburg: F. Perthes.

Wang, K., & Christopher B. B. (2002). A new look at the trade volume effects of real exchange rate risk. Cornell University Department of Applied Economics and Management Working Paper, No. WP 41.

World Bank. (2019). World Development Report 2019: The Changing Nature of Work. Washington, DC: World Bank. https://openknowledge.worldbank.org/ handle/10986/30435.

World Bank. (2017). https://www.enterprisesurveys.org/portal/index.aspx#/library?dataset =Enterprise%20Survey (accessed September 08, 2017)

World Bank. (2017). http://databank.worldbank.org/source=world-development-indicators

World Bank. (2020). World Development Indicators. https://databank.worldbank.org/source/worlddevelopmentindicators.

World Health Organization. (2015). Bangladesh Health System Review. Manila: Regional Office for the Western Pacific.

World Health Organization. (2016). Diabetes Country Profiles: Bangladesh. https://www.who.int/ diabetes/countryprofiles/bgd en.pdf?ua=1.

World Health Organization. (2019). Diabetes. Factsheets, November 10. https://www.who.int/news-room/fact-sheets/ detail/diabetes.

World Trade Organization. (2015). General Council–Least Developed Country Members–Obligations under Article 70.8 and Article 70.9 of the TRIPS Agreement with Respect to Pharmaceutical Product Patents. https://docs.wto.org/dol2fe/Pages/ FE Search/ FES S006.aspx?Query=(%20Symbol=%20(wt/l/971%20))&Language=ENGLISH& Context =FomerScriptedSearch&languageUIChanged=true#.

Zeira J.(1998). Workers, machines, and economic growth. *The Quarterly Journal of Economics*, 113(4), 1091-117.

Zhang, P. (2019). Automation, wage inequality and implications of a robot tax. *International review of Economics & finance*, 59, 500-509.

# CURRICULUM VITAE

[redacted]

[redacted]