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Institut d'études politiques de Paris
ÉCOLE DOCTORALE DE SCIENCES PO
Programme doctoral en économie
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Doctorat en sciences économiques

Three Chapters on Spatial and Urban Economics

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defended on 29th June 2020

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Résumé Long

Cette thèse se concentre sur deux questions importantes pour les pays en développement aujourd'hui, la pollution et l'écart entre les sexes, en utilisant les outils analytiques et empiriques de l'économie spatiale et urbaine.

Le premier chapitre étudie la question de la pollution atmosphérique et l'impact des politiques maîtrisant le problème, dans le contexte d'un pays en développement, la Chine. Je construis un modèle d'équilibre spatial avec la pollution atmosphérique endogène comme sous-produit de la production et de la consommation, où les travailleurs qualifiés et non qualifiés spatialement mobiles sont affectés négativement mais hétérogène par la pollution de l'air. L'utilisation d'une version calibrée du modèle sur les données en Chine en 2010, je montre qu'une réglementation stricte peut être une force centripète qui attire les travailleurs et la production vers le lieu réglementé tout en réduisant l'émission de polluants local et national. Ce résultat contraste avec les idées des théories traditionnelles qui voit la réglementation environnementale comme une force centrifuge pour l'économie locale. La migration des travailleurs appréhendant la qualité de l'environnement, les liens de l'entrées-sorties dans les réseaux commerciaux et l'ouverture au commerce international, influencent dans le mécanisme de ce résultat. J'envisage ensuite une politique hypothétique de réduction de 10 pour-cent des émissions industrielles nationales et je compare les stratégies sur la façon de répartir les responsabilités de la réduction aux villes. Je trouve que concentrer la responsabilité sur un nombre limité de villes riches peut surperformer une allocation égale en termes de bien-être et de production

économique.

Dans les pays en développement, les femmes souffrent traditionnellement d'une mobilité limitée et cela a été souligné comme le principale obstacle pour les femmes à trouver un emploi sur le marché du travail (ILO 2017). Dans le deuxième chapitre, co-écrit avec Mai Seki, nous évaluons l'effet d'un système de transport urbain moderne sur la participation des femmes et des hommes aux activités économiques. Notre cas est le «Delhi Metro», l'un des principaux exemples d'infrastructures de transport en commun. Dans ce chapitre, nous analysons les effets du Delhi Metro sur le taux d'activité des femmes et des hommes, d'après les données du panel des zones au niveau des cantons dans la ville de Delhi pendant la période de trois ans (1991, 2001 et 2011). Tandis que les données ont des limites pour comprendre en détail les caractéristiques de chaque résident, nous utilisons l'estimation de «difference-in-difference» (DID) contrôlant un effet fixe de localisation, avec un test de tendance parallèle. Les résultats suggèrent que la proximité du Delhi Metro augmente considérablement le taux de participation des femmes au travail (WPR), bien que l'effet sur le WPR masculin soit ambigu par la possibilité de montrer un signe opposé. Alors qu'il existe un certain nombre de mécanismes potentiels qui peuvent fournir ce résultat, nous développons un modèle théorique de navettage urbain et soutiennent qu'une réduction plus importante d'un coût de déplacement pour les femmes (en offrant un mode de transport plus sûr pour les navettes, par exemple), cela peut générer les motifs d'effets sur le WPR similaire à nos résultats empiriques.

Le troisième chapitre, co-écrit avec Minhaj Mahmud et Yasuyuki Sawada, rend compte de la première tentative de mesurer la valeur de la vie statistique (VSL) sur le risque de la mortalité par la pollution d'air dans les zones urbaines du Bangladesh, en utilisant la méthode de l'évaluation contingente (CV). Nous avons demandé aux individus la volonté de payer (WTP) pour la réduction du risque de mortalité par un programme d'amélioration de la qualité de l'air et avons constaté que la volonté de payer est corrélée avec le caractéristiques socio-économiques, l'état de santé et la perception du risque des

répondants, conformément aux études existantes. La moyenne d'après le bootstrap de VSL est comprise entre 17 480 et 22 463 USD en termes de parité de pouvoir d'achat, ce qui équivaut à 9,78-12,57 fois le PIB par habitant du Bangladesh. Compte tenu de notre cadre d'étude, les résultats que nous avons obtenus sont peut-être considérés comme une limite inférieure des estimations de VSL dans le contexte du risque environnemental au Bangladesh.

Dans ce qui suit, je présente des résumés plus détaillés de chaque chapitre.

Chapitre 1. Une analyse de l'équilibre spatial de la pollution atmosphérique en Chine

La pollution atmosphérique est l'une des principales causes de décès et de problèmes de santé dans le monde actuel, en particulier pour les pays à revenu faible et intermédiaire. La Chine est l'un des pays le plus gravement touchés par la pollution de l'air, qui représente 25 à 30 pour cent de la mortalité du monde par la pollution de l'air en 2015 (Landrigan et al. 2017). En principe, la pollution de l'air est une externalité négative, et l'intérioriser par la réglementation améliore le bien-être. Cependant, la réglementation environnementale est traditionnellement considérée comme un coût pour l'économie locale et il fonctionne comme une force centrifuge pour chasser les industries des régions réglementées. A travers par ce chapitre, je démontre que ce n'est pas toujours le cas et certains les régions peuvent jouir d'une force centripète de réglementation environnementale.

La contribution de ce chapitre est que je construis un modèle d'équilibre spatial où la mobilité des travailleurs hétérogènes joue un rôle non négligeable pour déterminer impact global et distributionnel des politiques environnementales. Au départ de conventionnel théories dans la littérature de l'environnement et du commerce, nous présentons les

travailleurs mobiles qui ont des goûts hétérogènes sur la qualité de l'environnement. Grâce à cette extension, nous obtenir plusieurs résultats qui peuvent contredire les vues traditionnelles et populaires sur la façon dont la politique environnementale affecte l'économie régionale et l'environnement. Par exemple, nous constater qu'il existe des cas où une politique environnementale plus stricte peut être bénéfique non seulement pour la qualité de l'air local mais aussi pour l'économie locale. De plus, nous montrons également que la même politique environnementale peut avoir des implications différentes selon l'endroit où cette politique est mise en œuvre. Dans certains cas, des politiques spatialement inégales peut avoir un meilleur impact sur le bien-être qu'une politique uniforme si nous prenons les réponses des gens via la migration.

Mon modèle de l'économie spatiale permet la migration des travailleurs à travers les villes de Chine. Les travailleurs choisissent les villes dans lesquelles leur bien-être est maximisé, et donc le bien-être attendu pour chaque type est égalisé à l'équilibre. Les travailleurs incluent la pollution de l'air comme un équipement local dans leur évaluation du bien-être. Une littérature grandissante qui révèle la demande des citoyens chinois pour une meilleure qualité de l'ambiance nous motive à introduire explicitement la pollution de l'air dans nos spécifications de bien-être.

De plus, notre modèle est nouveau car il introduit des travailleurs hétérogènes, divisés qualifiés et non qualifiés, confrontés à différentes demandes de entreprises industrielles. Leurs préférences diffèrent également en termes de goûts sur la qualité de l'environnement, par conséquent, les travailleurs qualifiés et les travailleurs non qualifiés souffrent différemment de la pollution atmosphérique. La littérature empirique récente révèle que les travailleurs qualifiés et non qualifiés ont des goûts différents en matière d'agrément et cela la différence compte pour déterminer la ville dans laquelle ils choisissent de vivre, de leurs revenus et du coût d'accès aux commodités locales préférées (c.-à-d. le coût du logement).

Grâce à ces extensions introduites dans notre modèle, nous obtenons des résultats

intéressants sur les impacts spatiaux de la politique environnementale locale qui sont différents de ceux conventionnels vus. Nous constatons qu'une réglementation locale plus forte n'entraîne pas toujours une pollution havre. Alors qu'une augmentation unilatérale de la taxe sur les émissions dans une ville augmente définitivement le coût de production qui réduit la compétitivité de l'industrie locale, cependant, l'amélioration de la qualité de l'air dans la ville ainsi que les effets de substitution entre les facteurs peuvent entraîner une délocalisation des travailleurs vers la ville avec des réglementations plus strictes. Cela améliore la production du secteur des services dans la ville et augmente son PIB réel.

Nous appliquons ensuite le modèle à quelques analyses politiques pertinentes pour la situation réelle en Chine. En réalité, le gouvernement central de Chine attribue ampleur différente de la responsabilité de réduction (0-30 pour-cent) selon les régions et les villes pour atteindre l'objectif national (10 pour cent, pour 2010) au total. Reflétant ce fait, nous comparons différentes stratégies d'allocation spatiale de la responsabilité de réduction qui atteint la même réduction de 10 pour-cent au niveau national. Par rapport à la référence stratégie qui attribue une ampleur de réduction uniforme à tous, certaines stratégies avec des allocations inégales se révèlent plus propices à l'amélioration du bien-être.

De plus, nous constatons que la politique nationale de réduction de 10 pour-cent peut avoir un effet différent sur les travailleurs qualifiés et les travailleurs non qualifiés. En moyenne, les travailleurs qualifiés reçoivent impact négatif sur leur revenu réel tandis que les travailleurs non qualifiés bénéficient de gains toutes les stratégies d'allocation comparées. Pour la plupart des stratégies, les impacts négatifs sur le PIB réel moyen est atteint par cette politique nationale de réduction, mais leur ampleur est minuscule. Il n'y a qu'une variation de 0 à -0,2 pour-cent du PIB réel total pour atteindre un 10 pour cent de réduction des émissions industrielles nationales. Étonnamment, une stratégie particulière qui concentre la responsabilité de la réduction dans un nombre limité de villes côtières plus riches présente un retour positif au PIB réel agrégé, ce qui signifie que les

coûts la réglementation peut générer des avantages économiques grâce à la réaffectation des ressources espace.

Alors que certains de nos résultats observent des rendements économiques positifs en raison de réglementation, notre modèle exclut tout mécanisme que la productivité industrielle bénéficie directement des réglementations. Par exemple, Porter and Linde (1995) soutiennent qu'une réglementation environnementale stricte peut inciter les entreprises industrielles à investir dans la technologie plus productive. En conséquence, la mise en œuvre de la réglementation augmente la productivité globale. En outre, la littérature empirique émergente fournit de nombreuses preuves de l'effet direct de la pollution atmosphérique sur la productivité des travailleurs. Cependant, notre approche exclut intentionnellement les effets directs de la réglementation sur la productivité et discuter de l'impact de la réglementation uniquement du point de vue des coûts pour chaque entreprise, afin que nous puissions nous concentrer sur les implications de la réallocation spatiale pour déterminer les résultats économiques et sociaux de la réglementation environnementale.

Chapitre 2. Effets hétérogènes de genre des transports publics urbains sur Emploi: preuves du métro de Delhi

Selon des études antérieures, les femmes des zones urbaines des pays en développement sortent de chez eux moins fréquemment et dépendent plus des transports publics que les hommes. La fourniture de transports publics sûrs et accessibles pourrait potentiellement améliorer la mobilité, condition nécessaire à leur participation active à l'économie. Cependant, il n'y a pas beaucoup de recherches quantifiant l'impact de transports publics, en particulier sur la façon dont les femmes et les hommes sont différenciellement affectés par les transports urbains.

Dans ce chapitre, nous analysons les effets du Delhi Metro, l'une des systèmes de transit rapide de masses les plus grandes dans le monde actuel développés depuis le début des années 2000, sur la participation des femmes et des hommes au travail. Nous nous concentrons sur le Delhi Metro pour trois raisons. Premièrement, Delhi est l'une des villes du monde qui luttent contre les graves problèmes de sécurité des femmes dans les espaces publics et les transports. Deuxièmement, l'Inde est confrontée à des défis participation et autonomisation des femmes. La participation des femmes au travail non agricole a été historiquement stagnant en Asie du Sud, et il y a même eu une tendance à la baisse en Inde au niveau national (Klasen and Pieters 2015; Andres et al. 2017). Pour la ville de Delhi, même si la participation des femmes au travail n'a pas diminué, sa croissance stagne par rapport à celle des hommes. Enfin, le Delhi Metro est l'un des meilleurs cas pour analyser l'impact des infrastructures de transport urbain de haute qualité dans les pays en développement, grâce à sa réputation de normes de service élevées. Cette réputation n'est pas seulement pour sa stabilité et la commodité, mais aussi pour la sécurité et le voyage confortable de ses passagers féminins. Motivés par ces raisons, nous émettons l'hypothèse que l'introduction d'un mode de transport sûr à Delhi aurait eu un effet significatif sur l'offre de main-d'œuvre féminine (l'hypothèse de la sécurité des transports), ainsi que d'autres facteurs, tels que la relocalisation résidentielle, l'évolution de la composition de la demande de travail et / ou de l'offre conjointe de travail au niveau des décisions familiales.

Dans cette étude, nous essayons de quantifier les effets hétérogènes de genre de la Delhi Metro sur les taux de participation au travail. Bien que notre objectif ait une grande pertinence politique, il est difficile d'obtenir une réponse quantitative rigoureuse en raison de graves limitations de données. Notre stratégie consiste donc à utiliser les meilleures données disponibles et à argumenter soigneusement limites. Plus précisément, nous utilisons le résumé du recensement primaire (PCA) qui fournit divers tableaux à partir des données du recensement de la population avec une distribution géographique

finement désagrégée dans le Territoire de la capitale nationale (NCT) de Delhi. Nous construisons un panel de Zones d'PCA pour trois années de recensement consécutives, 1991, 2001 et 2011. Comme mesure d'intervention, nous calculons une accessibilité de chaque zone PCA à la gare plus proche du métro, à l'aide de cartes des zones PCA et de l'alignement du Delhi Metro. Avec la variable de proximité du métro, nous effectuons une analyse des différences de différences (DID), contrôlant l'effet fixe de la localisation, pour évaluer si la proximité des stations de métro contribue à la croissance de la participation aux activités économiques non agricoles par des femmes et des hommes. Puisque nous construisons ces données de panel au niveau de l'unité géographique au niveau de la zone PCA pour trois cycles (1991, 2001 et 2011) avec deux périodes de prétraitement, nous pouvons examiner l'hypothèse de tendance parallèle qui est la condition préalable pour la DID, par incluant le terme "lead" dans l'équation d'estimation.

On note que l'effet de la proximité du métro de Delhi sur le taux d'activité féminine est positif, et que cela ne semble pas être le cas pour les hommes (bien au contraire). Ceci est une preuve suggestive qu'il pourrait y avoir un impact hétérogène entre les sexes. En d'autres termes, les femmes pourraient répondre plus positivement que les hommes à la proximité des stations de métro de Delhi à décider de travailler ou non.

Pour comprendre ces résultats empiriques, nous développons un modèle d'équilibre spatial des transports urbains et des déplacements domicile-travail. Nous modélisons explicitement le choix de navettage pour les femmes et les hommes urbains qui font face à des coûts de transport différents (coûts et temps de trajet plus coût du bien-être lié à la sécurité). Nous étudions la statique comparative du modèle pour voir comment un hypothétique projet Metro affecterait les taux de participation des femmes et des hommes au travail. Nous constatons que si le métro réduit les coûts de déplacement des femmes plus que les hommes, le WPR féminin augmente dans les zones plus proches du métro malgré le WPR masculin présentant une relation plus ambiguë (ou opposée). Cet exemple théorique est cohérent avec nos résultats empiriques. Cependant, nos résultats empiriques

ont une limite en ce que l'identification causale rigoureuse de l'impact et de l'investigation d'un mécanisme est affectée par la nature et l'étendue de la disponibilité des données. Mais, notre étude est l'une des premières tentatives pour mesurer quantitativement l'implication de genre d'un transport public urbain dans le contexte des mégapoles des pays en développement.

Chapitre 3. Volonté de payer pour la réduction des risques de mortalité dus à la pollution atmosphérique: Preuve du Bangladesh urbain

Selon Landrigan et al. (2017), 1 décès sur 6 est causé par la pollution dans le monde. Le Bangladesh, un pays densément peuplé qui a connu une urbanisation rapide au cours des décennies, a été classée comme la pire (8e pire) en termes de pollution atmosphérique dans 180 pays. De toute évidence, il existe un besoin urgent d'interventions publiques fortes pour contrôler la grave pollution atmosphérique actuelle. Quantifier le coût du bien-être de la pollution atmosphérique est une étape cruciale pour motiver les décideurs hiérarchiser de manière appropriée le contrôle environnemental. S'il n'est pas nécessairement facile d'obtenir une estimation fiable de la perte de bien-être résultant de décès (ou de morbidité) due à la pollution atmosphérique, parmi certaines méthodes conventionnelles, la méthode d'évaluation contingente (CV), qui utilise des scénarios hypothétiques et demande la volonté de payer des répondants (réduction des risques), reste une approche populaire. Dans le contexte du risque de mortalité, le WTP d'un individu pour le risque de mortalité réduction peut être convertie en valeur de durée de vie statistique (VSL) en divisant la valeur WTP par l'ampleur de la réduction du risque en question. Cependant, dans les pays en développement, moins d'études ont été menées pour mesurer le WTP pour réduction du risque de mortalité au moyen de la méthode d'évaluation contingente. Études CV sur la mortalité le risque causé par la pollution de

l'environnement est particulièrement limité dans le contexte des pays en développement.

À notre connaissance, il n'y a pas d'étude suscitant le WTP pour la réduction du risque mortel par la pollution de l'air dans le contexte du Bangladesh. Pour combler cette lacune, nous avons mené une enquête CV pour obtenir le WTP individuel pour une réduction du risque de mortalité par pollution atmosphérique à Dhaka et Chittagong, les deux plus grandes villes du Bangladesh. Dix grappes d'échantillonnage ont été choisies parmi deux villes (sept de Dhaka et trois de Chittagong), et un total de 1 000 chefs de ménages ont été choisis au hasard pour une entrevue en personne. Un scénario hypothétique sur la réduction du risque de mortalité par pollution atmosphérique a été expliquée et leur volonté de payer a été obtenus à l'aide de questions ouvertes. Nous avons obtenu 994 réponses valides pour les questions WTP qui ont été utilisées dans les analyses de régression révéler les relations entre le WTP et les attributs des répondants tels que l'âge, le revenu, l'éducation, l'état de santé et la perception des risques de pollution pour leur santé. La VSL moyenne est variait de 17 480 à 22 463 USD en PPA, ce qui équivaut à 9,78-12,57 fois le PIB par habitant la même année.

Notre étude peut être sujette à plusieurs types de biais. Par ces biais, notre scénario est basé sur la construction vers une estimation inférieure pour le VSL. Dans ce contexte, nous soutenons que l'estimation devrait être soigneusement interprétée comme une «limite inférieure» potentielle de la VSL dans le contexte de la réduction des risques environnementaux au Bangladesh.

Chapter 1

A Spatial Equilibrium Analysis of Air Pollution in China

Abstract¹

We construct a spatial equilibrium model with endogenous air pollution as a by-product of production and consumption, where spatially mobile skilled and unskilled workers are affected negatively but heterogeneously by air pollution. Using a calibrated version of the model based on data for China in 2010, we show that strict regulation can be a *centripetal* force that attracts workers and production toward the regulated place while reducing the local and overall emission of pollutants. This result is in contrast to the insights of traditional theories that sees environmental regulation as a *centrifugal* force for the local economy. The migration of workers who care environmental quality, input-output linkages in domestic trade networks, and openness to international trade, work in the mechanism delivering this result. We then consider a hypothetical policy to reduce national industrial emission by 10 percent and compare strategies on how to allocate reduction responsibilities across cities. We find that concentrating responsibility to a limited number of rich cities may outperform an equal allocation in terms of welfare and economic output.

1. The earlier version of this paper appears as JICA Research Institute Working Paper No.211.

1.1 Introduction

Air pollution is one of the leading causes of death and health problems in the current world.² Low and middle-income countries are substantially more polluted than richer countries, and the mortality due to air pollution concentrates in those countries. China is one of the most severely affected countries by air pollution along with India. For example, it accounts for 25-30 percent of global mortality from air pollution in 2015 (Landrigan et al. 2017). Thus, as when Chinese Premier Li Keqiang declared “war against pollution” in his 2014 statement, the leaders of the Chinese government also prioritize this issue.

In principle, air pollution is a negative externality, and internalizing it through regulation is welfare-enhancing. At the same time, environmental regulation is traditionally viewed as a cost to the local economy and it works as a *centrifugal* force to drive industries out from the regulated regions. However, these mechanisms may not necessarily be simple in an economy with many interconnected regions. China is a large country with a great regional diversity, where workers and firms move across regions. Also, regions in China are tied via input-output linkages and a local shock may propagate to other regions. Since environmental regulations affect local factor prices as well as amenities, the effect of regulation does not rest only within the regulated place: it may change the prices, industrial composition, and factor allocations of other regions. Therefore, the net impact of environmental regulation on the local and nationwide outcomes will depend on many things, and is not readily obvious.

To understand the impact of environmental regulation in this complex spatial context, this paper proposes a spatial general equilibrium framework in which air pollution is endogenous as a by-product of production and consumption. By incorporating a standard trade economy model plus pollution by Copeland and Taylor (2004) and spatial equilibrium models similar to those of (Redding and Rossi-Hansberg 2017; Caliendo et al. 2018; Faber and Gaubert 2019), our model allows analysis of how a local or

2. See <https://www.who.int/airpollution/en/>.

aggregate shock from pollution control regulations spatially propagates through trade and migration linkages. Using the model with an arbitrary number of cities that is calibrated to the data of China as of 2010, we conduct various policy simulations to understand the potential effects of local and national environmental policy at aggregated and disaggregated levels.

The key contribution of this paper is that we demonstrate that the mobility of heterogeneous workers matters in determining the aggregate and distributional impact of environmental policies. Departing from the conventional theories in the literature of environment and trade, we introduce mobile workers who have heterogeneous tastes with regard to environmental quality. Thanks to this extension, we obtain several results that may contradict to traditional and popular views on how local environmental policy affect the regional economy and environment. For example, we find that there are cases where stricter environmental policies may be beneficial not only for the local air quality but also for the local economy. In addition, we also show that the same environmental policy can have different nationwide implications depending on the place where such policy is implemented. In some cases, spatially uneven policies may have greater welfare benefit than a uniform policies if we take the people's responses through migration into account.

The model has three production sectors, namely, agriculture, manufacturing, and services. Among these, we regard the manufacturing sector as the polluting sector, respecting the fact that the majority of the anthropogenically contributed air pollution comes from manufacturing emissions in China. To represent the complex mixture of regulatory tools used in local environmental control, we introduce a Pigouvian emission tax for industrial emissions that is set by local government to regulate local firms' emissions of air pollutants. This setting of endogenous pollution from the production side echoes the standard analytical framework that decomposes local emissions of pollutants into the scale (size) of the local economy, the composition of local industries, and the environmental technology of local producers (Grossman and Krueger 1995; Copeland

and Taylor 2004). Quite intuitively, the model has the feature that the local emission increases with any increase in the size of the local economy, the rise of manufacturing sector's share in the economy, and the lower that environmental technology is (i.e. more emissions from a unit of manufacturing value of production).

In contrast to traditional analyses on the spatial distribution of air pollution in an international economy context (e.g. Copeland and Taylor 1994; Hubbard 2014), our model of the domestic spatial economy allows for the migration of workers across cities in China. Workers choose cities in which their welfare is maximised, and thus the expected welfare for each type is equalised in the equilibrium, following the tradition of Rosen (1979) and Roback (1982). Workers include air pollution as a local amenity in their welfare evaluation. A growing literature that reveals the demand from Chinese citizens for better ambient quality motivates us to explicitly introduce air pollution in our welfare specification. For example, studies on the hedonic pricing of housing show that people value air quality in their choice of housing location (Zheng, Fu, and Liu 2009; Zheng, Kahn, and Liu 2010; Zheng, Cao, and Kahn 2011; Zheng and Kahn 2013). Ito and Zhang (2016) use indoor air purifier purchase data between 2006 to 2012 to estimate the revealed willingness to pay (WTP) for reductions in exposure to air pollution as measured by PM_{10} .³ Freeman et al. (2017) use exogenous variations in $PM_{2.5}$ generated by the power plants in distant places in a city's upwind direction and find that people are willing to give up substantial amounts of money to breathe clean air.⁴ Chen, Oliva, and Zhang (2017) quantify the impact of air pollution on domestic migration in China, using the strength of thermal inversion as the exogenous source of variations in local air pollution. Their data also show that migrants head to cities with better air quality, holding other factors associated with the city's attractiveness constant.⁵

3. Their preferred estimates of the WTP to reduce PM_{10} by one unit for five years range from USD4.40 to USD5.46 per household (in 2005 exchange rate).

4. According to their main estimates, a one-unit decline in $PM_{2.5}$ in 2005 was worth USD 8.3 billion for the whole of China.

5. Thermal inversion is a meteorological phenomenon that reverses the normal relationship between

Furthermore, our model is novel because it introduces heterogeneous workers, divided into skilled and unskilled, and face different factor demands by firms. Their preferences also differ in terms of tastes on environmental quality, therefore, the skilled and unskilled are harmed differently by air pollution. The recent empirical literature reveals that skilled and unskilled workers have different tastes for amenity and this difference matters in determining which city they choose to live, through the balancing of their income and the cost of accessing preferred local amenities (i.e. housing cost). Moretti (2013), for example, finds that skilled labor in the U.S. will pay higher living costs than the unskilled to live in cities with superior amenity. In the context of urban air pollution in China, Chen, Oliva, and Zhang (2017) find that skilled labor more elastically responds to the level of air pollution. According to their estimates, the magnitude of the effect of a $1 \mu g/m^3$ increase in $PM_{2.5}$ in the air on the net-migration ratio (in percent) for college graduates or above is 0.9314 while it is 0.4723 for junior-high graduates or below.

Thanks to these extensions introduced in our model, we obtain interesting insights on the spatial impacts of local environmental policy that are different from the conventional views. The conventional view on the spatial impact of environmental regulation is the *pollution haven effect* (PHE) (Copeland and Taylor 2004), which asserts that strengthening local regulations will relocate polluting industries from the regulated region to other regions with laxer policies. This intuitively straightforward prediction is doubly undesirable for policy makers because stronger regulation hurts the local economic output, and because the effectiveness of regulation in reducing pollution is somewhat offset by increased emissions outside of the regulated region. We examine how this PHE emerges in our model, and find that a stronger local regulation does not always result in a pollution haven. While a unilateral increase in emission tax in a city definitely raises the production costs there that reduces the competitiveness of local industry, however, the improved air

altitude and air temperature. When it happens, air temperature in the upper-altitude is higher than that at the lower-altitudes. This is known as a typical climatic cause that worsens air pollution and they use the thermal inversion defined as above as an instrumental variable for the local level of air pollution.

quality in the city as well as the substitution effects among factors may however result in a relocation of workers towards the city with stricter regulations. This enhances the services sector production in the city and raises its real GDP. Moreover, the PHE outside of the city is substantially weakened.

Another feature that is important in the model is its flexible treatment of openness to international trade. Trade openness has important implications for how local regulations affect the spatial distribution of pollution within a country. Specifically, eliminating international trade tends to exaggerate PHE in the domestic economy, suggesting the importance of including the foreign market even in the case where the main focus of analysis is the distribution within a country. With international trade, the increased production cost from tougher regulation in a city results in an increase in the import of polluting varieties from foreign countries, which in turn suppresses the positive demand effect for polluting varieties from domestic suppliers. In other words, the PHE that takes place in the international arena weakens the PHE within a domestic economy. In short, more international openness is associated with a less pronounced PHE in the domestic sphere.

We then apply the model to a few policy analyses relevant to the real situation in China. Every five years, China sets a national reduction target for the aggregate industrial emission of pollutants as one of the policy targets in the Five-Year-Plan (FYP). This target is decomposed into sub-national reduction responsibilities that Provinces and prefecture-level cities try to achieve. In reality, the central government of China assigns different magnitudes of reduction responsibility (0-30 percent) across regions and cities to achieve the national target (10 percent, in 2010) as a sum of these regional reduction efforts. Reflecting this fact, we compare different spatial allocation strategies of reduction responsibility that achieve the same 10 percent national level reduction. Overall, our simulation suggests that a 10 percent reduction of aggregate emissions is likely improve the welfare of both skilled and unskilled labor. Compared to the reference strategy that

assigns a uniform reduction magnitude to all, some strategies with uneven allocations are found to be more welfare-enhancing.

In addition, we find that the national 10 percent reduction policy may have a different effect on skilled workers and unskilled workers. On average, skilled workers receive a negative impact on their real income while unskilled workers enjoy economic gains, across all the allocation strategies compared. For most of the strategies, negative impacts on average real GDP are achieved by this national reduction policy, but their magnitude is tiny. There is only a 0 to -0.2 percent change of aggregate real GDP required to achieve a 10 percent reduction in aggregate industrial emissions. Surprisingly, a particular strategy that concentrates reduction responsibility in a limited number of richer coastal cities exhibits a positive return to aggregate real GDP, meaning that economically costly regulation can generate economic benefits through the reallocation of resources across space. We repeat the same exercises assuming an autarkic China where no international trade takes place. The results show that in the absence of international trade, the welfare effect for skilled worker is larger while that for unskilled workers is lower compared to the case with international trade.

While some of our results observe positive economic returns as a result of stricter regulations, our model rules out any direct mechanisms that bring economic benefit from the regulations suggested by some literature. For example, Porter and Linde (1995) argue that strict environmental regulation may induce industrial firms to invest in cleaner technology that is more productive. As a result, the implementation of regulation boosts aggregate productivity. In addition, the emerging empirical literature provides rich evidence about the direct effect of air pollution on worker productivity. As one of the latest examples from China, He, Liu, and Salvo (2019) exploit exogenous variations in exposure to $PM_{2.5}$ to find its negative impact on the productivity of industrial workers in Chinese towns.⁶ However, our approach intentionally excludes the direct productivity effects of

6. See Zivin and Neidell (2018) for a short summary of global evidence in this regard.

regulation and discusses the impact of regulations purely from the cost point of view for each individual firm, so that we could focus on the implications of spatial reallocation in determining the economic and welfare outcomes of environmental regulation.

Our framework contributes to the literature of economic geography from a number of perspectives. To the best of our knowledge, this paper is the first to incorporate local air pollution and a heterogeneous labor force into a quantitative spatial equilibrium model. Desmet and Rossi-hansberg (2015) are predecessors who incorporate the environmental issue into spatial general equilibrium framework, but they focus on global warming where the impact of emissions works globally, without taking into account workers' heterogeneity. Balboni (2016) studies the spatial distribution of economic activity affected by road infrastructure and localized impact of environment (sea level rise on the Vietnamese coast due to global warming), however the environment (global warming) is exogenous in her setting. Our approach is novel in that it deals with endogenous environmental externalities in a spatial equilibrium framework where heterogeneous workers can migrate across regions and sectors.

The rest of the paper is organized as follows. Section 1.2 introduces the theoretical model and Section 1.3 summarizes the data and calibration procedures. We explain the model properties using numerical simulations of unilateral pollution control policy in Section 1.4. Section 1.5 describes how the model evaluate nationwide reduction target policies and compares different strategies of spatial responsibility allocation. Finally, Section 1.6 concludes the paper.

1.2 The Model

Our purpose is to build a quantitative model of the Chinese economy with endogenous air pollution. As motivated in the previous section, our interest rests in the spatial difference of economic activity and air pollution within China. Therefore, the model accommodates

a total of N locations, consisting of $N - 1$ locations in China and a single consolidated external location, the rest of the world (RoW). Locations in China, called “cities” in the rest of the paper, are denoted with index n (or i) $\in \mathcal{C}$. For the set of all locations in the model, including the RoW \mathcal{W} is used for the notation.

Preference To understand the heterogeneous impact of environmental policy across different type of people, we assume that the economy is populated with two types of labor, skilled and unskilled workers. We take this dichotomous setting for workers’ heterogeneity for the benefit of analytical tractability and calibration of the model to the data. Specifically, since the skill variable in our data is educational attainment, discrete categorization of the skill levels fits well in this context.

The number of skilled workers in n is denoted by L_n^k . The unskilled counterpart in n is L_n^u . The total supply of workers of type $t \in \{k, u\}$ is fixed, denoted by $L_C^t \equiv \sum_{n \in \mathcal{C}} L_n^t$. A worker ι of type $t \in \{k, u\}$ ’s preference

$$U_n^t(\iota) = \varepsilon_n^t(\iota) a_t(D_n) C_n^t B_n^t \quad (1.1)$$

where:

$$a_t(D_n) = \exp(-\xi^t D_n) \quad (1.2)$$

captures utility loss from ambient pollution in n , $D_n > 0$. We assume that a skilled worker is more sensitive to pollution, $\xi^k > \xi^u$, consistent with empirical findings such as Chen, Oliva, and Zhang (2017). $\varepsilon_n^t(\iota)$ is a Fréchet distributed idiosyncratic preference for city n by a type t worker ι , defined over all $n \in \mathcal{C}$ for each individual worker. The distribution function is identical for all locations, with mean 1 and dispersion parameter η^t . B_n^t is the average valuation of location n ’s exogenous amenity other than air pollution by type t workers.

Workers consume housing C_H , traded agricultural goods C_F , traded manufacturing

goods C_M , and non-traded services C_S . C_H is supplied and consumed only within the same n . For simplicity, C_H is the land whose supply is a fixed local endowment. The preference over goods is assumed to be;

$$C_n^t = \left(\frac{1}{\alpha} \left[\sum_{j=F,M,S} (C_{j,n}^t)^{\frac{\rho-1}{\rho}} \right]^{\frac{\rho}{\rho-1}} \right)^\alpha \left(\frac{C_{H,n}^t}{1-\alpha} \right)^{1-\alpha} \quad (1.3)$$

where $\rho > 1$ and $\alpha \in (0, 1)$. Workers of both types spend a constant fraction α of their income on goods and services other than housing. The expenditure shares within the non-housing goods are not constant and depend on local relative prices. Let $P_{j,n}$ denote the local prices of the $j(\in \{F, M, S\})$ sector goods in n . Then, the CES preference on manufacturing and traded services (the first parenthesis of (1.3)) ensures that the expenditure share on j -sector goods becomes $\alpha\chi_{j,n}$, where $\chi_{j,n} \equiv \frac{P_{j,n}^{1-\rho}}{P_{T,n}^{1-\rho}}$ and $P_{T,n} = \left(P_{F,n}^{1-\rho} + P_{M,n}^{1-\rho} + P_{S,n}^{1-\rho} \right)^{\frac{1}{1-\rho}}$. This assumption allows the expenditure share of non-traded services varies across locations.⁷ Note that the preference (1.1) ensures that skilled workers have a higher willingness to pay to reduce their exposure to air pollution. This is important for the analysis because we are interested in how environmental regulation works if there are heterogeneous mobile workers who differently value the environmental quality.

Production Sectors There are three production sectors in the model; (i) a competitive agricultural sector with constant returns to scale technology and zero trade cost between regions in China, (ii) a manufacturing sector under monopolistic competition with costly domestic trade and spatial heterogeneity of productivity that generates trade (a Ricardian), and (iii) a competitive services sector which only serves to the local market. In the model, the manufacturing sector emits air pollutants, while the other two sectors

7. Note that we assume that the parameters governing the preference over goods expressed in (1.3) is the same between skilled and unskilled workers. This means that the consumption share of each category of goods is identical between the skilled and the unskilled in the same city n . This is for the sake of simplicity, but does not seem to affect the qualitative results of the model.

are assumed to be non-polluting. Traditionally, the literature on pollution and trade has widely used two-sector models such as that by Copeland and Taylor (2004) to incorporate the “composition effect” into the analysis. In two-sector models, there are a modern polluting (industrial) sector and a non-polluting sector. The polluting sector is subject to environmental regulations, and regulation may affect the industrial composition of the two sectors through changes in relative factor prices. We assume that the manufacturing sector is polluting based on the fact that it accounts for the largest share of the emission of ambient pollutants in China (Zheng and Kahn 2013). However, differently from the traditional way, we assume two distinctive non-polluting sectors, agriculture and services. In China, both agriculture and services employ non-negligible shares of the labor force and they are different in many aspects. Specifically, the agricultural sector mainly employs unskilled labor while the services sector uses skilled labor more intensively. Given this difference in skill intensiveness, a two-sector model which aggregates agriculture and services into one single “non-polluting sector” may oversimplify the reality of the Chinese economy. In addition, the three-sector setting fits well in our empirical context because the data (output and employment) we use for calibration report the numbers for these three sectors.

Agricultural Production We assume that the agricultural sector is traditional and hires only unskilled labor. For the benefit of simplicity, we further assume that the agricultural output can be traded without trade cost, so that the price can be normalized to $P_{F,n} = 1, \forall n \in \mathcal{W}$. Specifically, the production is constant returns to scale and has the following form,

$$Y_{F,n} = A_{F,n} L_{F,n}^u \tag{1.4}$$

where $A_{F,n}$ is local productivity shifter. Local endowments such as land area and fertility are considered to be entered in this productivity shifter. $L_{F,n}^u$ is the employment of unskilled labor in the agricultural sector in n . Let w_n^u denote the wage of the unskilled

labor, then, in the equilibrium,

$$w_n^u = A_{F,n} \tag{1.5}$$

Production Technologies in the Manufacturing Sector The production technology of the manufacturing sector closely follows the Ricardian trade model proposed by Eaton and Kortum (2002), which have widely been used to study the domestic economic geography (see, Donaldson and Hornbeck 2016; Caliendo et al. 2018; Faber and Gaubert 2019). There are quite a few advantages of adopting their model. First, it allows dealing with an arbitrary number of locations that engage in trade. Second, while the model by Eaton and Kortum (2002) was originally designed to study international trade where the factors (such as labors) are immobile across national borders, the model can easily be extended to accommodate the migration of production factors. Third, the model can directly incorporate the canonical model of pollutant emission of Copeland and Taylor (2004).

There are infinitesimal intermediate manufacturing varieties in a fixed interval, indexed by $x \in [0, 1]$. An x -variety firm uses inputs from manufacturing and local services as well as two types of labors. A local competitive manufacturing final producer combines all the intermediate varieties that can be sourced from any cities within China and RoW and produce a manufacturing composite. This local final producer sells the composite to the local final consumers and local producers in manufacturing and services. The primary production unit in the manufacturing sector is the firms that produce manufacturing intermediates. Each of these firms produces an intermediate variety using a composite of inputs as specified below. Production by the intermediate firms generates an undesirable by-product, which is called pollutant. To reduce the emission of pollutant, the firm needs to divert a fraction of its inputs to abatement activities. Net emissions after abatement are a fraction of the primary gross emission.

Specifically, an intermediate x -variety producer in city n has the following technology.

$$\begin{cases} q_{M,n}(x) &= [1 - s_n(x)] \phi_n(x) A_{M,n} \tilde{m}_n(x) \\ \tilde{z}_{M,n}(x) &= \lambda_{M,n} \phi_n(x) A_{M,n} \tilde{m}_n(x) \\ z_{M,n}(x) &= [1 - s_n(x)]^{\frac{1}{\delta}} \tilde{z}_{M,n}(x) \end{cases} \quad (1.6)$$

where $q_{M,n}$ is the output volume, $\phi_n(x)$ is a variety x -specific random variable drawn from a Fréchet distribution with shape parameter $\tilde{\theta}$ and mean 1 whose CDF is given by $F(\phi) = \exp[\phi^{-\tilde{\theta}}]$. As in Eaton and Kortum (2002), $\phi_n(x)$ represents the efficiency of variety x production in city n . $A_{M,n}$ is a productivity shifter common to all manufacturing sector firms in n . This shifter is exogenous to individual manufacturing firms. \tilde{m}_n is the composite of input in Cobb-Douglass form which is given by

$$\tilde{m}_n(x) = [l_{M,n}^k(x)]^{\gamma_M^k} [l_{M,n}^u(x)]^{\gamma_M^u} [m_{M,n}^M(x)]^{\gamma_M^M} [m_{M,n}^S(x)]^{\gamma_M^S} \quad (1.7)$$

where l_M^k , and l_M^u are skilled labor and unskilled labor inputs, respectively. $m_{M,n}^M$ is the input of manufactured intermediate goods for manufacturing production, while $m_{M,n}^S$ is the input from services sector. The technology is constant returns to scale at the firm level with the input coefficients and satisfies that $\sum_{j' \in k, u, M} \gamma_{M,n}^{j'} = 1$. $s_n \in [0, 1]$ is the share of input composite \tilde{m}_n diverted for the pollution abatement activity. In other words, $(1 - s_n)$ of input is kept for the main production.

The second equation in (1.6) assumes a simple relationship between the inputs and generated pollution. The gross emission before abatement, $\tilde{z}_{M,n}(x)$ is assumed to be proportional to the total input ($\tilde{m}_{M,n}$) the firm uses for its operation. This is a strong but common assumption in this type of models for the benefit of analytical tractability. $\lambda_{M,n} > 0$ is coefficient that specifies the relationship between the input and emissions.

The third equation in (1.6) is for the end-of-pipe abatement technology. $z_{M,n}$ refers to net emissions, which is the pollution that is finally emitted to the environment after

abatement. $z_{M,n}$ depends on the gross emission and the abatement effort as measured by the share of the diverted input for abatement activity (s_n). For a given level of $\tilde{z}_{M,n}$, the net emission is smaller if more resources are used for abatement (i.e. larger s_n). $\delta \in (0, 1)$ is an inverse measure of abatement efficiency. A higher δ means that end-of-pipe technology is less efficient and more final pollution is emitted for given the potential emission and abatement resources.

Intermediate firms are price takers and perfect competition works in the market. Let $w_n^t, t \in \{k, u\}$, be the wages of type t worker, $P_{M,n}$ be the price of the final manufacturing composite, and $P_{S,n}$ be the services price in n , respectively. Since the input bundle $\tilde{m}_{M,n}$ is an output of the technology in (1.7), the cost minimization on the choice of primary inputs yields the following unit cost for producing a bundle, which is denoted by $\tilde{c}_{M,n}$,

$$\tilde{c}_{M,n} = \Psi [w_n^k]^{\gamma_M^k} [w_n^u]^{\gamma_M^u} [P_{M,n}]^{\gamma_M^M} [P_{S,n}]^{\gamma_M^S} \quad (1.8)$$

where Ψ is a constant.⁸ Following studies such as Antweiler, Copeland, and Taylor (2001), Copeland and Taylor (2004), and Shapiro and Walker (2018), we summarise the set of environmental regulations into a Pigouvian emission tax on unit emission of pollutant by the local manufacturing sector, denoted by ζ_n in n (the assumptions for ζ_n will be discussed below). Then, from (1.6) and $0 \geq s_n \geq 1$, the profit maximization problem of a firm becomes:

$$\max_{\tilde{m}_{M,n}(x), z_{M,n}(x)} p_{M,n} \left(\frac{z_{M,n}(x)}{\lambda_{M,n}} \right)^\delta (\phi_n(x) A_{M,n} \tilde{m}_{M,n}(x))^{1-\delta} - \tilde{c}_{M,n} \tilde{m}_{M,n}(x) - \zeta_n z_{M,n}(x) \quad (1.9)$$

The first order conditions for the problem (1.9) yields the optimal unit cost which is

8. Namely, $\Psi \equiv \left[(\gamma_M^k)^{\gamma_M^k} (\gamma_M^u)^{\gamma_M^u} \prod_{j'=M,S} (\gamma_M^{j'})^{\gamma_M^{j'}} \right]^{-1}$.

given by $\frac{c_{M,n}}{\phi_n(x)^{1-\delta} A_{M,n}^{1-\delta}}$, where

$$c_{M,n} = \left(\frac{\tilde{c}_{M,n}}{1-\delta} \right)^{1-\delta} \left(\frac{\lambda_{M,n} \zeta_n}{\delta} \right)^\delta \quad (1.10)$$

A final manufacturing good is produced by a competitive local aggregator. The final good is a composite produced by a CES function that use all the varieties $x \in [0, 1]$. Input varieties are sourced from the lowest cost region across all the locations $n = 1, \dots, N$, including an iceberg trade cost to ship the good from i to n , $\tau_{ni} > 1$. The aggregation function is

$$Q_{M,n} = \left[\int q_{M,n}(x)^{\frac{\sigma_M-1}{\sigma_M}} dx \right]^{\frac{\sigma_M}{\sigma_M-1}} \quad (1.11)$$

where σ_M is the elasticity of substitution. The price of the input variety x used for final production in n satisfies $p_{M,n}(x) = \min_{i \in 1, \dots, N} \left\{ \frac{c_{M,i} \tau_{ni}}{A_{M,i}^{1-\delta} \phi_i(x)} \right\}$. Exploiting the property of the Fréchet distribution for $\phi_i(x)$, the share of expenditure on varieties from region i in the total expenditure for manufacturing varieties in n is given by,

$$\pi_{ni}^M = \frac{(\tau_{ni} c_{M,i})^{-\theta} (A_{M,i})^\theta}{\sum_{i'=1}^N (\tau_{ni'} c_{M,i'})^{-\theta} (A_{M,i'})^\theta} \quad (1.12)$$

and the price of the final manufacturing good available in n is then given by

$$P_{M,n} = \left[K_M \sum_{i=1}^N (\tau_{ni} c_{M,i})^{-\theta} (A_{M,i})^\theta \right]^{-\frac{1}{\theta}} \quad (1.13)$$

where, $\theta \equiv \frac{\tilde{\theta}}{1-\delta}$ and $K_M \equiv \left(\Gamma \left(\frac{\theta - \sigma_M + 1}{\theta} \right) \right)^{\frac{1}{1-\sigma_M}}$ is a constant.

Services Sector Goods Service sector goods are treated as non-traded, in a similar way to Caliendo et al. (2018) and other studies. We admit that this is a strong assumption. This is because the overall trade cost required to deliver services to a distant customer

seems to be substantially higher than that of manufactured goods.⁹ Therefore, in the current model, we treat them as non-traded and the services firms only serve local customers within the city n . A services sector firm combines skilled labor, unskilled labor, and manufactured goods. The production function is given by:

$$Q_{S,n} = A_{S,n} [L_{S,n}^k]^{\gamma_{S,n}^k} [L_{S,n}^u]^{\gamma_{S,n}^u} [m_{S,n}^M]^{\gamma_{S,n}^M} \quad (1.14)$$

where, $m_{S,n}^M$ is manufacturing inputs of the services sector.¹⁰ The technology is constant returns to scale such that $\sum_{j' \in k, u, M} \gamma_{S,n}^{j'} = 1$ is satisfied. Note that we assume that $\gamma_{S,n}^{j'}$ varies across cities. Later we detail how we calibrate these with the data. $A_{S,n}$ is the productivity shifter of the services sector in n that is exogenous for individual services firms. Let $P_{S,n}$ denote the local price of the services goods in n . Cost minimization and free entry ensures that the price should satisfy

$$P_{S,n} = \frac{\Psi_{S,n}}{A_{S,n}} (w_n^k)^{\gamma_{S,n}^k} (w_n^u)^{\gamma_{S,n}^u} (P_{M,n})^{\gamma_{S,n}^M} \quad (1.15)$$

where $\Psi_{S,n}$ is a constant.¹¹

Goods Market Clearing In the equilibrium, all markets clear. Let $Y_{j,i}, \forall j \in \{F, M, S\}$ denote the total value of production of sector j in i . Similarly, $E_{j,n}$ denotes the value of expenditure on sector j in n . Firstly, the total agricultural supply should be equal to the demand,

$$\sum_{i \in \mathcal{W}} Y_{F,i} = \sum_{n \in \mathcal{W}} E_{F,n} \quad (1.16)$$

9. According to the main estimates by Gervais and Jensen (2019) on U.S. data, trade costs for the eleven sub-sectors in the services category range from 3.95 times (wholesale trade) to 28.67 times (real estate and leasing).

10. The services sector of course uses agricultural goods as well as land as inputs, however, we drop these from the production function for the sake of simplicity. According to China's input-output tables, their contribution is very marginal for the services sector, the coefficients for agricultural inputs and land are 0.016 and 0.039, respectively.

11. $\Psi_{S,n} = (\gamma_{S,n}^k)^{-\gamma_{S,n}^k} (\gamma_{S,n}^u)^{-\gamma_{S,n}^u} (\gamma_{S,n}^M)^{-\gamma_{S,n}^M}$.

For manufacturing varieties, the total value of production must be equal to the sum of demand from all the potential destinations, i.e., $Y_{M,i} = \sum_{n \in \mathcal{W}} E_{M,n} \pi_{ni}$. Using (1.12) and (1.13), this condition can be rewritten as:

$$Y_{M,i} = \tilde{A}_{M,n} c_i^{-\theta} \sum_{n \in \mathcal{W}} \tau_{ni}^{-\theta} E_{M,n} P_{M,n}^{\theta} \quad (1.17)$$

where, $\tilde{A}_{M,n} \equiv K A_{M,n}^{\theta}$. Since the services sector goods are non-traded, the local production should match local demand. Mirroring this equality in the services sector, the sum of the production values of the two traded sector should be equal to the sum of the demand for them, in every location. Therefore, we have

$$Y_{S,n} = E_{S,n}, \quad \forall n \in \mathcal{W} \quad (1.18)$$

$$Y_{F,n} + Y_{M,n} = E_{F,n} + E_{M,n}, \quad \forall n \in \mathcal{W} \quad (1.19)$$

Industrial Emission Revenue from emission charge As a means of environmental control, local government collects emission charges from manufacturing firms. Let $Z_{M,i}$ be the aggregate amount of pollutant discharged to the environment from manufacturing firms in i . Given the unit emission charge ζ_i in i , the i 's government collects $\zeta_i Z_{M,i}$. The first order condition for (1.9) yields:

$$\zeta_i Z_{M,i} = \delta Y_{M,i} \quad (1.20)$$

Local government employs skilled workers to implement pollution control. No production technology is specified for this control, while the demand for skilled workers of this environmental control task just has to satisfy a simple resource constraint,

$$w_i^k L_Z^k = \zeta_i Z_{M,i} \quad (1.21)$$

which means that the wage payment to the skilled employees equals to the revenue from emission charges collected from the manufacturing firms. This assumption can also be interpreted as that the local government rebates back the collected emission charges to skilled workers.

Land Market Local government collects land rent revenue and redistributes it to residents. For simplicity, we assume that the government redistributes the revenue so that it augments their wage income by the factor of $(1 + \mu)$ where $\mu > 0$. From the utility function, the total expenditure on land in n is $r_n H_n = (1 - \alpha)(1 + \mu)(w_n^k L_n^k + w_n^u L_n^u)$. At the same time, the revenue should be equal to the total amount redistributed, which means $r_n H_n = \mu(w_n^k L_n^k + w_n^u L_n^u)$. Then, $\mu = \frac{1-\alpha}{\alpha}$. This yields the equilibrium land rent given as

$$r_n = \frac{1 - \alpha}{\alpha} \frac{w_n^k L_n^k + w_n^u L_n^u}{H_n} \quad (1.22)$$

Expenditure on Goods As explained above, the income of a type t worker is wage income plus rebated land rent, thus w_n^t/α . Production of manufacture and services requires input goods other than labor. Given these, the expenditure for sector j in location n becomes:

$$\begin{aligned} E_{F,n} &= \chi_{F,n}(w_n^k L_n^k + w_n^u L_n^u) \\ E_{M,n} &= \chi_{M,n}(w_n^k L_n^k + w_n^u L_n^u) + (1 - \delta)\gamma_M^M Y_{M,n} + \gamma_{S,n}^M Y_{S,n} \\ E_{S,n} &= \chi_{S,n}(w_n^k L_n^k + w_n^u L_n^u) + (1 - \delta)\gamma_M^S Y_{M,n} \end{aligned} \quad (1.23)$$

Labor incomes and labor market clearing According to the assumptions about production functions, the total wage earnings of skilled and unskilled labors are given as follows,

$$\begin{aligned} w_i^k L_i^k &= \left((1 - \delta)\gamma_M^k + \delta \right) Y_{M,i} + \gamma_{S,n}^k Y_{S,i} \\ w_i^u L_i^u &= Y_{F,i} + (1 - \delta)\gamma_M^u Y_{M,i} + \gamma_{S,n}^u Y_{S,i} \end{aligned} \quad (1.24)$$

Note that these equations are the labor market clearing conditions, given that the total labor supply of type t workers in i is $L_i^t, t \in \{k, u\}$.

Emissions from Consumption Recent studies reveal that emissions from the consumption side, which arise when consumers use manufacturing products, are becoming increasingly important (Liu et al. 2016; Li et al. 2017).¹² Not only in the advanced countries, even in several developing countries such as China, emissions from the use of transportation (for example, vehicles) as well as emissions from housing (cooking and heating) consists a large share in the emission inventories. Therefore, here we introduce a simple mechanism of emissions from consumption, $Z_{R,n}$ as follows. Specifically, we assume that $Z_{R,n}$ is proportional to the real manufacturing expenditure with the fixed coefficient $\lambda_{R,n}$. Assume that the use of manufactured goods generates pollution (car, cooking equipment, air conditioning and heating, processed fuels, etc.). As the total consumption expenditure on manufacturing in n is given by $\chi_{M,n}(w_n^k L_n^k + w_n^u L_n^u)$ along with the price $P_{M,n}$, the residential emissions is given by

$$Z_{R,n} = \lambda_{R,n} \frac{\chi_{M,n}(w_n^k L_n^k + w_n^u L_n^u)}{P_{M,n}} \quad (1.25)$$

Emission to Pollution The anthropogenic emissions of pollutants such as SO₂, NO_x, and the primary emission of PM_{2.5}, contributes to the formulation of air pollution through various complex chemical reactions. Other than those pollutants from economic activities, sources such as sand storms from deserts, volcanos, and sea salt, plays an important role in determining the area's level of pollution, with climate conditions such as wind,

12. Karagulian et al. (2015) conduct a meta-analysis of local studies across the world and find that industrial emission constitutes 16-27 percent of the PM 2.5 pollution. The residential emission contributes 15-21 percent, and traffic contributes 15-18 percent, respectively (Aunan, Hansen, and Wang 2018; Karagulian et al. 2015). Liu et al. (2016) estimate that industry contributed around 50 to 60 percent of PM 2.5 while residential emission is responsible for 30 to 40 percent of it, respectively in Beijing, Tianjin, and Hebei area, throughout 2010. Transport and power contributed relatively smaller share. These findings motivate us to include emissions from non-industrial sources that we summarize as residential emission.

precipitation, humidity, and temperature. Thus, the mechanism that determines how emissions from human activity affects the local ambient quality is very complex, and a full-scale scientific weather model is needed to make a prediction of air quality for a given level of emissions. Unfortunately, the predictive models that are commonly used are designed for a short term prediction within a small geographical area. In our case, we intend to connect the annual sum of emissions to the annual average level of air quality, within a relatively large geographical unit.

Given this scientific limitation, a simple empirical relationship between local emission and local air quality is used for the mapping of emissions into pollution. Let D_n denote the level of air pollution (PM2.5 concentration) in n observed as concentration in the air (with the unit of $\mu g/cm^3$, for example), after the chemical process that transforms anthropogenic and natural primary pollutants into harmful particulates. Assume that D_n has the following relationship with the anthropogenic emissions in n ; $Z_n = Z_{M,n} + Z_{R,n}$, the sum of emissions from manufacturing production and residential emissions is then:

$$D_n = f(\tilde{X}_n)Z_n^\kappa \quad (1.26)$$

where κ is a coefficient on emission and $f(\tilde{X}_n)$ is a function of other local characteristics denoted by \tilde{X}_n .

Pollution control policy (emission tax) Local government sets the Pigouvian tax rate, denoted as ζ_n , as an emission charge. The literature on China's local environmental regulations (Rooij and Lo 2010; Wu et al. 2013; Wang 2013; Zheng et al. 2014; Jin, Andersson, and Zhang 2016) points out that China's local leaders compete with each other in their race for promotion among the hierarchy of the Communist Party. For prefecture level leaders, getting high performance evaluations from their upper-level officials (i.e. Provincial government), is thus the priority that determines their policy implementation. In the past, local GDP was the main indicator used for evaluation. This economy-focused

incentive system has long been criticized for a lack of consideration of sustainability. However, since the tenth Five Year Plan (FYP) period was initiated in 2001, the central government has begun to include environmental targets, such as emission reduction targets for air pollutants. Since the eleventh FYP (2006-2010), the Chinese government has introduced the target responsibility system (TRS) for environmental pollution that binds lower-level officers to accomplish the targets agreed with their upper-level leaders.

Our modelling of the local government problem reflects this Chinese context. In particular, we assume that the evaluation of the government n , denoted by V_n is defined by

$$V_n = -\xi_n^g Z_{M,n} + G_n^\omega \quad (1.27)$$

where $G_n = w_n^k L_n^k + w_n^u L_n^u$ is city n 's total value added (GDP), and $\omega \in (0, 1)$. $\xi_n^g > 0$ is the city n specific coefficient that reflects how much upper-level governments stress environmental quality in their evaluation of the government of n . The local government choose ζ_n that maximizes V_n . It is assumed that the local government ignores (or cannot know) the impact of its ζ_n on population, L_n^k and L_n^u , and the price index $P_{T,n}$, and regards them as given.

Under this assumption, a similar derivation for the Samuelson condition as in Antweiler, Copeland, and Taylor (2001) applies. The first order condition with respect to ζ_n in (1.27) yields:

$$\zeta_n = \frac{\xi_n^g}{\omega} G_n^{1-\omega} \quad (1.28)$$

(1.28) tells us that the emission tax is higher where the economic scale is larger. This is quite a simple specification, however, it reflects the observed relationship between emission intensity and the city's economic scale described in Section 1.A.3; which is that, the larger the city's economic scale is, the smaller the emission intensity from manufacturing. Given the pollution supply function (1.28), and the pollution function

(1.20), the equilibrium industrial emission is:

$$Z_{M,n} = \frac{\delta\omega}{\xi_n^g} G_n^\omega \frac{Y_{M,n}}{G_n} \quad (1.29)$$

Migration It has long been argued that domestic migration, especially rural-to-urban migration, is severely restricted in China under the “hukou” system. The majority of econometric research studies on China up to the early 2000s assumed that labor is immobile due to the hukou restriction (e.g. Au and Henderson 2006b, 2006a). However, this restriction has been gradually eased during the past two decades and the Chinese labor force is currently very mobile, although there still remains substantial social and institutional discrimination against migrants (Song 2014). In terms of volume, rural to urban migration has been very large and we cannot explain the massive urbanization and industrialization of China in the past few decades without inter-prefectural and inter-provincial migration. The urbanization rate (urban population share in total population) rose from 18 percent in 1978 to 53 percent in 2011 (Chen et al. 2013). In the past 30 years, urban population has increased by 440 million, and half of that is said to be attributable to rural to urban migration. Given these facts, it has become more appropriate than ever before to treat labor as geographically mobile in China. For example, using a similar approach, Baum-Snow et al. (2015) conducted a simulation study to assess the impact of road network improvements on population and production, assuming both perfect labor mobility and immobility. We follow the widely used Fréchet distributed “mobility frictions” (Baum-Snow et al. 2018) that are also assumed in the studies such as Baum-Snow et al. (2015), Donaldson and Hornbeck (2016), Redding (2016), Balboni (2016), and Faber and Gaubert (2019). In line with this strand of literature, we assume that both skilled and unskilled workers migrate across prefectures in China searching for the place that offer them the highest utility. For each type, the expected utility should be equalized across space in the equilibrium. Noting that the real income of type t worker

living in n can be written as $\left(\frac{1}{P_{T,n}}\right)^\alpha \left(\frac{H_n}{G_n}\right)^{1-\alpha} w_n^t$, and that the idiosyncratic location preference ϵ is Fréchet distributed, the spatial distribution of type t workers is then given by,

$$\frac{L_n^t}{L_C^t} = \frac{\left(\tilde{B}_n^t \exp(-\xi^t D_n) \frac{H_n^{1-\alpha} w_n^t}{P_{T,n}^\alpha G_n^{1-\alpha}}\right)^{\eta^t}}{\sum_{n' \in \mathcal{C}} \left(\tilde{B}_{n'}^t \exp(-\xi^t D_{n'}) \frac{H_{n'}^{1-\alpha} w_{n'}^t}{P_{T,n'}^\alpha G_{n'}^{1-\alpha}}\right)^{\eta^t}}, \quad \forall n \in \mathcal{C} \quad (1.30)$$

For outside of China, the RoW, population is fixed.

Equilibrium The *equilibrium* of this economy can be defined as follows: *Given the parameters, $\{\theta, \delta, \alpha, \tau_b, \eta^k, \eta^u, \xi^k, \xi^u, \rho, \omega, \kappa, \gamma_j^k, \gamma_j^u, \gamma_j^M, \gamma_j^S\}$, inter-city trade cost matrix $\{\tau\}$, and exogenous variables $\{A_{M,i}, A_{S,i}, B_i^k, B_i^u, \zeta_i^g\}$, the equilibrium is the vectors of quantities $\{Z_{M,i}, Z_{R,i}, D_i, L_i^k, L_i^u\}$, prices $\{w_i^k, w_i^u, r_i, \zeta_i, P_{M,i}, P_{S,i}\}$, values $\{Y_{F,i}, Y_{M,i}, Y_{S,i}, E_{F,i}, E_{M,i}, E_{S,i}\}$, and the manufacturing trade share matrix $\{\pi_{ni}\}$, that are given as the solutions to (1.26), (1.20), (1.25), (1.30), (1.24), (1.22), (1.28), (1.13), (1.15), (1.18), (1.19), (1.23), and (1.12).*

1.3 Quantification of the Model

Since the model cannot be solved analytically, we calibrate it to the observed situation of China in 2010 to conduct numerical exercises. The data for the observed variables include the population of skilled and unskilled workers, the value added of three industrial sectors (primary, secondary, and tertiary), the PM_{2.5} concentration, the emission of pollutants, and other variables that are used in the estimation procedure for some of the model parameters. The details of the data and the calibration strategy are explained in Section 1.A.2 and Section 1.A.4.

We combine multiple data sources to conduct the analysis. We focus on the 296 geographical units (270 prefecture-level cities and 26 counties directly under the Provinces) in the Eastern half of the mainland China. Four provinces and autonomous regions,

namely, Inner Mongolia, Xinjiang, Qinghai, Tibet, and islands (such as Hainan Province) are not included in these 296 units and treated as the RoW. Economic variables, such as the value added and employment of industries, are taken from the *China City Statistical Yearbook*, *China Region Economy Statistical Yearbook*, as well as the online supplementary material of Baum-Snow et al. (2017). Our analysis needs the amount of skilled and unskilled worker in each city. The best available proxy for the people’s skill level is educational attainment of the residents. Since the data on educational attainment of workers are not available (only adult population by degrees is available), we assume that the share of the skilled worker in all the worker in a city is equal to the share of adult population with at least senior high school degree out of the total adult population in the city. Environmental variables such as PM_{2.5} concentration and emissions of air pollutants are from the sources using satellite images provided by Donkelaar et al. (2016) and the MEIC database.¹³

The model requires the estimate of the iceberg trade cost for manufacturing intermediates between each pair of cities and between the RoW, τ_{ni} . Since the model yields a gravity equation of trade flow between each pair of cities, we can recover τ_{ni} as Caliendo et al. (2018) if we have a bilateral trade flow statistics. However, there is no available data on the bilateral flow of trade among the pairs of prefecture-level cities in China. Therefore, we have to construct it based on the distance and the quality of transport infrastructure. Specifically, we closely follow the data and the method by Baum-Snow et al. (2018) that uses the digitized map of China’s road network as of 2010 which is provided in their on-line appendix and calculate the shortest paths (shortest travel time) between each pair of cities by the Dijkstra algorithm (the average travel speed according to the grade of motorways is reflected). Then, we convert the calculated travel times in hours between each pair of cities into a matrix of iceberg trade cost.¹⁴

13. <http://www.meicmodel.org/index.html>

14. Specifically, the trade cost between city i and j , τ_{ij} , is given by $\tau_{ij} = 1 + 0.004(\text{hours of travel time}_{ij})^{0.8}$. See Baum-Snow et al. (2018) for the detail.

There is no information available for the wage rates of skilled workers and unskilled workers at the level of prefecture cities. We impute the skill-based local wages exploiting the model's equilibrium conditions and the sector-specific wage rates from the national level provided in the *China Statistical Yearbook*. Through the process of recovering the local wages for the skilled and unskilled workers, we also derive sector-specific input parameters for skilled and unskilled, γ_j^k and γ_j^u , so that the model based national average wage rates become equal to the observed ones.

We estimate the remaining parameters; goods expenditure share α , international border effect τ_b , labor supply elasticity η^t and taste for air pollution ξ^t for each of $t \in k, u$, the elasticity of substitution among three category of goods ρ , the emission tax elasticity to GDP, ω , and the elasticity of city PM_{2.5} with respect to city's pollutant emissions κ . Among them, the most important parameters are η^t and ξ^t , which are found to substantially affect the simulation results. To estimate these parameters, we exploit the equilibrium conditions that pin down the labor incomes (1.24) and migration (1.30). From (1.24) and (1.30), the population of type t labor in n can be expressed as:

$$\ln L_n^t = \beta_0 - \xi^t \frac{\eta^t}{\eta^t + 1} D_n + \frac{\eta^t}{\eta^t + 1} \ln \widetilde{W}_n^t + \tilde{\epsilon}_n^t, \quad \forall n \in \mathcal{C} \quad (1.31)$$

where: $\widetilde{W}_n^k \equiv \frac{((1-\delta)\gamma_M^k + \delta)Y_{M,n} + \gamma_{S,n}^k Y_{S,n}}{P_{T,n}^\alpha G_n^{1-\alpha}}$, $\widetilde{W}_n^u \equiv \frac{Y_{F,n} + (1-\delta)\gamma_M^u Y_{M,n} + \gamma_{S,n}^u Y_{S,n}}{P_{T,n}^\alpha G_n^{1-\alpha}}$, and D_n is the level of pollution derived by using the annual average concentration of PM_{2.5} as a proxy, respectively. The equation (1.31) gives the relationship between the population of type t worker in n and the air pollution and the real wage in n . We estimate (1.31) to obtain the values for ξ^t and η^t .

This method, of course, could be prone to endogeneity issues. Specifically, the OLS estimate of ξ^t can be overestimated (in terms of magnitude) if an unobserved productivity of the services sector raises both the services sector share in the city as well as the labor supply to the city. Similarly, the OLS estimates of η^t tend to be underestimated

by the existence of unobserved amenities that attract workers. On the other hand, unobserved productivity shocks may cause an overestimation of η^t . We borrow from existing studies to address these identification concerns. For air pollution terms that are critical in estimating ξ^t , we follow Freeman et al. (2017) and instrument air pollution (measured by PM_{2.5} concentration) by the SO₂ emission from thermal power plants within the up wind direction from the city (excluding that from their own city). The identification assumption is that the thermal plant emission from upwind locations affect the city’s worker population only through its impact on air pollution conditional on the control variables. For the estimation of η^t , we benefit from Baum-Snow et al. (2018) who estimated the impact of road infrastructure in 2010 on the employment and economic outcomes of Chinese cities. They instrument 2010 infrastructure variables with 1962 infrastructure variables. For identification, we assume that the 1962 infrastructure affects the population of 2010 skilled (unskilled) workers only through the real wage paid to them conditional on the controls.

Through these estimations, we try to verify that the model’s equilibrium condition holds in the real world in a meaningful way. Our estimates of labor supply elasticities, η^t , welfare effects of air pollution, ξ^t , and the Pigouvian tax parameter, ω , are within reasonable ranges compared to the existing studies, and are consistent with the model’s assumptions. The details of the calibration and estimation is explained in Section 1.A.4. Of course, it should be noted that our verification through estimation addresses a subset of equilibrium conditions. It is desirable therefore to have a more comprehensive check on whether the model well replicates the observed endogenous variables, as Tombe and Zhu (2019) do by exploiting intertemporal changes in the exogenous variables. Unfortunately, however, the full set of data required for that analysis is available only for 2010, preventing such an exercise that requires a city-level panel dataset. Minding these limitations, we examine how the qualitative results of the simulation change by the choice of these parameters in Section 1.5.

Table 1.1: Parameter Values

Parameter	Value	Source
θ	5	Baum-Snow et al. (2018)
δ	0.011	Shapiro and Walker (2018)
α	0.87	Estimated (expenditure share on housing, based on <i>China Statistical Yearbook 2011</i>)
τ_b	1.68	Estimated (applying equation (A.53) in the Appendix to China's export and import)
η^k	3.52	Estimated (equation (1.31))
η^u	1.16	Estimated (equation (1.31))
ξ^k	0.013	Estimated (equation (1.31))
ξ^u	0.0095	Estimated (equation (1.31))
ρ	3.45	Estimated (Search the value that minimize observed and model expenditure share over three goods category, at the Provincial level))
ω	0.466	Estimated (equation (A.58) in the Appendix)
κ	0.16	Estimated (OLS regressing PM _{2.5} on industry and consumption emissions)

Source: Author

We calibrate the remaining parameters borrowing the knowledge from existing literature: the Fréchet dispersion parameter for manufacturing productivity, θ , and the input share of pollutant emission (equivalent to the inverse of abatement efficiency), δ . Table 1.1 summarizes the calibrated and estimated parameters used in the simulation exercises.

1.4 Simulation Exercises to Study the Model's Properties

The main purpose of this paper is to understand the impact of pollution control policy on environmental, economic, and welfare outcomes. In what follows, we study several theoretical implications of the model using the calibrated model. We specifically focus on the exogenous change to pollution control policy which is captured by $\widehat{\xi_n^g}$. This parameter represents how much the evaluation of local government n is damaged by an increase in industrial emissions from its jurisdiction. We first examine how a regulatory

shock to a particular city n , captured by $\widehat{\xi}_n^g$, will have spatial impacts on economic and environmental variables. An increase in ξ_n^g for city n affects the outcomes of itself. In addition, it also have varied impacts on other cities. The signs and the magnitudes of the own effect and the spillover effects are not readily obvious, as the model accommodates various channels of impact that mutually interfere with each other.

Given this analysis, we further seek for desirable spatial allocation of responsibility to reduce emissions. Setting an aggregate emission reduction target to 10 percent, we compare various weighting strategies that differentiate localized reduction responsibility across cities, in addition to a uniform allocation that assigns the same magnitude (in percent) of reduction responsibility to all cities. We find that some strategies are superior to the uniform strategy. Interestingly, even though the stronger pollution control is costly for individual firms and we rule out technological mechanisms that cause that stricter regulation raises productivity, we find that a few strategies may result in an increase in national real GDP. We discuss in detail how these strategies are different in terms of environmental, economic and welfare outcomes.

Throughout the analysis, we examine how the key assumptions of the model affect the derived elasticities with respect to the shocks in the exogenous variables. Specifically, we compare our baseline model with counterfactual models that shut-out three important ingredients; the migration of workers, international trade, and preference for air quality. The counterfactual models give significantly different outcomes from those of the baseline, meaning that the relevance of these key assumptions as well as the potential sensitivity to the estimated parameter values.

As shown in the Appendix 1.A.1, the model allows us to employ the “method of change” proposed by Dekle, Eaton, and Kortum (2008) to solve for the counterfactual equilibrium without knowing the levels of unobserved variables.

1.4.1 Impact of Unilateral Policy Change in a City

We first illustrate the spatial propagation of impact from a unilateral policy change in a single city. As an example, we choose Beijing, Wuhan, and Deyang, and examine how the impact differs depending on the place the policy shock originates from. Let $i' \in \{\text{Beijing, Wuhan, Deyang}\}$ denote the city that receives unilateral policy change. We compute the elasticity of outcome variables in all the 296 cities with respect to $\widehat{\xi}^g$, which is a vector whose i' -th element is $\widehat{\xi}_{i'}^g = 1.1$ while keeping other elements to $\widehat{\xi}_i^g = 1$ for $i \neq i'$. This means that the city i' increases its regulatory parameter by 10 percent, while other cities keep it unchanged. The choice of magnitude at 10 percent is reasonable considering the policy context of China around 2010. China has set national level environmental targets for every Five-Year Plan (FYP), since its 11th FYP for the years 2006-2010. Under this FYP, a nationwide reduction target of the emission of industrial SO₂ was set to 10 percent of the level in 2005. In the 12th FYP, the SO₂ reduction target was set to 8 percent of the 2010 emission level, while the target of 10 percent reduction for NO_x was added (Aunan, Hansen, and Wang 2018).¹⁵ As (1.29) implies, if G and Y_M are constant, the elasticity of $Z_{M,n}$ with respect to ξ_n^g is -1. Therefore, a naive policy response to the national target to reduce emission by 10 percent is to raise ξ_g by 10 percent. We thus pick this level for our reference magnitude in conducting simulation studies. We also experiment with other magnitudes and find that the relationship with the size of magnitude and the elasticities is linear in general.¹⁶

There are several interesting results that contrast the model to conventional predictions. First, as indicated in panel (a) of Figure 1.1, the elasticity of industrial emission is greater than -1. This means that if the $\xi_{Beijing}^g$ rises by 10 percent, Beijing's industrial emission is only reduced by 9.59 percent. As equation (1.29) implies, it is not theoretically obvious

15. The national reduction target was disaggregated into Provincial level targets, which vary from 0 percent to 30 percent.

16. More precisely, the elasticity is weakly concave, with slightly larger elasticity when the policy magnitude is smaller.

whether the elasticity of industrial emission is larger or smaller than -1 , because it depends on how aggregate production G_n and manufacturing share $Y_{M,n}/G_n$ changes in response to ξ_n^g . Note that the nominal GDP (G) of Beijing responds positively to the stricter environmental regulation as shown in panel (i). In this case, a positive scale effect offsets the direct effect of increased ξ^g , and that results in an elasticity of industrial emission greater than -1 . The positive scale effect of the regulation in this case coincides with the increased employment (thus in-migration) of skilled and unskilled workers to Beijing as shown in panels (d) and (e). This is an effect that cannot be predicted by the models without mobility of production factors (Copeland and Taylor 2004).

Regarding the propagated effect to cities outside of Beijing, panel (a) of Figure 1.1 shows an interesting contrast to the standard theoretical prediction of the PHE. If a pollution haven emerges, strengthening the environmental regulations in Beijing will cause an increase of emissions somewhere outside of Beijing, through the relocation of polluting industry to areas with relatively less stringent environmental policies. However, as shown in panel (a), the elasticity is everywhere negative, which means that the PHE does not take place here. The reduced emission from Beijing is not offset by increased emissions in other places. The environmental impact is even amplified by the reduced emission outside of the city, induced by Beijing's local policy. The reason for this can be seen in panels (d) and (e), that depicts the elasticities of the labor supply of skilled and unskilled workers, respectively. Beijing attracts both types of labor through the strengthened regulations, with a higher magnitude for skilled labor (0.099 for skilled compared to 0.073 for unskilled). Policy changes in Beijing therefore slightly attract labor from almost all over China, and contract the scale of production scale in places other than Beijing, as panel (i) suggests. Furthermore, as seen in panel (j), the composition effect which is the share of manufacturing production in total production decreases everywhere including outside of Beijing. These structural changes in scale and composition ensure the reduction of emissions everywhere in China, in response to policy changes in Beijing.

To understand the reasons why these spillover effects in labor supply and production structure emerge, we need further elaboration. First, a comparison of panel (g) and (h) reveals that skilled worker real wage respond in a opposite way as unskilled worker real wage. For the skilled workers, the real wage decreases in Beijing and increases almost everywhere outside of that city. Conversely, the unskilled worker's real wage increases in Beijing but decreases in other cities. The SEE (*spatial equilibrium effect*) works here. Skilled workers put more weight on air quality than unskilled workers as our estimated coefficients satisfy $\xi^k > \xi^u$, consistent with the assumption in (1.1). Due to this, the improvement in air quality in Beijing is large enough for skilled workers to compensate for the decline in real wages there. As in panel (l), the influx of skilled workers is associated with the decline in service price in Beijing which contributes to raise the real wage of the unskilled worker (note that the nominal unskilled wage is fixed by assumption). Then, both skilled and unskilled labor partially relocate to Beijing, and drive down production outside Beijing. Furthermore, the increase in ξ^g in Beijing raises the unit production cost of manufacturing there as in (1.10), which has spatial spillover effect on the manufacturing price index as in panel (k). This affects manufacturing production costs everywhere in China because the sector uses manufacturing intermediates as its inputs, making the response of the composition effect negative everywhere in China as in (j). These complex but rich relationships among the variables all work together to influence how our environmental variables are determined.

For price indices, note that the magnitude of the manufacturing price change is slightly smaller in the regions surrounding Guangdong Province and Shanghai, that are close to the international port. Due to better access to international markets, these areas trade less (in terms of share) with Beijing in the initial equilibrium. Therefore, the impact of unit cost increase in Beijing due to stricter regulation is mitigated. Panel (l) shows the elasticity of services prices, P_S . Only 'own' elasticity is negative while the others are positive. This is consistent with the responses of labors in panels (e) and (f).

The services sector in Beijing benefits from the increased labor supply that drives down wages, while other cities will be affected by the reduced labor supply, as well as increases in the manufacturing price index as this is an input in the sector.

In summary, the economic implication of a unilateral policy change in our model is thus substantially different from the traditional PHE world. Stricter regulations in Beijing do not raise industrial emissions in other cities. Furthermore, higher $\xi_{Beijing}^g$ is not an economic burden for Beijing, while causing a slight damage to outside cities.

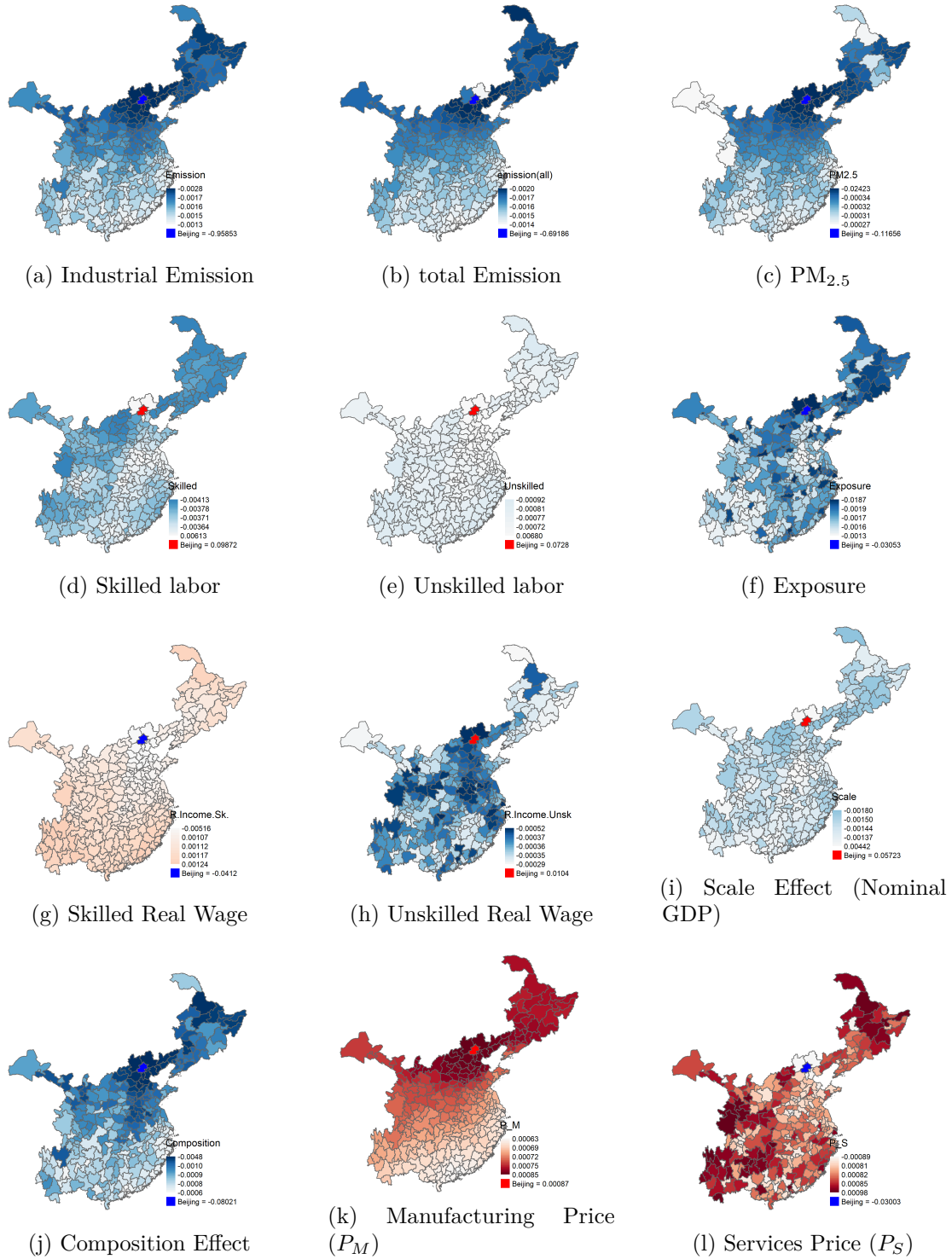
1.4.2 Where the Shock Originates Matters

By comparing the results of the same exercise for other epicenters of the shocks, namely Wuhan and Deyang, we examine whether these spatial patterns of the impact are universal. Figure 1.A.4 shows the results for the city of Wuhan, the capital city of Hubei Province located in the central part of China. Figure 1.A.5 shows the same for Deyang, a city in Sichuan Province. The spatial patterns of the propagation are fairly contrasting. As the panel (a) of Figure 1.A.4 depicts, a policy shock in Wuhan reduces the industrial emission of neighboring cities. However, as the distance from the origin grows, the magnitude of elasticity shrinks more rapidly than the case of Beijing, reaching close to zero in the middle distance from Wuhan. Then, the elasticity again declines (magnitude increases) slightly when going much further. In contrast to Beijing, the emission elasticity is no longer monotonic with respect to the distance from Wuhan, showing an inverted V-shaped curve. The example of the shock from Deyang, in Figure 1.A.5, shows a more exaggerated picture. In panel (a), the policy shock in Deyang exhibits a PHE in cities relatively closer to Deyang and the color turns red, except for a few direct neighbors.

1.4.3 Sensitivity to the Model's Key Assumptions

The model is different from the standard approach used to study the impact of local pollution control policy on national or global economies in three aspects. First, it allows

Figure 1.1: Illustration of the Spatial Effect of Policy Shocks from Beijing



Source: Author

Note: The maps depict elasticities computed against 10% change in the regulation parameter of Beijing ($\xi_{Beijing}^g$). Red colour indicates the positive computed elasticities, while the blue indicates the negative ones. The midpoint of the color palette is set to zero.

Table 1.2: Counterfactual Models

<i>Feature</i>	NMTW	NTW	NW	Benchmark
Domestic Migration	x	o	o	o
International Trade	x	x	o	o
Preference for Air Quality	x	x	x	o

Source: Author

Note: This table compares the features of the four models. “o” indicates that the model considers the feature as one of model’s key mechanisms. If “x”, the model treats the feature as restricted to zero.

for the production factor (workers) migration between cities. Second, workers care not only for their economic welfare but also environmental quality. Finally, it explicitly adds international trade to a domestic trade model. We ask what are the roles of these assumptions in determining the observed spatial effects.

To examine how sensitive the results on these assumptions, we compare three counterfactual models as explained below. Table 1.2 summarizes the features of the models we compare. Firstly, NMTW is a no-migration, no-trade, and no-welfare effect model. This counterfactual assumes that workers do not move from their current city, that trade takes place only within China, and that air pollution does not harm worker’s welfare. Note that this is equivalent to a domestic trade version of the model of Eaton and Kortum (2002) with pollution as a regulated production input. The NTW (no-trade and no-welfare effect) model relaxes NMTW by allowing domestic migration. But, international trade is still ruled out, meaning that the geographical scope of migration and trade is only within the domestic arena. The third counterfactual, NW, introduces international trade. Through this change, goods gain a wider scope of mobility than workers because they become mobile across international borders.

Figure 1.2 shows the features of the four models using the results of simulation for a unilateral 10 percent increase in Beijing, by setting $\widehat{\xi}_{Beijing}^g = 1.1$ while keeping it to 1 for the others. Panel (a) compares the elasticity of Beijing’s industrial emissions to its own policy change. All elasticities are negative and close to -1. Panel (b) plots

the relationship between the city's distance to Beijing and its elasticity for each of four models. The red is for the NMTW model. Elasticity is negative for the cities near to Beijing then turns positive as the distance grows. This normal domestic trade model shows that the pollution haven effect (PHE) occurs in space. The negative elasticity nearby cities corresponds to the effects on the manufacturing price index captured in the panel (c). Due to the linkage through costly trade, the price index (i.e. input price) of the nearby cities increases more than that in the distant cities, pushing the polluting production to relatively further locations. If domestic migration is allowed, the graph for the NTW model in blue shows that the curve becomes steeper than the case of the NMTW. The decline in real income near Beijing due to increases in the price index and the reallocation of manufacturing make the worker migrate to cities further from Beijing. Migration flow outward from the Beijing area makes the response of emissions more elastic than in the case of MNTW. Then, introducing international trade shifts the MTW curve down, as the graph for the NW model (in green) shows. By introducing international trade, firms in China face price competition with foreign firms. Stricter regulation in Beijing increases input costs in China through the increases in the price index, P_M , with a larger magnitude than in the foreign market. This decreases China's competitiveness in manufacturing and reduces the production scale of manufacturing in the cities in China. As a result, the elasticity of emission for the NW model is lower than for the NTW model, and the area with negative elasticity expands. Finally, adding the preference for air quality to the NW model delivers our benchmark model. As we can observe from panel (b), introducing this preference substantially reduces the slope of the emission elasticity with respect to the distance from Beijing. In the benchmark model, both skilled and unskilled workers care about air quality when choosing a residential location. Since Beijing and nearby areas reduce emission and pollution, both skilled and unskilled labor migrate toward Beijing. This shrinks the scale of production outside the Beijing area, and offsets the PHE by the increase in the price index.

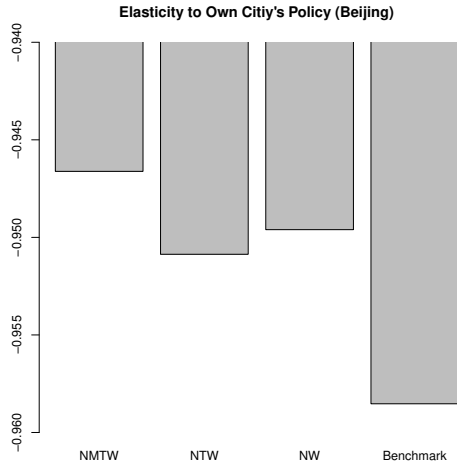
In contrast to the NTW model where tougher environmental regulation works as a *centrifugal* force on skilled labor, in the benchmark model it is a *centripetal* force. On the other hand, note that tougher regulation is always a centripetal force for unskilled labor. This happens due to the two substitutions that unskilled labor has between skilled labor and emissions. A tougher regulation of emission raises the price for emission, thus the factor demand for production shifts to demand more labor. However, due to the higher labor supply elasticity of skilled labor ($\eta^k > \eta^u$), skilled labor moves more sensitively in response to changes in the real wage, under the NW setting where they do not care about air quality. Unskilled labor is therefore a substitute for both emissions and skilled labor in the production of manufactured good and services.

In summary, the assumptions on migration and international trade play important roles in determining the behavior of the model. Allowing for migration or not in the model, or incorporating the welfare effect of pollution for workers, will significantly affect the degree of “distance decay” of the elasticity of emissions with respect to a cities’ distance from the epicenter city. Disregarding the migration or welfare effect of air pollution might lead overstatement of the local impact of stringent pollution control policies. The migration of workers may work to mitigate such local impacts, especially if they care about pollution as studied by Chen, Oliva, and Zhang (2017) and Freeman et al. (2017). Ignoring international trade may also lead to an exaggeration of the local effects of regulation and the potential of the pollution haven effect by missing the channel of foreign demand.

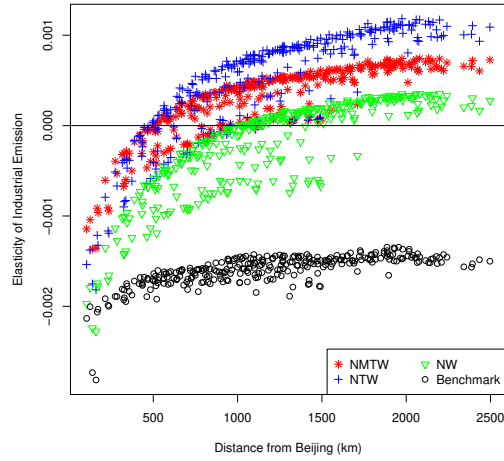
1.4.4 Comparing Aggregate Impacts of Local Policy

The spatial impact of local environmental policy differs with the location of any change that occurs. This suggests that the impact of local policy on aggregate outcomes may also vary depending on where the policy change happens. To show this, Figure 1.4 depicts the elasticities of the aggregate variables with respect to a local 10 percent increase in

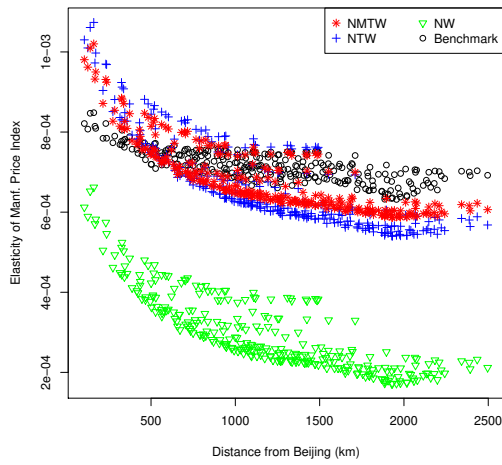
Figure 1.2: Model Comparison



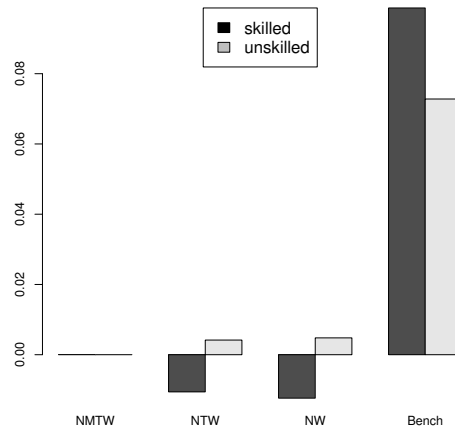
(a) Own-city Elasticity of Emission



(b) Distance and Elasticity of Emission



(c) Distance and Elasticity of P_M

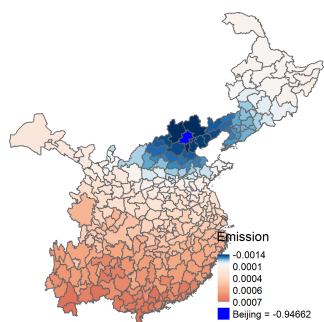


(d) Own-city Elasticity of labor

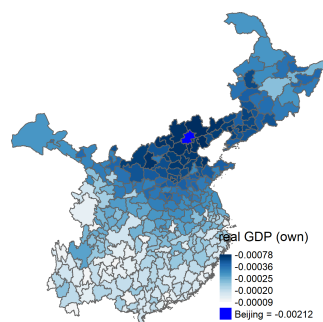
Source: Author

Note: Panel (b) and (c) depict the relationship between the distance from the city that the policy shock (environmental regulation) originates in (i.e. Beijing) and the elasticity of industrial emissions (b) or the price index (c) to the shock, comparing the benchmark model and three counterfactual settings, NMTW, NTW, and NW.

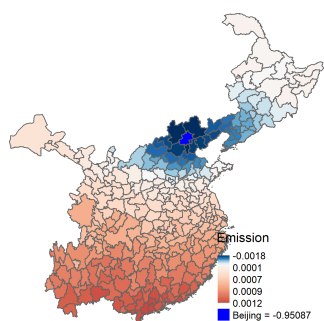
Figure 1.3: Counterfactual Models (Elasticities of Emission and Real GDP w.r.t. Regulation Shock in Beijing)



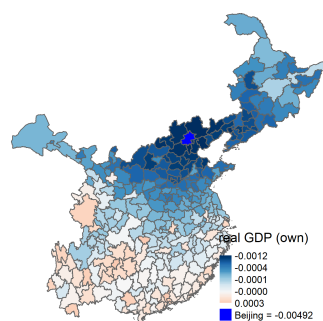
(a) NMTW: Emission



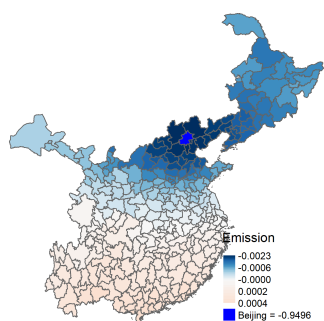
(b) NMTW: Real GDP



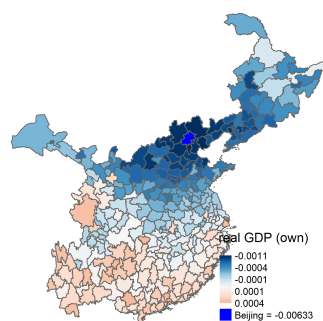
(c) NTW: Emission



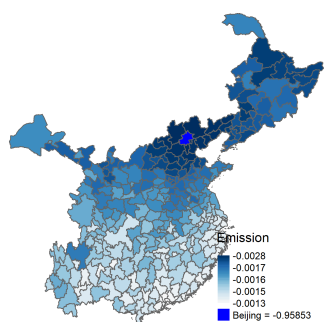
(d) NTW: Real GDP



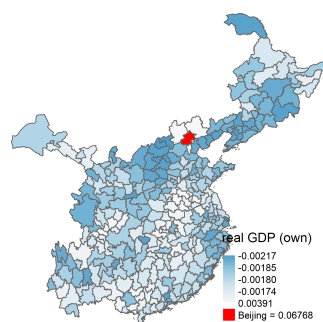
(e) NW: Emission



(f) NW: Real GDP



(g) Benchmark: Emission



(h) Benchmark: Real GDP

Source: Author

Note: The maps compares the four different models assuming the same policy shock (10 percent increase in ξ_n^g of the city n) happens in Beijing.

pollution control policy. The color and darkness of each map represent the sign and the magnitude of the elasticity of the national aggregate of the outcome variables with respect to this increase in the regulatory parameter ξ_n^g in each city.¹⁷

The elasticity of the aggregate emissions is depicted in panel (a). The elasticity is in fact highly correlated with the size of emissions from each city, with a correlation coefficient of -0.999. This is consistent with the previous observation we examined in the case of local policy in Beijing (and other two cities), where the elasticity of local emissions to policy in its own city is close to -1, while the magnitude of the elasticity of the cities outside of the epicenter city is far smaller than one, as shown in panels (a) and (b) of Figure 1.2. Figure 1.4 panel (b) shows the elasticity of the nationwide average exposure to air pollution, calculated as the change of population weighted average of PM_{2.5} concentration from the baseline. As shown in panel (a) and (b), emission and exposure elasticities are everywhere negative. There is no case where stricter policy in a city causes an aggregate increase in emissions or exposure to pollution. Despite the fact that there are cities such as Wuhan and Deyang where stricter regulation causes an increase of emissions in other cities, this PHE is not large enough to exceed the direct effect on the reduction of pollution in the epicenter and nearby cities.

The impact on aggregate economic variables is less straightforward. Panel (c) of Figure 1.4 illustrates how aggregate nominal GDP changes in response to strengthened pollution control policy in a city. Interestingly, there are 40 cities out of 296 whose increases in regulatory strength lead to a positive change in aggregate GDP. These cities tend to concentrate on the eastern coast where the most densely populated cities in China locate, such as Beijing, Tianjin, Shanghai, and Guangzhou locate. As confirmed in panel (i) of Figure 1.1, a unilateral change of regulatory strength in a city will increase the nominal GDP of its own and nearby cities while slightly reducing that of others. For those 40 cities with positive elasticities of aggregate nominal GDP, the positive effects on

17. Average exposure to air pollution is average PM_{2.5} concentration weighted by share of population.

GDP of its own and nearby cities surpasses the negative effects for the others. Panel (d) depicts the impact on aggregate real GDP. This elasticity is highly correlated with that for the nominal GDP. For this case, there are 36 cities whose real GDP elasticity is positive. If environmental regulation is strengthened in one of these 36 cities, it will contribute to overall economic growth.

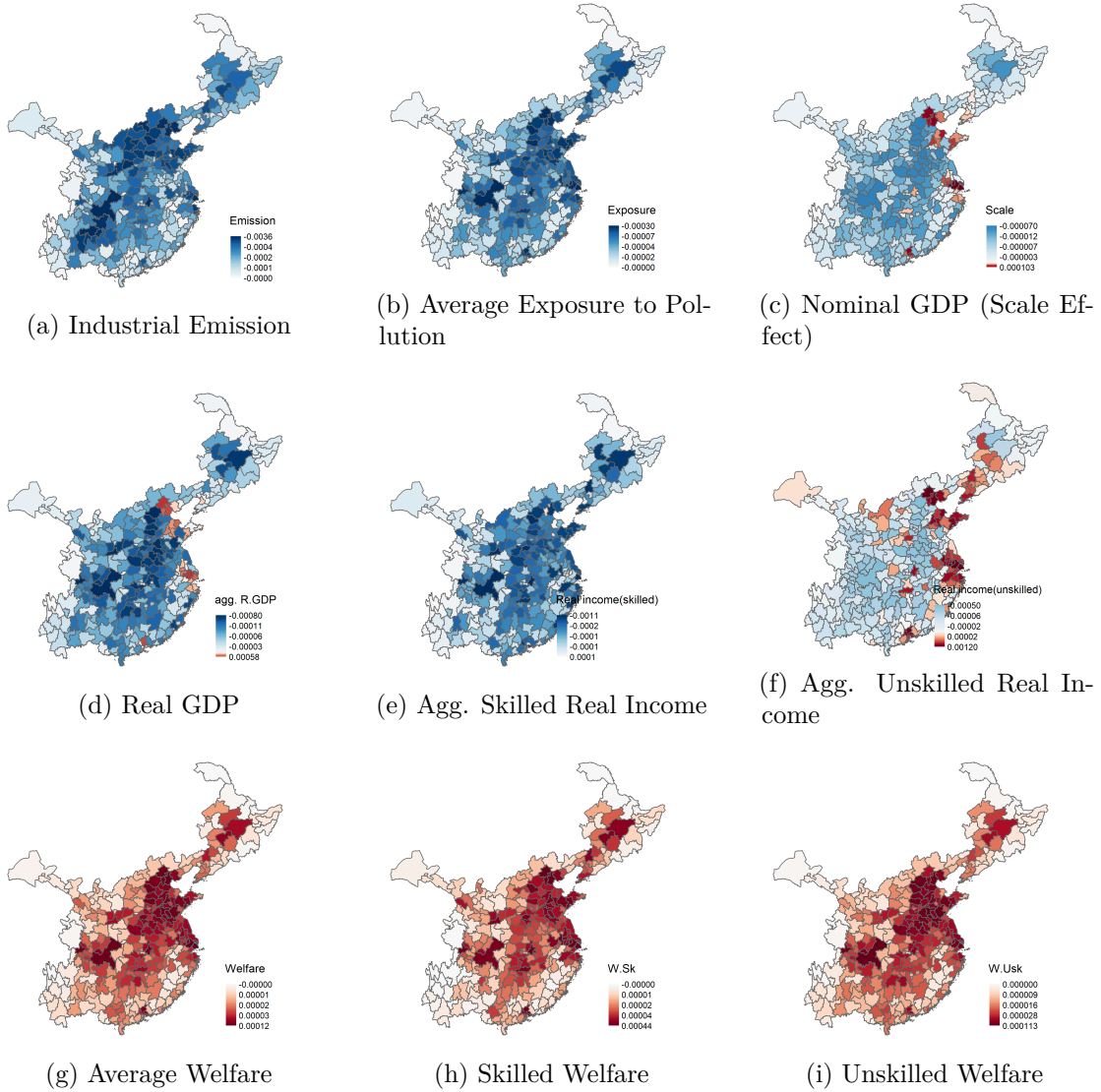
The economic impact of policy tends to favor unskilled workers more than the skilled. This is shown from the decomposition of the elasticity of real GDP into the effects on skilled and unskilled real incomes as in panel (e) and (f). Panel (e) and (f) reveal that skilled and unskilled workers face different consequences in terms of national average real income. For the skilled workers, national average real wage declines in most cases, except for 13 cities which are mainly located in the western and northern peripheries. On the contrary, the average real income of the unskilled increases if policy change takes place in the majority of coastal cities. There are a total of 108 cities that show the positive elasticity of average unskilled real wages.

Panels (g), (h), and (i) show the welfare elasticities with respect to the tightening of policy in each of 296 cities. The average welfare shown in panel (g) is calculated as the weighted average of skilled and unskilled welfare shown in (h) and (i).

1.5 Quantifying the Impact of National Level Policies

In the previous section, we examined the model's comparative statics of a unilateral policy change in a single city. The model also allows us to study the impact of pollution control policies under more realistic situations. Since the 11th Five-Year Plan (FYP), the government of China has set national level reduction targets of major pollutants. For example, in the 11th FYP that covers years from 2006 to 2010, a 10 percent reduction in aggregate SO_2 emissions to the level of 2005 was set as the target. To achieve this nationwide target, a complex political process is followed to assign the decomposed

Figure 1.4: Comparing Aggregate Impacts across Epicentres (Benchmark Model)



Source: Author

Note: The maps depicts the elasticity of the national aggregate of the variable of interest with respect to 10 percent increase in ξ_n^g of the city n .

targets to provincial and prefecture level administrations as their responsibilities for reduction. These regional targets are not uniform. Richer and populated areas have been assigned stricter targets, and the provincial targets vary from 0 percent to 30 percent during the 11th FYP (Stoerk 2017).

In what follows, we examine the impact of control policies at the national scale and the implications of different strategies on how to allocate reduction responsibilities across space. More specifically, we focus on the case where China tries to reduce aggregate (the national sum of) industrial emissions by 10 percent, reflecting the policy context in the 11th and 12th FYP, as discussed in the previous subsection. To reduce aggregate emission by 10 percent, how should the central government allocate reduction responsibilities across regions?

To answer this question, we compare the following six hypothetical responsibility allocations that achieve 10 percent reduction in aggregate emissions. In the model, our policy variable is ξ_n^g . As in equation (1.28), this parameter is an exogenous factor determining the Pigouvian emission tax ζ_n charged to industrial firms in city n . In the following policy experiments, we compare different ways to set the reformed policy $\xi_n^{g'}$, $\forall n$ so that the new equilibrium generates 10 percent less aggregate emission compared to the original equilibrium. There could be infinitely many options in how to set $\xi_n^{g'}$ to achieve an aggregate 10 percent reduction in emission. To simplify the discussion, we model the six policy allocation strategies as follows.

Let x_n denote the weight assigned to city n with $\sum_{n \in \mathcal{C}} x_n = 1$. Then, the reformed pollution control policy for the city n , $\xi_n^{g'}$, satisfies:

$$\frac{\xi_n^{g'}(x)}{\xi_n^g} = 1 + \mu_x x_n \quad (1.32)$$

where μ_x is a constant. Equation (1.32) implies that city n 's new regulatory parameter ($\xi_n^{g'}$) is $100 \times \mu_x x_n$ percent higher than its original, ξ_n^g . We then call the distribution of

Table 1.3: Targeting Strategies

Name	Weighting variable (x)	Constant (μ_x , mean and CI)**
(1) all	Equally weighted ($x_n = 1/N, \forall n \in \mathcal{C}$)	0.1039 [0.1038, 0.1040]
(2) zm	Industrial emission	0.0277 [0.0275, 0.0278]
(3) popden	Population density	0.1089 [0.1075, 0.1102]
(4) Rin_u	Elasticity of average unskilled real income*	0.0802 [0.0759, 0.0844]
(5) WELF	Elasticity of average welfare*	0.0498 [0.0495, 0.0500]
(6) TP	Inverse of time to nearest international port	0.1099 [0.1078, 0.1121]

Source: Author

Note: * Weight is zero for cities with negative elasticity.

** “Constant” (μ_x) for the equation (1.32) in the third column is calculated as a result of simulation. The square bracket in the third column shows the confidence interval of the estimated μ_x

x_n across $n \in \mathcal{C}$ the allocation “strategy” of the policy change to achieve the targeted national reduction in emissions. Table 1.3 summarizes the hypothetical strategies for our experiment; these are explained below. The simplest reference strategy is to assign the same magnitude of policy change to all the cities, which is called the “all” strategy. In this case, $x_n = 1/N, \forall n$. Regarding the constant, μ_x , we search for the value that achieves a 10 percent decline in aggregate emissions by iterating the equilibrium calculation until the aggregate emission reduction converges to the target. For this “all” strategy, the average of μ_{all} equals 0.1039, which means that all cities increase ξ^g by 10.39 percent to achieve 10 percent reduction in aggregate emissions.

One possible way to differentiate the allocation of reduction responsibility across cities is to assign higher weights to those cities where the problem is more serious. The second and third strategies are examples of this. The second strategy “zm” adjusts the weight, x_n , equal to city n ’s industrial emissions in the observed equilibrium, as of 2010 in our exercise. This ensures that large emitters face more stringent tightening of the regulations. While this strategy intuitively seems to be an efficient way to reduce aggregate emission, it is not obvious whether it is superior to other strategies in terms

of welfare and economic outcomes. The third strategy, “popden”, is another example of a strategy to assign targets according to a current observable conditions. In this case, we consider that the central government tries to prioritize cities with large affected populations. Then, it sets x_n equal to n ’s population density.

Instead of referring to the observed city characteristics, suppose that the central government knows the elasticity of aggregate outcomes with respect to local unilateral policy change in each city, as summarized in Figure 1.4. The fourth and fifth strategies utilize these known elasticities for unilateral policy intervention to cities. Suppose that the central government wants to achieve reduction targets without reducing the economic benefits of low income people. The “Rin_u” strategy intuitively aligns to this desire of the central government. This strategy assigns the weight according to the elasticity of average real incomes of unskilled workers that is depicted in the panel (f) of Figure 1.4. There are many cities whose tightening of regulations negatively affects the average real income (those in blue in the map). We set the weight for these cities at zero. In the “WELF” strategy, we assign a weight equal to the elasticity of the average welfare as shown in panel (g) of Figure 1.4, because higher welfare gains are expected from the policy. We also add a strategy, “TP”, that assigns the weight (x_n) according to the inverse of the travel time to the nearest international port from the city.

As revealed in the analyses on the unilateral policy change in a single city in the previous section, workers’ preferences for air quality play an important role in determining the spatial impact of policy. Although we use estimated values for these parameters that are quite similar to an existing study by Chen, Oliva, and Zhang (2017), the sensitivity of the simulation results to different parameter values should be checked. We thus conduct a parametric bootstrap using the estimation results for ξ^t , similar to Faber and Gaubert (2019). Specifically, we sample the alternative parameter values from a normal distribution with a mean equal to the point estimate and a standard deviation equal to the standard error of the estimate (adjusted by the delta method).

This bootstrap procedure is executed 100 times. For each trial, we calculate the changes in the equilibrium outcomes for six different strategies and stack the results to obtain the mean effect and its confidence interval.

Simulation Results The simulation results for the six targeting strategies summarized in Table 1.3 are shown in Figure 1.5. Panel (a) compares the impact on skilled worker welfare across the six strategies. Black graphs show the average and the 5 percent to 95 percent confidence interval as a percentage point change, simulated using the benchmark model. For all strategies, the impact on the skilled welfare is positive on average. The lower bound of the confidence interval at 5 percent is negative for all six strategies, suggesting that the welfare effect of the pollution control policy to reduce national emissions by 10 percent on the skilled labor is volatile with respect to the choice of parameter ξ^k that captures the preference of skilled workers for better air quality. Among the six strategies we examine, “Rin_u” strategy has a relatively higher average impact, but its variation is much larger compared to the other five strategies. We assume that the “Rin_u” strategy increases regulation a lot in a limited number of cities while keeping other cities from changing their level of environmental control. The result of the “Rin_u” strategy shown in panel (a) suggests that concentrating control intervention in a limited number of locations may deliver higher welfare gains on average, but that this outcome can be more sensitive to the unknown preference parameters.

Panel (b) depicts the impact on the unskilled worker’s welfare. The average impact is positive for all strategies. What is more, for each of the six strategies, the entire confidence interval stays on the positive side. Thus, pollution control policy is in general beneficial for the unskilled, and its sign is less sensitive to the preference parameter than for the case of the skilled worker.

Panels (c) and (b) show more clear contrasts of outcomes between the skilled and unskilled. While the average real income of the skilled workers always declines under

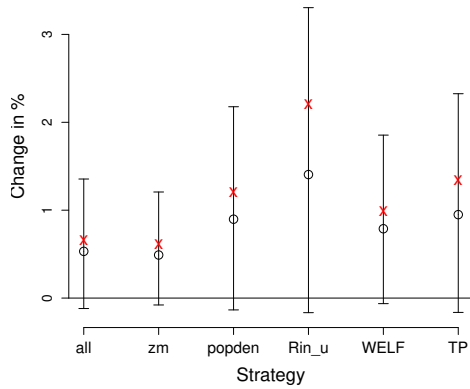
stricter pollution control policy, unskilled workers are always better off from such changes. For both skilled and unskilled workers, the magnitude of impact is the largest for the “Rin_u” strategy, while they are the most sensitive to the parameter values. As shown in panel (e), strengthening pollution control slightly reduces real GDP, but the magnitude is small and sometimes not substantially different from zero. The “Rin_u” strategy shows the outstanding sensitivity of this effect with respect to the choice of parameter values compared with other strategies, with a slightly positive average effect. Exposure to pollution will surely decline with the policy intervention, as shown in panel (f). Concentrating intervention to limited locations as in the “Rin_u” strategy will achieve the largest decline in exposure to pollution.

For all the panels, the red cross mark shows the average impact in the case where international trade is shut down. By comparing the cases with and without international trade, we can see that international trade pushes the impacts that favor the unskilled workers. Without international trade, the benefits for skilled workers shift up while those for unskilled workers shift down. This is especially so for the average real income of unskilled workers, as this is negative when international trade is absent while it is positive with trade.

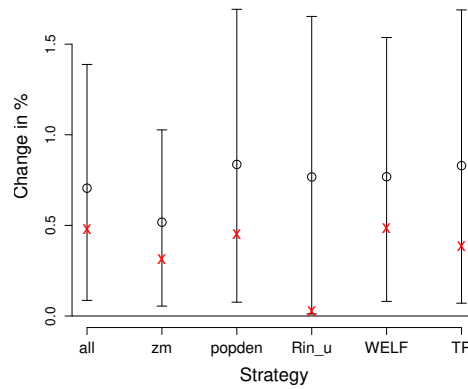
1.6 Conclusion

This paper develops a spatial equilibrium framework with endogenous air pollution to quantitatively study the impact of pollution control policies on welfare, economic, and environmental outcomes at regional and national scales. We calibrate the model to the Chinese economy’s situation in 2010 at the level of prefecture-level cities. Some of the important parameters are estimated by exploiting the model’s equilibrium conditions. To the best of our knowledge, this is the first attempt to explicitly incorporate endogenous air pollution into a quantitative spatial equilibrium framework. In our model, pollution

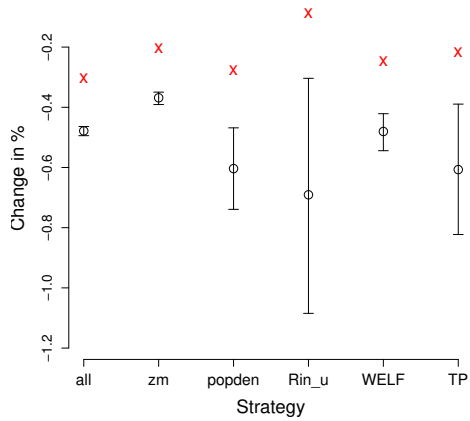
Figure 1.5: Comparing Strategies across the Models



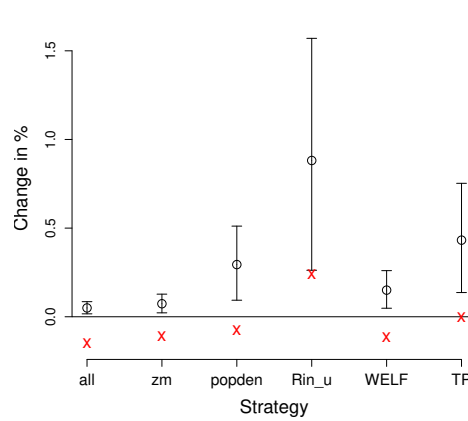
(a) Skilled Workers' Welfare



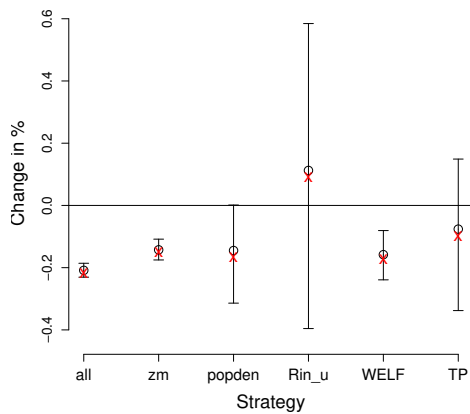
(b) Unskilled Workers' Welfare



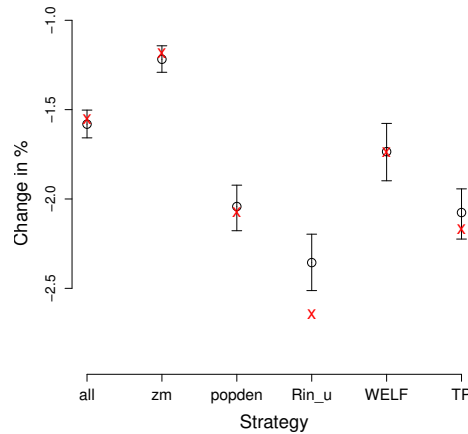
(c) Skilled Worker's Real Income



(d) Unskilled Worker's Real Income



(e) Real GDP



(f) Average Air Pollution Exposure

Source: Author

Note: These graphs depict the bootstrap mean and 5 percent confidence interval of the impact of nationwide policy to reduce aggregate emissions by 10 percent, as a percentage change of concerned outcome variables, across the six different targeting strategies. The black circle shows the mean of the effect and the lines stretching out from the circle shows the confidence interval. The red cross mark shows the mean of the impact when assuming China is a closed country.

control regulation is costly for firms as it may cause a reallocation of polluting industries to regions with more lax regulations, while this PHE can be (partially) offset by migration of workers who value air quality as a residential amenity.

We conduct a series of hypothetical simulations to study the implications of our theoretical model in a realistic setting. This approach allows the study of how a unilateral change of environmental policy in a single city can affect the city itself and other cities in China. In contrast to conventional trade-environment models, our spatial equilibrium framework with worker migration exhibits some cases where local environmental regulation delivers a positive economic benefit, even though regulation imposes additional costs on firms. Furthermore, in some cities, an increase in the local regulatory level may bring a positive economic return in terms of aggregate real GDP. These results emerge due to worker demands for better environmental quality and to let them migrate to an area where air pollution is reduced. In such cases, stricter regulation works as a *centripetal* force that attracts workers to the regulated regions, which coincidentally expands the scale of economic production.

Our approach is not free from shortcomings. First is that our discussion rests only within a static framework, ignoring the implication of dynamic changes. While our model can be regarded as a description of a steady state that will be reached in the long-run, this does not exclude the possibility that the observed results may not hold if dynamics are taken into account. Another caveat lies in the simplification of environmental quality into a single air pollution measure. While environmental quality has many dimensions, in the present paper we only care about ambient quality. Other important dimensions, such as water quality, soil quality, noise, radioactive pollution, biodiversity, and scenic beauty, are not covered. Moreover, within the category of the ambient pollution, the argument is simplified to where local air pollution can be represented by a single measure, $PM_{2.5}$ concentration. There are other important forms of air pollution such as nitrogen oxides, carbon monoxide, sulfur dioxide, and PM_{10} (which is a fine particulate matter that is

greater than $PM_{2.5}$). We also miss the emission of global pollution that destroy the ozone layers and cause greenhouse gas effects, such as chlorofluorocarbons and carbon dioxide.

However, our primary interest is in that local air pollution that directly affects people's health and their economic behavior, including their choice of residential location. $PM_{2.5}$ is one of the most commonly known pollutants that directly affects human lung and cardiovascular systems. Furthermore, its concentration is closely linked to other pollutants that have similar effects on human health. Therefore, we believe that focusing on $PM_{2.5}$ is a reasonable generalization to avoid overcomplexity and to overcome data limitations, without causing serious biases in our analysis.

1.A Appendix

1.A.1 An Algorithm to Obtain Counterfactual Equilibrium using Changes

This appendix describes a practical procedure to solve the counterfactual equilibrium of the model using the “change,” which is the ratio of the counterfactual equilibrium value of variable x to that of its original (observed, current equilibrium value).¹⁸ We denote the change of variable x as $\widehat{x} = \frac{x'}{x}$, where x' is the counterfactual value of variable x . The following discussion summarizes the procedure for solving exogenous changes in trade cost $\widehat{\tau}_{ni}$, manufacturing productivity, $\widehat{A}_{M,n}$, services productivity, $\widehat{A}_{S,n}$, and/or strength of local pollution control $\widehat{\xi}_{g,n}$. Note that we do not have to know the levels of unobserved exogenous variables consistent with the current equilibrium, $A_{M,n}$, $A_{S,n}$, and $\xi_{g,n}$.

1. Initial guess on factor price changes (skilled wage and Pigouvian tax for pollution), \widehat{w}_n^k and $\widehat{\zeta}_n$
2. Solve for $\widehat{P}_{M,n}$ and $\widehat{P}_{S,n}$ consistent with \widehat{w}_n^k and $\widehat{\zeta}_n$ using

$$\widehat{c}_n = \left[\widehat{w}_n^k \gamma_M^k \widehat{P}_{M,n}^{\gamma_M^M} \widehat{P}_{S,n}^{\gamma_M^S} \right]^{1-\delta} \widehat{\zeta}_n^\delta \quad (\text{A.33})$$

$$\widehat{P}_{M,n}^{-\theta} = \sum_i \pi_{ni} \widehat{\tau}_{ni}^{-\theta} \widehat{c}_i^{-\theta} \widehat{A}_{M,i}^\theta \quad (\text{A.34})$$

$$\widehat{P}_{S,n} = \widehat{A}_{S,n}^{-1} \widehat{w}_n^k \gamma_{S,n}^k \widehat{P}_{M,n}^{\gamma_{S,n}^M} \quad (\text{A.35})$$

3. Using the price vectors obtained in the previous step, update the trade shares according to:

$$\widehat{\pi}_{ni} = \frac{(\widehat{\tau}_{ni} \widehat{c}_i)^{-\theta} \widehat{A}_{M,i}^\theta}{\widehat{P}_{M,n}^{-\theta}} \quad (\text{A.36})$$

4. Using the vectors of price change obtained by the previous step, update the general

18. This approach was first proposed by Dekle, Eaton, and Kortum (2008), and has been widely used in the literature.

price index $\widehat{P}_{T,n}$ and expenditure share $\widehat{\chi}_{j,n}$, $j \in F, M, S$ as follows:

$$\widehat{P}_{T,n}^{1-\rho} = \chi_{F,n} + \chi_{M,n} \widehat{P}_{M,n}^{1-\rho} + \chi_{S,n} \widehat{P}_{S,n}^{1-\rho} \quad (\text{A.37})$$

$$\widehat{\chi}_{F,n} = \frac{1}{\widehat{P}_{T,n}^{1-\rho}}, \quad \widehat{\chi}_{M,n} = \frac{\widehat{P}_{M,n}^{1-\rho}}{\widehat{P}_{T,n}^{1-\rho}}, \quad \widehat{\chi}_{S,n} = \frac{\widehat{P}_{S,n}^{1-\rho}}{\widehat{P}_{T,n}^{1-\rho}} \quad (\text{A.38})$$

5. The expenditures on manufacturing and services goods, as well as their production in the counterfactual equilibrium are given by:

$$E'_{M,n} = \widehat{\chi}_{M,n} \chi_{M,n} \left(\widehat{w}_n^k w_n^k L_n^k + w_n^u L_n^u \right) + (1 - \delta) \gamma_M^M Y_{M,n} + \gamma_{S,n}^M Y_{S,n} \quad (\text{A.39})$$

$$Y'_{M,i} = \sum_n E'_n \pi'_{ni} \quad (\text{A.40})$$

$$Y'_{S,i} = E'_{S,i} = \widehat{\chi}_{S,n} \chi_{S,n} \left(\widehat{w}_n^k w_n^k L_n^k + w_n^u L_n^u \right) + (1 - \delta) \gamma_M^S Y_{M,n} \quad (\text{A.41})$$

6. Update land price and emissions:

$$\widehat{r}_n^{1-\omega} = \frac{\widehat{\zeta}_n}{\widehat{\xi}_{g,n}} \quad (\text{A.42})$$

$$\widehat{Z}_{M,n} = \frac{\widehat{Y}_{M,n}}{\widehat{\zeta}_n} \quad (\text{A.43})$$

$$\widehat{Z}_{R,n} = \widehat{\chi}_{M,n} \widehat{r}_n \quad (\text{A.44})$$

7. Then update the level of pollution:

$$D'_n = f(\bar{X}) (Z_{M,n}' + Z_{R,n}')^\kappa \quad (\text{A.45})$$

8. Update labor force distribution for each type $t = \{k, u\}$:

$$\widehat{L}_n^t = \frac{\left(\widehat{e}_n^t \widehat{w}_n^t \widehat{P}_{T,n}^{-\alpha} \widehat{r}_n^{\alpha-1} \right)^\eta}{\sum_j \frac{L_j^t}{L_c^t} \left(\widehat{e}_j^t \widehat{w}_j^t \widehat{P}_{T,j}^{-\alpha} \widehat{r}_n^{\alpha-1} \right)^\eta} \quad (\text{A.46})$$

where

$$\widehat{e}_n^t = \frac{\exp(-\xi^t D_n^t)}{\exp(-\xi^t D_n)} \quad (\text{A.47})$$

9. The skilled wage and total value added (GDP) are then updated by:

$$w_n^{k'} = \frac{[(1 - \delta)\gamma_M^k + \delta] Y_{M,n}' + \gamma_{S,n}^k Y_{S,n}'}{\widehat{L}_n^k L_n^k} \quad (\text{A.48})$$

and

$$G_n' = w_n^{k'} \widehat{L}_n^k L_n^k + w_n^u \widehat{L}_n^u L_n^u \quad (\text{A.49})$$

10. Obtain new values for factor prices \widehat{w}_n^k and $\widehat{\zeta}_n$ from:

$$\widehat{w}_n^k = \frac{w_n^{k'}}{w_n^k} \quad (\text{A.50})$$

$$\widehat{\zeta}_n = \widehat{G}_n^{1-\omega} \widehat{\xi}_{g,n} \quad (\text{A.51})$$

11. Iterate 2 to 10 until values converge.

1.A.2 Details of the Data

Population and value added Our unit of analysis is those prefecture-level cities or counties that are directly under Provinces plus the four direct-administered municipalities of China as of 2010, within the Eastern half of the mainland China. This area basically overlaps with the historical territory of the Han dynasty (B.C. 206 - A.D. 220). Four provinces/autonomous regions, Inner Mongolia, Xinjiang, Qinghai, Tibet, and islands (such as Hainan Province) are dropped from the analysis. We make this choice because the western part of China dropped from the analysis is economically and demographically very sparse compared to the Eastern half, holding only 4.3 percent of total population while occupying more than 51 percent of the land area. We thus follow other studies such as Baum-Snow et al. (2018) in keeping our focus on the Han part of China. The area

consists of 296 geographical units (270 prefecture-level cities and 26 counties directly under the Provinces). The Economic variables, such as the value added of primary, secondary, and tertiary industries, are taken from the *China City Statistical Yearbook* and *China Region Economy Statistical Yearbook* of 2011 that report their values as of 2010. Employment variables are constructed benefiting from the online supplementary materials of Baum-Snow et al. (2017) that originally aggregated the *2010 Population Census* at the level of counties. In the county-level aggregate of the census, the employment in primary, secondary, tertiary industries is provided. These are summed to the level of prefecture cities as the employment of three industry strata to obtain the aggregate labor force in the location. Then, we compute the amount of skilled labor by multiplying the total labor force with the share of population with at least a senior high school degree. The remaining labor is treated as unskilled.¹⁹

PM_{2.5} Concentration The yearly PM_{2.5} concentration is computed from raster images provided by Donkelaar et al. (2016), which are available from `fizz.phys.dal.ca/~atmos/martin/?page_id=140`. This is the estimated level of PM_{2.5} concentration on the surface using the satellite image of aerosol. Raster images cover all the ground surface of the earth annually since 2000. A growing number of recent studies use this set of satellite images of PM_{2.5} to recover the spatio-temporal variations of China’s air pollution, especially for obtaining the spatially disaggregated situation before 2014 when China started detailed and frequent official reporting of air pollution.²⁰ There are a few advantages in using this satellite data. Until the early 2010s, China had reported situations of local air pollution for only a limited number of cities (only around 100 cities). Since the satellite

19. Combes et al. (2019) define skilled labor as employees received at least technical or vocational training after completing senior high school, which may be stricter than our definition of the skilled labor. The country-level aggregates we use do not report the the number of people enrolled in technical or vocational schooling after senior high school, while the number of people with college degree is available. Therefore, we do not know from our data how many of those who completed senior high but not college received additional education such as technical and vocational training.

20. Examples include Chen, Oliva, and Zhang (2017) and Freeman et al. (2017).

images by Donkelaar et al. (2016) are the raster information of $0.01^\circ \times 0.01^\circ$ mesh containing the annual average concentration of $\text{PM}_{2.5}$, covering all over the world since 1998, the researchers basically calculate the level of pollution of an arbitrary geographical unit. Secondly, as argued by Chen et al. (2013), the official data on air pollution seem to be incorrect because of manipulation by the local authorities. Satellite images are generally considered to be more reliable. The spatial distribution of the annual average concentration of $\text{PM}_{2.5}$ within each prefecture-level unit is depicted in Figure 1.A.1.

Pollutant Emission Inventory We rely on satellite based data on the emission of the ambient pollutants that are the primary sources of $\text{PM}_{2.5}$. We use the MIX database from MEIC²¹, maintained by the researchers from the leading universities in China. The database provides the gridded ($0.25^\circ \times 0.25^\circ$) emission inventory of major pollutants such as SO_2 , NO_x , and primary $\text{PM}_{2.5}$. The monthly gridded emission inventory is used to construct the annual sum of emission in each grid and vectorize the raster data by calculating the mean level of emission for each prefectural polygon.

Particulate matter is formed primarily through combustion of fuels as well as natural sources. In addition, secondary particulates emerge from other pollutants such as SO_2 and NO_x , then finally form the particulate matter observed in the air. When we estimate (1.26) to obtain coefficient κ and $f(\tilde{X}_n)$, we follow Sun et al. (2017) who assume that the $\text{PM}_{2.5}$ concentration in n consists of the local emission of primary $\text{PM}_{2.5}$ as well as SO_2 and NO_x emissions that contribute as secondary sources. For this purpose, therefore, we exploit the emission inventory data of these important pollutants. Importantly, the MEIC emission inventory provides the local emission of those pollutants from four different sources; industry, power generation, traffic, and residences. This allows us to disentangle the emissions from the production side and the residential side, denoted by Z_M and Z_R in the model, respectively. In practice, we calibrate Z_M by the sum of the emissions of

21. <http://www.meicmodel.org/index.html>

Table 1.A.1: Emission of Major Pollutants from Sources (unit: kilotonne)

	Power	Industry	Residential	Transport
SO ₂ (sum)	7,079.0	19,134.7	3044.9	202.1
(mean)	247.5	66.9	10.6	0.7
NO _x (sum)	7,753.8	9,954.0	990.0	6,158.2
(mean)	27.1	34.8	3.5	21.5
Primary PM _{2.5} (sum)	746.4	5,430.0	4,138.0	442.9
(mean)	2.6	19.0	14.5	1.5

Based on gridded emission inventory dataset from MEIC (<http://www.meicmodel.org/index.html>)

SO₂, NO_x, and primary PM_{2.5} from industry and power generation. For Z_R , we use the sum of the same set of pollutants from the traffic and residential sources. Table 1.A.1 summarizes the emissions of each pollutants from the four different sources.

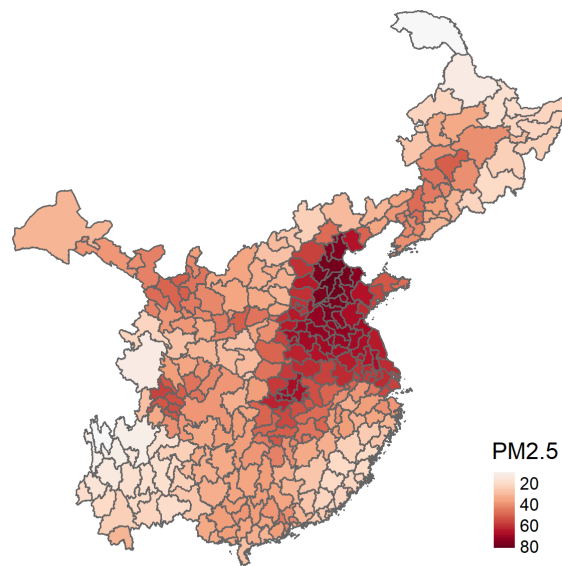
Other variables As detailed below, we use a set of control variables in the estimation of labor supply elasticity, η^t , and parameter of disutility from pollution ξ^t . Our identification strategy use the same instrumental variables and control variables as Baum-Snow et al. (2018), such as population as well as the share of high school graduates in 1982, and so on. We thus benefit again from their online appendix. In addition, we also add climate control variables such as precipitation and temperature since these can simultaneously affect the level of pollution and people’s residential choice, which is equivalent to the labor supply in the model. For these climate variables, we use the satellite images from “TerraClimate” database (Abatzoglou et al. 2018).²² From the raster files of monthly records, we calculate the annual average precipitation and temperature within the boundary of each prefecture-level unit.

1.A.3 Spatial Distribution of Pollution in China

Figure 1.A.1 illustrates the spatial distribution of PM_{2.5} (particulate matters smaller than 2.5 micrometers) concentration in the populated Eastern half of China (“Han” China) in

²². The data can be downloaded from <http://www.climatologylab.org/terraclimate.html>

Figure 1.A.1: PM_{2.5} Concentration (μ/m^3) in 2010



Source: Author

Note: Based on Donkelaar et al. (2016), the mean level of PM_{2.5} within the boundary of each city is depicted.

2010. PM_{2.5} is small particle that is one of the most harmful to the human body. In the area around Zhongyuan (Central Plain) in the South of Beijing, and including Tianjin, Hebei, Henan, and Shandong Provinces, the level of pollution is collectively very high. In this area, the long-term population-weighted exposure to PM_{2.5} concentration exceeds $64\mu\text{g}/\text{m}^3$.²³ This area also contains China's major megalopolises where densely populated cities are clustered across a large space to accommodate more than 300 million people. By this overlap of pollution and population, huge numbers of people face significant health risks. The welfare consequences of this unhealthy spatial distribution are seriously undesirable.

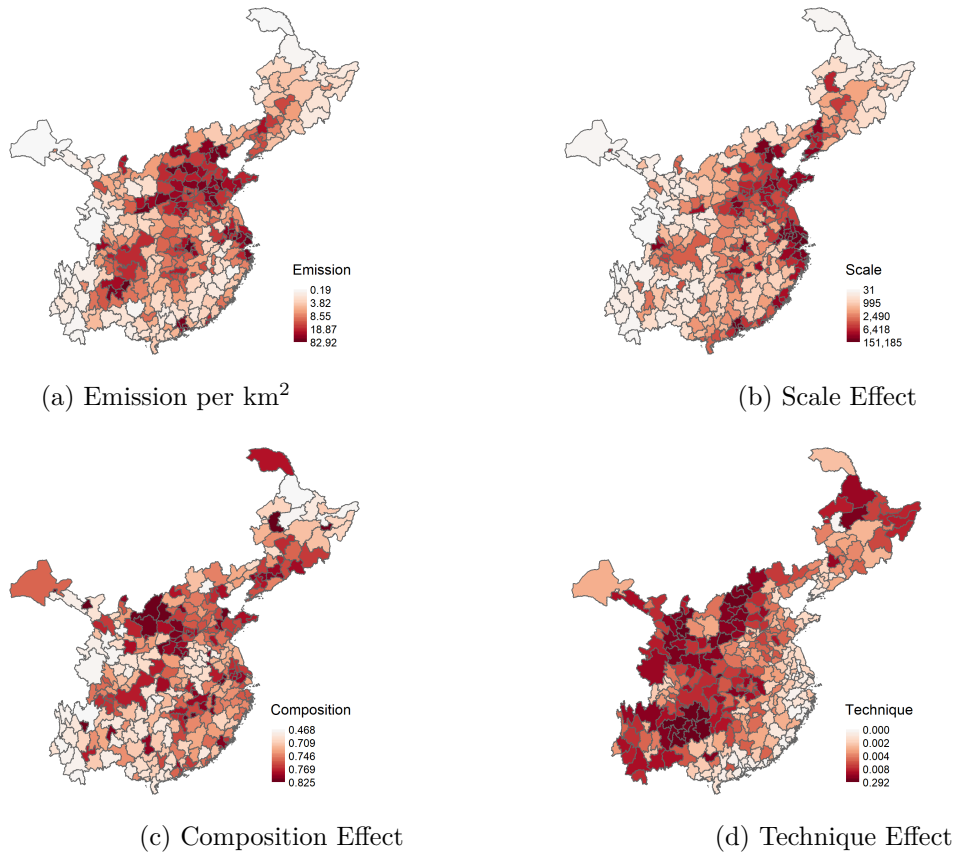
As seen in the introduction, the spatial distribution of PM_{2.5} concentration is not uniform across space. Spatially uneven distribution can also be found for the anthropogenic emission of major ambient pollutants. The maps in Figure 1.A.3 display the spatial patterns of anthropogenic emission for the three major ambient pollutants, sulfur-dioxide (SO₂), nitrogen-oxides (NO_x), and the primary emission of PM_{2.5}, produced from human activities.²⁴ From a visual examination, the spatial patterns are highly correlated between that of emissions and that of the PM_{2.5} concentration level.

The spatial distributions of pollution and emission shown above are highly associated with the distribution of economic activities across space. In short, the agglomerated regions generate a lot more pollutants and are significantly severely polluted. To see this, we follow the decomposition proposed by Grossman and Krueger (1995) that separates amount of emissions into (i) scale effect, (ii) composition effect, and (iii) technique effect. Scale effect is the amount of total economic production (per area) from a region of a city. Composition is the share of output value from polluting industry. In our case, this refers to the output share from the secondary sector (manufacturing and power generation). The

23. Long-term population-weighted exposure is the average of annual average PM_{2.5} concentration weighted by residential population. For reference, the U.S. standard for the long-term population-weighted exposure is $12\mu\text{g}/\text{m}^3$.

24. Primary PM_{2.5} refers to the emission of particulate matters with a diameter of less than 2.5 micron that is generated directly from the combustion of fuels and other materials. This is different from the concentration of PM_{2.5} within a given mass of outdoor air.

Figure 1.A.2: Decomposition of Industrial Emission



Source: Author

Note: The emission amount is the sum of SO₂, NO_x, and primary PM_{2.5} from industrial and power generation sources. See Section 1.A.2 for the details of the data definition. Scale effect is in 10,000 RMB per km² and technique effect is in kilo-tonnes per km². All the data are from 2010. See Section 1.A.2 for the details of data used.

technique effect equals to the emission intensity of that polluting industry, which is the amount of emissions per unit of output value. This reflects the environmental efficiency of the polluting industries in the region. Furthermore, in models like this paper presents, the technique effect is proportional to the inverse of the Pigouvian emission tax imposed on a unit emission, as will be discussed later. More specifically, the decomposition is expressed as an identity for the total industrial emission from region i as follows:

$$\underbrace{Z_i}_{\text{emission}} = \underbrace{Y_i}_{\text{scale}} \times \underbrace{\frac{Y_{M,i}}{Y_i}}_{\text{composition}} \times \underbrace{\frac{Z_{M,i}}{Y_{M,i}}}_{\text{technique}} \quad (\text{A.52})$$

where $Z_{M,i}$ is the total emission from polluting sectors (say, manufacturing) in i , Y_i is the total economic output in i including sectors other than polluting sector (such as services). $Y_{M,i}$ is the polluting sector's output. This decomposition helps us to capture which of the factors of economic scale, composition of production, or environmental efficiency (regulation) is more relevant than others in explaining the spatial distribution of pollution and emission.

Figure 1.A.2 collects the maps showing the decomposition of the industrial emissions that make up the major part of China's anthropogenic pollutant emissions. Panel (a) illustrates the industrial emissions, the sum of SO₂, NO₂, and primary PM_{2.5} emissions from manufacturing and power generation. Panels (b), (c), and (d) show the decomposition of Panel (a), based on the identity (A.52). Panel (B) shows the scale effect. Its spatial distribution overlaps with (a), suggesting that scale matters for these emissions. Cities with denser economic activity tend to emit larger amount of pollutants. Panel (c) is for the composition. Composition is also positively correlated with the emission. Emissions are likely in large cities with higher secondary sector shares. On the contrary, the distribution of technique effect shown in panel (d) does not overlap with that of emissions. Correlations of each of the three factors with emission are 0.775 (scale), 0.536 (composition), and 0.032 (technique), respectively, which supports the visual observation

from Figure 1.A.2 on the relevance of the scale followed by the composition, as well as the irrelevance of the technique effect. This is in contrast to the evidence on the development of U.S. manufacturing firms during recent decades, as illustrated by Shapiro and Walker (2018). They argue that in the U.S., the technique effect has dominated the overall trend in the emissions of air pollutants. However, note that the correlation between scale effect and technique effect is -0.606 , meaning that emission intensity is lower where economic density is higher. This can also be confirmed from panel (b) and (d) of Figure 1.A.2, where the scale shows a east-high west-low distribution, while the technique one is west-high east-low. In summary, the geographical distribution of pollutant emission and pollution in China largely overlaps with the distribution of economic density. Thus, economic agglomeration, especially industrial agglomeration, means agglomeration of pollution as well. While the environmental efficiency is expressed as the level to which the technique effect partially offsets the scale effect, it is not large enough to perfectly cancel out the scale and composition effect.

1.A.4 Calibration and Estimation

Bilateral trade cost between cities Bilateral trade cost between locations is not directly observable in our data. In general, there are two approaches to estimate bilateral trade cost from available data in the trade and geography literature. The first and traditional approach that has been mainly used in the international trade literature is to recover it by using the gravity equation with bilateral trade flow data (Head and Mayer 2004). The theory employed in this paper also yields a gravity equation that allows the implementation of this method. However, the key limitation of this method is data availability. While bilateral trade data between every pair of locations are required, these are largely unavailable for domestic trade. For China, Poncet (2003, 2005) and Tombe and Zhu (2019) are among the researchers using this approach. As the Chinese domestic trade flow matrices are provided only at the level of Provinces and for a limited number

of years, their analyses are restricted to the Provincial level. The second method is to impute the trade cost using the travel time (or distance) between the pair of locations, as employed by Donaldson and Hornbeck (2016) and Baum-Snow et al. (2018). Typically, a shortest path algorithm (e.g. the Dijkstra Algorithm) is used to calculate travel time to reach from one place to another based on digital maps of transportation infrastructure networks. The calculated travel time matrix are converted into a bilateral iceberg trade cost matrix using the known parameters that pin down the relationships between the freight shipment time and the cost. Our focus on the prefecture-level analysis naturally rules out the first approach because there is no bilateral trade data at this level of granularity in China. Therefore, it is necessary to closely follow the data and methods employed by Baum-Snow et al. (2018) to recover the trade cost matrix.²⁵ Particularly, we benefit from the online appendix of Baum-Snow et al. (2018) and use the historical highway network digital maps as of 2010. The Dijkstra Algorithm is used to compute the shortest paths between each pair of cities.

International Trade Cost For international trade in the M sector goods, we assume that the trade cost for city i is the trade cost to reach its closest international port multiplied by the border effect. Let τ_{Xi}^j denote the trade cost between i and the RoW. Then, assume that $\tau_{Xi} = \tau_b \tau_{port(i)i}$, where, τ_b a common border effect and $\tau_{port(i)i}$ is the transportation cost to the closest port from i . τ_b can be recovered by applying the gravity equation as explained in Head and Mayer (2004), by using China’s national exports \mathcal{E} , national imports \mathcal{I} ,²⁶ total production of manufacturing goods in RoW, $Y_{M,X}$, and

25. Another novel approach, which has recently emerged, is to use the freight cost quotations provided by logistics companies. The advantages of using this approach to two other conventional approaches is detailed in Yang (2018).

26. According to the China Statistical Yearbook 2011, China’s manufacturing exports in 2010 were 10,047 billion RMB and imports were 6,129 billion RMB. We implicitly assume the trade imbalance (positive net export) in manufacturing goods is offset by the net import of agricultural goods.

China's total expenditure on manufacturing goods E_C , as follows:

$$(\tau_b)^{-2\theta} = \frac{\mathcal{E}\mathcal{I}}{(Y_X - \mathcal{E})(E_C - \mathcal{I})} \quad (\text{A.53})$$

With $\theta = 5$ as will be explained below, we obtain $\tau_b = 1.68$.²⁷

Input shares and Wages Data on local skilled and unskilled wages are not available. However, the average wage in each sector at the national level is provided in *China Statistical Yearbook*. Average wage in a sector j , w_j is given by $w_j = \frac{w^k L_j^k + w^u L_j^u}{L_j^k + L_j^u}$. Noting that the production function in both the manufacturing and services sectors is Cobb-Douglas, $w^k L_j^k = \tilde{\gamma}_j^k V_j$ and $w^u L_j^u = \tilde{\gamma}_j^u V_j$ follow, where V_j is the value added of sector j and $\tilde{\gamma}_j^t = \frac{\gamma_j^t}{\gamma_j^k + \gamma_j^u}$, $t \in k, u$ is the type t share in the value added. Using these relationships, we can compute the skilled labor share using:

$$\tilde{\gamma}_j^k = \frac{w^k (w_j - w^u)}{w^j (w_k - w^u)} \quad (\text{A.54})$$

It is assumed that the agricultural sector employs only unskilled labor, hence the national agricultural wage is equal to the national unskilled wage w^u . Similarly, it is assumed that the financial intermediation sector employs only skilled labor and that the national skilled wage w^k equalises to the national wage rate in the financial intermediation sector. With these w^u and w^k , in addition to the wage rates in the sub-sectors shown in Table 1.A.5, we can obtain the skilled labor share for each j . Among the sub-sectors whose average wage rates are available in the China Statistical Yearbook, one sub-sector ("Agriculture, Forestry, Animal Husbandry and Fishery") can be categorized as primary industry (F in the model), four sub-sectors ("mining," "Manufacturing," "Electricity," and "Construction") into secondary industry (M), and the remaining fourteen sectors into

27. Baum-Snow et al. (2018) instead set $\tau_b = 1.15$ based on the review by Anderson and Wincoop (2004). This number could be too old to be consistent with the data in 2010, and does not necessarily reflect the situation of developing countries such as China.

the tertiary (S) industry. Then, we compute the skilled labor share of the $J \in F, M, S$ industry is:

$$\tilde{\gamma}_J^k = \frac{\sum_{j \in J} w_j L_j \tilde{\gamma}_j^k}{\sum_{j \in J} w_j L_j} \quad (\text{A.55})$$

Given the input shares of intermediate goods in production of the M and S industries, namely, γ_M^M , γ_M^S , and $\gamma_{S,n}^M$ in (1.7) and (1.14), the input shares of skilled and unskilled labor in these industries are given by $\gamma_M^t = \tilde{\gamma}_M^t(1 - \gamma_M^M - \gamma_M^S)$ and $\gamma_{S,n}^t = \tilde{\gamma}_S^t(1 - \gamma_{S,n}^M)$.²⁸

At the prefecture-city level, we have neither sectoral wages nor skilled/unskilled wages. Instead, the value added in each of three industries, denoted here by $V_J, \forall J \in F, M, S$, is used. We then use the obtained labor shares and value added to recover the skilled and unskilled wages in city n by:

$$w_n^k = \frac{\frac{(1-\delta)\gamma_M^k + \delta}{(1-\delta)(1-\gamma_M^M - \gamma_M^S)} V_{M,n} + \frac{\gamma_{S,n}^k}{1-\gamma_{S,n}^M} V_{S,n}}{L_n^k} \quad (\text{A.56})$$

$$w_n^u = \frac{V_{F,n} + \frac{(1-\delta)\gamma_M^u}{(1-\delta)(1-\gamma_M^M - \gamma_M^S)} V_{M,n} + \frac{\gamma_{S,n}^u}{1-\gamma_{S,n}^M} V_{S,n}}{L_n^u} \quad (\text{A.57})$$

Expenditure share (α) We calibrate α using the expenditure shares of consumers provided in the China Statistical Yearbook 2011. On average, households in China spend 13% of their total expenditure on housing, thus we set $\alpha = 0.87$.²⁹

The elasticity of trade with respect to trade cost (dispersion parameter θ)

There are several studies that estimate trade elasticity θ . While the majority of these are in the context of international trade, it is possible to find a number of examples on how to apply these estimates in the study of domestic trade. Baum-Snow et al. (2018) set $\theta = 5$ while experimenting $\theta \in [3, 10]$. Tombe and Zhu (2019) sets $\theta = 4$. Bryan and Morten (2019) use the range 4 to 8 in the context of domestic trade in Indonesia,

28. From China's input-output table as of 2007 provided in *China Statistical Yearbook 2011*, we set $\gamma_M^M = 0.6859$ and $\gamma_M^S = 0.1004$, respectively.

29. This value is the same as Tombe and Zhu (2019) who also study the equilibrium in 2010.

referring to Allen and Arkolakis (2014) who use the value of 8 and Bernard et al. (2003) who found that $\theta = 4$. Caliendo et al. (2018) analyze the heterogeneous impact of local productivity shocks to aggregate the U.S. economy using the Ricardian model of trade with disaggregated sectors. They employ the estimates of the trade elasticity of detailed sectors by Caliendo and Parro (2015) that study the welfare effects of NAFTA on the U.S. economy. While the elasticity varies a lot across sub-sectors, their main estimates of the aggregate level elasticity (including agriculture, mining, and manufacturing sub-sectors) range from 3.29 to 4.55. Gervais and Jensen (2019) estimate θ in the context of the U.S. domestic trade incorporating services sector trade, finding that the mean value of θ for manufacturing goods is 8.14. Faber and Gaubert (2019) choose $\theta = 6.1$ based on the estimates by Adao, Arkolakis, and Esposito (2018) as well as Head and Mayer (2014). In summary, there seems to be no consensus on the value of θ for domestic trade, but previous studies tend to choose values between 4 and 8. We take $\theta = 5$ following Baum-Snow et al. (2018).

Input share of pollutant emission (δ) Little is known about the value of δ , the input share of pollutant emission which is also the inverse efficiency of abatement technology. To the best of our knowledge, Shapiro and Walker (2018) is the only study that provides an estimate for δ consistently with a general equilibrium model with trade like ours. They estimate δ s for detailed U.S. manufacturing sub-sectors using factory level abatement investment data covering a long period of time (1990s to 2008). While their estimates of δ greatly vary across the sub-sectors, they report an average for the manufacturing sector as a whole is $\delta = 0.011$. Since estimating δ for China is difficult with the currently available data as explained below, we use this value for the simulation analysis.

Data on abatement expenditure of Chinese manufacturing firms is not available at prefecture-level granularity. Therefore, it is impossible to choose an estimation strategy similar to that of Shapiro and Walker (2018). Another possible way to estimate

δ for China is to use the ratio of emission levy revenue to manufacturing output, as equation (1.20), which is a way Shapiro and Walker (2018) actually avoid. If we assume that δ is constant across space, we can technically recover it only with nationwide total emission levy revenue and the value of industrial output. While official statistics of the emission levy revenue are available from the *China Environment Yearbook*, it should be noted that the levy revenue may cover only a fraction of the wide range of expenditure that the term $\zeta_i Z_{M,i}$ in (1.20) represents. In fact, the ratio of the total emission levy to industrial output in China is less than 0.00001. If the estimate of Shapiro and Walker (2018) for U.S. manufacturing firms is correct, this means that abatement efficiency of Chinese manufacturing firms is 100 times superior to that of the U.S. firms, which is simply incredible.³⁰ According to a dataset for international comparison by the OECD (https://stats.oecd.org/Index.aspx?DataSetCode=ENV_ENVPOLICY), the ratio of environment related tax to industrial output is around 1 percent which can also support our choice of δ , even if the assumptions leading to this number are not clear.

Elasticity of substitution among three category of goods (ρ) There is only limited guidance in the literature on the appropriate value of ρ , the elasticity of substitution among the three categories of goods. As pointed out by Faber and Gaubert (2019), ρ should be smaller than the elasticity of substitution between the varieties within the same category of goods. In our case, this means that $\rho \leq \theta + 1$ should be satisfied. We search for the value of ρ in this range such that the model derived consumption expenditure share of manufacturing goods at the national level is equal to the observed data. This exercise gives the value $\rho = 3.45$ that is used throughout the analyses in this paper.

30. The system of environmental control is complicated. In China, along with emission levies on designated pollutants, the government sets the targets for reducing the aggregate emissions of selected pollutants. For achieving the target, local governments in China uses variety of policy instruments. For example, local governments sometimes order polluting plants to shut down or relocate. Polluting firms implicitly pay substantial costs for lobbying (or even bribing officials as reported by Rooij (2006)) in order to avoid such sanctions. Therefore, it seems appropriate to assume there is more implicit expenditure than actually observed as emission levies that the manufacturing firms in China spend for realising the observed combination of emission and production.

labor supply elasticity (η^t) and disutility from pollution (ξ^t) We estimate the elasticity of labor supply of each type of worker (η^t) as well as the parameters of the welfare impact of pollution (ξ^t) that are consistent with our model. Equation (1.31) is estimated to recover η^t and ξ^t consistent with the model. The existing literature provides guidance on the identification concerns and possible solutions.³¹ As discussed in Faber and Gaubert (2019), OLS estimation of labor supply elasticity, the coefficient on the real wage term, or aggregate real factor income $\ln \widetilde{W}_n^t$ in our case, can be downward biased due to unobserved confounding factors in labor demand and supply. In addition, estimates for ξ^t can also be biased because there is the possibility of omitted variable bias and reverse causality. For example, as the same as the estimate of the real wage term, unobserved labor demand shock can be either positively or negatively correlated with pollution, D_n , because that can cause more emission as well as strengthen regulations through the local government’s endogenous response (1.28). Furthermore, local amenities consisting B_n^t , such as climate characteristics, may simultaneously affect D_n and L_n^t .

To address these identification concerns, we use the set of instruments and controls that Baum-Snow et al. (2018) use to estimate the causal impact of 2010 road infrastructure on prefecture’s demographic and economic outcomes. They instrument 2010 road infrastructure measures by those of 1962. More specifically, in their main specification, their variables of interests are the log efficiency road unit and the log time to nearest international port, both reflecting infrastructure quality in 2010. The efficiency road unit is the length of road infrastructure weighted by average travel speed within a 450km radius of each prefecture minus the weighed road length within own prefecture. The time to the nearest international port is the shortest travel time to the closest international port out of nine candidates. They instruments these 2010 infrastructure variables by their 1962 counterparts, arguing that these instruments are exogenous to 2010 demographic and economic variables conditional on several historical and geophysical controls.³² Based

31. See Faber and Gaubert (2019), Fajgelbaum et al. (2019), and Fajgelbaum and Gaubert (2019).

32. Baum-Snow et al. (2018) justify that 1962 variables are exogenous to the contemporaneous shocks

on Baum-Snow et al. (2018)'s argument, we instrument $\ln \widetilde{W}_n^t$ and D_n by these 1962 variables and an exogenous climate variable. The rationale for instrumenting $\ln \widetilde{W}_n^t$ is straightforward. 1962 infrastructure variables predict current employment, wages, and industrial composition well but they are not correlated with unobservable contemporaneous productivity and amenity shocks. The unobserved shocks that simultaneously affect 1962 infrastructure placement and contemporaneous productivity are assumed to be eliminated by the set of historical and geographical controls. For pollution, we instrument this with the SO₂ emission from power plants located in the upper-wind direction of the city. The constructed instruments are similar to the IV2 of Freeman et al. (2017). Instead of coal consumption by upper-wind thermal electricity plant, we use the emission of SO₂ by power plants, due to data availability. Our IV is the sum of SO₂ emission from power plants within the 90 degree-sector of 500 km radius from the city, minus the emissions within own city.

The first stage results are shown in Table 1.A.3. The three variables of interest, the level of PM_{2.5} concentration, the log of \widetilde{W}_n^t for $t = \{k, u\}$ are regressed on the same set of the instruments and control variables. The three variables on the top of the table are the instruments.³³ Table 1.A.4 shows the second stage results. The first two columns are for the OLS estimates, while the column (3) and (4) show the results of IV estimations. As expected, the OLS estimates on the real wage terms ($\ln \widetilde{W}_n^t$) are downward biased compared to the IV estimates. The implied values of η^t from our IV estimates are $\eta^k = 3.52$ and $\eta^u = 1.16$, respectively. Interestingly, our IV estimates on PM_{2.5} are

determining 2010 demographic and economic outcomes based on the historical context of China's road development during the pre-economic reform period. In 1962 when China was under the socialist planning economy before economic liberalisation in the 1980s, the roads were primarily designed to move agricultural goods between villages using non-motorised vehicles. Therefore, the road development then did not concern the production and logistics for the manufacturing goods using late 20th century technologies. At the same time, despite not being designed for the motorised vehicles, the existence of 1962 roads provided the right-of-the-way for the alignment of the highways whose planning and construction started in 1990s.

33. Given that the 1962 log road efficiency unit is not significant for $\ln \widetilde{W}_n^k$ and $\ln \widetilde{W}_n^u$ as shown in Table 1.A.3, we also estimate the version without this instrumental variable. The second stage results are qualitatively the same.

very close to the estimates of the impact of PM_{2.5} level on the migration of skilled and unskilled labor by Chen, Oliva, and Zhang (2017) which are -0.0093 for skilled labor and -0.0047 for unskilled labor. Given these estimates, the implied values are $\xi^k = 0.013$ and $\xi^u = 0.0095$.

Coefficient of policy elasticity to GDP (ω) As in (1.28), the elasticity of pollution control policy with respect to GDP is $1 - \omega$. Taking the log of (1.28) and noting that $\zeta_n = \delta \frac{Y_{M,n}}{Z_{M,n}}$, we have

$$\ln \zeta_n = \beta_0 + (1 - \omega) \ln G_n + \ln \xi_n^g \quad (\text{A.58})$$

We estimate ω by OLS estimation of (A.58). Endogeneity concerns come with any omitted variables that are simultaneously related to ζ_n and G_n . Specifically, the model implies two reverse causalities that flow from ζ_n to G_n . First, the lowered pollution that is induced by higher ζ_n will increase labor supply from the migration equation (1.30), then positively affect G_n . In contrast, high ζ_n increases the production costs in the manufacturing sector (1.10) and may contract total value added G_n . To address these concerns, we instrument $\ln G_n$ by the historical market access that is proxied by the 1962 road efficiency unit and the 1962 time to nearest port. Additionally, to control for any shocks that might be simultaneously correlated with 1962 infrastructure variables and $\ln \xi_n^g$, we include a Province capital dummy, an environmental priority city dummy, the historical level of pollution that is proxied by the level of PM_{2.5} annual average concentration in 1999, the log of the distance to coast, and four variables that capture 1982 demography, as shown in Table 1.A.2. Provincial capital has specific political and economic importance and it is reasonable to assume that their status as Provincial capitals simultaneously affected the 1962 infrastructure placement as well as the unobserved shocks to the current environmental regulations captured in ξ^g . In our sample cities, there are 105 environmental priority cities whose environmental performance are reported in the annual *China Environment Yearbook*. Again, priority cities should have a specific

shock in ξ^g which might be also correlated with the 1962 infrastructure variables if economic development after 1962 affected the probability of them being chosen as a priority city.

The results are shown in Table 1.A.2. Our IV estimate on the log of GDP is 0.544 which implies that $\omega = 0.466$.

Table 1.A.2: Estimation of the Environmental Regulation Equation

	<i>OLS</i>	<i>IV</i>
	(1)	(2)
log of GDP, $[1 - \omega]$	0.645*** (0.096)	0.544** (0.270)
Provincial Capital	-0.110 (0.170)	-0.073 (0.207)
Priority City	-0.243*** (0.093)	-0.207 (0.132)
log of PM _{2.5} , 1999	0.103 (0.100)	0.129 (0.125)
Log km to coast	-0.167*** (0.029)	-0.182*** (0.052)
Log prefecture population, 1982	-0.468*** (0.137)	-0.384 (0.245)
Log city centre population, 1982	-0.099 (0.085)	-0.119 (0.099)
Share of population with high school, 1982	0.174 (0.366)	0.249 (0.395)
Share of population in manufacturing, 1982	0.507 (0.501)	0.811 (0.852)
Constant	4.043*** (1.064)	4.591** (1.881)
Observations	283	283
R ²	0.523	0.520
Adjusted R ²	0.507	0.504

Source: Author

Note: Heteroskedasticity robust standard errors are given in the parentheses. In the IV estimation, the log of GDP is instrumented by log 1962 road efficiency unit and log 1962 time to nearest port as in Baum-Snow et al. (2018). *p<0.1; **p<0.05; ***p<0.01

Elasticity of PM_{2.5} to emission (κ) The relationship is specified as in (1.26). We estimate the logarithm of the equation by proxying D_n using the aerial concentration of PM_{2.5}($\mu g/cm^3$) and Z_n using the total emission of SO₂, NO_x, and the primary PM_{2.5} emissions from both production and consumption sources (Z_M and Z_R). In turn, κ is estimated by OLS and the value obtained is $\kappa = 0.16$. The exponential of the constant term plus the residual recovers ξ_n^g .

Table 1.A.3: First Stage Estimates for the Labor Supply Equation

	<i>Dependent variable:</i>		
	PM _{2.5}	ln \widetilde{W}^k	ln \widetilde{W}^u
	(1)	(2)	(3)
Log road efficiency unit, 1962	7.514*** (2.363)	-0.057 (0.141)	-0.115 (0.126)
Log time to nearest port, 1962	-2.715*** (1.002)	-0.292*** (0.060)	-0.222*** (0.053)
Log power plant emission in upwind	0.329** (0.141)	-0.003 (0.008)	-0.002 (0.008)
Provincial Capital	4.586** (2.253)	0.615*** (0.135)	0.452*** (0.120)
Log prefecture population, 1982	6.823*** (1.899)	0.575*** (0.114)	0.644*** (0.101)
Log city centre population, 1982	-2.048 (1.493)	-0.105 (0.089)	-0.131 (0.080)
Share prefecture population with high school, 1982	1.253 (5.420)	0.833** (0.324)	0.750*** (0.289)
Share prefecture population in manufacturing, 1982	-22.326** (8.841)	3.175*** (0.529)	2.273*** (0.471)
Log prefecture area	-9.017*** (1.431)	0.117 (0.086)	0.080 (0.076)
Log prefecture area	0.520 (0.783)	-0.085* (0.047)	-0.062 (0.042)
Log km to coast	1.407*** (0.495)	-0.016 (0.030)	-0.013 (0.026)
West Region	-0.283 (1.668)	-0.185* (0.100)	-0.179** (0.089)
East Region	2.973* (1.653)	0.070 (0.099)	0.071 (0.088)
Log city centre roughness	-3.233*** (0.591)	-0.002 (0.035)	-0.016 (0.031)
Log prefecture roughness	-2.298*** (0.496)	-0.035 (0.030)	-0.041 (0.026)
Log precipitation	-0.007*** (0.002)	-0.0004*** (0.0001)	-0.0003*** (0.0001)
Log mean temperature	0.001 (0.118)	0.032*** (0.007)	0.026*** (0.006)
Constant	15.944 (37.515)	-0.832 (2.243)	0.874 (1.998)
Observations	283	283	283
R ²	0.772	0.742	0.740
Adjusted R ²	0.757	0.726	0.723
Residual Std. Error (df = 265)	8.072	0.483	0.430
F Statistic (df = 17; 265)	52.646***	44.874***	44.285***

Source: Author

Note: Heteroskedasticity robust standard errors are in the parentheses. *p<0.1; **p<0.05; ***p<0.01

Table 1.A.4: Estimating the Labor Supply Equation

	<i>Dependent variable:</i>			
	$\ln L_n^k$	$\ln L_n^u$	$\ln L_n^k$	$\ln L_n^u$
	<i>OLS</i>	<i>OLS</i>	<i>IV</i>	<i>IV</i>
	(1)	(2)	(3)	(4)
PM _{2.5} , $[-\xi^t \eta^t / (\eta^t + 1)]$	0.002 (0.002)	-0.001 (0.002)	-0.010** (0.004)	-0.005 (0.003)
$\ln \widetilde{W}^k$, $[\eta^k / (\eta^k + 1)]$	0.706*** (0.075)		0.779*** (0.141)	
$\ln \widetilde{W}^u$, $[\eta^u / (\eta^u + 1)]$		0.521*** (0.133)		0.537*** (0.138)
Provincial capital	0.242*** (0.055)	-0.102 (0.063)	0.258*** (0.084)	-0.092 (0.063)
Log prefecture population, 1982	0.370*** (0.069)	0.551*** (0.100)	0.458*** (0.096)	0.580*** (0.100)
Log city centre population, 1982	-0.113*** (0.041)	-0.039 (0.036)	-0.142*** (0.045)	-0.047 (0.036)
Share prefecture population, with high school, 1982	0.332** (0.158)	-0.044 (0.172)	0.339* (0.181)	-0.036 (0.170)
Share prefecture population, in manufacturing, 1982	0.294 (0.332)	-1.091*** (0.386)	-0.415 (0.590)	-1.265*** (0.424)
Log prefecture area	0.092** (0.042)	0.004 (0.042)	-0.060 (0.066)	-0.040 (0.055)
Log city centre area	0.029 (0.022)	0.011 (0.021)	0.042 (0.026)	0.014 (0.021)
Log km to coast	-0.014 (0.013)	-0.007 (0.014)	0.018 (0.021)	0.002 (0.014)
West Region	-0.134*** (0.049)	0.096* (0.055)	-0.139** (0.062)	0.093* (0.056)
East Region	-0.210*** (0.039)	-0.052 (0.039)	-0.169*** (0.047)	-0.038 (0.040)
Log city centre roughness	0.031 (0.027)	0.042 (0.039)	-0.010 (0.030)	0.031 (0.038)
Log prefecture roughness	0.022 (0.014)	-0.013 (0.018)	-0.005 (0.020)	-0.021 (0.021)
Log precipitation	-0.0001*** (0.00004)	-0.0001 (0.00005)	-0.0002*** (0.0001)	-0.0001* (0.0001)
Log mean temperature	0.006* (0.003)	0.005 (0.003)	0.004 (0.004)	0.005 (0.003)
Constant	-3.062*** (0.863)	-1.473* (0.817)	-2.324** (0.981)	-1.284 (0.824)
Observations	283	283	283	283
R ²	0.923	0.885	0.907	0.883
Adjusted R ²	0.918	0.878	0.902	0.876
Residual Std. Error (df = 266)	0.237	0.248	0.260	0.249
F Statistic (df = 16; 266)	199.438***	127.470***		

Source: Author

Note: Heteroskedasticity robust standard errors are in the parentheses. *p<0.1; **p<0.05; ***p<0.01

Table 1.A.5: Imputed Skilled Share in the Labor Income Across Sectors

Detailed Sector	Categorization	Average Wage (Yuan)	Employment (10,000 people)	Imputed Skilled Share ($\frac{\gamma_j^k}{\gamma_j^k + \gamma_j^u}$)
Agriculture, Forestry, Animal Husbandry and Fishery	F	16717	375.7	0.000
Mining	M	44196	562.0	0.706
Manufacturing	M	30916	3637.2	0.366
Production and Distribution of Electricity etc.	M	47309	310.5	0.759
Construction	M	27529	1267.5	0.226
Traffic, Transport, Storage and Post	S	40466	631.1	0.633
Information Transmission, Computer Services	S	64436	185.8	0.956
Wholesale and Retail Trades	S	33635	535.1	0.457
Hotels and Catering Services	S	23382	209.2	0.000
Financial Intermediation	S	70146	470.1	1.000
Real Estate	S	35870	211.6	0.522
Leasing and Business Services	S	39566	310.1	0.614
Scientific Research, Technical Service	S	56376	292.3	0.878
Management of Water Conservancy, Environment	S	25544	218.9	0.127
Services to Households and Other Services	S	28206	60.2	0.257
Education	S	38968	1581.8	0.600
Health, Social Security and Social Welfare	S	40232	632.5	0.628
Culture, Sports and Entertainment	S	41428	131.4	0.653
Public Management and Social Organization	S	38242	1428.5	0.583

Source: Author

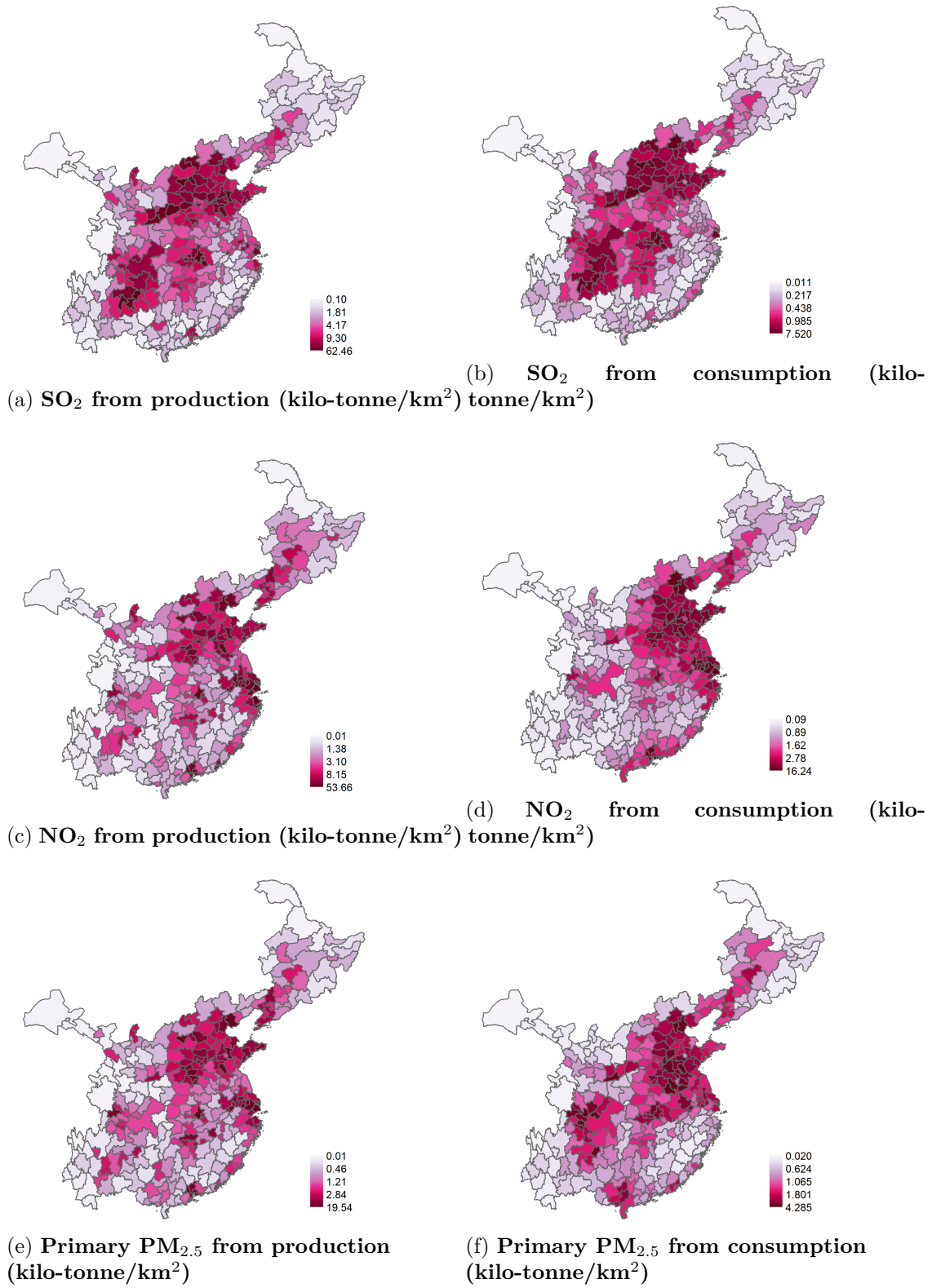
Based on China Statistical Yearbook 2011 (Table E0405 and E0415)

Categorization: F = Agriculture, M = Manufacture, S = Traded Services, H = Housing Services.

Agriculture assumed to employ 100% unskilled labor. We assume hotel and catering sector is the entry point sector for rural agricultural unskilled worker whose wage rate is at the indifferent level compared with agricultural wages taking urban living cost into account.

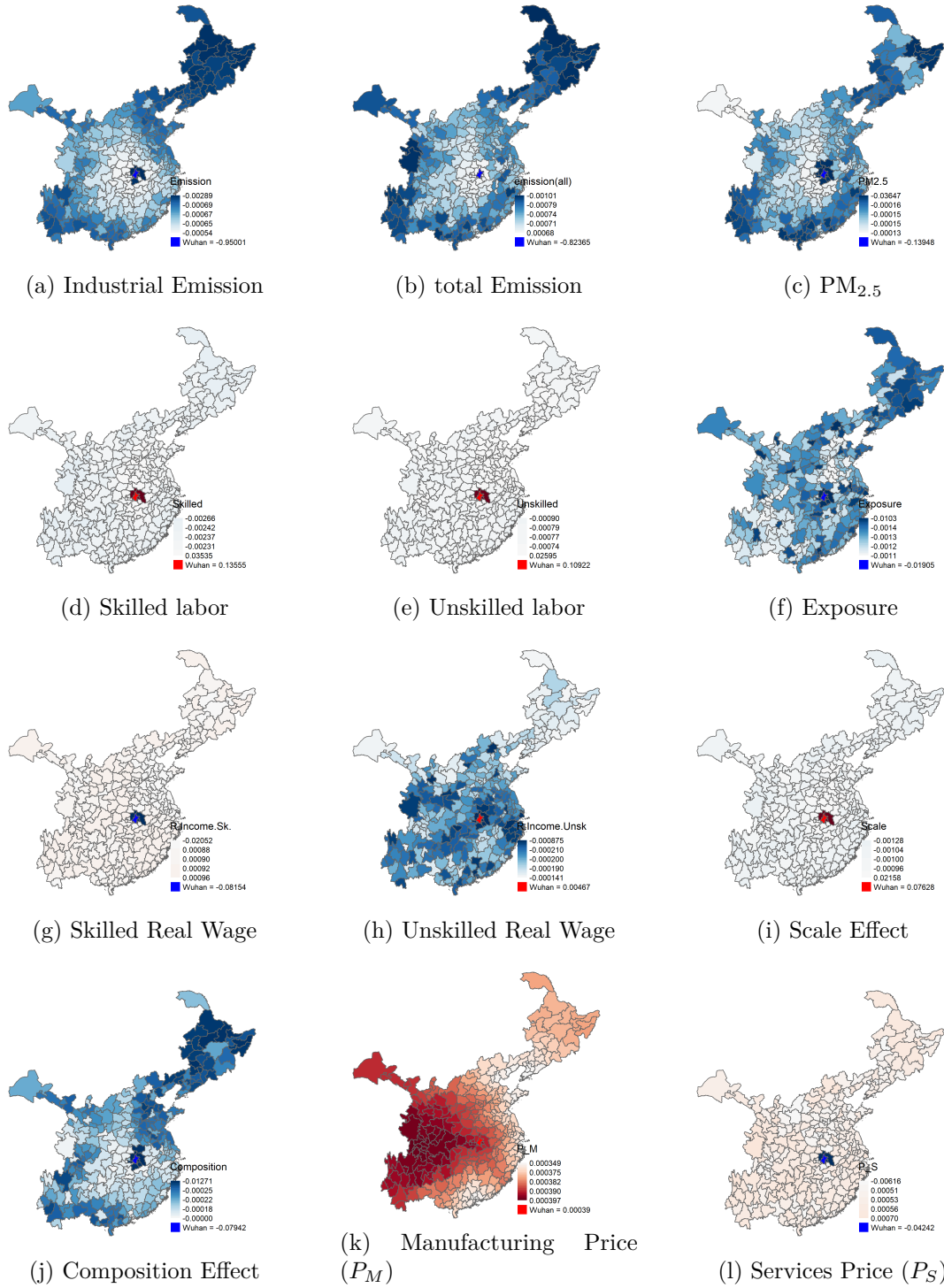
We assume that $w^u = w_{agriculture}$ and $w^k = w_{finance}$, where w^u is unskilled wage and w^k is skilled wage, respectively. Then, for given sector wage, w_j , the skilled workers share in labor income in the sector is imputed by $\frac{\gamma_j^k}{\gamma_j^k + \gamma_j^u} = \frac{w^k(w_j - w^u)}{w_j(w^k - w^u)}$.

Figure 1.A.3: Emission of Pollutants from Production and Consumption Sources



Source: Author

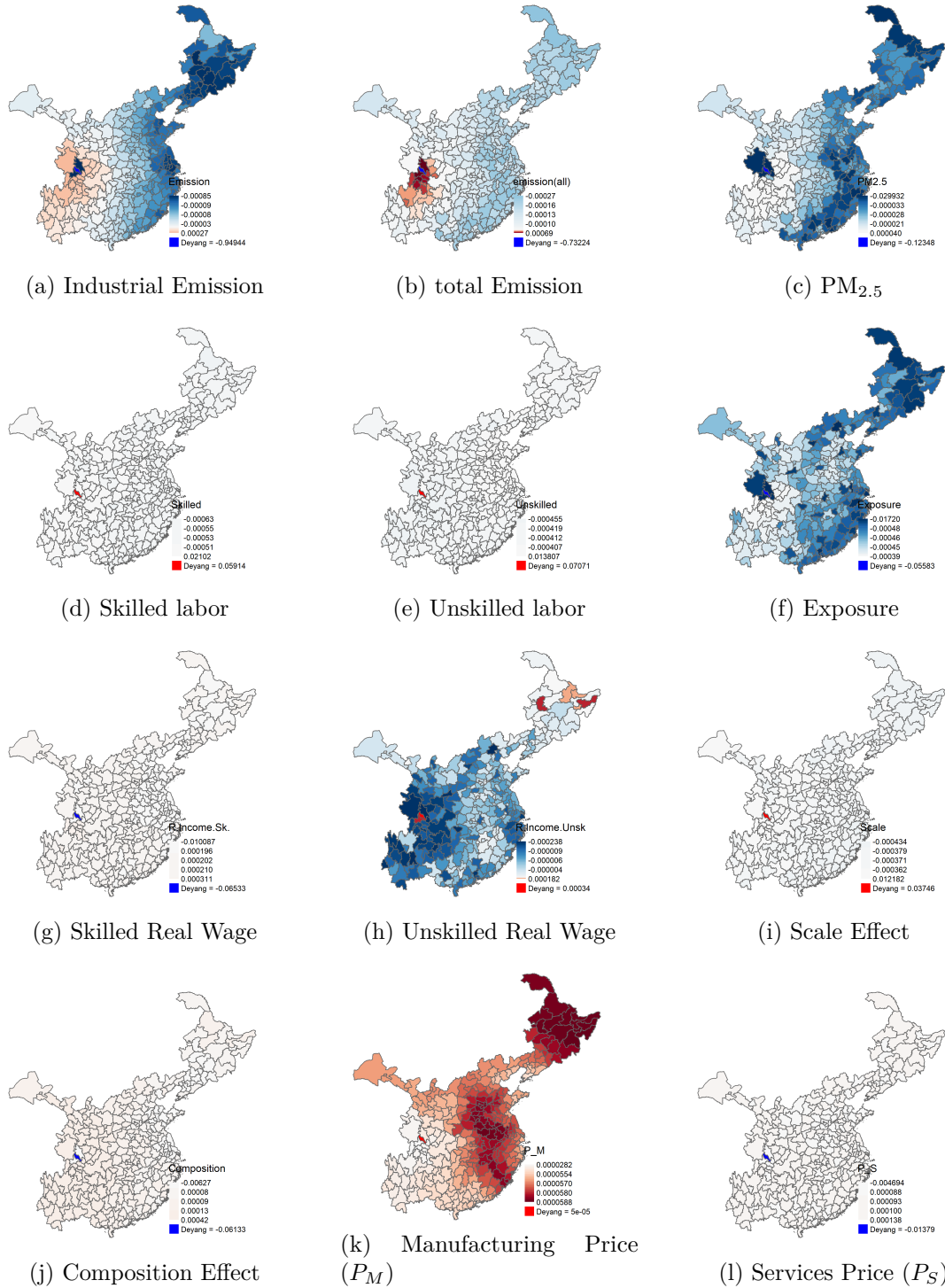
Figure 1.A.4: Illustration of the Spatial Effect of Policy Shock from Wuhan



Source: Author

Note: The maps depict elasticities computed against a 10 percent change in the regulation parameter of Wuhan (ξ_{Wuhan}^g). The red color indicates the positive computed elasticities, while the blues indicate negative ones. The midpoint of the colour palette is set to zero.

Figure 1.A.5: Illustration of the Spatial Effect of Policy Shock from Deyang



Source: Author

Note: The maps depict elasticities computed against a 10 percent change in the regulation parameter of Deyang (ξ_{Deyang}^g). The red color indicates the positive computed elasticities, while the blues indicate negative ones. The midpoint of the colour palette is set to zero.

Chapter 2

Gender Heterogeneous Effects of Urban Public Transportation on Employment: Evidence from the Delhi Metro

*This chapter is a joint work with Mai Seki*¹

Abstract

The Delhi Metro is one of the leading examples of a recent urban mass transit infrastructure project in a developing country where women have traditionally suffered from constrained mobility. In this paper, we analyze the effects of the Delhi Metro on the work participation rate of women and men, using a three-period (1991, 2001, and 2011) panel data of township-level zones within the city of Delhi. While the data has limitations in understanding the characteristics of individual residents in detail, we employ a difference-in-differences estimation controlling for a location fixed-effect, with a parallel trend test. The results suggest that the proximity to the Delhi Metro stations significantly increases the female work participation rate (WPR), whereas its effect on the male WPR is ambiguous with the potential to have an opposite sign. While there are number of potential mechanisms that can deliver this result, we develop a theoretical urban commuting model and argue that a larger reduction in the commuting cost for females (by offering a safer commuting mode of transportation, for example) can generate the quantified patterns of the effects on the WPR. Overall, our results relate to the literature on the quantification of the contribution of urban transport infrastructure towards inclusive growth and poverty reduction.

1. The earlier version of this paper appears as JICA Research Institute Working Paper No.207.

2.1 Introduction

In the past seventy years, the share of urban dwellers has steadily increased in developing countries, and this trend will continue in the coming decades (United Nations 2019). India is one of the main contributors to the global urban population growth, which is projected to add 416 million urban residents by 2050. To mitigate traffic congestion accompanied by the continuing urbanization, many countries including India are investing in urban public transportation systems. While the overall mobility of residents improves and city production capacities expand, gender inequality of mobility in urban areas remains an unresolved issue (Peters 2013; Uteng 2011; Hyodo et al. 2005). According to previous studies, women in the urban areas of the developing countries go out of home less frequently, and depend more on public transportation than men. The provision of safe and accessible public transportation could potentially improve female mobility, a necessary condition for their further active participation in the economy.

In fact, a gender mainstreaming in the infrastructure projects of developing countries has gained attention from policy makers over the past decade (Asian Development Bank 2013; African Development Bank Group 2009; UN Women 2014; World Bank 2010). However, there is still only a limited amount of research quantifying the development impact, especially on how women and men are differentially affected by urban transport development.² There are studies that have discussed gender heterogeneity in commuting time to work and its impact on labor supply (Gutiérrez-i-Puigarnau and Ommeren 2010; Gimenez-nadal and Molina 2014; Gimenez-Nadal and Molina 2016; Zax 1991; Black, Kolesnikova, and Taylor 2014); however, they do not necessarily focus on public transportations in a given country context, except the ones by Kawabata and Abe (2018) and Gaduh, Gracner, and Rothenberg (2018). Kawabata and Abe (2018) analyze the

2. There is a large literature on the effect of subways on employment density in the developed countries such as that by Redding and Turner (2015). However, very few impact evaluations of urban transportation exist in the developing countries. Majority features rural roads and some major studies discuss inter-city highways or railroads (Seki, 2016).

commuting and labor supply patterns of married couples, resident in the greater Tokyo metropolitan area using GIS. Gaduh, Gracner, and Rothenberg (2018) estimate an equilibrium model of commuting choices with endogenous commuting time to assess the impact of counterfactual transportation policies, using the data collected for the detailed urban transport plannings in Jakarta before and after the Bus Rapid Transit (BRT) system was commissioned. Each of these studies on gender-heterogeneous commuting time suggest the importance of examining the heterogeneous impact of public transportation on employment by gender, rather than simply an overall effect. More closely related studies have documented the correlations between the access to transportation and labor market outcomes such as income or employment in developing countries (Hyodo et al. 2005; Goel and Tiwari 2016; Glick 1999). These studies use cross-sectional data, so we decide to further extend this line of research by utilizing panel data. A similar line of research using panel data from Lima, Peru on BRT and light rail system is summarized in a working paper by Martínez et al. (2018). But the most relevant analysis, which is ongoing, can be found in the field-experiments being conducted in Lahore, Pakistan for assessing the impact of providing women-only-wagons (a safety measure) to feed into a BRT system on female employment (Majid, Malik, and Vyborny 2018).³

In this paper, we analyze the effects of the Delhi Metro, one of the largest mass rapid transit systems in the current world that has been developed since the early 2000s, on the work participation of women and men, to provide quantitative evidence on whether a high quality urban public transportation system contributes to an improvement in female economic participation. We focus on the Delhi Metro for three reasons. Firstly, Delhi is one of the cities in the world fighting against severe concerns for female safety in public spaces and transportations (Jogori and UN Women 2011; Safetipin 2016). According to a Thomson Reuters Foundation Annual Poll in 2017, “New Delhi, the world’s second most

3. Majid, Malik, and Vyborny (2018) reports the effects of BRT on congestion, and a progress of the RCT based impact analysis of safe commuting for female is available in the J-PAL’s website: <https://www.povertyactionlab.org/evaluation/impact-public-transport-labor-market-outcomes-pakistan>

populous city with an estimated 26.5 million people, was ranked as the worst megacity for sexual violence and harassment of women alongside Brazil's Sao Paulo.”⁴ Also, an UN Women supported survey in Delhi shows that 95 per cent of women and girls feel unsafe in public spaces in their 2013 report. Even after the introduction of the Delhi Metro, the situation is still severe but it was even worse before. Recent studies reveal that safety matters to females that have choices in their lives. For example, Borker (2017) finds that safety of school-commuting route has a direct impact on the university choice among the female students in the city of Delhi. In her study, she finds that the willingness to pay for women for a school-commuting route that is one standard deviation safer is an additional 18,800 rupees (290 USD) per year, relative to men, which is an amount equal to double the average annual college tuition. Secondly, India faces challenges over female economic participation and empowerment. Female non-agricultural labor participation has been historically stagnant in South Asia, and there has even been a declining trend in India at the national level (Klasen and Pieters 2015; Andres et al. 2017). For the city of Delhi, while the labor participation of women has not declined, its growth has been stagnating compared to that of men. Lastly, Delhi Metro is one of the best cases to analyze the impact of high quality urban transport infrastructure in developing countries, given its reputations for high service standards. This reputation is not only for its stability and convenience, but also for the safety and comfortable travel of its female passengers. Based on the interviews with users, the introduction of Delhi Metro is shown to have drastically changed transportation choice for women, due to the high standard of safety in the Metro system (Takaki and Hayashi 2012; Onishi 2017). Motivated by these factors, the existence of the female mobility issue, concerns for female labor supply, and a suitable treatment, we hypothesize the introduction of a safe mode of public transportation in Delhi would have had a non-negligible effect on the supply of female labor (the commuting-safety hypothesis), along with other factors, such as residential

4. <https://poll2017.trust.org/>

relocation, compositional change in labour demand and/or family-level joint labor supply decisions. In this study, we try to quantify the gender-heterogeneous effects of the Delhi Metro system on work-participation rates as the first step in our analysis, solely due to the data limitation.

While our aim has a great policy relevance, it is a difficult research question to obtain a rigorous quantitative answer on because of severe data limitations. First, the standard identification concerns from the non-random location of physical infrastructure are inevitably applicable. This fundamental identification challenge cannot be resolved even if there will be more detailed data available except when there is a suitable natural experiment. Moreover, other impeding facts, like the lack of appropriate individual-level data that covers the period before and after the commission of the Metro as well as the fact that a long time has past since the initial commission of the Metro in 2002, keep us away from making a rigorous causal arguments in an ideal empirical setting.

Our strategy is therefore to use the best-available data and carefully argue its empirical limitations. More specifically, we use the Primary Census Abstract (PCA) which provides various tabulations from the Population Census data for finely disaggregated geographical areas within the National Capital Territory (NCT) of Delhi. We construct a panel of PCA zones for three consecutive census years, 1991, 2001, and 2011. As the measure of intervention, we calculate an accessibility from each PCA zone to the nearest metro station, using maps of PCA zones and the alignment of the Delhi Metro. With the calculated treatment variable, proximity to the Delhi metro, we conduct a difference-in-differences (DID) analysis, controlling for location fixed effect (time-invariant unobserved heterogeneity), to assess whether the proximity to metro stations contributes to the area's growth in female and male participation in non-agricultural economic activities. Since we construct these panel data at the level of the PCA zone-level geographical unit for three rounds (1991, 2001, and 2011) with two pre-treatment periods, we can examine the parallel trend hypothesis which is the prerequisite for DID, by including the "lead"

term in the estimation equation.

We find that the effect of the proximity to the Delhi Metro on female work participation rate is positive, and that the same does not seem to hold for men (rather the opposite). This is suggestive evidence that there could be a gender-heterogeneous impact from the Delhi Metro system on the decision of economic participation. In other words, women might respond more positively than men to the proximity to the Delhi Metro stations in deciding whether or not to work.

To understand these empirical findings, we develop a spatial model of urban transportation and commuting. We explicitly model the commuting choice of female and male urban residents who face different commuting costs (fees and travel time plus safety-related welfare cost). We study the model's comparative statics to see how a hypothetical Metro project would affect female and male work participation rates across different zones in a city. We find that if the Metro reduces female commuting costs more than men's, female WPR increases in zones closer to the Metro despite male WPR exhibiting a more ambiguous (or opposite) relationship. This theoretical example shows consistent patterns with our empirical results.

Our empirical findings have a limitation, however, in that the rigorous causal identification of the impact or investigation of a mechanism is affected by the nature and extent of the available data. For example, the gender wage gap or gender-heterogeneous comparative advantage in specific skills may result in higher demand for female workers rather than male workers near the metro. However, we do not have gender-specific wage data or skill-level employment information by gender at such a fine geographical unit, so these hypotheses are currently unable to be separated from the commuting-safety hypothesis. Nevertheless, our study is one of the first attempts to quantitatively measure the gendered implication of a large scale urban public transport development in the context of megacities in developing countries.

The rest of the paper is organized as follows. In Section 2.2, we briefly go over the

background of the Delhi Metro project. Section 2.3 describes the data and Section 2.4 discusses empirical specifications. Section 2.5 reports the results. In Section 2.6, we develop a spatial urban model that shows that the commuting-safety hypothesis has an equilibrium that is consistent with our empirical findings. Section 2.7 discusses the limitation of our method and potential directions for future research.

2.2 Background of Delhi Metro

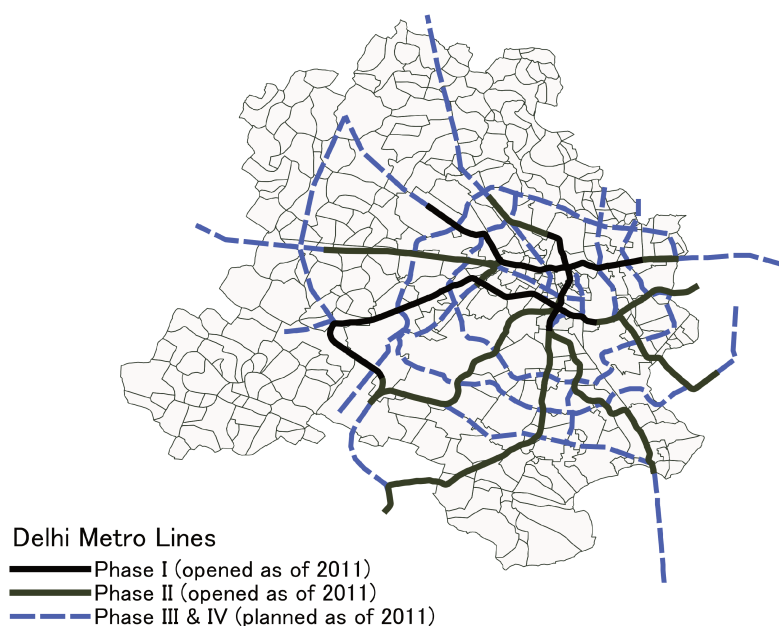
As the country's third urban mass rapid transit system (MRT) and the first of its kind in the capital city, the Delhi metro project has been developed over the past seventeen years. The first phase of Delhi Metro project consisted of the 58 stations and lines covering 65km and commissioned during 2002-2006. Following the Phase I, Phase II built 85 stations and lines covering 125km, which were commissioned during 2008-2011. As of the end of 2011, Phase III and Phase IV were in the planning stage. The geographical alignments of the Delhi Metro lines in the different phases are shown in Figure 2.1.

The novelty of the Delhi Metro project is the fact that it focused on the safety and inclusiveness from its planning stage. Adaptation of women-only car, barrier-free design, rubbish control for keeping train clean, and security check at the entry have contributed towards providing safe public mass urban transportation for the citizens of Delhi. Overall, the Delhi Metro has gained a reputation for high standard of facility and operation that ensures safety and comfort for female passengers (Takaki and Hayashi 2012; Onishi 2017).

Prior to the introduction of the Delhi Metro, safety concerns in the public transportation system had been severe for women in Delhi (Jogori and UN Women 2011; Safetipin 2016). While affordable and reliable urban transportation plays a vital role in engaging in either income-generating activities and schooling in optimal locations, or other activities such as household chores, family visits, or leisure, it is not difficult to hypothesize that the limitation of safe modes of transportation was taxing for women in trying to get

access to these social and economic opportunities. Given such a context, the introduction of a relatively safe public transportation system has had a potential impact to drastically change women's behavior in Delhi.

Figure 2.1: Delhi Metro Alignment



Source: The authors construct this map based on GIS maps procured from the following GIS map vendors. Base-map with zone boundaries: Zenrin Co., Ltd. Metro Alignment: Compare Infobase Ltd.

2.3 Data

We use the Primary Census Abstract (PCA) of India's Population Census in 1991, 2001, and 2011, published by the Office of the Registrar General and Census Commissioner, Ministry of Home Affairs. The PCA provides aggregates of population census enumeration at the level of a small local administrative unit and/or a ward of constituency. In 1991, entire area of the NCT of Delhi was divided into towns, villages, and charges.⁵ Since the geographical boundaries of administrative units change overtime, we interpolate the data

⁵ Charge is an electorate unit which disintegrated the central part of Delhi in the 1991 Census. In the 1991 Census, disaggregated data for the MCD (Municipal Corporation of Delhi), consisting the central part of the NCT of Delhi, were reported at the level of Charge.

of 2001 and 2011 based on area size so that the boundary is consistent with that of 1991. We carry out spatial interpolation as follows. To simplify the explanation, we consider the case of two period, period 0 and period 1. Suppose there are a total of J_0 zones in the period 0, indexed as $j_0 = 1, \dots, J_0$. In period 1, suppose there are a total of K_1 zones indexed as $k_1 = 1, \dots, K_1$. The boundaries of zones are not in general consistent between the two periods, which means that a zone in period 0 intersects with multiple zones in period 1. Consider a particular zone j_0 of the period 0 which intersects with multiple period 1 zones. Let $S_{j_0}^1$ denote the set of these period 1 zones intersecting with j_0 . For each of these period 1 zones $k_1 \in S_{j_0}^1$, the area can be divided into a part intersecting with j_0 , denoted as $a_{k_1}^{j_0}$, and the remaining part, $a_{k_1}^{-j_0}$ which does not intersect with j_0 . Our spatial interpolation calculates the period 1 value of zone j_0 statistics by taking a weighted average of the statistics of the intersecting period 1 zones in $S_{j_0}^1$. More specifically, the interpolated value of variable x for zone j_0 in period 1 is given by:

$$\tilde{x}_{j_0}^1 = \sum_{k_1 \in S_{j_0}^1} \frac{a_{k_1}^{j_0}}{a_{k_1}^{j_0} + a_{k_1}^{-j_0}} x_{k_1} \quad (2.1)$$

This interpolation only applies to the variables in levels, such as population and the number of workers. For the variables in rates, we calculate them using the interpolated level variables. For example, a rate variable r which is defined as the ratio of two level variables x and y , or $r = \frac{y}{x}$, we obtain the period 1 interpolated value by $\tilde{r}_{j_0}^1 = \frac{\tilde{y}_{j_0}^1}{\tilde{x}_{j_0}^1}$. To check the robustness of the key results of this interpolation, we add the analyses using only those zones with consistent boundaries over time in Section 2.A.3 of the appendix.

To represent the economic participation of each gender group from the available statistics, we calculate “(non-agricultural) work participation rate” (“WPR” hereafter). The work participation rate is measured by the ratio of the number of “main workers” (works more than 6 months per year) in “other sectors” (other than cultivators, agricultural

labourers, or household industry workers)⁶ divided by the adult population⁷, for each gender. This indicator is different from the labor force participation rate (LFPR). While the denominator of LFPR is usually the working-age population above the age of 15, the denominator of WPR is the (imputed) adult population. Moreover, the numerator is also different because the definition of being a labor force includes those who are employed and unemployed, while that of work participation rate does not include those who are seeking for a job. These definitional differences make WPR either smaller or larger than LFPR, which is an empirical question because the difference in the denominators depends on how all-ages population minus two times the 0-6 population differs from the population over 15. In fact, the urban areas' LFPR during these periods has increased from 14.7 percent to 15.5 percent, while Delhi's WPR increased from 7.06 percent to 7.91 percent. Though the levels are different due to the definitional difference discussed above, the trend is consistent across the two measures.

Our treatment variable is the proximity of a zone (a town, a village, or a charge based on the 1991 administrative boundaries) to its nearest Metro Phase I and II stations. To represent the proximity to Metro stations, we measure the average distance using the coordinates of boundaries of towns and villages, as well as the alignment of the Metro stations. The average distance measure is constructed as follows: (i) A large number of equally spaced points (about 0.5 million) are generated and plotted over the entire area of Delhi; (ii) From each point, the nearest Metro station is searched and the distance from the point to the nearest Metro station is calculated. For a point k located within the boundary of zone i , this distance is denoted as $d_{k(i)}$; and (iii) The average distance

6. The "Other Sector": All workers, i.e., those who have been engaged in some economic activity during the last one year, but are not cultivators or agricultural labourers or in the Household Industry, are 'Other Workers(OW)'. The type of workers that come under this category of 'OW' include all government servants, municipal employees, teachers, factory workers, plantation workers, those engaged in trade, commerce, business, transport banking, mining, construction, political or social work, priests, entertainment artists, etc. In effect, all those workers other than cultivators or agricultural labourers or household industry workers, are "Other Workers".

7. Since the adult population is not given in PCA, we impute it by "total population - 2 x (population of 0 to 6 ages)", base on the population pyramid of India.

to the nearest Metro station(s) of the zone i , D_i , is then calculated as

$$D_i = \frac{\sum_{k(i)} d_{k(i)}}{N_i} \quad (2.2)$$

where, N_i is the number of points in zone i . D_i is smaller (i.e. the treatment intensity is larger) if i is closely located to Metro stations opened during 2002-2011, after the commission of the Phase I and II Metro network. Average distance measures to the the Metro Phase III and IV (only under the planning phase in 2011) are also calculated in the same manner to better define the comparison group that is more likely to share the similar unobserved characteristics regardless of the assigned treatment. In addition, we use the total population, the number of children, the number of households, the number of literal residents, and the number of residents scheduled caste (each by gender) from the PCA tables as control variables in the main analysis (the analysis without these controls are available in the robustness check).⁸

The descriptive statistics is shown in the Table 2.1. The upper table summarises our time-invariant variables, and the lower one is for time-variant variables. Our time-invariant variables are the distances to the Phase I and II metro stations that had commissioned by 2011, and those of the Phase III and IV which had not yet opened. On average, distance to the nearest Phase I or Phase II metro station is 5.2 km. Since the location of the planned metro stations, those of Phase III and IV, are more stretched out to the suburbs, the average distance to the Metro station is shorter 3.3km.

The time-variant variables are the outcome variables and control variables used in the estimation. Female WPR has been substantially lower than that of males throughout two decades since 1991. However, their average WPR has increased from 5.3 percent in 1991 to 7.9 percent in 2011, while men's WPR has grown from 40.4% to 45.3% during the same

8. Under the constitution of India, scheduled caste is defined as follows. <http://socialjustice.nic.in/writereaddata/UploadFile/Compendium-2016.pdf>. India's Census follows this definition. See http://censusindia.gov.in/Census_And_You/scheduled_castes_and_sceduled_tribes.aspx.

period. In contrast to the national level decline in labor force participation of women, the small increase of their WPR in Delhi might be partially due to the contribution of the Delhi Metro.

Figure 2.2 depicts kernel density estimates for the distribution of female and male WPRs for years 1991, 2001, and 2011. First, we can observe that the WPR distributions are distinctly different between the two gender groups in each year. That of females are clustered at lower rate of WPR with smaller variance, in contrast to that of males. Secondly, there is a subtle, but universal shifts of female WPR distribution towards the right. This suggests that the rate was improving almost everywhere in the distribution for women. Male WPR initially had a flat distribution in 1991 while it had evolved into a single peaked one in 2001. We do not observe a distinct shift in the distribution from 2001 to 2011.⁹

Figure 2.3 shows the spatial distribution of WPR of females and males for the two census years, 2001 and 2011. The dark-red zones are places with the highest WPR and the dark-blue zones are with the lowest WPR. The top two panels, 2.3a and 2.3b show women's WPR. The bottom two, 2.3c and 2.3d are those for men.

9. The T-test comparing the means of WPR across different years show that the mean WPR has significantly increased over time for both genders. We also conduct the Kormogolov-Smirnov test to statistically assess whether the WPR distribution changes across years. The results indicate that women's WPR has different distribution across three census years, while the men's distribution between 2001 and 2011 are not statistically distinguishable. The results are reported in Table 2.A.1 in the Appendix

Table 2.1: Summary Statistics

Time-invariant variables	(1) N	(2) mean	(3) sd
Dist. to Phae I or II Metro St. (km)	342	5.239	4.763
Dist. to Phae III or IV Metro St. (km, used for sub-sample selection)	342	3.274	3.145

Time-variant variables	1991			2001			2011		
	(1) N	(2) mean	(3) sd	(4) N	(5) mean	(6) sd	(7) N	(8) mean	(9) sd
Female WPR	332	0.0531	0.0599	342	0.0706	0.0369	342	0.0791	0.0371
Male WPR	332	0.404	0.131	342	0.439	0.0812	342	0.453	0.0674
Female to male WPR ratio	332	0.118	0.0993	342	0.161	0.0864	342	0.171	0.0644
Household Size	332	5.562	0.982	342	5.283	0.478	342	5.038	0.396
Children Share	332	0.184	0.0369	342	0.150	0.0235	342	0.124	0.0171
Female to male literacy ratio	332	0.698	0.163	342	0.817	0.0679	342	0.865	0.0485
Female to male SC ratio	327	1.007	0.155	342	1.042	0.0574	342	1.027	0.0362

Note: The upper table summarizes the time-invariant variables. The lower one is for the time-variant variables.

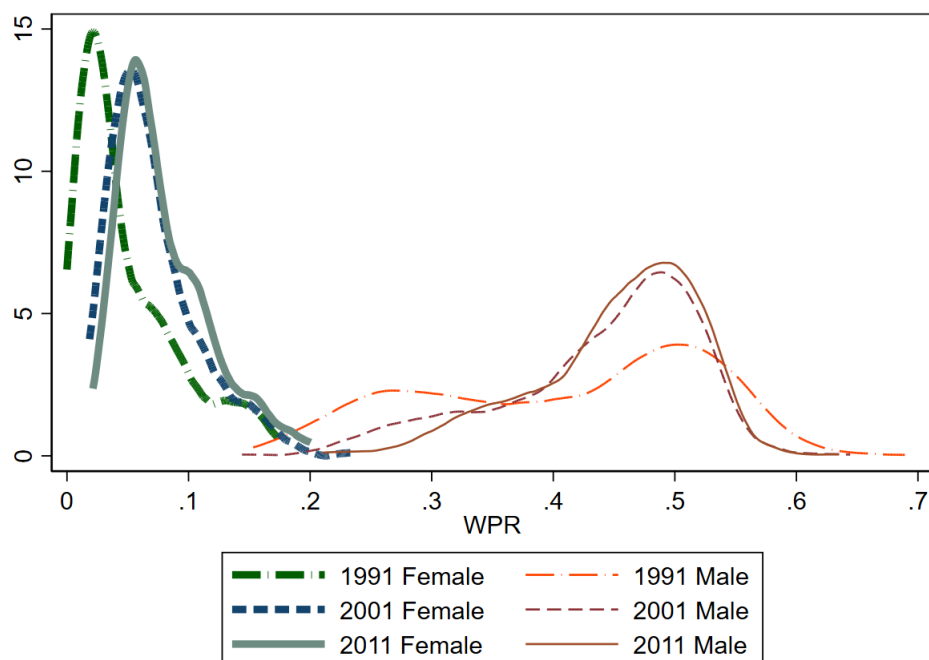
2.4 Empirical Strategy

As described in Section 2.3, our data is neither experimental nor quasi-experimental. The unit of observation is aggregated at the level of zones (town or ward), which divide the NCT (National Capital Territory) of Delhi into 342 geographical units. Using a panel data of zones in Delhi for 1991, 2001 and 2011, we employ the difference-in-difference (DID) method with two pre-treatment periods (1991, 2001). In estimation, we check for parallel pre-trend by exploiting these two pre-treatment periods. Specifically, we estimate the following equation:

$$Y_{it} = \beta_0 + \beta_{-1}(D_i \times Pre_t) + \beta(D_i \times Post_t) + \delta X_{it} + \theta_t + \alpha_i + \epsilon_{it}, \quad (2.3)$$

Where, Y_{it} is the outcome variable of zone i at year t ; D_i is the treatment variable, the log of average distance to nearest Phase I or II metro station, Pre_t is a time dummy

Figure 2.2: Kernel Distribution of Female and Male WPR, 2001 and 2011

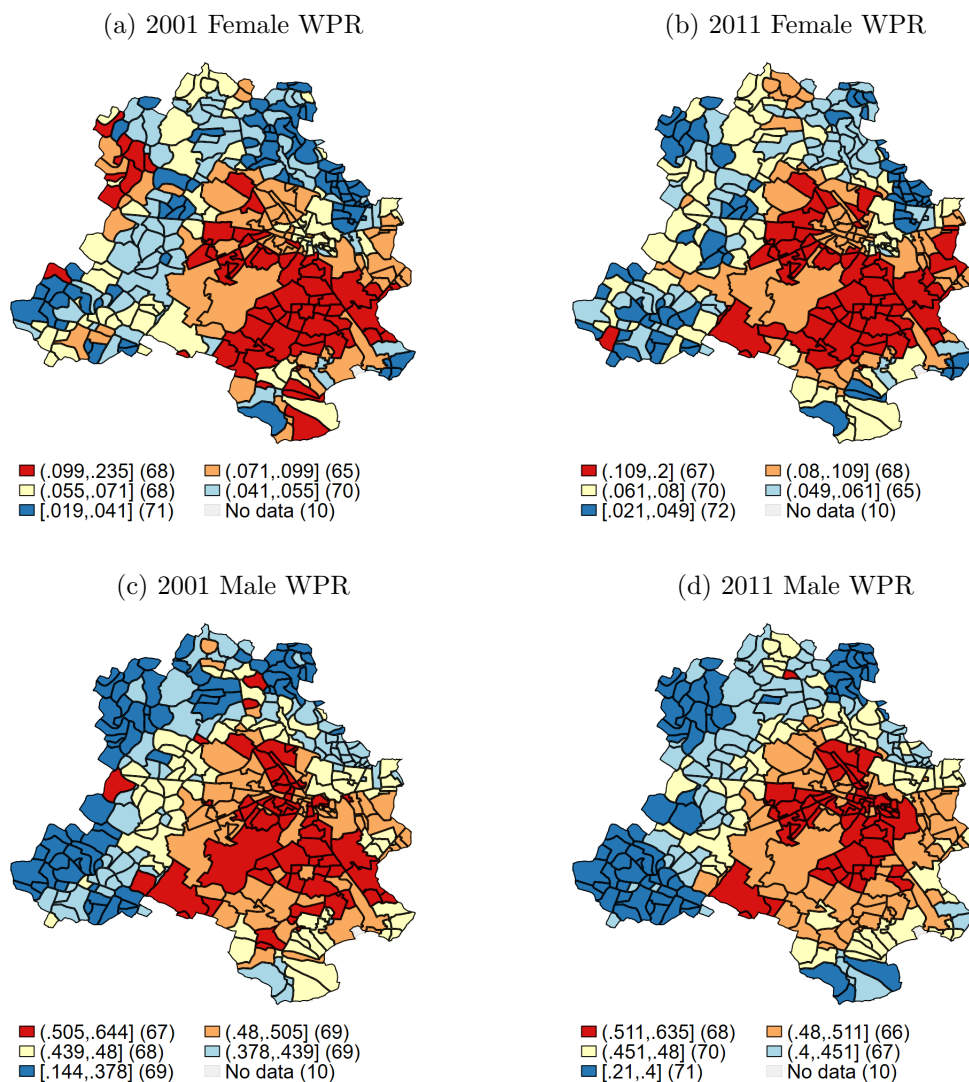


Source: Authors

taking 1 when $t = 1991$ and 0 otherwise. $Post_t$ is another time dummy taking 1 if $t = 2011$ and 0 otherwise. Coefficient β is our central interest. This is the post-treatment effect of the distance to the metro station on the outcome. β_{-1} captures the correlation between a zone's distance to the metro station and the outcome variables in 1991. If β_{-1} is insignificant, we will not reject the hypothesis that pre-trend is not associated with the distance to a metro station, suggesting that the parallel pre-trend hypothesis holds. The same strategy has been used in studies such as Autor (2003) and Kearney and Levine (2015). X_{it} is a vector including other time-variant location specific characteristics such as average household size, share of children (under 6 years old) in the population, female literacy rate relative to male, and ratio of share of scheduled caste between female and male.¹⁰ The first two variables are introduced to control for the variations in the

10. For clarity, variables are given by; average household size = $\frac{\text{Population}}{\text{Number of Household}}$; share of children (under 6 years old) in the population = $\frac{\text{Number of Children (under 6)}}{\text{Population}}$; female literacy rate rela-

Figure 2.3: Spatial Distribution of WPR for females and males, in 2001 and 2011



Source: Authors

presence of dependents in household (i.e. elderly and children) which are not directly measured in the PCA. The latter two control for the variation in the gender inequality.¹¹ Lastly, θ_t is year fixed effect, α_i is a zone-level fixed effect, and ϵ_{it} is the error term.

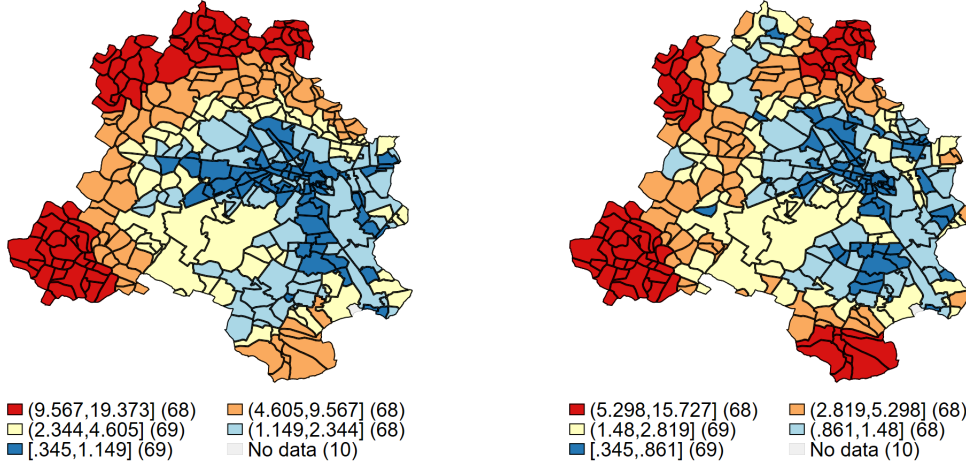
tive to male = $\frac{\text{female literacy rate}}{\text{male literacy rate}}$; and ratio of share of scheduled caste between female and male = $\frac{\text{share of scheduled caste in female population}}{\text{share of scheduled caste in male population}}$

11. In the separate regression, we check that these variables do not seem to be the consequences of the treatment $D_i \times Post_t$, allowing us to included them as controls in the equation.

Figure 2.4: Distance to Commissioned and Planned Metro Stations

(a) Distance to Commissioned (PH I & II) Metro Stations

(b) Distance to Planned (PH III & IV) Metro Stations



Source: Authors

The goal of this paper is to empirically assess how the Delhi Metro differently affects the economic participation of women and men. More specifically, we investigate whether the zones closer to the Delhi Metro station have observed more increase in work participation of the residents than those in zones further away from metro stations, separately for women and men. In the empirical analyses below, we focus on four measures of work participation, female WPR, male WPR, a ratio of a zone’s female WPR to male WPR ($= WPR(women)/WPR(men)$), or “WPR ratio” in short; and WPR for total residents (sum of females and males).

For the treatment variable, D_j , we define the (log) distance to the nearest Phase I or II Delhi Metro station. The reason for this choice of continuous treatment variable is twofold. Firstly, we would like to avoid a discretionary construction of a treatment variable, which is unavoidable when using discrete variables (i.e., we do not know from which kilometer it is “proximate” to the metro). Secondly, it is rather easier to interpret the results.

We estimate this equation 2.3 with a standard fixed effects estimator. The coefficient

β will capture the treatment effect, and the sign and the magnitude of this coefficient is our central concern. β_{-1} is the coefficient on the “lead” term. We expect that β_{-1} is insignificant under the common trend assumption. Please note that the insignificance of β_{-1} , is only suggestive evidence that the two sets of zones (in this case near and far from the new metro stations) would have evolved similarly in the absence of the intervention. It is not decisive as to whether there is unobserved heterogeneity across regions affecting the change in outcome variables or not. In fact, recent studies such as Kahn-Lang and Lang (2019) as well as Jaeger, Joyce, and Kaestner (2018) note that the parallel pre-trends do not necessarily imply parallel trends.

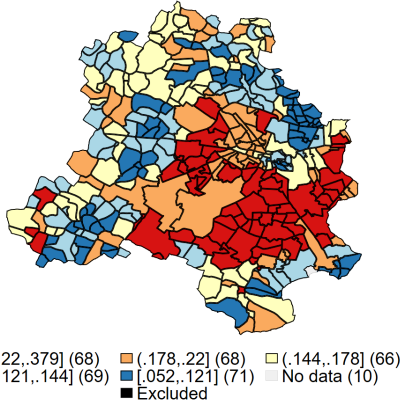
We conducted the estimation across various sub-samples to see how the results are sensitive to the selection of the comparison group. We compare five sub-sample defined as follows; (1) All the zones in Delhi (Figure 2.5a); (2) includes only the zones within 10km reach from the nearest commissioned (Phase I or II) station or the nearest planned (Phase III or IV) Metro station (Figure 2.5b); (3) includes only the zones within 5km reach from the nearest commissioned (Phase I or II) station or the nearest planned (Phase III or IV) Metro station (Figure 2.5c); (4) trims the zones in the subset (2) so that it include only zones at least 10km further from the CBD of Delhi, Connaught Place (Figure 2.5d); and (5) trims the zones in the subset (3) so that it include only zones at least 10km further from the CBD of Delhi, Connaught Place (Figure 2.5e).

2.5 Results

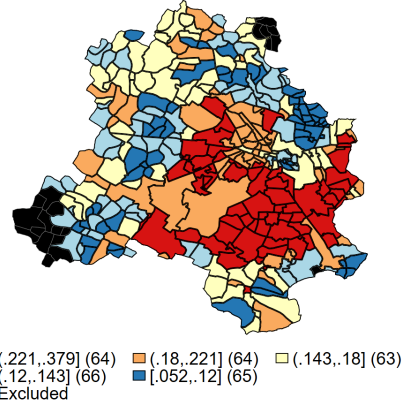
Tables 2.2-2.5, report the results of the estimations across different specifications. Table 2.2 reports the estimation results of equation (2.3) taking the female WPR as the outcome. For all the five subset analyses, our treatment variable, D_{it} , is significant at the 1 percent significance level with negative signs, except for column (5) where significance is at the 5 percent significance level. Negative coefficient indicates that being close to the

Figure 2.5: Subsample Definition and “WPR ratio” in 2011

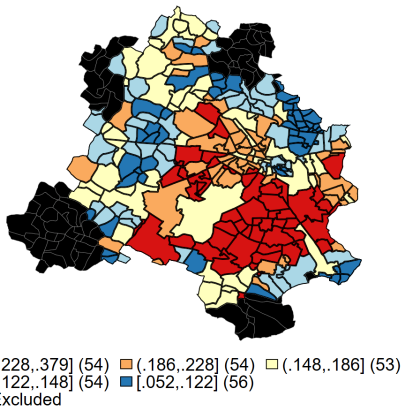
(a) All zones in Delhi (1)



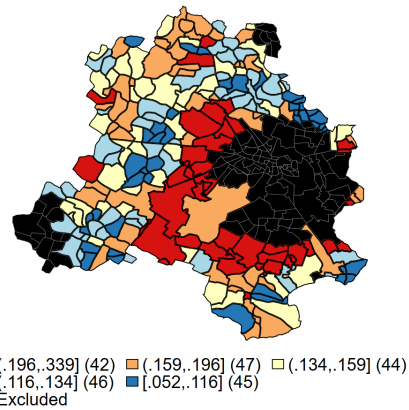
(b) Within 10km reach from commissioned and planned Metro Stations (2)



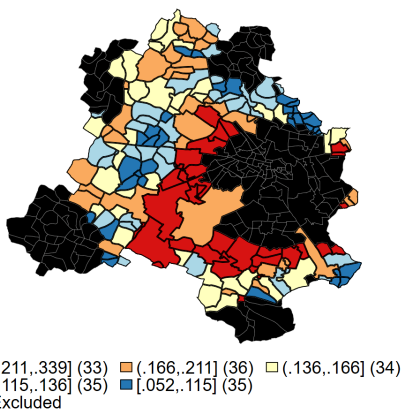
(c) Within 5km reach from commissioned and planned Metro Stations (3)



(d) Within 10km reach from commissioned and planned Metro Stations and at least 10km further from the CBD (4)



(e) Within 5km reach from commissioned and planned Metro Stations and at least 10km further from the CBD (5)



Source: Authors

commissioned Metro station makes female work participation rate higher. For example, for the full sample case, shown in column (1) of the Table 2.2, if the distance to the nearest Phase I or II station becomes doubles, female WPR decreases by 0.558 percentage points. Given that the mean of female WPR in 2011 was 7.91 percent, this implies that doubling the distance around the mean distance of 5.239km will reduce WPR of females to 7.35 percent.

Columns (2) and column (3) of Table 2.2 limit the sample zones to within 10km and 5km access to any Metro station regardless of whether they had already been commissioned as of 2011 (i.e., “control group” is restricted to the areas near Phase III or IV). We regard that the zones closer to the planned network are “selected” for Delhi Metro intervention, but the metro service is not yet available at that point in time, so they may share the similar unobserved heterogeneity with zones close to the commissioned stations, which affect the change in outcomes.¹² By estimating the model of columns (2) and (3), we compare the outcomes in zones for those who got access to metro stations earlier with those who would get it later. Therefore, by estimating the model only in those areas close to either the commissioned or planned metro stations, we compare outcomes in zones between the areas gaining access to the metro stations earlier (before 2011) and those would gain access later (post 2011).

We also note that the effect seems to be stronger outside the central area. The magnitude of the coefficient is greater for column (4), the outer area subsample, than that of column (2) (the cut-off at 10 km). The same argument applies to the comparison between columns (3) and (5), where the cut-off is 5km.

The results shown in the Table 2.2 suggest that a positive effect of the accessibility to the Delhi Metro for females exists throughout all the specifications. Furthermore, for

12. To identify the causal impact of transport system, it is common to use planned but never developed routes as control group; however, there is no such locations in Delhi Metro’s case. Instead, we adopt an idea close to the phase-in approach for improving our identification. The phase-in approach in our context (or in transportation infrastructure projects in general) still suffers from the remaining endogeneity bias due to the non-random construction timing/order of projects.

all columns, the coefficients on the “lead” term are insignificant, which means that the common pre-trend assumption holds for these sets of analyses.

Table 2.3 shows the results for the effects on male WPR. Contrary to the case for females, all the coefficients on the distance to a commissioned Metro station are positive and significant at the 1 or 5 percent significance level. The parallel pre-treatment trend assumption is overall satisfied except for column (3) whose coefficient β_{-1} term is negative and statistically significant at the 10 percent level. Furthermore, the magnitude of the effect does not vary across subsamples, ranging from 0.00801 to 0.00975, compared to the case for females as shown in Table 2.2. From the results in Table 2.2 and Table 2.3, it turns out that the proximity to the Delhi Metro station affects positively for female WPR while its effects is negative for that of male. Given that the mean of WPR for males in 2011 is 45.3%, this implies that doubling the distance around the mean distance of 5.239km will increase the WPR of males to 46.2%.

Table 2.4 reports the results when the outcome variable is the WPR ratio between female and male. Consistent with the results in Table 2.2 and Table 2.3, the coefficients on the distance to commissioned station are negative and significant at the 1 percent level. The results implies that the gap of WPR between females and males becomes slightly smaller (i.e. WPR ratio increases) in zones closer to commissioned Metro station. The key identifying assumption is again the common trend, and it seems to be satisfied for the trend between 1991 and 2001 as the coefficient β_{-1} is insignificant.

Finally, Table 2.5 reports the results when the total WPR is used as the outcome. Total WPR is the sum of female and male main workers in the non-agricultural sector divided by total adult population. For the first three columns show significantly positive coefficients on the distance to the nearest commissioned Metro station, meaning that proximity to a Metro station has a negative effect on total work participation. However, as shown in columns (4) and (5), the effect becomes no longer significant in suburban subsamples. This is mainly due to the imprecision in smaller sample sizes as the point

estimates do not change in magnitude comparing to columns (1)-(3), while the standard errors are larger. In the area outside of the CBD premises, proximity to the Metro does not change the overall work participation.

We add several robustness checks to address a series of technical concerns. The first relates to the control variables we included in the estimation equation. If the control variables are endogenous to the treatment variable, the inclusion of the controls in the equation is problematic (Angrist and Pischke 2009). Therefore, we conduct the same estimations without the control variables, as reported in Tables 2.A.2-2.A.5 of Section 2.A.2 of the Appendix. For women, the results are qualitatively the same as our main estimation. For men, we have qualitatively similar results for our variable of interest (“Dist. to Metro (2011)”) without control variables compared with the case of our main model reported in Table 2.3. However, the β_{-1} term becomes highly significant in this case. This implies that the control variables we include in the main analyses capture the pre-trend heterogeneity for the case of male WPR well.

We also check the sensitivity of the results against our method of interpolating the data so that the boundary definition of the “zones” would be consistent with that of 1991. In Appendix 2.A.3, we introduce an illustrative explanation of our interpolation method and its potential effects on the statistical outcomes. We also report the estimation results only using the data of zones with consistent boundaries. Again, the female results are stable, while the male ones are sensitive to the choice of sample zones.

From the empirical findings above, we can summarize the effects of the Delhi Metro on the work participation as follows. Firstly, female WPR in 2011 is higher in zones close to the Delhi Metro station, while it is lower in the more distant zones whereas male WPR is instead higher in these zones. From the results of robustness checks, estimating the equation without controls and using only the 1991-boundary consistent subsample, we find that the results for male WPR are sensitive to the settings while female ones are stable overall. Therefore, it is safe to conclude that in the areas closer to Metro, the

economic participation of women expanded more intensively than that of men. Secondly, for women, the magnitude of the effects is larger in the suburban subsamples. This means that the heterogeneous responses by gender caused by the access to the Delhi Metro might be more pronounced in the suburban area than in the CBD. Thirdly, partially reflecting the fact that women are positively affected by proximity and men are negatively affected, the total WPR is negatively affected, because the effects on men surpass those on women. The last point suggests that it is important to separately analyze the effects of transportation between females and males without averaging out the overall effects.

What is the mechanism that delivers this gender differentiated outcomes? One potential story could be an additional mobility benefit that the Delhi Metro may provide for women. The Delhi Metro is a mass rapid transit system which did not exist before in that city, where road vehicles such as buses, three-wheelers, and rickshaws, are the major mode of the transportation. The Delhi Metro has given citizens a faster and more reliable (predictable) method for travel in the city. The time-saving effect of the Metro system contributes to a reduction of the travel cost of both males and females who use the system. Before the introduction of the Metro, it is a plausible conjecture that female mobility was substantially more constrained than men, considering the safety issues including sexual violence on public transport. If the Delhi Metro secures a mode that allows females to travel more safely than on other traditional modes, the effective travel cost for might be reduced by more than just the time-saving effect. If this additional benefit is large, then whether to live in the neighbourhood of the Metro station should matters more to the mobility of females than to that of males. To argue this implication more formally, Section 2.6 introduces a theoretical model that explains this potential mechanism.

Other than that, there are a couple of other mechanisms that could generate gender-heterogeneous effects. Firstly, labor demand might change by the introduction of the Metro and that could be gender-heterogenous. For example, the manufacturing sector

might relocate its factories and offices outside of the downtown core, while service sector jobs might flourish downtown. Each sector might attract workers of a different gender. One possibility is that males are mainly in manufacturing, and this causes their residences to move further away from the metro, which is rather concentrated near the downtown core, as the factories relocate to the suburbs. An alternative possibility is that women tend to take job openings in service sector, and residents near the metro start working as it stimulates demand for service sector jobs. Secondly, a reduction of congestion and travel time that can plausibly benefit both females and males but in different magnitudes, encourages the residents to commute further. Nevertheless, it also induces in-migration of workers into areas near the Metro stations, and this results in higher work participation rates and housing prices in those areas.¹³ The resulting residential relocation itself is hard to analyze due to the data limitations, but the impact through this channel could be gender-heterogeneous as well. Thirdly, it is also important to note that the family level decision process can complicate male and female labor supply decisions. For example, if a family (couple) faces a reduction of travel time by the Metro and a high paid job becomes available to the husband, one of the possible responses is the wife's withdrawal from labor market activity (increase home production), substituting for this an increase in the male labor supply (i.e., intensification of division of labor). When all of these effects are combined, it is possible that the family with a male-bread winner moved away from the metro into more reasonably priced residential areas and his wife resigns job or does not seek employment. This story, however, cannot fully explain a subtle but statistically significant gain in female WPR closer to the metro stations, so we still think our safe-commuting hypothesis will survive the further tests in future research. The remaining challenge would be to separately identify the safe-commuting hypothesis versus gender-heterogeneous shifts in labor demand (with crowd-out and/or location segregation

13. How WPR and housing price react also depends on the elasticity of housing supply, the spatial allocation of industries within cities, and wage and many other things, making the actual signs and magnitude of the impact ambiguous.

by industry-gender combination) because both stories can explain the current empirical findings on females.

Table 2.2: Effects of Proximity to the Delhi Metro on the Female Work Participation Rate (Difference-in-Differences)

VARIABLES	(1) ALL	(2) d < 10km	(3) d < 5km	(4) d < 10km & CBD > 10km	(5) d < 5km & CBD > 10km
Dist. to Metro(2011, β)	-0.00558*** (0.00146)	-0.00688*** (0.00166)	-0.00418*** (0.00152)	-0.00906*** (0.00230)	-0.00453** (0.00207)
Dist. to Metro(1991, β_{-1})	0.00186 (0.00316)	0.00173 (0.00355)	0.00505 (0.00376)	0.00152 (0.00362)	0.00479 (0.00430)
Household Size	-0.0855*** (0.0317)	-0.0852** (0.0344)	-0.0810** (0.0317)	-0.0898* (0.0463)	-0.0797* (0.0439)
Children Share	-0.124*** (0.0215)	-0.131*** (0.0226)	-0.136*** (0.0256)	-0.113*** (0.0222)	-0.129*** (0.0263)
Female to male literacy ratio	-0.0923** (0.0396)	-0.0938** (0.0397)	-0.0589 (0.0419)	-0.123*** (0.0330)	-0.0911** (0.0376)
Female to male SC ratio	-0.0629*** (0.0214)	-0.0727*** (0.0256)	-0.0454* (0.0261)	-0.0831*** (0.0295)	-0.0553* (0.0295)
Constant	-0.0402 (0.0650)	-0.0519 (0.0690)	-0.0636 (0.0758)	-0.0192 (0.0739)	-0.0593 (0.0804)
Year Dummy	YES	YES	YES	YES	YES
Observations	1,006	948	801	654	507
R-squared	0.443	0.449	0.431	0.529	0.470
Number of id	342	322	271	224	173
Adj-R	0.438	0.444	0.426	0.523	0.462

Note: Standard errors are clustered at the individual zone

*** p<0.01, ** p<0.05, * p<0.1

“d < km” if sample zones with distance to Phase I - IV stations within x km

“CBD < km” if sample zones locate further than x km from the CBD

2.6 Theoretical Explanation with a Spatial Commuting Model

The empirical results indicate that the commission of the Delhi Metro raises the work participation rate of women living nearby the Metro stations, while its effect is ambiguous for men (this is the opposite of women in our main specification, but it is highly sensitive to the inclusion of control variables).

In what follows, we try to argue that the observed results in WPR for women and

Table 2.3: Effects of Proximity to the Delhi Metro on the Male Work Participation Rate (Difference-in-Differences)

VARIABLES	(1) ALL	(2) d < 10km	(3) d < 5km	(4) d < 10km & CBD > 10km	(5) d < 5km & CBD > 10km
Dist. to Metro(2011, β)	0.00862*** (0.00217)	0.00993*** (0.00225)	0.00975*** (0.00237)	0.00801** (0.00327)	0.00829** (0.00329)
Dist. to Metro(1991, β_{-1})	-0.00638 (0.00493)	-0.00829 (0.00525)	-0.0102* (0.00609)	0.00160 (0.00428)	-0.00281 (0.00485)
Household Size	-0.347*** (0.0334)	-0.332*** (0.0333)	-0.334*** (0.0330)	-0.360*** (0.0404)	-0.359*** (0.0410)
Children Share	-0.0362 (0.0412)	-0.0432 (0.0427)	-0.0719* (0.0368)	-0.00120 (0.0460)	-0.0471 (0.0308)
Female to male literacy ratio	0.0268 (0.0525)	0.0191 (0.0522)	0.0522 (0.0649)	-0.0329 (0.0202)	-0.0140 (0.0263)
Female to male SC ratio	0.0353 (0.0433)	0.0163 (0.0450)	0.0451 (0.0477)	0.0510 (0.0460)	0.0742 (0.0506)
Constant	0.951*** (0.103)	0.918*** (0.104)	0.883*** (0.0986)	1.011*** (0.106)	0.943*** (0.0808)
Year Dummy	YES	YES	YES	YES	YES
Observations	1,006	948	801	654	507
R-squared	0.462	0.456	0.455	0.609	0.600
Number of id	342	322	271	224	173
Adj-R	0.457	0.451	0.449	0.604	0.594

Note: Standard errors are clustered at the individual zone

*** p<0.01, ** p<0.05, * p<0.1

“d < km” if sample zones with distance to Phase I - IV stations within x km

“CBD < km” if sample zones locate further than x km from the CBD

men can be caused by the heterogeneous reduction of commuting cost by gender, owing to the Metro. Here, the commuting cost includes not only fees and opportunity cost, but also a safety-related welfare cost. Especially, using a simple theoretical model of urban spatial economy, we find that women’s WPR is positively associated with proximity to the Metro while men’s response is opposite (or ambiguous), if the reduction of commuting cost by the metro is much larger for women than men.

Our theoretical model basically follows the modelling strategy by Ahlfeldt et al. (2015) and Monte, Redding, and Rossi-Hansberg (2018), who study the residence-commuting choice of households within an urban area. Like their approach, we model the heterogeneity

Table 2.4: Effects of Proximity to the Delhi Metro on a ratio of the Work Participation Rate of Females over that of Males (Difference-in-Differences)

VARIABLES	(1) ALL	(2) d < 10km	(3) d < 5km	(4) d < 10km & CBD > 10km	(5) d < 5km & CBD > 10km
Dist. to Metro(2011, β)	-0.0166*** (0.00438)	-0.0210*** (0.00476)	-0.0120*** (0.00395)	-0.0278*** (0.00676)	-0.0160*** (0.00542)
Dist. to Metro(1991, β_{-1})	0.000604 (0.00674)	0.00132 (0.00748)	0.0120 (0.00760)	-0.00377 (0.00919)	0.0101 (0.00969)
Household Size	-0.138** (0.0556)	-0.145** (0.0598)	-0.131** (0.0546)	-0.164** (0.0809)	-0.134* (0.0753)
Children Share	-0.265*** (0.0412)	-0.279*** (0.0411)	-0.230*** (0.0410)	-0.280*** (0.0532)	-0.219*** (0.0459)
Female to male literacy ratio	-0.130** (0.0567)	-0.128** (0.0569)	-0.0700 (0.0614)	-0.172*** (0.0466)	-0.117** (0.0541)
Female to male SC ratio	-0.153** (0.0614)	-0.131** (0.0563)	-0.0770* (0.0460)	-0.164** (0.0730)	-0.0952* (0.0539)
Constant	-0.136 (0.117)	-0.151 (0.120)	-0.0805 (0.120)	-0.120 (0.149)	-0.0575 (0.135)
Year Dummy	YES	YES	YES	YES	YES
Observations	1,006	948	801	654	507
R-squared	0.348	0.361	0.387	0.379	0.365
Number of id	342	322	271	224	173
Adj-R	0.343	0.356	0.381	0.372	0.355

Note: Standard errors are clustered at the individual zone

*** p<0.01, ** p<0.05, * p<0.1

“d < km” if sample zones with distance to Phase I - IV stations within x km

“CBD < km” if sample zones locate further than x km from the CBD

of individual choice following Eaton and Kortum (2002), and introduce an Fréchet distributed idiosyncratic welfare shock across destination and employment status that gives a convenient functional form for the destination choice in the equilibrium.

2.6.1 The Spatial Commuting Model

Let us assume a square-shaped city which consists of J equally sized zones. In each zone j , M_j number of men and F_j number of women live for all j for $1, 2, \dots, J$. They don't move to other zones in the city, for the sake of simplicity. Thus, the residential population in each zone is fixed in the model. We denote gender as G , which takes F or M in what

Table 2.5: Effects of Proximity to the Delhi Metro on the Work Participation Rate of the Sum of Females and Males (Difference-in-Differences)

VARIABLES	(1) ALL	(2) d < 10km	(3) d < 5km	(4) d < 10km & CBD > 10km	(5) d < 5km & CBD > 10km
Dist. to Metro(2011, β)	0.00326** (0.00152)	0.00326** (0.00163)	0.00406** (0.00160)	0.00131 (0.00233)	0.00289 (0.00218)
Dist. to Metro(1991, β_{-1})	-0.00233 (0.00381)	-0.00328 (0.00419)	-0.00299 (0.00475)	0.00170 (0.00321)	0.000285 (0.00364)
Household Size	-0.254*** (0.0264)	-0.248*** (0.0278)	-0.249*** (0.0261)	-0.266*** (0.0359)	-0.263*** (0.0351)
Children Share	-0.0787*** (0.0295)	-0.0859*** (0.0309)	-0.103*** (0.0284)	-0.0578* (0.0317)	-0.0900*** (0.0232)
Female to male literacy ratio	-0.0296 (0.0444)	-0.0339 (0.0443)	-0.000773 (0.0518)	-0.0773*** (0.0210)	-0.0543*** (0.0229)
Female to male SC ratio	0.0118 (0.0295)	0.00323 (0.0296)	0.0314 (0.0315)	0.0116 (0.0281)	0.0355 (0.0297)
Constant	0.539*** (0.0757)	0.519*** (0.0785)	0.499*** (0.0778)	0.582*** (0.0779)	0.531*** (0.0648)
Year Dummy	YES	YES	YES	YES	YES
Observations	1,006	948	801	654	507
R-squared	0.474	0.466	0.467	0.642	0.634
Number of id	342	322	271	224	173
Adj-R	0.469	0.461	0.461	0.638	0.629

Note: Standard errors are clustered at the individual zone

*** p<0.01, ** p<0.05, * p<0.1

“d < km” if sample zones with distance to Phase I - IV stations within x km

“CBD < km” if sample zones locate further than x km from the CBD

follows. For each region and gender, a fixed reservation wage r_j^G is assured for every residents if an individual does not receive labour wage. Each person can work anywhere in the city and will be compensated with a zone j specific wage w_j . If a resident in j works in j' , she or he has to incur an iceberg type commuting cost $\tau_{jj'}^G \geq 1$.¹⁴ Therefore, effective wage that a zone j resident of gender G working in j' receives $w_{j'}/\tau_{jj'}^G$.

An individual consumes a homogeneous variety (numéraire) at an unity price. In addition, he or she draws an idiosyncratic utility shock for all the potential employment status, denoted by $\epsilon_{jm}(i)$. This is a shock of individual i living in j , whose employment

14. Within the same zone, we do not assume no commuting cost, meaning that $\tau_{jj}^G = 1$.

status is m . The employment status m takes H if i chooses not to work and m takes j' if she commutes to j' for work. $\epsilon_{jm}(i)$ follows Fréchet distribution with mean B_m , which corresponds to the average amenity level of m , and dispersion parameter η with the CDF given by $F(\epsilon_{jm}) = \exp[-B_m \epsilon^{-\eta}]$. Given these idiosyncratic shocks (ϵ_{jm}), the effective wage rates in all destination zones ($w'_j/\tau_{jj'}^G$), and the reservation wage level in the own residential zone (r_j^G), the individual i chooses whether he or she works and where to commute so that his or her welfare is maximized. Thus the welfare of individual i can be defined as

$$V_{G,j}(i) = \max\{\epsilon_{jH} r_j^G, \epsilon_{j1} \frac{w_1}{\tau_{j1}^G}, \dots, \epsilon_{jJ} \frac{w_J}{\tau_{jJ}^G}\}. \quad (2.4)$$

Each zone produces a homogeneous product using labor and land. Land is a fixed endowment to zones. Let N_j denote the supply of labor to city j and D_j is the land endowment. We assume a simple Cobb-Douglas production function;

$$Y_j = A_j N_j^\beta D_j^{1-\beta}. \quad (2.5)$$

where A_j is j 's productivity shifter and $\beta \in (0, 1)$. The goods market is perfectly competitive, and workers regardless of their gender receives wage, w_j , which is equal to the marginal productivity of labor.

In the equilibrium, the residents choose whether to work ($m = H$ if they do not work) and the destination of commuting if they work ($m = j'$). Labor and land are fully employed in each zone in the city, and the goods market clears. Therefore, the equilibrium of the urban economy can be defined by the equations below. Firstly, thanks to the property of Fréchet distribution of individual's idiosyncratic utility shock ϵ , the probability that a gender G resident in j decides to commute to zone j' is equivalent to the share of gender G residents in j commuting to j' as follows

$$\pi_{jj'}^G = \frac{B_{j'}(w_{j'}/\tau_{jj'}^G)^\eta}{B_H(r_j^G)^\eta + \sum_k B_k(w_k/\tau_{jk}^G)^\eta}, \quad \forall G = \{F, M\}. \quad (2.6)$$

Given the above shares and the fixed population of men and women in each zone, the total labour supply to zone j is then given by

$$N_j = \sum_{j'} \pi_{j'j}^M M_{j'} + \sum_{j'} \pi_{j'j}^F F_{j'}. \quad (2.7)$$

Finally, the equilibrium wage is equal to the marginal product of labour,

$$w_j = \beta A_j D_j^{1-\beta} N_j^{\beta-1}. \quad (2.8)$$

The equilibrium work participation rate (WPR) of gender G in j is 1 minus the inactive rate. From equation (2.6), this is given as

$$WPR_{G,j} = 1 - \frac{B_H(r_j^G)^\eta}{B_H(r_j^G)^\eta + \sum_k B_k(w_k/\tau_{jk}^G)^\eta}, \quad \forall G = \{F, M\}. \quad (2.9)$$

2.6.2 Comparative Statics of Transportation on WPR by Gender

Our main concern is how a heterogeneous change in commuting cost across gender ($t_{jj'}^G$) induced by the development of urban transportation network would affect the work participation rates of men and women in each zone ($WPR_{G,j}$). Especially, we are interested in whether there are cases where the decline in commuting cost has opposite WPR results for men and women.

Since the model is not analytically solvable, we conduct numerical simulations to examine its properties. We consider a square-shaped model economy consisted with total $J = \tilde{J} \times \tilde{J}$ tiles. For simplicity, we assume that the productivity (A_j), land (D_j), and average amenity level (B_j) take the value of 1 for every zone. Each zone is populated with a normalised population of men and women, namely $M_j = 1$ and $F_j = 1$, $\forall j = 1, \dots, J$. There are two universal parameters in the model, the share of labour in production, β , and the shape parameter for the Fréchet distribution of destination preference, η . We set

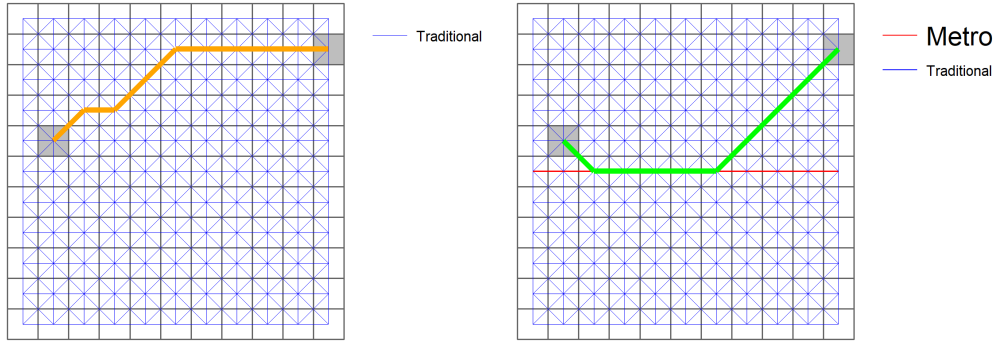
$\beta = 0.8$ and $\eta = 4$ following the literature.¹⁵

The transportation network is defined as the set of gender differentiated iceberg commuting cost between any pair of adjacent zones. For any pair of adjacent zones j and j' , the link (node) between the two zones has either “traditional” or “metro” transit mode, denoted by $t(jj')$ which takes value 0 if the link jj' has “traditional” transit or 1 if it has “metro” transit. Let p_t^G denote a per unit distance traveling cost for a particular gender G by a specific mode of transportation t . Traditional mode of transportation incurs $p_0^G > 1$ of wage per unit distance for a gender G commuter. Here, we are trying to replicate the situation before the Delhi Metro is commissioned. With the “metro”, travelling one unit distance costs $p_1^G > 1$, while we assume that the metro is cheaper in terms of the welfare cost of travelling than the traditional mode and that means $p_0^G > p_1^G$. The reduction of welfare cost is trying to represent an improved safety due to the Metro. In general, we denote the gender G commuting cost between these two adjacent zones j and j' as $\tau_{jj'}^G = p_{t(jj')}^G d_{jj'}$, where $t(jj') = \{0, 1\}$ and $d_{jj'}$ is the distance between j and j' . The commuting cost between the non-adjacent pairs of zones is defined as the least cost path to reach from j to j' .

Figure 2.6 schematically depicts the city zones, its transport network, and the commuter’s routing for the case of $\tilde{J} = 11$. The square tiles with black border lines are the zones. The centroids of adjacent zones are connected with blue lines that represent the nodes of the transportation network. For adjacency, we adopt the “queen” adjacency criteria which admits the two zones are adjacent even if only the corner is shared. Therefore, lines of diagonal directions are also included in the network. In panel (2.6a), we assume that the entire transportation network is served by the “traditional” mode and thus the entire network is colored in blue. It incurs $p_0 = 2$ of commuting cost per

15. $\beta = 0.8$ refers to the choice by Ahlfeldt et al. (2015) in their calibration of the model which has a similar production assumption. Both Ahlfeldt et al. (2015) and Monte, Redding, and Rossi-Hansberg (2018) estimate the parameters corresponding to our η for Berlin and the U.S. cities, respectively, and obtain the values between 3 to 5. Thus, we pick 4 for our analysis. Note that their shape parameters for the shock govern people’s simultaneous choice of residence and commuting. Instead, in our model, residence is fixed.

Figure 2.6: City Zones, Transport Network, and Commuters' Routing



(a) Route without Metro

(b) Route with Metro

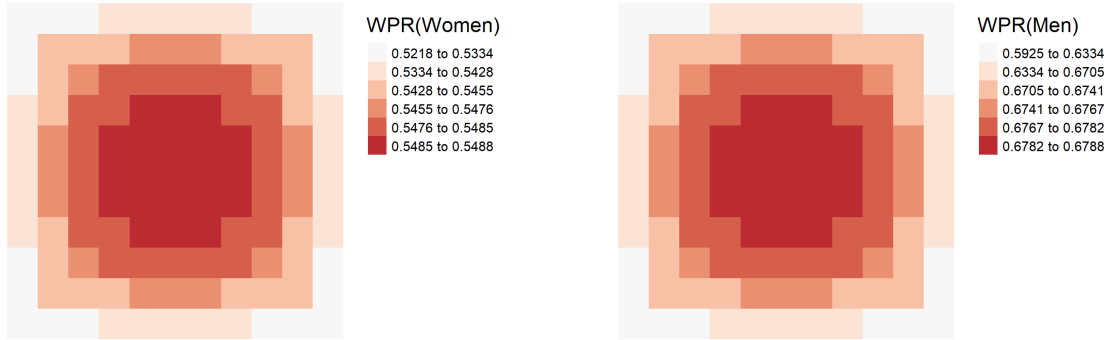
Source: Authors

Note: In the panel (a), all the nodes on the network (in blue) requires $p_0 = 2$ commuting cost to travel. One of the least cost path between the two grey shaded zones is depicted as the orange thick line. Instead, in the panel (b), the travel cost on the East-West corridor in the middle which is depicted as a red line reduces to $p_1 = 1.5$, while the remaining nodes in blue stay at the level of p_0 . The resulting least cost paths to travel between the two grey shaded zones changes to the green thick line.

a unit distance. Let us consider the case of commuter's routing between the two grey colored zones. Under this environment without "metro", (an example of) the commuter's routing becomes the thick orange line, which realises the least cost. Instead, in panel (2.6b), we introduce a East-West "metro" line depicted in red. In this example, the unit distance cost is reduced to $p_1 = 1.5$ only on this red line. Travelling along the red line incurs fewer costs for commuters than passing through the blue traditional nodes. This will divert the least cost path between the two zones from that in the panel (2.6a) to the one like the green thick line in the panel (2.6b).

In the simulation analysis, we differentiate the traditional commuting cost of females and males. Reflecting the anecdotal context, we assume that the traditional welfare cost of commuting is higher for females than that for males. Specifically, we set $p_0^F = 2$ for females, while $p_0^M = 1.5$ for males. Figure 2.7 show the model's equilibrium WPRs for

Figure 2.7: WPR of Females and Males in the Initial Equilibrium (No Metro)



(a) Women’s Initial WPR ($p_0^F = 2$)

(b) Men’s Initial WPR ($p_0^M = 1.5$)

Source: Authors

Note: Spatial distributions of women’s and men’s WPR across zones, assuming that the entire urban transport network is traditional. To express women’s disadvantage in the mobility in the initial equilibrium, commuting cost per unit distance is 2 for women and 1.5 for men on every node of the network.

females and males given by equation (2.9), when the entire urban transport network is traditional as shown in Figure 2.6a. For both women and men, the WPR is higher in the central zones in the city, while it gradually reduces in the peripheral zones. Female WPR is much lower than for males. For females, the WPR ranges from 0.5218 to 0.5488. For males, the range shifts up to 0.5925 to 0.6788. These figures imply two things. Even on a featureless plain with equally distributed population and a featureless transport network, the residents of central location are more likely to work than those living in the periphery. In general, the higher the commuting cost is, the lower is the work participation rate. These results partially explain the situation of Delhi in 2001 that is depicted in Figure 2.3.

Figures 2.8, 2.9, and 2.10 depict the simulated changes in female and male WPR in response to the introduction of the Metro from East to West in the middle of the city, just as the red line in Figure 2.6b indicates. Figure 2.8 illustrates the impact of the Metro

development when it reduces the commuting cost along the Metro corridor by 5% for both females and males. Namely, women's commuting cost reduces to 1.9 on the corridor (along the thick black line), while for men it becomes 1.425. For females as in the panel (a), the effect on the WPRs ranges from 0.0004 to 0.6019 percent, which are all positive but very marginal. And a clear "distance decay" pattern can be observed. Increasing the magnitude of commuting cost reduction for women will change not only the female WPR but also the male one. The male WPR shown in panel (b) responds in a more complicated way. While the positive impact is large in the immediate neighbourhood of the Metro alignment, the WPR interestingly reduces in a few spots locating relatively close to the Metro. In the majority of zones, the increase in the female WPR surpasses that of males. For the same magnitude of benefit (5 percent reduction in commuting cost), the group with severer initial deprivation will on average achieve larger gains. As in panel (c), the aggregate impact on the zonal employment is everywhere positive. In this case, the negative impact on male WPR in some zones is perfectly offset by the positive impact on female WPR.

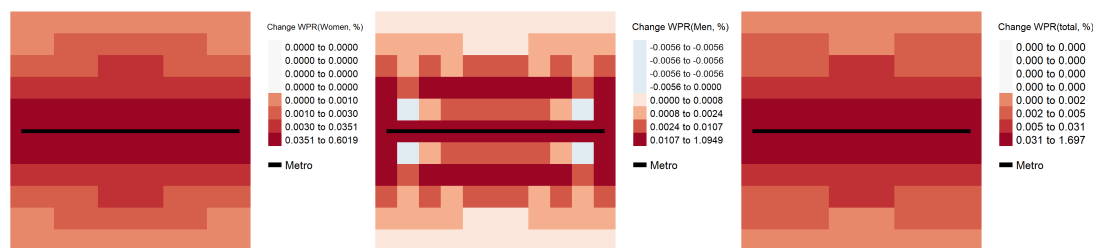
In Figure 2.9 and Figure 2.10, we compare the cases of the Metro development that reduces female commuting costs more than that of males. Figure 2.9 illustrates the response of the WPRs when the Metro reduces female commuting cost along the Metro alignment to 1.425, which is the same level as the male metro commuting cost. With this relatively huge decline in female commuting cost on the Metro (28.75% reduction from the original), female WPR and male WPR show different responses. We observe an overall increase of female WPR, while male WPR declines in a large number of zones except for some specific places. Female WPR increases more in the central area where metro development happens. On the other hand, male WPR exhibits a more complicated response. Even in locations that are close enough to the Metro line, male WPR can decline (blue to grey shades in panel (b)). This shows a complex interdependent mechanism that the Metro development may deliver for women and men. For males

in the immediate neighbourhood of the Metro alignment, the greater convenience for commuting leads more of them to seek employment. However, males in zones which are the second closest to the Metro line are crowded out from work due to the increased work participation of female residents and incoming commuters. In this case, the relationship between the distance to Metro and male work participation rates becomes ambiguous. Interestingly, the decline in male work participation slightly exceeds the female increase in a few locations. This is shown in panel (c) of Figure 2.9. Four zones near the both ends of the metro line exhibit an aggregate decline in overall WPR.

Figure 2.10 is a far more stringent case where the Metro serves much better for women than men and the female commuting cost reduces to 1.2 against the male cost of 1.425. In this case, while the results for females are qualitatively the same as that of Figure 2.9, the male WPR reduces almost everywhere in the city. The crowd out in the labor market contributes to reduce male work participation, especially within the central zones that the Metro most serves. The area with total employment decline expands in this case compared to the case in Figure 2.9, as shown in panel (c).

In summary, our empirical results can be at least partially explained by the mechanisms of this model - the gender differentiated commuting cost and interdependent relationship through the labor market. If the commuting cost reduction by the Metro is larger for females (who would be more constrained for mobility without it) than males, the adjustment through the local labor market will result in a positive effect of proximity to the Metro station on female WPR and an ambiguous effect on male WPR. Of course, we do not argue that the model describes the decisive mechanism that delivers our empirical results. There could be a number of other mechanisms that are consistent with these results. This simulated model is the display of one possible mechanism. Especially, in the current analysis our model rules out endogenous residential choice of agent within the city. If people move in the city to maximize their utility, the effect of metro on female and male WPR can either be mitigated or amplified. Furthermore, we assume a

Figure 2.8: The Change of WPR after the Commission of an East-West Metro:
Case with 5 percent Reduction for both Females and Males on the East-West Corridor



(a) Women's WPR Change (b) Men's WPR Change (c) Total WPR Change

Source: Authors

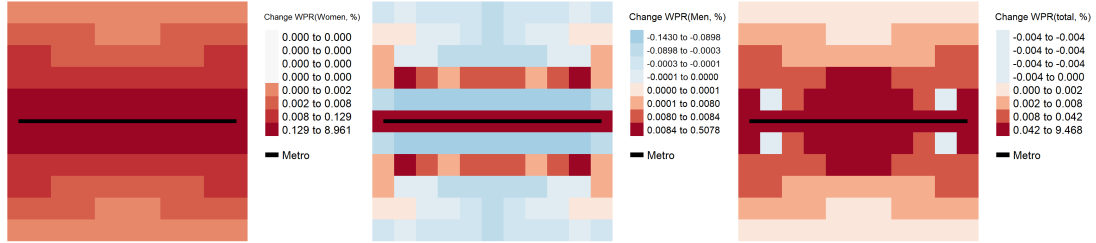
Note: Panels depicts changes in female and male WPR when the commuting costs of the East-West corridor reduces to $p_1^F = 1.9$ (by 5%) and $p_1^M = 1.425$ (by 5%) reduction, from the initial p_0^G by the introduction of the Metro. Panel (a) is for females, panel (b) for males, and panel (c) for the total (females plus males), respectively.

single employment sector where both female and male workers compete. We can instead introduce multiple employment sectors so that gender sorting of working sector can be observed. In such a model, the key mechanism of our current results, the crowding out of male workers by the influx of female workers in the local labor market, may not happen.

2.7 Conclusion

In this study, we analyze the effect of the proximity to the Delhi Metro station which have opened up during the Phase I and Phase II of the project, from 2002 to 2011, on the work participation rate of females and males, using the Indian census that provides various demographic information of more than 300 geographical zones within Delhi. Thanks to the data structure with two pre-treatment period observations, we employ the Difference-in-Differences estimation controlling for a zone fixed effect, and jointly verify the common trend assumption during the pre-treatment periods. The overall results suggest that the proximity to the Metro station is positively related to female work

Figure 2.9: The Change of WPR after the Commission of an East-West Metro:
Case where females and males achieve the same commuting cost on the Metro

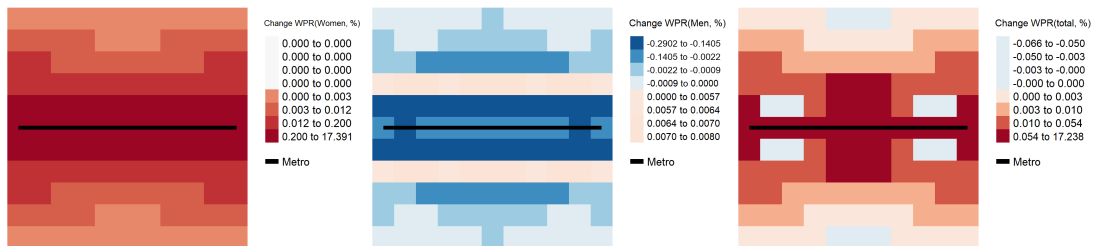


(a) Women's WPR Change (b) Men's WPR Change (c) Total WPR Change

Source: Authors

Note: Panels depicts change in female and male WPR when the commuting costs on the East-West corridor reduces to $p_1^F = 1.425$ (by 28.75%) and $p_1^M = 1.425$ (by 5%) reduction, from the initial p_0^G . Panel (a) is for females, panel (b) for males, and panel (c) for the total (females plus males), respectively.

Figure 2.10: The Change of WPR after the Commission of an East-West Metro:
Case where female commuting costs on the Metro become cheaper than male commuting costs



(a) Women's WPR Change (b) Men's WPR Change (c) Total WPR Change

Source: Authors

Note: Panels depicts change in female and male WPR when the commuting costs on the East-West corridor reduces to $p_1^F = 1.2$ (by 40%) and $p_1^M = 1.425$ (by 5%) reduction, from the initial p_0^G . Panel (a) is for females, panel (b) for males, and panel (c) for the total (females plus males), respectively.

participation, while the relationship between proximity to the Metro and male WPR is ambiguous, possibly having an opposite relationship to the case of females.

These findings provide suggestive evidence that the Metro encouraged females to participate in economic activities more than it did for males. This could be realized by, according to our conjecture, that the Delhi Metro might provide a safer mode of transportation that would benefit females who have suffered from safety problems more than males. With an parsimonious spatial urban model with commuting choice, we show that the larger reduction of commuting cost for females than males along with the Metro alignment can deliver important spatial patterns of this change in female and male WPRs that are similar to the ones empirically quantified.

However, we still need further investigation to know the causal link and the precise mechanisms behind it. More specifically, with the current dataset we cannot tell exactly why the positive effect on female rather than male economic participation is observed. At this stage, we only succeed in documenting the gender-heterogeneous correlation between proximity to the Metro and employment outcome. It is unclear whether the improved safety of commuting path has encouraged women to take a job outside of their home, since we do not directly observe their commuting choices. Alternative stories driven by labor demand can generate the same pattern of work participation rate. For instance, the Delhi Metro could have stimulated commercial activities around the Metro stations, such as retail shops, restaurants, offices, and so on. If some female oriented services (either by gender-wage gap or stakeholders' preference/discrimination) flourish in areas near stations, this would create more female employment opportunities than those for males. In this case, it would not be the safety of the Metro facility itself but the type of industries attracted to the premises of the Metro stations that would generate the observed pattern of female and male work participation rates. We leave remaining questions for future research with more detailed data.

2.A Appendix

2.A.1 Additional Information for Descriptive Statistics

Table 2.A.1: statistical test for the difference of distribution

	(1) female (91 vs 01)	(2) female (01 vs 11)	(3) male (91 vs 01)	(4) male (01 vs 11)
	<i>p</i> -values			
T-test (mean)	0.000	0.0013	0.000	0.0056
K-S test	0.000	0.007	0.000	0.120

Note: “T-test” reports the p-values the T-test to compare means of the WPR across years. “K-S test” reports the results (p-values) of the Komogorov-Smirnov test for comparing two distributions of WPR across years. Column (1) is for female WPR between 1991 and 2001. Column (2) is for male WPR between 2001 and 2010. Column (3) and (4) report the same for men.

2.A.2 Estimates without Controls

This section provides the estimation results without control variables as a robustness check to our main results in Section 2.5. If our control variables (household size, children share, female to male literacy ratio, and female to male ratio of scheduled caste) are also the outcome of the development of the Delhi Metro, this may bias the estimates for our variable of interest. We only keep our variables of interest, the distance to the Metro station (2011) and its lead term, then perform a fixed effect estimation. Table 2.A.2 and Table 2.A.3 show the estimation results for female and male WPR, respectively.

Table 2.A.2: Female WPR, without Controls

VARIABLES	(1) OLS ALL	(2) OLS d < 10km	(3) OLS d < 5km	(4) OLS d < 10km & CBD > 10km	(5) OLS d < 5km & CBD > 10km
Dist. to Metro(2011, β)	-0.00782*** (0.00149)	-0.00945*** (0.00167)	-0.00617*** (0.00149)	-0.0107*** (0.00236)	-0.00642*** (0.00205)
Dist. to Metro(1991, β_{-1})	-0.00204 (0.00234)	-0.00155 (0.00284)	0.000932 (0.00302)	-0.00115 (0.00368)	0.00312 (0.00409)
Constant	0.0708*** (0.00123)	0.0725*** (0.00128)	0.0738*** (0.00112)	0.0661*** (0.00179)	0.0663*** (0.00164)
Observations	1,016	957	808	663	514
R-squared	0.157	0.151	0.220	0.101	0.152
Number of id	342	322	271	224	173
Year Dummy	YES	YES	YES	YES	YES
Adj-R	0.153	0.147	0.217	0.0957	0.146

Note: Standard errors are clustered at the individual zone

*** p<0.01, ** p<0.05, * p<0.1

“d < km” if sample zones with distance to Phase I - IV stations within x km

“CBD < km” if sample zones locate further than x km from the CBD

Table 2.A.3: Male WPR, without Controls

VARIABLES	(1) OLS ALL	(2) OLS d < 10km	(3) OLS d < 5km	(4) OLS d < 10km & CBD > 10km	(5) OLS d < 5km & CBD > 10km
Dist. to Metro(2011, β)	0.00697*** (0.00243)	0.00839*** (0.00234)	0.00727*** (0.00274)	0.0143*** (0.00332)	0.0135*** (0.00400)
Dist. to Metro(1991, β_{-1})	-0.0273*** (0.00451)	-0.0285*** (0.00480)	-0.0315*** (0.00628)	-0.0190*** (0.00650)	-0.0232*** (0.00843)
Constant	0.439*** (0.00197)	0.447*** (0.00197)	0.465*** (0.00207)	0.424*** (0.00261)	0.446*** (0.00291)
Observations	1,016	957	808	663	514
R-squared	0.248	0.251	0.218	0.289	0.259
Number of id	342	322	271	224	173
Year Dummy	YES	YES	YES	YES	YES
Adj-R	0.245	0.248	0.214	0.285	0.254

Note: Standard errors are clustered at the individual zone

*** p<0.01, ** p<0.05, * p<0.1

“d < km” if sample zones with distance to Phase I - IV stations within x km

“CBD < km” if sample zones locate further than x km from the CBD

Table 2.A.4: WPR gap (female to male), without Controls

VARIABLES	(1)	(2)	(3)	(4)	(5)
	OLS ALL	OLS d < 10km	OLS d < 5km	OLS d < 10km & CBD > 10km	OLS d < 5km & CBD > 10km
Dist. to Metro(2011, β)	-0.0207*** (0.00449)	-0.0257*** (0.00491)	-0.0151*** (0.00396)	-0.0330*** (0.00692)	-0.0193*** (0.00550)
Dist. to Metro(1991, β_{-1})	-0.00882 (0.00573)	-0.00738 (0.00666)	0.00342 (0.00651)	-0.00972 (0.00899)	0.00685 (0.00914)
Constant	0.161*** (0.00290)	0.163*** (0.00295)	0.157*** (0.00228)	0.158*** (0.00415)	0.148*** (0.00338)
Observations	1,016	957	808	663	514
R-squared	0.177	0.177	0.256	0.132	0.185
Number of id	342	322	271	224	173
Year Dummy	YES	YES	YES	YES	YES
Adj-R	0.174	0.173	0.253	0.127	0.179

Note: Standard errors are clustered at the individual zone

*** p<0.01, ** p<0.05, * p<0.1

“d < km” if sample zones with distance to Phase I - IV stations within x km

“CBD < km” if sample zones locate further than x km from the CBD

Table 2.A.5: WPR for total adult population, without Controls

VARIABLES	(1)	(2)	(3)	(4)	(5)
	OLS ALL	OLS d < 10km	OLS d < 5km	OLS d < 10km & CBD > 10km	OLS d < 5km & CBD > 10km
Dist. to Metro(2011, β)	0.00115 (0.00168)	0.00104 (0.00169)	0.00146 (0.00189)	0.00431* (0.00242)	0.00525* (0.00273)
Dist. to Metro(1991, β_{-1})	-0.0170*** (0.00340)	-0.0173*** (0.00374)	-0.0180*** (0.00466)	-0.0139** (0.00606)	-0.0153** (0.00756)
Constant	0.274*** (0.00148)	0.279*** (0.00150)	0.290*** (0.00155)	0.265*** (0.00203)	0.278*** (0.00222)
Observations	1,016	957	808	663	514
R-squared	0.195	0.182	0.168	0.198	0.186
Number of id	342	322	271	224	173
Year Dummy	YES	YES	YES	YES	YES
Adj-R	0.192	0.179	0.163	0.193	0.180

Note: Standard errors are clustered at the individual zone

*** p<0.01, ** p<0.05, * p<0.1

“d < km” if sample zones with distance to Phase I - IV stations within x km

“CBD < km” if sample zones locate further than x km from the CBD

2.A.3 Discussion on Data Interpolation

As argued in Section 2.3, the geographical boundaries of zones in Delhi have not stayed constant during the three rounds of the census, thus we have to interpolate the observed statistics in 2001 and 2011 so that the boundaries are consistent with those of 1991.

We therefore examine the sensitivity of our results to the interpolation method by comparing our main results in Section 2.5 with the case where we limit the estimation sample only to the zones with consistent boundaries throughout 1991 to 2011. Out of 342 sample zones, 222 keep their boundaries constant across three periods. We repeat the same estimations for the WPR of females and males with this constant boundary subset. The results are shown in Table 2.A.6 and Table 2.A.7. The results generally support the prediction on the direction of bias.

Firstly, compared to the main estimates for female WPR shown in Table 2.2, the estimates with the boundary consistent subsets show the qualitatively similar results (Table 2.A.6). For all the five specifications, the effect of the distance to metro station is negative, and the magnitude is about twice as large as that in Table 2.2. This implies that using the interpolated data gives to smaller estimates for the *positive* effect of the proximity to the Metro station, which is consistent with the explanation with the illustrated example in the Appendix 2.A.3.

Table 2.A.7 shows the results for male WPR with the same subset. While the coefficients on the “Distance to Metro (2011)” are all positive for our main estimation, the results with the subset are neither positive nor significant. For males, the results are less stable across different specifications. The estimates for male WPR are sensitive to the sample choice as well as interpolation method for inconsistent zone boundaries.

Table 2.A.6: Female WPR only with consistent boundary zones

VARIABLES	(1) OLS ALL	(2) OLS d < 10km	(3) OLS d < 5km	(4) OLS d < 10km & CBD > 10km	(5) OLS d < 5km & CBD > 10km
Dist. to Metro(2011, β)	-0.0123*** (0.00212)	-0.0148*** (0.00233)	-0.0134*** (0.00255)	-0.0131*** (0.00219)	-0.0119*** (0.00223)
Dist. to Metro(1991, β_{-1})	0.000202 (0.00362)	0.000573 (0.00416)	0.00517 (0.00429)	-0.00377 (0.00347)	0.000738 (0.00365)
Household Size	-0.0881** (0.0393)	-0.0892** (0.0435)	-0.0725* (0.0411)	-0.101** (0.0500)	-0.0808* (0.0478)
Children Share	-0.156*** (0.0252)	-0.166*** (0.0262)	-0.161*** (0.0295)	-0.153*** (0.0213)	-0.154*** (0.0232)
Female to male literacy ratio	-0.0966** (0.0397)	-0.0989** (0.0397)	-0.0672 (0.0424)	-0.124*** (0.0335)	-0.0946** (0.0379)
Female to male SC ratio	-0.0556** (0.0247)	-0.0674** (0.0314)	-0.0389 (0.0305)	-0.0800** (0.0309)	-0.0480 (0.0293)
Constant	-0.102 (0.0881)	-0.116 (0.0954)	-0.130 (0.101)	-0.0786 (0.0932)	-0.109 (0.0934)
Observations	646	588	441	552	405
R-squared	0.417	0.428	0.388	0.524	0.464
Number of id	222	202	151	190	139
Year Dummy	YES	YES	YES	YES	YES
Adj-R	0.412	0.422	0.379	0.519	0.456

Note: Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

d < x km if sample zones with distance to Phase I - IV stations within x km

CBD < x km if sample zones locate further than x km from the CBD

Table 2.A.7: Male WPR only with consistent boundary zones

VARIABLES	(1) OLS ALL	(2) OLS d < 10km	(3) OLS d < 5km	(4) OLS d < 10km & CBD > 10km	(5) OLS d < 5km & CBD > 10km
Dist. to Metro(2011, β)	-0.00394 (0.00313)	-0.00367 (0.00336)	-0.00603 (0.00394)	-0.00120 (0.00304)	-0.00416 (0.00300)
Dist. to Metro(1991, β_{-1})	-0.00255 (0.00583)	-0.00479 (0.00643)	-0.00454 (0.00728)	-0.0109** (0.00466)	-0.0115*** (0.00426)
Household Size	-0.378*** (0.0424)	-0.360*** (0.0427)	-0.349*** (0.0410)	-0.374*** (0.0456)	-0.358*** (0.0440)
Children Share	-0.0709* (0.0368)	-0.0783** (0.0378)	-0.0847** (0.0403)	-0.0635* (0.0323)	-0.0830*** (0.0202)
Female to male literacy ratio	0.0198 (0.0512)	0.0116 (0.0507)	0.0388 (0.0639)	-0.0337 (0.0208)	-0.0210 (0.0244)
Female to male SC ratio	0.0543 (0.0504)	0.0371 (0.0525)	0.0590 (0.0570)	0.0452 (0.0513)	0.0702 (0.0526)
Constant	0.909*** (0.115)	0.871*** (0.118)	0.864*** (0.119)	0.908*** (0.109)	0.866*** (0.0834)
Observations	646	588	441	552	405
R-squared	0.504	0.503	0.512	0.610	0.622
Number of id	222	202	151	190	139
Year Dummy	YES	YES	YES	YES	YES
Adj-R	0.500	0.497	0.505	0.606	0.616

Note: Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

d < xkm if sample zones with distance to Phase I - IV stations within x km

CBD < x km if sample zones locate further than x km from the CBD

Chapter 3

Willingness to Pay for Mortality Risk Reduction from Air Pollution: Evidence from Urban Bangladesh

*This chapter is a joint work with Minhaj Mahmud and Yasuyuki Sawada*¹

Abstract

This paper reports on the first attempt to measure the value of statistical life (VSL) in the context of mortality risk from air pollution in urban Bangladesh, using the contingent valuation (CV) method. We asked individuals willingness to pay (WTP) for mortality risk reduction from air quality improvement program and found that willingness to pay is correlated with the socio-economic characteristics, health status, and risk perception of the respondents, consistently with existing studies. The bootstrapped mean of VSL is ranged from 17,480-22,463 USD in purchasing power parity terms, which is equivalent to 9.78-12.57 times of GDP per capita of Bangladesh. Considering our study setting, the results we obtained may be regarded as a lower bound of VSL estimates in the context of environmental risk reductions in Bangladesh.

1. The earlier version of this paper appears as JICA Research Institute Working Paper No.190.

3.1 Introduction

Rapid urbanization in developing countries has been causing serious environmental and health risks from various sources that requires urgent policy attention. Overpopulation and a lack of regulation over industrial activities is creating major environmental problems such as air pollution in developing country cities and exposing their people to serious health risks. According to Landrigan et al. (2017), 1 in 6 deaths is caused by pollution worldwide. For example, Bangladesh a densely populated country witnessing rapid urbanization in the last decades² has been ranked as the worst (8th worst) in terms of air pollution (environmental performance index) amongst 180 countries³. Recent World Health Organization data reveal that the air quality in Dhaka reaches a yearly average of $90 \mu\text{g}/\text{m}^3$ of PM_{2.5}, which is 9 times as high as the WHO's safety standard level.⁴ Obviously, there is an urgent need for strong public interventions to control current severe air pollution.

Quantifying the welfare cost of air pollution is a crucial step in motivating policymakers to appropriately prioritize environmental control. While it is not necessarily easy to obtain reliable estimate for the welfare loss from fatalities (or morbidity) due to air pollution, among a few popular methods, the contingent valuation (CV) method, which employs hypothetical scenarios and asks the respondents' willingness-to-pay (WTP) for a risk reduction scheme, remains a popular approach for quantifying the benefits from such risk reduction.⁵ In the context of mortality risk, an individual's WTP for mortality risk

2. From 1996 to 2016, Bangladesh's urban population has grown by 113%, from 27 million to 57 million, while total population add 34% during the same period. The urbanisation rate reached to 35% in 2016 from 22% in 1996 (<https://data.worldbank.org/indicator/SP.POP.TOTL?end=2016&locations=BD&start=1995>).

3. <http://epi.yale.edu/country/bangladesh>

4. <http://breathelife2030.org/city-data-page/?city=110>

5. There is a emerging literature that exploits exogenous shocks to assess the cost of air pollution or benefit of reducing air pollution. For example, Chang et al. (2016) use an exogenous fluctuation in PM_{2.5} monitoring records to estimate the impact of air pollution on worker's productivity. They find that the benefit of reducing pollution is sizeable; the decline of PM_{2.5} concentration happened during 1999 and 2008 resulted in generating nearly 20 billion USD in benefit. Reviewing the recent evidence on the negative impact of air pollution on labour market performance and human capital accumulation,

reduction can be converted to the value of a statistical life (VSL) by dividing the stated WTP by the magnitude of risk reduction in question (see Hammitt and Graham 1999).

CV studies on fatal risk reduction has been mainly conducted in developed countries.⁶ Environmental hazards including ambient pollution are among the popular scenarios of the cause of death in existing studies in developed countries, among others, such as traffic accidents and diseases (OECD 2012). However, in developing countries regardless of the cause of fatal risk, fewer studies have been conducted for measuring the WTP for mortality risk reduction using the contingent valuation method. CV studies on mortality risk caused by environmental pollution is especially limited in the context of developing countries. China is the most studied country in the developing world, with relatively large number of published researches (e.g. Wang and Mullahy 2006; Hammitt and Zhou 2006; Guo, Haab, and Hammitt 2007).⁷ Other countries include India (Bhattacharya, Alberini, and Cropper 2007), Turkey (Tekesin and Ara 2014), Thailand (Vassanadumrongdee and Matsuoka 2005; Gibson et al. 2007), Mongolia (Hoffmann et al. 2012), and Brazil (Arigoni Ortiz, Markandya, and Hunt 2009). Consequently, estimates of VSL in emerging and developing countries is scarce. In Table 3.1, we summarize the findings from the above mentioned studies.⁸

Zivin and Neidell (2018) argue the importance of a huge economy-wide benefit of clean air that reduces less-severe health hazards to normal and healthy people.

6. A few reviews and meta-analysis papers have been published on contingent valuation for pollution related mortality risk, such as OECD (2012), Kochi, Hubbell, and Kramer (2006), Desaignes et al. (2011), Dekker et al. (2011), and World Bank and Institute for Health Metrics and Evaluation (2016), which rely on studies conducted in developed countries. On VSL studies including those using revealed preference approach, there are several meta-analysis papers, such as Robinson (2017), Masterman and Viscusi (2018), Narain and Sall (2016), Viscusi and Masterman (2017a, 2017b), Lindhjem et al. (2011), Hoffmann, Krupnick, and Qin (2018), and W. Kip Viscusi (2017), that discuss the extension of the scope to the context of developing countries.

7. More studies are found for China regarding WTP for air quality improved policies, as summarised in Wang and Zhang (2009). However, in those studies, life saving scenario is not explicit and the VSL is not reported (except for Wang and Mullahy (2006) and Guo, Haab, and Hammitt (2007)). Wang and Zhang (2009) conducted survey in April 2006 in 5 urban districts in Ji'nan city, China. Their scenario was an improvement in the city's air quality from Class III status (at the time of survey) to Class II in the Chinese standard. There was no life-saving implication in the scenario and they obtained 100 Chinese yuan of WTP to this pollution reduction problem (with 49.3% zero-WTP).

8. See also Figure A2 and Table C1 in Robinson, Hammitt, and O'Keeffe (2017) for the list of studies on VSL in developing countries (not limited to environmental context).

There exists a handful of studies focusing on VSL in the context of Bangladesh using different methodological approaches. One approach is using the benefit transfer method, by extrapolating the estimates obtained from meta-analysis of surveys conducted in developed countries. For example, Miller (2000) suggests that a Bangladeshi VSL lies in the range between USD30,000 and USD1,000,000, or 131 - 2,762 times of per capita GDP. Robinson, Hammitt, and O 'Keeffe (2017)'s benefit transfer estimate for Bangladesh is 142,709 USD (in 2015 international dollar), based on the international research using stated preference method. Viscusi and Masterman (2017b) instead provides a benefit transfer estimate from the revealed preference studies in the U.S. that gives 205,000 USD.

To our knowledge, there is no study eliciting WTP for fatal risk reduction from air pollution in the context of Bangladesh.⁹ To bridge this gap, we conducted a CV survey to elicit individuals WTP for a reduction of mortality risk from air pollution in Dhaka and Chittagong, the two largest cities in Bangladesh.¹⁰ Ten sampling clusters were chosen from two cities (seven from Dhaka and three from Chittagong), and a total of 1,000 household heads were randomly selected for a face-to-face interview. A hypothetical scenario on reducing mortality risk from air pollution was explained and their willingness-to-pay was obtained using open-ended questions. We prefer open-ended questions to closed-ended ones because they provide more information, and are less prone to overestimation. We obtained 994 valid answers for the WTP questions which were used in regression analyses to reveal the relationships between WTP and respondents' attributes such as age, income, education, health condition, and perception of pollution risks to their health. The measured WTP are associated with individual characteristics in

9. Khan, Brouwer, and Yang (2014) estimate WTP of Bangladeshi households for arsenic safe drinking water, by applying a double discrete choice value elicitation approach. On average, households are willing to pay about 5 percent of their disposable household income for getting access to arsenic safe drinking water. Their purpose is to measure WTP for practical alternatives to reduce risk of arsenic exposure, and mortality risk reduction is not directly taken into the scope of study.

10. These large cities severely suffer from environmental pollutions, mainly due to the emissions from vehicles. For example, according to Bangladesh Statistical Pocket Book 2007 published by the Bangladesh Bureau of Statistics, it is estimated that air pollution causes 15,000 premature deaths in Dhaka per year, implying that 125 people out of 10,000 die from air pollution in Dhaka every year.

similar ways as in past studies. Based on the regression analysis, we employed bootstrap resampling to estimate the mean and median WTP as well as those confidence intervals. The mean VSL is ranged from 17,480 to 22,463 USD in PPP, which is equivalent to 9.78-12.57 times GDP per capita in the same year.

Our study may be subject to several types of bias. The first concern is scope bias as we do not explicitly test for the sensitivity of stated values to the magnitude of risk reduction assumed. Given that the magnitude of risk reduction we set (5 in 10,000) is relatively larger than what is used in the existing international examples, VSL in our case is likely to be underestimated. Furthermore, in our hypothetical scenario, fatal risk originates from “environmental” source and it is reduced by a “public” intervention by the government. As revealed by OECD (2012), “environmental” and “public” provisions in the risk scenario significantly reduce the stated VSLs. Therefore, our scenario is by construction leaned towards having lowered estimates for the VSL. Taking this background into account, we argue that the estimate should be carefully interpreted as a potential “lower bound” of VSL in the context of environmental risk reduction in Bangladesh.

The remaining part of this paper is structured as follows. In Section 3.2, we introduce the study design including the details of data collection and description of data. Section 3.3 explains the empirical strategies to estimate the determinants of WTP then describes the results, followed by the estimation of the average and confidence interval of the mean and median VSL by using sample bootstrapping. In Section 3.4, we discuss the validity of our estimates. The final section concludes the paper.

3.2 Study Design

This study benefits from a household survey conducted by the JICA Research Institute in the selected areas in Dhaka and Chittagong, from June 6 to July 17 in 2013.¹¹ Total

11. The survey was implemented by the Economic Research Group (ERG) based in Dhaka.

Table 3.1: Existing Studies on VSL in Developing Countries

Authors	Cities/Survey Year/Sample Size	Mortality Risk Context	Implied VSL	Ratio of VSL to Annual Income
Wang and Mullahy (2006)	Chongqing (China) / March 1998 / 500 residents (482 valid ans.)	5/100,000 reduction of mortality risk by air pollution	286,000 CNY (102,509 USD in PPP)	80 times
Hammitt and Zhou (2006)	Beijing, Anqing, rural Anqing (China) / July 1999 / 3,700 adults	Mortality risk reduction by air pollution from 70/10,000 to 10/10,000 or 20/10,000 (Double-bounded, dichotomous-choice)	4,220 USD (Lowest estimated median for Anqing) to 16,900 USD (Highest estimated median for Beijing)	2.5 times (Anqing), 6.3 times (Beijing)
Bhattacharya, Alberini, and Cropper (2007)	Delhi (India) / Oct-Dec 2005 / 1,200 adults	Multiple scenarios in the context of traffic accident risk: Risk reduction ranging from 4/100,000 to 30/100,000.	1.3 million Rupees (150,000 USD in PPP) for the most exposed respondents	9.6 times
Tekesin and Ara (2014)	4 cities in Turkey in June-July 2012/ 1,248 adults	Discrete choice experiment across 4 fatal risks (lung cancer, other cancers, respiratory diseases, and traffic accident): Risk reduction ranging from 1/10,000 to 8/10,000, per year.	0.74 mil TL (0.49 mil USL in PPP)	39 times
Mahmud (2009)	30 villages in rural Bangladesh in 2003. 780 household heads	reductions in mortality risk by a vaccination program: Reduction of risk either by 25% or 50%.	103,074 Taka to 168,905 Taka	From 3.55 times to 5.82 times
Vassanadumrongdee and Matsuoka (2005)	Bangkok (Thailand)	Mortality risks from air pollution and traffic accidents	0.74-1.32 mil. USD (Air Pollution) 0.87-1.48 mil. USD (Traffic)	314 times (for lower estimate for air pollution)
Gibson et al. (2007)	Rural villages in Thailand / Sept 2003 /	Comparison of two scenario villages with different mortality risks from landmine explosion (comparing risk of 4/10,000 and 2/10,000 per year)	0.25 mil. USD	397 times
Hoffmann et al. (2012)	Ulaanbaatar (Mongolia) / Winter 2010 / 629 people aged over 40 years old.	5/10,000 and 10/10,000 mortality risk reduction by policies to mitigate air pollution (various scenarios for checking scope validity are included)	0.50 mil USD for latent (cancer) risk 0.57 mil. USD for contemporaneous (resp. Disease) risk	257 times and 293 times, respectively
Arigoni Markandya, and Hunt (2009)	Sao Paulo (Brazil) / March 2003 / 283 literate employees in middle or higher social class	5/1,000 mortality risk reduction from air pollution over 10 years	0.77 mil. USD (median estimate), 1.31 mil. USD (mean estimate)	258 times (for median estimate)

Note: Annual income used in the last column is the average income of survey respondents.

11 enumerators trained by ERG conducted face-to-face interview by visiting the house of each respondents randomly sampled as described below. The main purpose of the survey was to collect the data on people's stated preferences for hypothetical risk reduction programs implemented by the government. The total number of surveyed households was 1,000, with 700 from Dhaka and 300 from Chittagong.

3.2.1 Questionnaires

Stated preferences for mortality risk reductions were elicited through the two sections in the survey questionnaire. The first section conducted a choice experiments among multiple risk reduction programmes that were hypothetically designed to reduce mortality caused by several type of risks (namely, traffic accidents, air pollution, water pollution, and maternity). In the second part, the respondents were asked their willingness to pay for a government scheme to reduce air pollution in Dhaka (or Chittagong) that will reduce the risk of dying from air pollution. The program was framed as a government intervention to control vehicle maintenance to reduce pollutant emission from motorized vehicles, which can reduce the mortality rate in each city from 125 per 10,000 persons to 120 per 10,000.¹² In this paper, we analyze the second part of the stated preference survey focusing on WTP for mortality risk reduction from air pollution.

The enumerators explained to the respondents that the annual death caused by air pollution in Dhaka counts 15,000, and that this number means that 125 people out of 10,000 dies from air pollution per year given the population of Dhaka (12 million). Then, we gave a hypothetical policy scenario that could reduce the mortality risk from 125/10,000 to 120/10,000, though government intervention to control vehicle pollutant emission. The WTP is directly measured through the following two questions:

12. The government of Bangladesh has already carried out reforms in the auto-rickshaw (three-wheeler) sector in Dhaka to reduce air pollutant emissions. In 2003, it forced the owners to replace petrol engines to CNG (compressed natural gas) engines. This transformation was well implemented and Bangladeshi citizens are quite aware of that success.

Q1 : “If you are told that the death risk in Dhaka due to air pollution can be reduced by a government initiative from 125 out of 10000 to 120, would you then spend for it?”

Q2 : (For the respondent who answered “yes” to Q1) “What is the maximum amount which you would be willing to pay annually to decrease your yearly death risk from 125 out of 10000 to 120?”

For the respondent who answers “No” to the first question, the enumerator asks why he or she does not want to pay for the program. ¹³

Before the respondents stated their preference on risk reduction programs, they were asked to answer around 70 questions on their socio-economic characteristics and preferences, such as; household demographics, income and expenditure, asset holdings, incidence of death and sickness, victimization experiences from accidents and other misfortunes, health conditions (current condition as well as chronic disease history), smoking behaviour, and perception about the health risk caused by environmental pollution of their residential areas. Just before they entered the stated preference part, we provided training on the concept of probability and risk reduction, followed by a test for ensuring the respondents’ understanding. The language of implementation was Bangla and the questionnaire was field tested and revised to facilitate understanding before the survey was conducted. To motivate their responses, a small gift was offered to the respondents.¹⁴ The full questionnaire is provided in the Appendix of Mahmud, Sawada, and Yamada (2019).

13. Note that the magnitude of mortality risk reduction was a change of 0.05 percentage points. This is ten times larger than the scenario used by Wang and Mullahy (2006) for Chongqing, China, but much smaller than Mahmud (2009) used for rural Bangladesh.

14. The Gift is worth of 100 Taka either in cash or equivalent in kind, depending on the respondent’s choice. 75% received cash, 20% received a gift, 1.5% were indifferent, and 1.5% declined to accept cash or a gift

3.2.2 Sampling Design

We conducted a stratified-cluster sampling for the two largest cities in Bangladesh, Dhaka and Chittagong. Each city had three strata, based on the situation in surface water pollution level. Out of six strata, two strata in Dhaka had three sampling clusters in each. Therefore, the total number of clusters was ten. 100 households were selected at random from each stratum, to construct the 1,000 sample households.

Selection of Strata and Clusters

As we focused only on major urban areas where people are more exposed to environmental risks compared to rural areas, the selection of survey clusters in Dhaka and Chittagong was based on actual level of environmental pollution to understand urban dwellers' preferences for risk reduction. At the time the survey was conducted, there was no information available for the spatial variation of air pollution within these cities. However, for water pollution, geographically detailed information was available both for Dhaka and Chittagong. For Dhaka, World Bank (2006) identified water pollution level in different areas in Dhaka based on Biochemical oxygen demand (BOD). BOD is the amount of dissolved oxygen needed by aerobic biological organisms in a body of water to break down organic material present in a given water sample at certain temperature over a specific time period. BOD exceeding 6 *mg/l* implies that the water is polluted and not acceptable as pure drinking water. Depending on the level of BOD, the areas were categorized as Red, Orange, Yellow and Blue.

The regions marked as Red represent the areas that have the most polluted water sources in Dhaka. The Red regions denote the presence of BOD, 500% beyond the standard (6 *mg/l*). Areas near the Buri ganga river, including Fatulla, Kutubpur, Shyampur, Sutrapur, Kotwali, Lalbag, Kamrangirchar, Hazaribag, Adabar, Gabtali; areas near Tongi bridge, including Machimpur, Abdullapur, Tongi bazar, Natun Bazar, Rajabari, and areas near the Balu river, including Kayetpara, Balurpar, Baburjayga,

Tejgaon, Kahelpara, Sarulia, Kanchpur, Siddhirganj, Sona mia bazaar are marked as Red. Out of these areas, three, Kamrangirchar, Tongi bazar, and Hazaribag, were randomly selected for the survey. This is our first sampling stratum and we refer this as “Dhaka-Most Polluted” stratum in what follows. From this stratum, three sampling clusters were randomly selected, giving 300 respondents in total.

The Orange regions represent mildly polluted areas attached to water bodies and correspond to 200-500% beyond the standard level of BOD. Areas near the Turag river including Shah Ali, Solahati, Mhimagar, Diabari, Nalbhog; areas near the Sitalakhya river, including Sombaria bazar, Nabigonj bazar, Dankunda bazar, Hajiganj, Nabinagar, Kashipur, Baktabali bazar, Bhabaniganj; other areas near the Sitalakhya river including Noapara bazar, Rupsi bazar, Purbagaon, Chhatian, Ulaba, and Kayetpara; and areas near the Balu river including Gobindapur, Talia, Rayer dia bazar, Palashia, Bhaturia, and Purbachal are marked as Orange. Three of these regions, Shah Ali, Diabari and Nabinagar were randomly selected for the survey. We label this stratum with three clusters (300 respondents) as “Dhaka-Medium Polluted” stratum.

The yellow regions correspond to less polluted water bodies containing 100-200% BOD beyond the standard BOD level. This region was skipped due to the fact that pollution variation is captured in Red and Orange regions. The blue regions have the least polluted water sources within the BOD standard which are acceptable as sources of drinking water after conventional treatment. Maniknagar is randomly chosen from the Blue stratum. This stratum is a singleton cluster.

For Chittagong, the selection of the sampling cluster is based on the information provided by a previous study of surface water quality in Chittagong (Zuthi, Biswas, and Bahar 2009). Chittagong Water Supply and Sewerage Authority (CWASA) has divided its water supply network into four routes. Zuthi, Biswas, and Bahar (2009) conducted an assessment of the water quality in all the four routes. All the water samples collected from the different routes of CWASA distribution had BOD₅ concentrations greater than

the permissible value of 0.20 parts per million (ppm). Among the four routes, the Route 2 was found to be most severely polluted with average BOD5 level of 5.2 ppm. From the Route 2, Shershah Colony is randomly selected for our survey cluster.

Route 1 was the second most severely polluted water route in Chittagong. The BOD5 concentration level was 3.6 ppm. From this route, Garibullah Shah Majar Road area was randomly selected for the survey. The Route 4 was the least polluted among the four routes, and an area consisting of Riazuddin Bazar and Enayet Bazar was randomly chosen from this route.

In summary, we set six strata based on city and water pollution levels, with three strata in each city corresponding to the most-polluted, medium-polluted, and the least-polluted sections of the city. We draw ten sampling clusters from these strata. For the first two strata, Dhaka-Most Polluted and Dhaka-Medium Polluted, we have three clusters in each stratum. However, the remaining four, we have only one cluster in each stratum, making these “singleton” strata.

Both World Bank (2006) and Zuthi, Biswas, and Bahar (2009) cover only the areas nearby water route such as river, canal, and lakes. Since the random selection of clusters are made from the list of areas found in these two environmental studies, our cluster sampling frame does not correspond to either administrative or statistical area in Dhaka and Chittagong. In addition, the areas are not strictly defined, which means that the basic information necessary to construct a sampling frame such as area size, boundary, and population were missing. Therefore, our sample only roughly represents the urban and suburban population living nearby surface water, and it is impossible to put sampling weights to produce strict representativeness.

Random Selection of Respondents

From each of the selected clusters in Dhaka and Chittagong, 100 households were drawn randomly. As explained above, we did not have the documentation of sampling frame

such as total population in each area. In practice, randomization was carried out by a “random walk” of enumerators, starting from a randomly chosen house and selecting the next household at a fixed X -th interval. Depending on the approximate total number of households in these areas, the randomization criteria such as choosing every 3rd or 5th or 7th or X -th household was selected on the spot. In the case of rejection, the enumerator was asked to move to the next household and follow the randomization accordingly.

Basically, the interval X set by enumerators for their random visits of household was larger for the areas with more households. This implies that the probability of being selected for a sample was smaller (i.e. weight should be high) for the populated area. This sampling method roughly ensures that the total area is equally covered within each cluster. However, we unfortunately do not have sufficient information on the population of our sampling clusters. Furthermore, we cannot identify in which cluster the enumerator chose which skip rule (i.e. the interval X) for selection of households. Under such condition, it is impossible to calculate the sampling weight to recover the national or city-level representativeness, and our estimate may therefore be biased from the population statistics at the national level or city level.

3.2.3 Description of the Data

Table 3.2 summarizes basic statistics of the variables used in the analysis. Out of total 1,000 respondents, 271 answered “No” to Q1, the question whether they have a willingness to pay for the hypothetical government program to reduce mortality caused by air pollution either in Dhaka or Chittagong (framed depending on the place of survey). However, among the 729 who said “yes” to Q1, there are 16 respondents who failed to appropriately answer Q2 which asked them to specify the amount they would be willing to pay. Out of those 16, 10 are revealed to have been miscoded as “yes” for Q1 despite the true answer was “no”. The remaining 6 respondents seem to have answered “yes”, but that was not successfully recorded to Q2. Thus, by dropping these 6 unsuccessful

observations, the number of observations appropriate for analysing the WTP became 994. The number of respondents who said they were willing to pay (Q1) and specified the amount (Q2) was 713 out of 994 (71.7 %). The mean value of log WTP is 5.465, corresponding to 236.3 Taka by taking exponential.

The average log per capita expenditure was 8.384 (its exponential value is 4376.5 Taka).¹⁵ This is equivalent to 168.6 USD in PPP of 2011 price, 50 % higher than the national average of 112.2 USD according to the PovcalNet of the World Bank. This is reasonable because we only sample from the urban population. The mean log age is 3.51 (its exponential is 33.4). About 61% of respondents were male. More than 60% of respondents completed at least primary school and were literate. Among them, 22.1% had tertiary or higher degrees.

The main monetary cost item associated with the damage from air pollution is medical care. Therefore, the level of household's medical expenditure might be related to its willingness to pay for pollution reduction measures. The average share of medical care in total monthly expenditure was 8.7 percent. As many as 29.0% regularly or sometimes smoked.

We also collected respondents' perceptions regarding a few urban health risk factors, such as water quality and air quality. For water quality, the average score on the health risk they perceived from the neighbourhood water was 2.03, almost around the second lowest ranking where the score is scaled from 1= very low risk to 5 = very high risk, and 2 is put a description as "some risk". Regarding air quality, perceived risk on health is higher than that for water with the average score was 2.39, which is in between "some risk" and "moderate risk". The perception of own health condition as well as disease experiences were also recorded. The average self-reported health score was 3.4, lying

15. In terms of income earned, 64% falls in the middle-income class with their earnings being greater than 10,000 Taka but less than 30,000 Taka monthly. More than a quarter of sample households earned incomes greater than 30,000 Taka. Since income data is collected only by asking in which income bracket the respondent's household falls, we use monthly expenditure per capita as a proxy for the household's monetary earning in what follows.

in between “fair” and “good”. A bit surprisingly, many has had suffered from chronic diseases; 57.4% answered that they experienced undesirable health conditions such as asthma, respiratory disease, bronchitis, chronic cough, diabetes, heart disease, of high or low blood pressure.

Since air pollution mitigation policy to reduce fatal risk is basically a public policy with strong externality, social capital of individual citizen might be relevant in determining whether and how much he or she wants to contribute. For the proxy of social capital, we adopted a popular GSS Trust question by asking respondents’ degree of agreement with the statement “Most people can be trusted”, which measures the level of interpersonal trust.¹⁶ The score is scaled from 1 = “strongly disagree” to 6 = “strongly agree”. The average score was 3.59, which means that people are almost neutral about this statement.

Column (6) of Table 3.2 shows the design effect for each variable, which is the ratio of the variance when our complex sampling design is taken into account, to the variance assuming simple random sampling. Design effect varies across variables, ranging from 0.17 to 13.52. In general, design effects gets larger as intra-cluster correlation grows. While there are several variables for which our sampling design outperform random sampling, it should be noted that variables which is likely to be geographically correlated tend to have large design effect, such as expenditure, highway travel frequency, and perception to health risk by environmental hazards.

3.3 Estimating Determinants of WTP

Using the data presented in the preceding section, we first estimate the determinants of WTP consisting of the determinants of probability to agree to pay for pollution reduction policy and the determinants to the amount of WTP conditional on having any willingness. We employ the commonly used “Two-part model” estimation. This approach (Duan

16. The detail of this variable is explained in Mahmud and Sawada (2018).

Table 3.2: Descriptive Statistics

VARIABLES	VARIABLES Description	(1) N	(2) mean	(3) sd	(4) min	(5) max	(6) DEFF
Dependent variables							
Yes	Have Positive Willingness to Pay	1,000	0.713	0.453	0	1	2.28
l_WTP	Willingness to Pay (log)	713	5.465	1.589	1.609	10.60	0.50
Explanatory Variables							
l_pc_exp	Per capita expenditure (log)	995	8.384	0.550	6.695	10.36	3.98
l_Age	Age (log)	991	3.513	0.318	2.890	4.369	0.55
Male	Male	1,000	0.609	0.488	0	1	2.15
l_HHsize	Household Size (log)	998	1.500	0.397	0	3.611	0.93
Nchild	Number of Children under 5	999	0.514	0.682	0	4	0.36
mededuc	Medium Education Attainment	1,000	0.386	0.487	0	1	1.95
higheduc	High Education Attainment	996	0.221	0.415	0	1	0.40
Trust	Most people can be trusted (6 scales; 6 = strongly agree)	997	3.587	1.577	1	6	2.73
lifesat	Degree of life satisfaction (10 grads; 10=very satisfied)	999	7.388	2.146	0	10	1.13
religious	degree of religiousness	1,000	0.639	0.481	0	1	0.96
toilet_share	sharing toilet with other HH	1,000	0.495	0.500	0	1	2.20
mob_adult	mobile per head	997	0.585	0.334	0	3	1.64
TV	Having TV	1,000	0.853	0.354	0	1	1.56
agLand	Havig agricultural land	1,000	0.326	0.469	0	1	0.58
l_highwayFreq	highway travel frequency (times per year, log)	999	2.279	1.862	0	5.481	5.21
meanTransp	having means of transportation	1,000	0.197	0.398	0	1	1.15
medishare	Medical expenditure share	997	0.0868	0.114	0	0.775	0.61
smoking	Smoking (Regularly or Sometimes)	1,000	0.291	0.454	0	1	1.98
health1	Self-reported Health (5 grades; 5=very healthy)	996	3.405	0.782	1	5	0.63
health2	Health Condition (Chronic Disease)	1,000	0.574	0.495	0	1	1.16
AfDW	Affected by Drinking Water	1,000	0.187	0.390	0	1	0.57
AfResp	Affected by Resp. Disease	1,000	0.189	0.392	0	1	0.63
victAcc	victimised by traffic accidents (self/hh/friends)	1,000	0.293	0.455	0	1	0.21
witnessAcc	witnessed traffic accidents last year	1,000	0.354	0.478	0	1	1.11
sickold	Sick elderly in hh	1,000	0.232	0.422	0	1	0.41
lostchild	having lost child	1,000	0.196	0.397	0	1	1.84
matdeath	any maternal death in HH	1,000	0.237	0.425	0	1	0.49
misfortune	victimised by misfortune (theft, disaster, etc.)	1,000	0.259	0.438	0	1	0.64
pRwater	Perceived Health Risk from Neighbourhood Water Quality	995	2.033	1.228	1	5	13.52
pRair	Perceived Health Risk from Neighbourhood Air Quality	996	2.387	1.296	1	5	4.98
pRroad	Perceived Risk of Road Safety	991	2.886	1.371	1	5	3.82
diff_choice	Feeling difficult to answer (Fatigue)	1,000	0.469	0.499	0	1	2.07
negative	negatie feeling to the interview	1,000	0.266	0.442	0	1	0.19
rec_cash	Prefer cash	1,000	0.751	0.433	0	1	0.54
rec_gift	Prefer gift	1,000	0.192	0.394	0	1	0.17
suv_dur	survey duration (minutes)	1,000	120.0	11.27	87	151	0.55

Mesurement units are in the parentheses of the second column. Variables without measurement units are binary variables. DEFF refers to the design effect: the variance when taking the sampling design into account divided by the variance when simple random sampling is assumed.

et al. 1983; Wang and Mullahy 2006; Hammitt and Zhou 2006) is used to separately estimate (i) the probability of “yes” to the question of whether the respondent has a willingness to pay, and (ii) the amount of WTP conditional on positive WTP. The first part, we estimate the following equation by Probit.

$$\text{Prob}(WTP > 0) = f_1(X_1\beta_1) \quad (3.1)$$

In (3.1), X_1 summarizes the vector of determinants. The second step is the estimation of WTP amount conditional on $WTP > 0$. Our estimation equation is the OLS as below:

$$\ln(WTP|WTP > 0) = f_2(X_2\beta_2) \quad (3.2)$$

The vector of determinates, X_2 can be different from X_1 . In the following analysis, we use a common variable set, $X = X_1 = X_2$.¹⁷

As explained above, our sampling is stratified and clustered. Therefore, estimation should respect the complexity of the sampling design. Since the sampling weight attached to each cluster is not recoverable, we compare the results across different sub-samples, to grasp potential bias from unweighted aggregation. Furthermore, another technical difficulty arises from the small number of clusters, where we have only three clusters in two strata in Dhaka, and remaining six strata are singleton with only one cluster. As pointed out by Cameron and Cameron (2015), when the number of cluster is very few (below 30), standard bias correction methods for the standard errors, such as White heteroskedasticity robust variance-covariance matrix estimator, cannot always mitigate the over-rejection problem. For the estimation of standard errors, we use the “wild cluster bootstrap” procedures according to the recommendation in Cameron and Cameron (2015).

17. As a robustness check, we estimate the “Type-II Tobit” specification so that we can verify whether the endogenous selection to answer the second part of the questionnaire (the amount) matters for the results. The estimation Results were very similar to the Two-Part model results presented in the paper, and are therefore not shown in this text for the sake of space.

More specifically, “score wild bootstrap” by Kline and Santos (2012) is used for the probit estimation, and “wild bootstrap procedure” of six-point version proposed by Webb (2014) is used for the linear estimation of WTP amount.¹⁸

3.3.1 Regression Results

Table 3.3 and Table 3.4 summarise the results of estimating equation (3.1) and equation (3.2), across different sub-samples. Each column corresponds to a sub-sample we analyse. The standard errors or p-values are not shown for the sake of space, while the star indicates the level of significance calculated using wild cluster bootstrap methods as explained above. Column (1) is for all the sample when ignoring the strata and treating the clusters as 10 independently and randomly chosen ones. Column (2) restricts the analyses to the seven clusters from Dhaka, ignoring the strata within them. Column (3) is the same for Chittagong. Two strata in Dhaka, Dhaka-Most Polluted and Dhaka-Medium Polluted, have three clusters in each, enabling us to use the wild bootstrap methods. The results for the Dhaka-Most Polluted stratum are shown in Column (4), and those for the Dhaka-Medium Polluted stratum are in Column (5).

In general, we find a consistent pattern of estimates on expenditure, age, and educational attainment. These three variables are the basic ones which are usually included in the existing studies in other countries. The signs of our estimates are in line with those past studies; positive coefficient on the expenditure, negative on age, and positive for the educational attainment. The significance of the coefficients varies across the sub-sample.

We included some unique variables and examine their relationship with the respondent’s WTP. The first set of variables are related to the respondents’ attitude towards life and social relationship, measured as trust, life satisfaction, and religiousness. Trust is negatively associated with the probability of having a willingness to pay as in Table 3.3. Its coefficients are significant when estimated overall the samples as in column (1), only

18. In estimation, we benefit from a STATA command “boottest” (Roodman et al. 2018) for bootstrapping.

for Dhaka (column (2)), and for Chittagong (column (3)) in Table 3.3. For the amount of WTP conditional on having any willingness to pay, trust does not show consistent results across different sub-samples. Life satisfaction seems to have positive relationship both in the selection and level equations, while results are not conclusive because they are insignificant for most of the sub-samples.

Variables related to the respondents' asset holding are also included, namely, the number of mobile phones per adult, possession of TV, agricultural land, and means of transport such as motorbike and car. Asset holding is in general related positively to WTP. Especially, in the level equation estimates shown in Table 3.4, number of mobile phones and possession of means of transport consistently and positively significant across different sub-sample specifications. This implies that the asset variables can improve the model's explanatory power, while these asset holding variable are correlated with income variables alone.

We asked the respondents' frequency of using highway. This is the log of the number of travels the respondent has made during past one year. Interestingly, this variable consistently has a positive coefficient for both the selection equation and the level equation, with significance for multiple cases. Potentially, this might happen because the variable is capturing the respondent's type of job or wealth which cannot be fully captured by the expenditure and asset variables.

Since mortality risk from air pollution is closely related with health, we examine the association between WTP and a series of health related variables, including health related activities such as medica expenditure share and smoking, self-reported health status, and objective health status as the incidence of chronic illness and air/water-borne diseases. There is no outstanding variable with a strong relationship to WTP, either in the selection or in the level equation.

We include variable related to the respondents' experience on misfortunes so that we can capture the potential impact of such experiences on WTP through affecting their risk

preferences. In general, none of the variables is very distinct in explaining the relationship both in the selection and level equations. Being a victim of an accident is positively (but insignificantly) related to the probability of having positive WTP in the selection equation. Contrarily, having a sick elder member in household is consistently negatively related.

Regarding the respondents' risk perception on the residential environment, high perception of water and air pollution may be positively related to the amount of WTP conditional on having any willingness to pay.

These three sets of variables, related to health, misfortunes, or environment, can capture the respondents' perception on probability of dying which is positively associated with the VSL in theory, as described in Hammitt (2017). The results indicate that the first two category of variables does not seem to strongly support this hypothesis, while it could apply to the third category which is directly related to environmental pollution, the issues the mortality risk in the survey is framed.

3.3.2 Bootstrap Estimation of Mean (Median) WTP and VSL

Using the results of estimation of the selection and level equations in the previous section, we now calculate the mean and median of WTP and their confidence intervals using bootstrap resampling. The estimation results give the functional forms for the probability of “yes” for Q1, $\text{Prob}(y_1 = 1) = f_1(\mathbf{x}'_1\beta_1)$, and the log of the WTP amount that is given as an answer to Q2, $\ln(y_2|y_1 = 1) = f_2(\mathbf{x}'_2\beta_2)$. Using the obtained functional forms, we calculate the predicted value of WTP of individual i , \hat{y}_{2i} , conditional on observed \mathbf{x}'_{1i} and \mathbf{x}'_{2i} :

$$\hat{y}_{2i} = f_1(\mathbf{x}'_{1i}\hat{\beta}_1) \times \exp\left(f_2(\mathbf{x}'_{2i}\hat{\beta}_2)\right) \quad (3.3)$$

The individual predicted values calculated by (3.3) is used to construct the mean or median of WTP. Furthermore, we repeat the same procedure for the bootstrapped samples

Table 3.3: Selection Equation Estimates (Probit)

Dependent Variable = Yes					
VARIABLES	(1) All	(2) Dhaka	(3) Chittagong	(4) S1	(5) S2
l_pc_exp	0.258 *	0.175	0.464	0.217	0.255
l_Age	-0.409 **	-0.201	-0.922 **	-0.147	-0.0278
Male	0.307 ***	0.317 ***	0.188	0.167	0.389 *
l_HHsize	0.127	0.0580	0.294	0.272	0.133
Nchild	0.0184	0.00331	0.0570	-0.0369	0.167
mededuc	0.318 ***	0.238 ***	0.515 *	0.232	0.354
higheduc	0.193	0.153	0.215	0.337	-0.0498
Trust	-0.0772 ***	-0.0476 *	-0.183	-0.0386	-0.0654
lifesat	0.0467 **	0.0415	0.0459	0.0268	0.122
religious	0.0476	-0.0268	-0.00503	-0.209	0.136
toilet_share	0.173	0.291 **	-0.140 *	0.267	0.363
mob_adult	0.114	0.296	-0.189	0.151	0.189
TV	0.0246	-0.0538	0.160 *	-0.185 *	0.110
agLand	0.124	0.294 **	-0.292	0.280	0.237
meanTransp	0.0144	0.188	-0.458 *	0.416	-0.0817
l_highwayFreq	0.0676 *	0.0648	0.0948	0.0907	-0.0234
medishare	0.373	-0.0324	1.283	0.201	-0.195
smoking	0.0324	0.0918	0.00706	0.145	0.187 *
health1	-0.0434	-0.0200	-0.0703	0.000156	-0.0798
health2	0.131	0.0878	0.377	0.393 *	-0.117
AfDW	-0.0146	0.0521	-0.300	-0.0322	-0.122
AfResp	-0.164	-0.160	-0.285	-0.168	-0.0585
victAcc	0.295	0.226	0.395	0.235	0.0313
witnessAcc	0.0226	-0.0579	0.250	-0.149	0.131 *
sickold	-0.309 *	-0.231	-0.518	-0.187	-0.889
lostchild	0.0565	0.152	-0.248	0.0430	0.198
matdeath	-0.0274	0.0714	-0.130	-0.153	-0.00299
misfortune	0.00941	0.0833	-0.207	-0.00538	0.375 *
pRwater	-0.0509	-0.0391	0.0116	-0.0267	0.134
pRair	-0.0683	-0.0984	0.116 *	0.0208	-0.301
pRroad	-0.0354	-0.0161	-0.0925	-0.0390	0.262
diff_choice	-0.0936	-0.202 *	0.275	-0.0767	-0.431 *
negative	-0.224 **	-0.317 **	-0.112	-0.478	-0.219
rec_cash	0.295	0.261	0.255	-0.400	0.837 *
rec_gift	0.527 *	0.510	0.684	-0.154	1.017 **
suv_dur	0.000978	0.00154	-0.00125	-0.000846	-0.00230
Constant	-1.042	-1.178	-0.568	-1.343	-3.116
Observations	957	672	285	289	287
Pseudo-R	0.113	0.130	0.209	0.103	0.238

Column (4) for the Dhaka-Most Polluted Stratum (S1) only
Column (5) for the Dhaka-Medium Polluted Stratum (S2) only
*** p<0.01, ** p<0.05, * p<0.1. S.E. is not shown for space
p-values are calculated using Score Wild Cluster Bootstrap

Table 3.4: Level Equation Estimates (OLS)

Dependent Variable = l_WTP					
VARIABLES	(1) All	(2) Dhaka	(3) Chittagong	(4) S1	(5) S2
l_pc_exp	0.841 ***	0.568 **	1.443	0.458	0.675 *
l_Age	-0.0976	-0.0122	-0.00840	0.180	-0.511
Male	0.0404	-0.313 **	0.717	-0.438	-0.177
l_HHsize	0.750 ***	0.830 ***	0.734	0.606	1.033 *
Nchild	0.0342	0.143	-0.309	0.0449	0.168
mededuc	0.129	0.106	0.282	0.0401	0.124
higheduc	0.119	0.300	-0.195	0.540	0.228
Trust	0.0355	-0.00139	0.160	0.00608	0.0383
lifesat	0.0225	0.0127	-0.0572	-0.0439	0.0288
religious	-0.126	-0.252 *	0.219	-0.180	-0.413 *
toilet_share	-0.00915	0.00610	-0.0648	-0.273	0.184
mob_adult	0.342 **	0.492 *	0.169 *	0.603 *	0.388
TV	0.0630	0.00862	0.390	-0.397	0.304
agLand	0.0437	0.146	-0.352	-0.0435	0.221
meanTransp	0.312 **	0.352 ***	0.495 *	0.258	0.565 *
l_highwayFreq	0.0814	0.0911 *	0.0364	0.0639 *	0.104
medishare	-0.690	-0.140	-0.838	0.565	-0.427
smoking	0.466 **	0.494 ***	-0.0519	0.643	0.482
health1	0.256	0.284	0.426	0.183	0.335
health2	0.0663	0.0720	0.0911	-0.0574	0.420 *
AfDW	-0.00185	0.0157	-0.0557	0.266	-0.334
AfResp	0.00864	0.00619	-0.323	0.0290	0.0854
victAcc	0.0664	0.239	0.00177	-0.0853	0.532 *
witnessAcc	-0.278 *	-0.269	-0.540	0.280	-0.500 *
sickold	0.108	0.338 **	-0.248	0.0168	0.681 *
lostchild	-0.0785	-0.168	0.280	-0.489	-0.255
matdeath	-0.127	-0.0396	-0.309	-0.143	0.125
misfortune	-0.0793	-0.0396	0.00187	-0.403 *	0.226
pRwater	0.136 **	0.0723 *	0.296	0.0275	0.125
pRair	0.0341	0.0599 ***	-0.199 *	0.0811	0.0650 *
pRroad	-0.0206	-0.0237	0.0912	0.0449	-0.154
diff_choice	-0.0142	-0.104	0.479	-0.201	-0.0321
negative	-0.449 **	-0.427	-0.404	0.111	-0.801 *
rec_cash	0.218	0.293	2.054	0.190	0.110
rec_gift	0.249	0.165	2.458	-0.0605	0.176
suv_dur	-0.00317	-0.00329	-0.00270	-0.0124	0.0161 *
Constant	-4.168	-2.033	-12.71	1.061	-4.513
Observations	685	477	208	185	229
R-Squared	0.216	0.221	0.460	0.303	0.326
Adj R-Sq.	0.173	0.157	0.346	0.133	0.199

Column (4) for the Dhaka-Most Polluted Stratum (S1) only

Column (5) for the Dhaka-Medium Polluted Stratum (S2) only

*** p<0.01, ** p<0.05, * p<0.1. S.E. is not shown for space

p-values are calculated using Wild Cluster Bootstrap with Six-Points

for 4,000 times to obtain the confidence intervals for the mean (median) estimates using the results of the previous section.

The VSL is obtained by dividing WTP by the magnitude of risk reduction in the scenario (5/10,000). In order to construct confidence intervals for the mean (median) WTP, we use the bootstrap re-sampling method.¹⁹ The estimation procedure is as follows: the bootstrap resampling is made at the cluster level. For each round of re-sampling, we estimate selection equation and level equation on the bootstrapped samples, and calculate the predicted WTP using (3.3) for each re-sampled observation. Mean (or median) WTP over this predicted WTP across bootstrapped observations are then calculated. This process is repeated for 4,000 times to obtain the bootstrapped average and confidence intervals for the mean WTP.

Table 3.5 summarises the estimation results, across different sub-samples. The average VSL in PPP USD ranges from 17,480 to 22,463. The average VSL is the smallest for the case of all the sample is used, and it is the largest for the strata 2 (Dhaka-Medium Polluted). The confidence interval is the narrowest for strata 2 with only 1,234 USD, while it becomes very large for the case of Chittagong (16,632 USD). To understand the large variability of the estimated VSLs, Table 3.7 show key descriptive statistics and predicted values of mean WTP and VSL of each of 10 clusters. Chittagong's wide confidence interval compared to other subgroup seems to be caused by the ShehShah cluster (Column (8) of Table 3.7) whose average amount of willingness to pay conditional on having any willingness to pay is very low (195.4 Taka) compared to other clusters. DEFF (Design Effect) of each mean estimate is also reported in the table. Here, DEFF is defined as the ratio of the variance of mean VSL by bootstrapping accounting for our complex sampling design, to the variance of mean VSL calculated when the bootstrapping is carried out by a simple random resampling from the pool of all 1,000 observations.

Table 3.6 shows the bootstrap estimation results of the median VSL. Compared with

19. The procedure is similar to Wang and Mullahy (2006).

the mean VSL, there is no systematic relationship between the estimated average median VSL and the sample size. And the estimated values are all significantly smaller than those for mean VSL.

Bangladesh's nominal GDP per capita in 2013 was 46,322 Taka.²⁰ Therefore, the estimated mean VSL is about 9.78-12.57 times of GDP per capita (5.03-7.61 times for median VSL estimate). This is much higher than the estimate of mean VSL by Mahmud (2009) at between 3.55 times and 5.82 times GDP per capita at the time of survey²¹. However, in terms of a multiple of GDP per capita, our estimated VSL is much smaller than CV studies in other countries. For example, Wang and Mullahy (2006)'s result implies that the median VSL is 70.32 times average nominal income, calculated from WTP for reducing mortality risk from air pollution in Chongqing, China. Miller (2000) conducts a meta-analysis of 68 VSL studies in developed countries and found that stated VSL is typically about 120 times of GDP per capita. In Section 3.4, we will further discuss on the validity of our estimates and how we can position it among the international examples.

3.4 Discussion on the Validity of Results

CV method is a widely used methodology to evaluate the monetary value of goods whose market values cannot be observed directly. However, it has long been criticised for its reliability and practical usefulness for policy making. Hausman (2012) summarises the methodological limitations of contingent valuation method. He categorises the problems which are commonly observed in the existing contingent valuation studies into three; (i) Hypothetical bias, (ii) Discrepancy between willingness to pay (WTP) and willingness to

20. <https://data.worldbank.org/indicator/NY.GDP.PCAP.KN?locations=BD>

21. The survey was done in 2003 and nominal GDP per capita then was 29,010 Taka. His mean VSL estimates ranged from 103,074 Taka to 168,905 Taka, depending on different settings. However, the study deals with very large risk reduction and VSL is inversely proportional to the size of the risk reduction offered.

Table 3.5: Estimates of Mean VSL

	(1) Average	(2) Confidence Interval (5%)	(3) Confidence Interval (95%)
All sample (N=1,000, DEFF = 2.51)			
mean WTP (Taka)	226.6	198.0	256.5
VSL (Taka)	453,200	396,000	513,000
VSL (PPP USD)	17,480	15,274	19,786
Dhaka (N=700, DEFF=1.54)			
mean WTP (Taka)	248.5	225.3	274.7
VSL (Taka)	497,000	450,600	549,400
VSL (PPP USD)	19,169	17,380	21,190
Chittagong (N=300, DEFF=3.03)			
mean WTP (Taka)	271.2	164.2	379.8
VSL (Taka)	542,400	328,400	759,600
VSL (PPP USD)	20,920	12,666	29,298
Only Dhaka-Most Polluted Stratum (N=300, DEFF = 1.24)			
mean WTP (Taka)	260.2	228.1	291.8
VSL (Taka)	520,400	456,200	583,600
VSL (PPP USD)	20,072	17,596	22,509
Only Dhaka-Medium Polluted Stratum (N=300, DEFF = 0.36)			
mean WTP (Taka)	291.2	283.1	299.1
VSL (Taka)	582,400	566,200	598,200
VSL (PPP USD)	22,463	21,838	23,072

The conversion rate between US dollar and Bangladesh Taka, 1USD=78.2049 BDT, as of June 30, 2013 (Bangladesh Bank) is used for calculating US dollar values. The PPP conversion factor of Bangladesh Taka into international dollar (at 2011 price) was 1USD = 25.927BDT.

(See <https://data.worldbank.org/indicator/PA.NUS.PPP?locations=BD>).

DEFF refers to the design effect the variance when taking the sampling design into account divided by the variance when simple random sampling is assumed.

Table 3.6: Estimates of Median VSL

	(1) Average	(2) Confidence Interval (5%)	(3) Confidence Interval (95%)
All sample (N=1,000, DEFF=2.42)			
median WTP (Taka)	153.6	133.3	177.0
VSL (Taka)	307,200	266,600	354,000
VSL (PPP USD)	11,849	10,283	13,654
Dhaka (N=700, DEFF=2.09)			
median WTP (Taka)	176.2	161.1	197.6
VSL (Taka)	352,400	322,200	395,200
VSL (PPP USD)	13,592	12,427	15,243
Chittagong (N=300, DEFF=3.76)			
median WTP (Taka)	116.5	80.92	168.5
VSL (Taka)	233,000	161,840	337,000
VSL (PPP USD)	8,987	6,242	12,998
Only Dhaka-Most Polluted Stratum (N=300, DEFF=0.78)			
median WTP (Taka)	167.0	162.2	173.6
VSL (Taka)	334,000	324,400	347,200
VSL (PPP USD)	12,882	12,512	13,391
Only Dhaka-Medium Polluted Stratum (N=300, DEFF=0.37)			
median WTP (Taka)	162.3	151.2	171.1
VSL (Taka)	324,600	302,400	342,200
VSL (PPP USD)	12,520	11,664	13,199

The conversion rate between US dollar and Bangladesh Taka, 1USD=78.2049 BDT, as of June 30, 2013 (Bangladesh Bank) is used for calculating US dollar values. The PPP conversion factor of Bangladesh Taka into international dollar (at 2011 price) was 1USD = 25.927BDT.

(See <https://data.worldbank.org/indicator/PA.NUS.PPP?locations=BD>).

DEFF refers to the design effect the variance when taking the sampling design into account divided by the variance when simple random sampling is assumed.

Table 3.7: Descriptive Statistics and Predicted Value of WTP at Each Cluster

VARIABLES	(1) Hazaribag	(2) strata= 1 Kamrangir	(3) Tongi	(4) Dhaka Diabari	(5) strata= 2 ShahAli	(6) Nobinagar	(7) strata= 3 Maniknagar	(8) strata= 4 ShehShah	(9) Chittagong strata=5 GoribullahShah	(10) strata= 6 Riaz Uddin & Enayet
Have Positive Willingness to Pay	0.770	0.590	0.540	0.814	0.765	0.850	0.660	0.717	0.680	0.790
Amount of Willingness to Pay	816.6	835.7	574.4	764.1	1,216	741.1	953.0	195.4	1,099	1,045
Per Capita Expenditure (Taka/Month)	4,395	4,510	5,677	4,526	5,920	4,336	6,223	4,846	6,315	4,860
Age	36.65	35.15	35.56	34.43	36.86	34.17	34.37	34.60	34.90	36.18
Male	0.560	0.560	0.490	0.598	0.735	0.860	0.540	0.596	0.590	0.560
Household Size	5.410	4.710	4.939	4.443	4.546	4.610	4.720	5.202	5.300	4.950
Medium Education Attainment	0.420	0.340	0.450	0.320	0.367	0.550	0.380	0.354	0.340	0.340
High Education Attainment	0.140	0.153	0.180	0.124	0.235	0.130	0.340	0.354	0.398	0.160
Perceived Health Risk from Neighbourhood Air Quality	3.570	3.450	2.960	2.093	2.299	1.455	2.450	1.980	1.808	1.778
Predicted mean WTP (Implied VSL, PPP USD)	399.5 30,817	369.2 28,480	494.8 38,169	313.0 24,145	682.1 52,617	354.5 27,346	360.2 27,786	99.42 7,669	698.0 53,843	272.8 21,044

accept (WTA), and (iii) Scope bias.

The first problem, the hypothetical bias, stems from the fact that the contingent valuation method relies on hypothetical questions about the non-market goods that are unfamiliar to the people in their daily life. Since hypothetical questions may not always be associated with people's actual experience, a substantial discrepancy between what they say and what they do (if they actually face the situation) can emerge. Hausman (2012) reports hypothetical bias usually overestimates the true price of a non-market good. Viscusi and Masterman (2017b) assert that revealed preference studies using the Census of Fatal Occupational Injuries (CFOI) of the U.S. are relatively favourable because they are not subject to biases introduced by hypotheticals, instead of using stated preference results. In addition, they suggest that the best way to calculate a VSL for a country with insufficient data is to "transfer a base VSL from the United States calculated using the labor market estimates", by extrapolating the country's value from the US base value and the income elasticity of the VSL.

Despite this universal scepticism to the stated preference approach, global evidence does not always discourage the use of the method. By a parametric meta-regression analysis on the studies in the U.S, U.S. Environmental Protection Agency's Office of Policy (2016) revealed that there is no distinct differences in the estimated VSL between the revealed preference studies and the stated preference studies.²² This is a counter-evidence to the common concern that the stated preference method is highly susceptible to hypothetical bias (which is often supposed to be a larger VSL estimate with the stated preference to the revealed preference).

We believe that our estimates are not significantly affected by the hypothetical bias. Firstly, while the argument by Hausman (2012) focuses mainly on the cases of goods which are distant from the need of fatal risk reduction, our scenario (fatal risk reduction)

22. See Table 9. of U.S. Environmental Protection Agency's Office of Policy (2016) for the detail. It argues that the stated preference studies are about 15 percent lower on average than those from the revealed preference studies, but this is not a statistically significant difference.

is more closely tied to their daily decision making. Studies using revealed preference methods support that the risk reduction is people's daily issue and that they are willing to trade off money to reduce this. For example, Viscusi and Aldy (2003) provide market evidence using revealed preference that shows that people are willing to spend money to reduce their mortality risk in their daily life. Since hypothetical questions work better for issues closely related to the daily life risk reduction that are common and familiar than for unfamiliar public goods provision, it is reasonable to assume that hypothetical bias is less of a concern in our case.

In addition, our questionnaire design helps respondents to think more realistically. In existing studies, it is common to ask about WTP first followed by questions related to their socio-economic characteristics of the respondents. In our case, we introduce respondents to various risks people face in their daily life in Bangladesh, train and elicit their understanding of risk concepts, their own risk perceptions. Also, we asked questions related to socio-economic situation including income and consumption expenditures, cultural background, record of individual health problems, etc. After these questions, the WTP questions were asked in the final section of the questionnaire. This two-step structure encourages the respondents to consciously reflect their own socio-economic as well as physical status, and provides the respondent a very good setting in answering the valuation question more thoughtfully and credibly.²³

The discrepancy between WTP and WTA is not a major concern in the context of fatal risk reduction, as in our case. First of all, NOAA panel report (Arrow et al. 1993) recommended WTP instead of WTA in the context of contingent valuation studies. In addition, WTP seems more appropriate regarding values for reducing mortality risk from air pollution, because the policy implications of WTA values are not obvious in the context of improving air quality.²⁴

23. As far as we know, there is no study examining the impact of the style of questionnaires, especially about when the WTP questions are asked during the survey.

24. Due to this theoretical concern, most of the existing studies on mortality risk reduction have focused

Scope bias challenges two assumptions of VSL: that respondents correctly understand the probability of death (e.g. the fatal risk of 1/1000 is ten times more dangerous than the risk of 1/10000), and the willingness to pay is approximately linear with respect to the risk reduction magnitude (which is called near-proportionality). In the literature of contingent valuation, a “scope test” with multiple questions of different risk reduction magnitude is often conducted to deal with this problem. Since we did not conduct a scope test with multiple questions of different risk reduction magnitudes, our estimates of VSL potentially suffer from this problem. However, while the lack of scope test could limit the reliability of our VSL estimate to some extent, we still believe our analysis delivers useful information because the survey respondents received enough training to understand the probability concept and the urban air pollution situation in Dhaka (Chittagong). We provided examples and tested the respondents on their understanding of probability, and they generally got high scores, as seen below. As Mahmud (2009) shows, facilitating respondents’ better comprehension through training prior to the questioning WTP is crucial in the mitigation of scope bias.

3.4.1 Respondents’ Understanding of Risk and Risk Reduction

In the following two subsections, we discuss the plausibility of our estimates from various perspectives. Firstly, as we argued above, one of the important prerequisites for conducting contingent valuation studies is the good understanding of the concept of risk and risk reduction held by the respondents. Given generally low education profile of respondents where about 40% of the respondents have only primary or lower-level education, we paid special attention in training and examining their ability to correctly answer risk and risk reduction problems.

Before introducing our hypothetical risk reduction scenario and asking about their

on WTP. Gibson et al. (2007) measured both WTP and WTA for landmines removal programs in Thailand, and it is the only previous case that compares the values from the two methods, to the best of our knowledge. They find no significant difference between the two methods. Given these, we find that our approach to use only WTP is appropriate.

Table 3.8: Respondents' Understanding of Risk and Risk Reduction

Question	Correct Respondent ($N = 1000$)
The risk of dying in Road A is 1 in 10,000 and the risk of dying in Road B is 3 in 10,000. Which road is more risky? (Correct Answer = B)	987 (98.7%)
Which of the three risk reductions is preferable? (Correct Answer = 3)	991 (99.1%)
1. 40 in 100,000 to 30 in 100,000	
2. 40 in 100,000 to 20 in 100,000	
3. 40 in 100,000 to 10 in 100,000	

willingness to pay for it, we explained the concepts of risk reduction in detail followed by an examination. The exam checks that respondents correctly compare the level of risk and the magnitude of risk reduction. The results are summarised in Table 3.8. Almost all the respondents understood the concept of risk and risk reduction correctly. 98.7% of the respondents answered correctly when they asked to compare the level of mortality risk between two roads. Furthermore, 99.1 % of them correctly chose the option among three hypothetical risk reductions. Out of total 1,000 respondents, 980 respondents (98%) answered the both question correctly. The 20 respondents who could not answer either of questions correctly received follow-up training until they finally understood.²⁵

3.4.2 Assessment with Theory and Past Studies

We further argue the validity of our estimate from theoretical perspective. Hammitt (2017) theoretically argues how income, mortality risk, health, life expectancy, and social norms, affect the amount of VSL. According to the standard theory, income or expenditure

²⁵ In a regression analysis, we include dummy of making incorrect answers. However, this is not significant (the result is not reported in Table 3.3 and Table 3.4)

is positively associated with VSL, as expected. Instead, higher survival probability (due to healthier life, etc.) can be negatively associated because of the “dead-anyway effect” (Pratt and Zeckhauser, 1996), reflecting that if current probability of death is high, the VSL is large because the expected opportunity cost of current spending decreases. The impact of life expectancy at the time of survey is ambiguous as is the expected future health status. The impact of framing risk reduction as government programmes is also theoretically ambiguous.²⁶

OECD (2012) (or Lindhjem et al. (2011))²⁷, conducts a comprehensive meta-regression of VSL on various stated preference studies in OECD countries, aiming at pinning down relationships between VSL amount and characteristics of population and survey material. They conclude that income and risk reduction size are positively and negatively associated with VSL, with strongly significant coefficients. If the risk context is related to environmental issues, there is also a strong indication that the stated VSL tends to be lower. If the risk reduction is framed as a public good, the VSL is again likely to be lower compared to when it is being considered as a private issue.²⁸

As a precious example of a non-OECD country which is comparable to ours, Guo, Haab, and Hammitt (2007) used a stated preference survey in Chengdu, China, on the WTP for reducing the risk of asthma and death from air pollution problem. Their survey was designed to analyse the impact of design choice, which is relevant to our case: (1) whether the risk reduction measure is contextualised as a public/governmental provision or as a private good, (2) in case it is a public provision, how respondents’ belief in the effectiveness of government programs matters. According to their analysis, framing the

26. Hammitt (2017) does not support simply transferring the VSL of one country to another, because the theory suggests that VSL value can be affected by many factors not only income, such as life expectancies and social norms, which are greatly diverse across nations.

27. Specifically, chapter named “Meta-regression analysis of value of statistical life estimates”.

28. According to one of the estimated results that is most relevant to our setting (Table 3.4 in OECD (2012)), elasticity of VSL with respect to income is 0.783, with respect to the magnitude of risk reduction is -0.577, respectively. If the cause of fatality is framed as an environmental issue, the value of VSL declines by 0.606 (60.6%). If risk reduction program is framed as an public goods, it reduces the stated VSL by 91.3%.

risk reduction as a public provision significantly reduces the stated VSL, compared to the case where it is explained as a private good. Furthermore, they found that respondent confidence in the effectiveness of government programs significantly increase the VSL.

Our study context in Dhaka and Chittagong, Bangladesh, is a case of a very low income country, with a scenario with relatively large magnitude of risk reduction (1/2000), and framed as a environmental public goods. According to OECD (2012), this feature is strongly leaned to smaller VSL estimates. If our VSL is perfectly align with the model of OECD (2012), the VSL should be 30,930 USD ²⁹ Our mean estimates, ranging from 17,480 to 22,463 USD, are not seriously far from this value based on OECD (2012)'s model. Our estimates is therefore largely in line with past stated preference studies in OECD countries, with potentially hitting the lower bound of VSL.³⁰

3.5 Conclusion

Our study is the first attempt to provide estimates of monetary value of air pollution risk reduction using the contingent valuation method in two major cities in Bangladesh. Based on the collected data and regression results for selected individual characteristics,

29. Using the regression coefficient from the meta-analysis (see footnote 28 for detail), the VSL from our survey consistent with their model can be calculated by,

$$30,930\text{USD} = 3\text{mil.USD} \times \left(\frac{2023}{30601}\right)^{0.783} \times \left(\frac{1/2000}{1/10000}\right)^{-0.577} \times \exp(-0.606) \times \exp(-0.913) \quad (3.4)$$

where, the mean VSL , the mean income (in GDP per capita), and risk reduction magnitude of OECD (2012)'s study samples, were 3 million USD, 30,601 USD, and 1/10000, respectively. The annualized average expenditure from our survey is 2,023 USD. The coefficients were taken from the Model V of Table 3.4 of OECD (2012). If we use the coefficients of model IV of the same table, the value further drops to 24,733 USD. Bangladesh is a country where people may attach especially lower value when the risk reduction program is designed as a “government” program. In Bangladesh, the government can collect fewer tax per GDP compared to other countries and only 1.2% of population pay income tax. It is probable that many people do not think they are responsible for financing public policies and therefore framing the hypothetical program as a governmental one could have a large negative impact.

30. We calculate the elasticity of VSL to expenditure by regressing log of predicted VSL on log of per capita expenditure. For all the sample, the elasticity is .955. Only for Dhaka, it is .652, while it rises to 1.661 for Chittagong. For the Stratum 1 and the Stratum 2, it is .643 and .581, respectively. These values are within the range found from past studies (e.g. Robinson, Hammitt, and O’Keeffe 2017; Viscusi and Masterman 2017b; OECD 2012; Hammitt and Robinson 2011).

we calculated the bootstrapped average of mean and median WTPs as well as those of a VSL. The estimated mean VSL is ranged from 17,480 to 22,463 USD in PPP of or 9.78 to 12.57 times GDP per capita in 2013. While this could be interpreted as a substantial private contribution to the risk reduction program with large externality, the estimated VSL is much smaller compared to studies conducted in other countries. This might be related to scope bias, as suggested in earlier literature in economics and psychology that argue that people tend to overestimate small risks and underestimate large risks (e.g. Tversky and Kahneman 1992; W. K. Viscusi 1992; Kahneman and Tversky 2000). In addition to this scope bias, our estimate could also be prone to bias due to aggregation of unweighted observations. However, as examined in Section 3.4, our estimates are not out of the range of the existing studies summarised in Robinson, Hammitt, and O 'Keeffe (2017). Moreover, ours are not very far from the value obtained from a benefit transfer exercise using the result of OECD (2012).

Given these potential issues surrounding the valuation exercise, it is important to carefully interpret the estimates and we should not treat them as generic (context free) VSL in Bangladesh. Rather these may be regarded as a lower bound of benefit estimates for environmental policies or programs aiming at fatal risk reductions.

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