

Three Essays on the Economic Impact of Firm Activity

by

Chengying Luo

B.A. in Economics, Shanghai Jiao Tong University, China, 2013

M.A. in Economics, University of Pittsburgh, 2014

Submitted to the Graduate Faculty of
the Dietrich School of Arts and Sciences in partial fulfillment
of the requirements for the degree of

Doctor of Philosophy

University of Pittsburgh

2019

UNIVERSITY OF PITTSBURGH
DIETRICH SCHOOL OF ARTS AND SCIENCES

This dissertation was presented

by

Chengying Luo

It was defended on

April 25th 2019

and approved by

Randall Walsh, Department of Economics

Douglas Hanley, Department of Economics

Daniel Berkowitz, Department of Economics

Jeremy Weber, Graduate School of Public and International Affairs

Dissertation Director: Randall Walsh, Department of Economics

Copyright © by Chengying Luo
2019

Three Essays on the Economic Impact of Firm Activity

Chengying Luo, PhD

University of Pittsburgh, 2019

This dissertation studies the economic causes and consequences of firm activity. The first chapter explores the impact of large initial public offerings (IPOs) in U.S. stock markets on local economic activity. Utilizing a spatial, difference-in-differences estimation framework, I find that going public leads to an increased number of businesses in the IPO firms' industries and higher employment, wages, and housing prices in the vicinity of the firms' headquarters. Information aggregated in the IPO process plays an important role in explaining housing price dynamics at different stages of IPOs. Neighborhoods close to firm headquarters experience modest growth in income, a smaller share of low-income residents, and an increase in the number of nearby restaurants.

The second chapter studies the effects of international environmental policies on firms' production and innovation, aggregate growth, and climate change. I build a two-country and two-sector endogenous growth model where clean and dirty technologies innovate to compete for global market leadership in final good production. I find that clean research subsidies and carbon taxes are effective in directing production and innovations to clean technology, though carbon taxes may encourage dirty innovation abroad. I characterize the unilateral optimal policy path implied by the model and microeconomic estimates. I find that optimal policy makes heavy use of research subsidies and it can secure a transition to clean technology globally with international knowledge spillover.

The third chapter investigates how consumer reviews affect employment decision. I combine reviews from Yelp.com and information on the employment and wages of local businesses in Pittsburgh. Using a regression discontinuity framework that exploits Yelp's rounding thresholds, I find that an extra star rating leads to higher employment and total wage bills, while it does not affect average wage per worker. This effect also holds for other service industries. Using textual analysis on consumer reviews, my results show that consumer reviews on employees services do not seem to change employment decisions significantly.

Table of Contents

Preface	xi
1.0 Introduction	1
2.0 Initial Public Offerings and Local Economic Activity: Jobs, Housing Markets, and Demographics	3
2.1 Introduction	3
2.2 Background: IPOs and the Local Economy	8
2.3 Data	11
2.3.1 IPO Data	11
2.3.2 Business Pattern and Income Data	12
2.3.3 Housing Price Data	13
2.4 Empirical Methodology	14
2.4.1 Effects of IPOs on the Local Economy	14
2.4.2 Effects of IPOs on Real Estate Markets	15
2.5 Empirical Results	16
2.5.1 Effects of IPOs on the Local Economy	16
2.5.2 Effects of IPOs on Real Estate Markets	18
2.5.2.1 Primary Difference-in-Differences Results	19
2.5.2.2 Falsification Tests and Housing Composition Analysis	20
2.5.2.3 Heterogeneity Analysis	21
2.5.3 Effects of IPOs on Demographics and Amenities	22
2.6 Conclusions	24
2.7 Figures and Tables	26
3.0 International Competition in the Race to Clean Technology	47
3.1 Introduction	47
3.2 Model	52
3.2.1 Preferences and Endowments	52

3.2.2	Production	53
3.2.3	Innovation and the Quality Ladder	55
3.2.4	Trade and Market Equilibrium	57
3.2.5	The Carbon Cycle	61
3.2.6	Value Functions	62
3.2.7	Firm Entry and Innovation	63
3.3	Data	65
3.3.1	External Calibration	65
3.3.2	Initial Patent Stock	66
3.3.2.1	Patent Data	66
3.3.2.2	Patent Classification	67
3.3.2.3	Patent to Step Distribution	69
3.3.3	Simulated Method of Moments	69
3.4	Policy Analysis	70
3.4.1	Laissez-Faire	70
3.4.2	Unilateral Policy	71
3.4.2.1	Carbon Tax	71
3.4.2.2	Research Subsidy	71
3.4.2.3	Carbon Tariffs	72
3.4.2.4	Carbon Tariffs	72
3.5	Conclusion	72
3.6	Figures and Tables	74
4.0	Consumer Reviews and Employment Decisions: Evidence from Yelp.com	93
4.1	Introduction	93
4.2	Data	96
4.2.1	Yelp	96
4.2.1.1	The Content of Consumer Review on Yelp.com	97
4.2.2	Employment and Wage Data	98
4.3	Empirical Methodology	99
4.4	Empirical Results	100

4.4.1	Cross-Section Results	100
4.4.2	RDD Results	101
4.4.3	Reviews on Employee Services and Management Decision	102
4.5	Conclusion	103
4.6	Figures and Tables	104
Appendix A. Proofs and Additional Theoretical Results		120
Appendix B. Computational and Estimation Algorithms		125
Bibliography		127

List of Tables

1	Summary of IPOs	37
2	Summary of Offering Proceeds by Expectation	38
3	Summary Statistics of Housing Data	39
4	Impact of IPO Activity on the Local Economy	40
5	Impact of IPO Activity on the Same 3-Digit NAICS Establishments	41
6	Impact of IPO Activity on Property Values	42
7	Falsification Tests of the Effects of IPO Activity on Property Values	43
8	Housing Composition Regression Results	44
9	Heterogeneous Effects of IPO Activity on Property Values	45
10	Impact of IPOs on Demographics and Amenities	46
11	Externally Calibrated Parameters	89
12	Model Fit	90
13	Internally Calibrated Parameters	91
14	Optimal Unilateral Carbon Tax Policies	92
15	Confusion Matrix for Predictions on the Test Data	109
16	Summary Statistics of Businesses on Yelp in Pittsburgh	110
17	Impact of Yelp Rating On Employment and Wage	111
18	RD Estimates - Restaurants (bandwidth: 0.01 stars)	112
19	RD Estimates - Difference Bandwidths	113
20	RD Estimates - All Services Business (0.01 stars)	114
21	RD Estimates - Non Restaurants (Bandwidth: 0.05 stars)	115
22	Regression Discontinuity Estimates - Restaurants (Lagged Dependent Variables)	116
23	Response to Reviews on Services - Employment	117
24	Response to Reviews on Services - Total Wage	118
25	Response to Reviews on Services - Average Wage	119

List of Figures

1	Post-IPO Capital Expenditures and Employment Growth	26
2	The IPO Process	27
3	Corporate Headquarters of IPO Firms	28
4	Effects of IPOs on Proximate Firms by Year	29
5	Effects of IPOs on Wages by Year	30
6	Effects of IPOs on the Same 3-Digit NAICS Industries by Year	31
7	Treatment/Control Boundary Analysis	32
8	Housing Price Residuals Plots	33
9	Effects of IPOs on Demographics by Year	34
10	Effects of IPOs on Amenities by Year	35
11	Effects of IPOs on Household Sorting	36
12	The Trade Flow	74
13	Carbon Emission and Concentration: Data and Model Implications	75
14	Patents Classification	76
15	Laissez-Faire	77
16	Time Path of Temperature Under Laissez-Faire	78
17	Optimal Unilateral Carbon Tax - US	79
18	Time Path of Temperature Under Optimal Unilateral Carbon Tax - US	80
19	Optimal Unilateral Carbon Tax - CN	81
20	Time Path of Temperature Under Optimal Unilateral Carbon Tax - CN	82
21	Optimal Unilateral Research Subsidy - US	83
22	Time Path of Temperature Under Optimal Unilateral Research Subsidy - US	84
23	Optimal Unilateral Research Subsidy - CN	85
24	Time Path of Temperature Under Optimal Unilateral Research Subsidy - CN	86
25	Optimal Unilateral Carbon Tariffs - US	87
26	Optimal Unilateral Carbon Tariffs - CN	88

27	Businesses on Yelp in Pittsburgh	104
28	Yelp Review Trend	105
29	Yelp Rating Distribution	106
30	Yelp Rating Schedule	107
31	Discontinuous Changes in Rating	108

Preface

I want to express my most sincere appreciation to my thesis committee members - Professor Randall Walsh, Douglas Hanley, Daniel Berkowitz, and Jeremy Weber - not only for their for his continual enthusiasm and unconditional support through this process, but also for their insightful feedback. To the many friends, colleagues, and professors I met in Pittsburgh, you make this six years of study a great journey.

A special thanks to my parents and my fiancé Xingye Da. Thank you all for your constant support and love. I could not have done this without you.

1.0 Introduction

My research involves the fields of urban economics, international economics, and public economics. The main focus of my research has been to understand the firm behavior and its various impacts on the economy by combining original data with reduced-form regressions, machine learning techniques, and micro-founded macro models.

In the first chapter, “Initial Public Offerings and Local Economic Activity: Jobs, Housing Markets, and Demographics,” I study the impact of firms going public on the local economy. I approach this problem by utilizing a spatial, difference-in-differences estimation framework by comparing changes in outcomes (employment, business patterns, housing prices, and resident income) before and after an Initial Public Offering (IPO) for areas very close to the IPO firms’ headquarters with areas slightly farther away. I find that going public leads to an increased number of businesses in the IPO firms’ industries and higher employment, wages, and housing prices in the vicinity of the firms’ headquarters. I further compare IPOs of different expected and final offering proceeds and find that firms with above-expected proceeds lead to a larger housing price effect post-IPO compared with the IPO announcement stage, and vice versa. Neighborhoods close to firm headquarters experience modest growth in income, a smaller share of low-income residents, and an increase in the number of nearby restaurants.

My second dissertation chapter studies the optimal international climate policies to encourage firms to switch from dirty to green (clean) technologies. In this joint paper with Douglas Hanley, “International Competition in the Race to Clean Technology”, we build a two-country, two-sector (clean, dirty) trade model in which clean and dirty technologies compete in production. Research and carbon tax effectively encourage production and innovations in clean technology, though carbon taxes may encourage dirty innovation abroad and generally cannot avoid the carbon leakage. We estimate the parameters of the model using the US and China micro-data on firm-level output, R&D, and patents. We then characterize the optimal unilateral policy path that using carbon taxes, research subsidies and tariffs respectively. we find that optimal policy makes heavy use of research subsidies and it can

successfully secure a transition to clean technology globally with international knowledge spillover.

In my third chapter, “Consumer Reviews and Employment Decisions: Evidence From Yelp.com”, I study how consumer reviews affect the employment decision. Internet review platforms inform consumers about product quality and hence shift consumer demand. At the same time, these reviews are also frequently read by business owners and may be used to monitor their employees. I investigate this question by combining reviews from Yelp.com and information on the employment and wages of local businesses in Pittsburgh. Using a regression discontinuity design, I find that an extra star rating leads to a 3.5 increase in the quarterly number of employees and a \$2,800 increase in the quarterly total wage bill, while it does not have any impact on average wage per worker. This effect also holds for other non-food service industries. By conducting sentiment analysis on text reviews regarding customer services, my results show that employment decisions do not seem to be affected by the content of consumer reviews on employee services.

2.0 Initial Public Offerings and Local Economic Activity: Jobs, Housing Markets, and Demographics

2.1 Introduction

Going public is one of the most significant events over the lifecycle of a firm. Initial public offerings (IPOs) improve firms' access to capital and allow early investors and employees to cash out. This process is critical to the economy's ability to generate wealth, employment, and innovation (Borisov et al., 2015; Bernstein, 2015). From 2000 to 2015, there were an average of more than 200 IPOs in U.S. stock markets each year, collecting \$879 billion (in 2015 dollars) in total gross proceeds. The important role of the IPO market in the economy led the U.S. government to enact the Jumpstart Our Business Startups Act, which is intended to encourage small businesses and startups to raise funds through the IPO market, following the decrease in small business activity in the wake of the 2008 financial crisis.

Although the importance of IPOs is widely acknowledged, it is unclear how firms going public affects the local economy around their corporate headquarters. There is often significant controversy when local governments provide substantial subsidies to retain or attract the corporate headquarters of emerging companies. In a widely-debated recent example, the city of San Francisco offered a payroll tax exemption to Twitter for six years, worth an estimated \$22 million, to keep the company from moving out of the city.¹ Supporters of these policies point to the social and economic benefits of retaining or attracting company headquarters, for example, growing employment, agglomeration economies, and revitalizing neighborhoods. However, a primary concern of opponents is the impact of the rapid growth of the company, especially with its upcoming IPO, which may drive up housing prices and rents and force some residents to move.

1

On Twitter's tax break, see, e.g., Twitter tax break could cost SF tens of millions more after IPO, *SFGATE*, (2013); What the Twitter tax break means for San Francisco, *TIME*, (2014); Tax breaks for Twitter bring benefits and criticism, *The Wall Street Journal*, (2016). As another example, to attract Amazon's second headquarters, Newark, New Jersey, offered \$7 billion in tax incentives; Chicago would reportedly offer at least \$2 billion; and Maryland offered more than \$5 billion.

In this paper, I evaluate the causal impact of firms going public on the local economy. Understanding this impact is important, as residents and local governments must grapple with the economic impacts of having a firm going public in their jurisdiction. The main reason why IPOs could affect the local economy is that going public provides firms access to public capital markets, which consequently relaxes their financial constraints. Firms significantly increase post-IPO investment in physical and human capital, as shown in Figure 1. Dougal et al. (2015) show that firms headquartered nearby tend to increase investment as a result of agglomeration economies through skill or knowledge spillovers, sharing infrastructure, consumption externalities, and so on. The increase in investment and rise of agglomeration economies are likely to attract more skilled workers to live nearby, thus driving up local housing prices. Meanwhile, newly cashed-out executives and early employees are also potential homebuyers in local real estate markets. In all, this creates an incentive for food service businesses to open restaurants in the area. Analyzing housing prices is a particularly useful way to understand the local economic value of an IPO, as the net effect of a firm going public is reflected in housing prices. A successful IPO may have a positive impact on local housing prices at corporate headquarters. However, even if a firm invests significantly in capital and employment post-IPO, it is still possible that the net effect on the local housing market could be negligible in magnitude if the firm makes the investment outside the area of the corporate headquarters, or even negative if negative externalities, such as traffic congestion and construction noise, outweigh the benefits.

In this paper, I focus on three related questions. First, I study the effect of going public on local employment, labor earnings, and the number of establishments around the firms' headquarters, focusing on the key question of whether IPOs lead to an agglomeration of similar businesses in the IPO firms' industry. Second, I investigate whether IPOs have a causal impact on local housing markets. Specifically, I examine whether the information aggregated in the IPO process has any impact on the housing price dynamics at different stages of the IPOs. Third, I explore whether the increased demand in local housing markets generated by IPOs has caused local demographic changes (resident income), and resulting amenity shifts (restaurants).

I assemble a unique database that includes the information of all listed U.S. firms in the

top 10th percentile of offering proceeds in the U.S. stock markets from 2000 to 2012, combined with data on zip-code business patterns, single-family residential housing transactions, and resident income. The data can be used to measure the impact of IPOs on the local economy while addressing the potential endogeneity of the location and timing of IPO firms. The economic literature on spatial agglomeration has recognized that such spillover effects are often highly localized (Rosenthal and Strange, 2003; Arzaghi and Henderson, 2008; Ahlfeldt et al., 2015). Based on this point, I test for the effect of going public on local economic activity in a close proximity to the corporate headquarters. I approach this problem by utilizing a spatial, difference-in-differences estimation framework by comparing changes in outcomes (employment, business patterns, housing prices, and resident income) before and after an IPO for areas very close to the IPO firms' headquarters with areas slightly farther away.

I find that IPOs have a positive and significant effect on the local economy. Zip codes that are physically close to an IPO firm experience growth in total employment and wages. The number of businesses in the IPO firm's industry established nearby significantly increases, while the total number of businesses of all industries almost does not change. Firms with higher IPO proceeds have a larger impact on the local economy. I also find evidence to suggest that the number of small firms (fewer than 50 employees) in the same industry as the IPO firm increases more than that of larger firms (more than 50 employees), while the corresponding employment effects on these firms are similar.

Next, I investigate the impact of IPOs on proximate housing prices. The primary analysis suggests that the sales prices of houses located within 2.5 miles of an IPO's headquarters increase by about 3.0%, 3.3%, and 1.3% following the announcement, listing, and lockup expiration of the IPO, respectively, compared with one year before the announcement.² These effects are most pronounced among firms raising above the median offering proceeds in the sample. It does not appear that these price impacts are caused by a change in the composition of the houses that sold. Meanwhile, housing price trend and falsification tests provide no evidence of a spurious, positive effect due to differential housing price growth

2

I sometimes refer to an IPO announcement as an IPO filing, and use the terms pricing and listing interchangeably.

at the corporate headquarters. I compare IPOs of different expected offering proceeds and final proceeds collected, and find that firms with above-expected proceeds lead to a larger housing price effect post-IPO compared with the IPO announcement stage, and vice versa.

Finally, I conclude by testing the extent to which the positive housing price impacts are related to cashed-out wealthy individuals. I examine this question by investigating how IPOs influence local demographic characteristics and amenities. The estimation results show that zip codes that are close to corporate headquarters, especially those within 1 to 3 miles from headquarters, have higher income and a significantly lower share of low-income residents while the number of wealthy individuals does not change significantly. Meanwhile, I find weak evidence that new restaurant openings increase in neighborhoods close to the sample firms. Overall, it does not appear that these effects are driven by newly cashed-out individual, rather than post-IPO investment and job opportunities.

This work makes several important contributions to the literature. First, it is related to recent papers that highlight the importance of IPOs for the real economy. Kenney et al. (2012) and Weild et al. (2013) show that IPOs have significant employment effects. For example, IPOs in the United States created 2.3 million jobs between 1996 and 2010. Borisov et al. (2015) show that public firms experience the most significant increase in their employment during the three-year period post-IPO. Bernstein (2015) studies the effects of going public on innovation and concludes that firms experience an exodus of skilled inventors following the IPO. However, due to increased access to capital, public firms attract new human capital and acquire external innovation. Although a large body of research examines the performance changes of firms around their IPO, this paper shows the economic spillover of going public outside the firm itself.

Second, this paper contributes to a growing literature estimating local economic spillovers from firm headquarters. Card et al. (2010) find that the presence of corporate headquarters significantly increases the level of charitable giving in a city. Moreover, each \$1,000 increase in the market value of the firms headquartered in a city yields \$0.60-\$1.60 to local nonprofits. Greenstone and Moretti (2004) show that the opening of a large manufacturing plant is associated with increases in labor earnings (in the new plant's industry), property values, and public expenditure on local services in the counties that successfully attracted the

plant. Greenstone et al. (2010) further show that the plant opening has an agglomeration effect, and this effect is more significant for incumbent plants that share similar labor and technology pools with the new plant. Dougal et al. (2015) suggest that local agglomeration economies lead to a firm's investment being highly sensitive to the investments of other firms headquartered nearby, even those in very different industries. Consistent with these studies, my results suggest that IPO firms increase investment post-IPO and give rise to an employment increase and agglomeration effect, driving up local housing prices.

The investigation of the real estate market consequences and demographic changes from IPOs also contributes to recent empirical research on urban gentrification. Sieg et al. (2004) find that the successful Clean Air Act regulation in Los Angeles led to environmental gentrification, the process of significant housing prices rise in communities with large improvements in air quality, with wealthy households generally moving in. Zheng and Kahn (2013) find that government-financed green space and public transit trigger rising local home prices, new housing construction, higher-income and better-educated residents, and new restaurants openings in the vicinity of these areas. Billings et al. (2018) find that an unintended consequence of the 2002 No Child Left Behind policy has been to increase housing prices and homebuyer income in previously failing school attendance zones, which give priority in lotteries for oversubscribed schools. More generally, this paper contributes to understanding how IPOs affect housing values and neighborhood composition. This is important, as states and cities across the country continue to experiment with tax break policies to attract or retain IPO firms.

Most closely related to this paper are two recent studies that examine the spillover effects of public ownership. Butler et al. (2016) find that IPOs are positively correlated with estate prices, employment, and wages in a metropolitan statistical area (MSA). Cornaggia et al. (2018) find that county-level employment, wages, and population growth rates decline after correcting for endogeneity, as firms geographically expand their business operations outside their home county following an IPO. While related, this paper has several key differences. First and most importantly, their studies focus on identifying the impact of going public by comparing economic growth in MSAs/counties where firms complete their IPOs to growth in areas where firms withdraw their IPO filings. In contrast, my goal is to understand the

spillover effects in the immediate neighborhood. I take a different approach to geography, using a more restrictive notion of local community when constructing the treatment and control areas. Specifically, I define a local community as the area within 5 miles surrounding each IPO firm’s headquarters. As a result, this definition of local community is much smaller than the MSAs in Butler et al. (2016) and counties in Cornaggia et al. (2018), which mitigates the issue of differential time trends in the treatment and control area and having firms going public at the same year and in the same county. Second, instead of focusing on the overall effect of an IPO, I explore the process through which IPOs affect the real estate market. I pay special attention to identifying separately the impacts of the IPO announcement, listing, and lockup expiration, as firms and the general public gather and aggregate market information at these different stages. I use the difference in unexpected proceeds to understand the heterogeneous housing price effects. Third, by exploring comprehensive zip-code income and establishment data, I analyze the channel through which the IPO effect operates to understand the potential demographic changes from IPOs.

The paper is organized as follows. Section 2 provides background on the IPO process and why it may affect the local economy, followed by a description of the data in section 3. Section 4 describes the estimating strategy, and section 5 presents the empirical results. Finally, section 6 concludes.

2.2 Background: IPOs and the Local Economy

For most firms, the primary reason why they choose to go public is the desire to raise equity capital for the firm and create a public market in which the founder, early employees, and other shareholders can convert some of their wealth into cash at a future date (Ritter and Welch, 2002). While IPOs can be the most advantageous way of raising capital to facilitate future growth, they are also associated with a substantial amount of cost and risk. Lowry (2003) discusses that a firm’s demand for capital, investor sentiment, and stock market conditions are determinant in timing an IPO. Once the senior executives decide to initiate an IPO, they must file an initial registration statement, usually Form S-1, to the Securities and

Exchange Commission (SEC), which contains the firm's business and financial information. After filing Form S-1, the firm markets the equity issuance to investors. The transition from private firm to public firm typically takes about three to five months. For shares not sold in the offering, pre-issue shareholders commit to a specified lockup period, usually lasting 90 to 180 days, during which they agree not to sell any shares.³ Figure 2 provides the timeline of a typical IPO process in the sample.

Theoretically, in the absence of capital market frictions, the transition to public equity markets should have no impact on the local economy. However, under financial frictions, selling equities publicly improves firms' access to capital. This can have a positive impact on the local economy, because such capital is likely to finance more investments and thus increases firms' demand for employees. Kenney et al. (2012) report that firms that went public from 2001 to 2011 created 822 jobs on average. Borisov et al. (2015) find that firms significantly increase post-IPO investment in human capital compared with the pre-IPO stage, and experience the most significant increase in their employment at the IPO stage of their public lifecycle. Meanwhile, the growth of an IPO firm may cause an increase in agglomeration economies, with skill and knowledge spillovers. Dougal et al. (2015) find that a firm's investment has strong positive relation with the investments of other firms headquartered nearby, even those in very different industries. They suggest that local agglomeration economies are important determinants of firm investment and growth. Moreover, firms invest more, leading to the development of infrastructure such as airports, roads, ports, green spaces, and so forth. Overall, the IPO firm itself and the businesses it attracts in its vicinity will expand by hiring more workers. Wages will be bid up in this area. The increase in employment also creates a higher demand for real estate and thus drives up housing prices.

Another possible channel of the impact of IPOs on the local real estate market is that early employees and other shareholders cash out through the stock market. IPOs such as Facebook and Twitter create hundreds, even thousands of millionaires and a handful of billionaires. These newly cashed-out individuals are likely to buy homes near the corporate headquarters, as they seek a short commute to work, leading to increased demand in the

3

These pre-issue shareholders are generally insiders, such as company founders, owners, managers, employees, and venture capitalists who are holding a company's stock before it goes to public.

local real estate market. In all, increasing labor demand, rising agglomeration economies, and high-income individuals could potentially drive up property values. This will also induce new restaurants to open in the area. As new restaurants and other local amenities become available, this will further attract people to live near the IPO firm.

However, one important concern is that if the housing market is efficient and complete, local residents can anticipate an IPO and buy up the housing prices before the announcement, in which case, the study would not detect a discrete jump in housing prices due to IPO activity. However, research on housing markets in the United States indicates a lack of information efficiency (Case and Shiller, 1989, 1990). Unlike financial institutions and investors, homebuyers are unsophisticated market participants and tend to combine investment and consumption motives in their purchase decisions. And the high transactions costs in the housing market make short-selling more difficult than in almost any other asset market (Meese and Wallace, 1994). Furthermore, even without housing market inefficiency, housing price movements may be driven by information aggregated in the IPO process. First, The IPO completion is highly uncertain due to market fluctuations. After submitting the initial registration form, filing firms have the option to withdraw the IPO filing. Withdrawals are common in IPO markets, and approximately 20% of all IPO filings ultimately are withdrawn from the SEC (Bernstein, 2015). Second, because of asymmetric information between investors and the firm and the inefficiency of the underwriters setting the expected price range, the final offer price is hardly predictable based on information that is available when the initial price range is set (Lowry and Schwert, 2004). Van Bommel and Vermaelen (2003) show that firms' unexpected capital expenditures during the year after the IPO are significantly positively correlated with the unexpected price adjustment. Their estimates suggest that an IPO firm that receives above-expectation proceeds increases its capital expenditure by 1.34% of total assets, while a below-expectation IPO is followed by a downward adjustment of capital expenditure by 1.33% of total assets. If the information on how much capital a firm collects and later spends is a key factor for the change in housing prices, then a below-expected final offer IPO is likely to lead to a lower housing price effect at the IPO stage than the announcement stage. I present a test for this hypothesis in section 2.5.2.3.

2.3 Data

This paper combines comprehensive data on IPO firms, single-family housing transactions, individual income tax statistics, and zip-code business patterns. This section describes the data in more detail.

2.3.1 IPO Data

I collected data on all firms that went public starting in 2000 from Nasdaq's website. Following common filtering criteria, real estate investment trusts, closed-end funds, rights, units, foreign issues, and American depository receipts were excluded. However, because I only have access to housing data between 2000 and 2012, I focus on all IPOs that were filed by U.S. firms between 2000 and 2012 for which I have corresponding housing data. The analysis is limited to the 74 IPOs with issuing size above the 90th percentile of all IPOs in the original sample.⁴ I obtained detailed information on the address, SIC code, filing dates, pricing dates, and lockup expiration period of the IPO firms. Table 1 provides a summary of this data set over time and space. The locations of the IPO firms are shown as dots in Figure 3. Most of the firms are located in large metropolitan areas.

I hypothesized in section 2.2 that the potential difference between the expected and actual IPO prices could have countervailing influences on housing prices. To test this hypothesis, I hand collected expected IPO proceeds from firm IPO prospectuses. After comparing the expected proceeds with the final proceeds collected, I divided the firms into three groups: above expectation, within expectation, and below expectation. Table 2 shows a summary of the offering proceeds of these IPOs by group. In general, firms raising higher-than-expected final offering proceeds have lower median expected offering proceeds initially compared with the other groups.

⁴

Firms that changed headquarters during the IPO process are excluded. Firms headquartered in New York City are also dropped, because there are very few single-family housing transactions.

2.3.2 Business Pattern and Income Data

To capture economic activity at the local level, I use the Zip Code Business Patterns from 1998 to 2014 from the U.S. Census Bureau. The data set provides information on number of employees, annual payroll, total number of establishments, and the number of establishments by employment-size class for detailed industries classified by North American Industry Classification System (NAICS) codes. An establishment is a single physical location where business is conducted or services or industrial operations are performed,” such as a factory, an assembly plant, restaurant, a warehouse. I explore the agglomeration effect by collecting NAICS codes for the sample of the listed firms from the Compustat database and then merging them with the Zip Code Business Patterns data. I use three-digit NAICS codes to identify firms in the same industry. To understand the spatial shifts of local amenities, I also obtained the number of restaurants from the data set, by focusing on establishments with three-digit NAICS code 722, which is defined as food services and drinking places.

The analysis of the demographic changes uses the Internal Revenue Service (IRS) Individual Income Tax Statistics - ZIP Code Data for 2004-2014. The IRS currently provides these data for 1998, 2001, 2002, and 2004-2014. I only use data for 2004-2014 for consistency. The income variable from the IRS is important, because it tracks the incomes of consumers living inside a given zip code, as opposed to business statistics, which provide wage and employment statistics for individuals who are working, but not necessarily living, in a zip code (Mian and Sufi, 2009). By combining the IRS income data for different years, I create a panel of IRS tax return-based data on the average adjusted gross income (AGI) per return, share of individuals with AGI less than \$25,000 (lowest category), and share of individuals with AGI greater than \$200,000 (highest category) by zip code.⁵ I construct the sample areas by taking all zip codes with a centroid within 5 miles of the nearest IPO firm headquarters.

5

It was not until 2006 that the IRS Individual Income Tax Statistics started reporting the size of the group with AGI greater than \$200,000. I use this information to explore whether IPOs lead to an increase in the number of wealthy individuals in the vicinity of corporate headquarters following the IPO.

2.3.3 Housing Price Data

The housing price data are from a large housing transaction data set of single-family residential properties across the United States between January 1, 2000 and December 31, 2012. The data come from DataQuick, which provides the history of housing transactions and characteristics for houses in a large number of U.S. counties. The data consist of information on the sales price; date; and structural characteristics, such as square footage, number of bathrooms, number of bedrooms, year built, and lot size. Using these characteristics, I refined the data, removing outlying observations, love and affection sales, and houses built prior to 1900.

The data set also includes the exact location of all the properties, which was used to calculate the distance between each house and the nearest IPO firm headquarters. Using the Graphical Information System, each house is matched to the closest IPO firm headquarters within a 10-mile radius. The distances to those firms are then recovered. Houses that are not within 10 miles of any firm are dropped. The analysis focuses on the treatment and control groups within a 5-mile radius, to minimize the threat of any location-specific unobservable differences that may affect the price dynamics. Section 2.5.2.1 discusses the sensitiveness for the choice of a 2.5 mile cutoff for the treatment and control groups.

Table 3 provides summary statistics for the attributes of the houses in the primary housing data set. The columns labeled “within 2.5 miles,” “2.5 to 5 miles,” and “5 to 10 miles” provide summary statistics for houses within these distances to an IPO firm. The summary statistics indicate that houses that are closer to an IPO firm tend to be smaller, somewhat older, and have fewer rooms. In general, the differences in housing characteristics between houses within 2.5 and 2.5 to 5 miles are smaller than those within 2.5 and 5 to 10 miles. These differences in housing characteristics suggest that corporate headquarters are not chosen in random locations. However, the empirical strategy does not explicitly rely on treated properties being similar to control properties, but on similar housing price trends between these two areas over time.

2.4 Empirical Methodology

I seek to study the causal impact of a firm going public on the local economy. I discuss that going public allows firms to raise capital for investments in not just capital expansion, but also human capital. Meanwhile, early employees and shareholders cash out from the IPO market. The increase in investments may give rise to agglomeration economies. These are likely to attract richer and more educated people to live nearby and induce new restaurants to open in the area. As new restaurants and other local amenities become available, this will further attract people to live near the IPO firm. Meanwhile, the rising local housing demand will drive up housing prices in the vicinity of IPO firms. The empirical work will study each aspect in this chain. Because the business pattern and income data have different geographic units and frequency compared with the housing transaction data, I use two identification strategies to study the effects.

2.4.1 Effects of IPOs on the Local Economy

I first focus on estimating the economic spillovers of an IPO on local employment, wage bills and the number of establishments in the geographically proximate zip codes. I follow Zheng and Kahn (2013) by assuming that the relationship between the outcome variables and IPO activity follows a linear model:

$$Y_{zjt} = \alpha + \beta_1 Post-File_j + \beta_2 Post-File_j \cdot Dis_z + \delta_t + \eta_z + \varepsilon_{zjt}$$

where the dependent variable Y_{zjt} is a measure of outcome variables (employment, wage, income, etc.) on local economic activities in zip code z when paired with IPO firm j in year t . *Post-File* an indicator variable taking a value of 1 if firms file for an IPO. Dis_z is the distance of the centroid of zip code z to corporate headquarters. I control for year and zip-code fixed effects. I focus on the 3 years before and after the IPO filing in this analysis. The coefficients of interest are β_1 , which captures the local economic spillover effects following IPO activities compared with three years earlier, and β_2 , which shows whether the places close to IPO firms have a larger effect relative to places that are farther away post-IPO filing.

To interpret the estimates from the baseline equation as causal effects of IPOs on local communities, it must be true that zip codes that are close and far from corporate headquarters would have experienced equal average economic growth in the absence of IPOs. I test for preexisting differences in income trends using the event-study framework of Jacobson et al. (1993), by examining the effect of going public in each year before and after an IPO filing. This transforms the baseline specification in equation (2.4.1) into:

$$\log(Y_{zjt}) = \alpha + \sum_{k=-2}^3 \beta_1^k Year_{zt}^k + \sum_{k=-2}^3 \beta_2^k Year_{zt}^k \cdot Dis_z + \delta_t + \eta_z + \varepsilon_{zt}$$

Thus, the estimate of β_2^k allows testing whether IPO effects are increasingly likely to occur near the corporate headquarters over time. To rule out potentially confounding pre-IPO trends in local economic growth, I expect $\beta_2^k \approx 0, \forall k < 0$.

2.4.2 Effects of IPOs on Real Estate Markets

For the empirical evaluation of the effects of going public on local housing prices, I use a quasi-experimental hedonic approach. In general, the transaction price of a property is a function of the characteristics of that property as well as those of the neighborhood. Applications of this technique have included attempts to understand the value of education quality (Black, 1999), air quality (Chay and Greenstone, 2005), urban redevelopment (Haninger et al., 2014), and accessibility to a department store (Pope and Pope, 2015). I employ a difference-in-differences strategy comparing houses in areas closer to IPO firm headquarters with those in areas slightly farther away. The baseline hedonic model takes the following form:

$$\begin{aligned} \log(P_{ijt}) = & \alpha + \beta_1 File_{ij} + \beta_2 List_{ij} + \beta_3 Lockup_{ij} + \delta^j Treat_{ij} \\ & + \gamma_1 Treat_{ij} \cdot File_{ij} + \gamma_2 Treat_{ij} \cdot List_{ij} \\ & + \gamma_3 Treat_{ij} \cdot Lockup_{ij} + \mathbf{X}_{it} \cdot \omega + \eta_{jt} + \varepsilon_{ijt} \end{aligned}$$

where $\log(P_{ijt})$ is the natural log of the sales price for property i around firm j at time t . $Treat_{ij}$ is a group of indicators for an individual house i within the treatment area of an IPO firm j . $File_{ij}$ equals 1 if firm j files an IPO but has been not listed. $List_{ij}$ equals 1 if

firm j prices an IPO and is in the lockup period. $Lockup_{ij}$ equals 1 if the lockup expires. \mathbf{X}_{it} is a vector of housing characteristics of property i at time t . η_{jt} are year-by-month-by-firm fixed effects. I also include treatment-by-year-month fixed effects for some estimation specifications to control for treatment-specific time fixed effects. The parameters of interest in this specification are the estimates of γ_1, γ_2 , and γ_3 . The estimated impact of an IPO announcement is given by γ_1 ; the impacts of IPO pricing and lockup expiration are given by γ_2 and γ_3 , respectively.

Ultimately the impact of firms going public on housing prices depends on the sorting of households into, and out of homes near corporate headquarters in general equilibrium. An empirical investigation of household income changes takes the following form:

$$\log(Y_{zjt}) = \alpha + \delta Post-File_j + \sum_{k=1}^5 \beta^k D_z^k + \sum_{k=1}^5 \gamma^k D_z^k \cdot Post-File_j + \delta_t + \eta_z + \varepsilon_{zt}$$

where $D_z^k, k \in \{1, 2, 3, 4, 5\}$ are spatial indicator variables of zip codes or houses within $k - 1$ to k miles of a corporate headquarter, and the omitted indicator variable is an indicator for homes between 5 and 10 miles from the nearest IPO firm. The key parameters in this specification are the estimates for interactions terms of each of these spatial indicator variables with post-filing indicator. These parameters shows the local effect on the treated spatial zones.

2.5 Empirical Results

2.5.1 Effects of IPOs on the Local Economy

I begin by quantifying the effects of IPOs on the local economy by estimating equation (2.4.1). In column (1) in Table 4, I report estimates using the sample of all 74 IPO firms. The estimates suggest that zip codes that are physically close to IPO firm headquarters experience some growth in annual employment, although the effect is not statistically significant. Taking the total number of establishments in a zip code as the dependent variable, as in panel (b) column (1), the estimates are very close to zero, suggesting there is little change in the

number of firms post-IPO. All the estimated coefficients of the two wage outcomes are consistently positive and statistically significant, indicating that after a firm goes public, zip codes in the vicinity of the corporate headquarters have higher wage bills and average wages per worker, and zip codes that are closer to the firm experience a larger increase in wages.⁶ I further allow the impacts of going public to vary by firms' final proceeds (below and above median) in columns (2) and (3) in Table 4. All the estimated coefficients for employment, total number of establishments, and total wage bill are consistently larger and more significant for IPOs collecting above-median proceeds, and vice versa. However, the estimated coefficients for average wage per worker are more pronounced for firms with lower final proceeds, suggesting that wages are less likely to be bid up around large firms. This is consistent with the literature that local market concentration gives firms monopsony power that they use to keep wage down (Azar et al., 2017; Benmelech et al., 2018; Rinz, 2018).

To explore the agglomeration effect of IPOs, I then estimate spatial patterns of geographically proximate firms within the same 3-digit industry as the IPO firm.⁷ The results in column (1) in Table 5 show that the number of businesses in the IPO firm's industry increases by 17% overall post-IPO. Furthermore, if a zip code's distance from an IPO firm headquarters is one standard deviation closer than the others, the total number of establishments within the same industry increases by 7.0% in this zip code post-IPO. The coefficients are highly significant. Again, the median split of the sample by IPO proceeds in columns (2) and (3) shows that larger IPOs attract more businesses within the same industry to establish nearby. I also investigate the agglomeration effect by separating the firms by employment size. Inspection of the models in columns (4) and (5) shows that the changes in the number of same 3-digit firms are mainly driven by the increase in the number of small firms with fewer than 50 workers. However, considering employment in these firms, the corresponding employment effect from attracting big and small firms could be similar. Combining the findings in Table 4, the estimation results suggest that agglomeration of businesses within the same industry is the major source of change in the analysis. This result is consistent with

⁶

The results still holds but are smaller if I exclude zip codes of the IPO firm headquarters.

⁷

The Zip Code Business Pattern data set does not provide employment data for any specific industry. Therefore, I use the number of firms by industry to explore the agglomeration effect.

the literature that finds that the agglomeration effect is larger in industries sharing similar labor and technology pools (Greenstone et al., 2010).

To understand how these effects evolve over time, I estimate the outcome variables in Tables 4 and 5 and plot the estimated coefficients of year dummies β_1^k and the distance-by-year interaction terms $\beta_2^k, k \in [-2, 3]$ in Figures 4 and 6. These plots also provide an opportunity to judge the validity of causal inferences on IPO effects. Panel (a) in Figure 4 presents the estimated coefficients for total employment. There is almost no changes in total employment in zip codes closer to the corporate headquarters of IPO firms in the years before the IPO. Local employment starts to increase following the IPO. However, panel (b) presents no evidence on significant changes in the total number of establishments. Panels (c) and (d) show that the total wage bill and wages per worker slightly rise in the year prior to the IPO filing, but the magnitudes of the changes are small relative to the rise in wages post-IPO. There is compelling evidence of agglomeration effects in the time trends shown in Figure 6. The number of businesses within the same industry as the IPO firm increases immediately and significantly in areas within 5 miles of the IPO firm headquarters post-IPO, while the number was decreasing pre-IPO. And zip codes that are close to the firm share a very similar trend. The figures support the validity of the design of the analysis, as there is little evidence of differential trends prior to the IPO announcement.

In sum, these results show that firms going public have positive effects on employment and labor earnings, and that they attract an increased number of firms in the same 3-digit industries in the vicinity of IPO firms. In the following subsections, I study the impacts on local housing markets, demographics, and amenities.

2.5.2 Effects of IPOs on Real Estate Markets

This subsection starts by examining the effect of IPOs on local housing prices in surrounding areas. It then conducts robustness checks on the findings – a falsification test and a housing composition analysis. Finally, the subsection presents a heterogeneity analysis to understand the housing price dynamics in the IPO process.

2.5.2.1 Primary Difference-in-Differences Results Table 2.7 presents the coefficient estimates of hedonic regression comparing housing prices of treated properties located within a 2.5-mile ring of an IPO firm to control properties in the immediately adjacent area. The regressions all include treatment-by-firm fixed effects and structural characteristics of the properties described in Table 3. The coefficients in column (1) suggest that houses located within 2.5 miles of the IPO firm see increases in their sales price of about 4.2% after the IPO filing compared with one year before the IPO filing. The coefficients on the interaction terms of treatment and post-lising and expiration in column (1) show that this effect is approximately 3.7% when firms price stocks at U.S. stock exchanges and 4.9% after lockup expiration. As reflected in column (2), these results are robust and significant to year-by-month-by-firm fixed effects. However, the housing price effect decreases in magnitude to 3.0% for the IPO announcement. The coefficients on IPO pricing and the lockup expiration effect drop to 3.3% and 1.3%, respectively. Overall, an IPO increases housing prices in the proximate area by 1%-3% comparing to the pre-IPO level. As reflected in column (3), these results are robust when using a broader housing market as the control group. However, the coefficients are slightly smaller and noisier but consistent with the previous estimates, because these estimates may suffer from significant bias due to compositional differences in the sample, or the larger treatment area may include properties that are not affected by IPO activity. I have so far been using a window of one year before and after an IPO in the regression. The window could be wider or narrower. I redo the difference-in-differences analysis, extending the temporal window to include housing data from two years before and after an IPO in column (4) in Table 2.7, and in column (6), I narrow the temporal window to include houses sold half a year before and after the IPO. The main findings are robust to these changes in temporal choices. To control for different housing price time fixed effects between the treatment and control areas, I add year-by-month-by-treatment fixed effects in columns (5)-(6). The coefficients of IPO pricing are again significantly positive, and the estimates in column (5) are slightly larger than the estimates in column (3), suggesting an approximately 3%-5% overall increase in the prices of homes within 2.5 miles of firms that went public relative to homes 2.5 to 5 miles away.

To test the sensitiveness of the cutoff delineating the treated and control areas, I limit

the sample to properties within 5 miles of corporate headquarters. Starting with a 1.5-mile ring, I re-estimate equation as the size of the treatment area increases by a 0.1 mile ring each time until it reaches a 3.5-mile ring. Figure 7 plots the post-announcement, pricing, and lockup expiration coefficient estimates together with their 90% confidence intervals. With an ideal experiment, it would be possible to detect the true treatment effects knowing the exact delineating boundary between the treated and control areas. Otherwise, the definition would likely be too small or too large. In both cases, the misaligned treatment-control boundaries would lead to systematic underestimates of the mean difference in housing prices between the true treatment and control areas. Thus, a plot like Figure 7 would be an inverse-U shape. For all the estimates, post-IPO activity is significantly positive from 2.5 to 3 miles. Beyond 3 miles, the coefficient estimates and their confidence intervals rapidly diminish to zero.

A key assumption in the difference-in-differences identification strategy is that housing price trends for areas near an IPO firm and areas slightly farther from the firm would have been the same had the firm not gone public. To provide graphical evidence, I regress the log-price on a set of housing characteristics, year-by-month-by-firm fixed effects, and treatment-by-firm fixed effects. Figure 8 plots the daily residuals for treated properties and untreated properties along with a local linear fit before and after the IPO announcement. The graph shows that the pre-IPO announcement trend of treated properties is generally similar to untreated properties, but there is a slightly upward price trend for properties located within 2.5 miles of an IPO firm. Although this is consistent with the conjecture that the local housing market can somehow anticipate the IPO event, there is a noticeable and discrete increase in prices occurring in the treated area following the announcement. I also account for this in the empirical analysis, by fitting time trends for the treatment group as in columns (4) to (6) in Table 2.7. Figure 8 suggests that homebuyers pay about 0.03 log price lower before the firm files for an IPO and after that, the homeowners pay a premium for homes within 2.5 miles of an IPO firm. The residual plots presented in Figure 8 are compelling evidence of an IPO effect.

2.5.2.2 Falsification Tests and Housing Composition Analysis This subsection provides falsification tests to check whether the increase in housing prices after an IPO is

due to differential trends in housing prices of homes near corporate headquarters relative to housing prices farther away. To conduct the falsification tests, I re-estimate the model by including false IPO dates. The false dates are set to two years and three years prior to the announcement, pricing, and lockup expiration dates of IPOs. Table 7 presents the falsification tests for the baseline models. Columns (1) and (3) re-estimate the hedonic price model using a window of one year before and after the IPO. I change the temporal window to two years pre- and post-IPO in columns (2) and (4). Of all 12 interaction coefficient estimates that are estimated in Table 7, only one is statistically significant (at the 10% level), providing no evidence of a positive effect due to differential housing price growth before IPOs.

So far, the analysis has established that firms going public has a positive effect on housing prices in treated areas close to IPO firms. This outcome could reflect shifts in housing demand and supply. If there is a large compositional change in the types of houses that transacted before and after, then this may signal that the observed housing price effects are at least partially driven by supply rather than demand. I explore this issue by running a series of regressions using the same data as in the primary analysis, with key housing characteristics on the left-hand side and interactions on the right-hand side. These regressions continue to control for year-by-month-by-firm and treatment-by-firm fixed effects. Once again, the coefficients on the treatment area indicators interacted with IPO activities are of primary interest, as they signal whether there were substantial changes in these housing characteristics after the IPO activities. Table 8 presents the results from these regressions. None of the interaction coefficient estimates is statistically significant. Taken as a whole, the evidence suggests that the housing price effect is not likely driven by the supply side.

2.5.2.3 Heterogeneity Analysis The baseline model relies on the assumption that the IPO effect is the same across different stages of the IPO activity for every firm. In section 2, I hypothesized that the unexpected final price changes may lead to different price effects from the IPO announcement and pricing stages. For example, DreamWorks Animation SKG Inc., the world-famous maker of computer-generated animated feature films, raised \$812 million by selling 29 million shares at \$28 apiece – higher than the \$23 to \$25 expected

price range in the company’s prospectus. This is a 12% increase even compared with the highest expected capital raised. Higher offering proceeds increase firm’s capital expenditure to finance investments and employment (Van Bommel and Vermaelen, 2003), thus leading to a higher price effect at the IPO stage.

I address this issue by dividing the firms into three groups: above, within, and below expectation, based on the expected IPO price range in the SEC filings of IPO firms. To explore whether the amount of the offering’s proceeds matters, I also perform heterogeneity analysis on firms collecting above the median proceeds in the IPO sample. Table 9 shows the results for these specifications. Column (1) suggests that firms that experience higher-than-expected offering proceeds have a significant impact on housing prices, starting from listing in the stock markets. Column (2) suggests a sharp decline in the effect on housing prices after firms reveal a lower-than-expected offering price. Column (3) shows that the price effects for the announcement and pricing stages are not statistically different, although the announcement effect is not statistically significant. Columns (4) and (5) suggest that the positive housing price impact from the IPOs that collect above median proceeds in the sample is larger and more significant relative to the baseline samples, while the impact is smaller from below-median IPOs. Overall, these results confirm the intuition that the treatment effect would be larger at the time of pricing for firms that collect more capital than expected, and vice versa.

2.5.3 Effects of IPOs on Demographics and Amenities

I have shown that going public is associated with a significant increase in housing prices. In theory, IPOs could have an impact on local real estate markets through two main channels. First, an IPO provides immediate access to the capital market in the form of initial proceeds, relaxing financial constraints. Firms significantly increase post-IPO investments and employment, potentially giving rise to local agglomeration economies. The employment effect and agglomeration economies may drive up housing prices. Second, the IPO market allows early employees and investors to cash out, increasing the number of rich individuals at the corporate headquarters. These people are likely to buy houses themselves, leading to

an increase in local housing prices.

To understand the importance of the second channel channel, I use the annual zip-code income data to test for direct evidence of demographic changes. Table 10 presents the results, based on equation (2.4.1). Column (1) presents the regression results with the logarithm of average gross income as the dependent variable. Consistent with the expectation, the coefficient of the interaction term of distance and post-filing is negative, although it is not statistically significant. Column (2) shows the regression results for the same specification but taking the share of residents with income less than \$25,000 as the dependent variable. The results show that there is a significantly smaller share of low-income groups living in the vicinity of the IPO firm. Furthermore, Figure 5 plots the coefficients of the year dummies and interaction terms. Panel (b1) in Figure 5 shows the estimated coefficients of the year dummies pre-and post-IPO. That the estimates start to decline and become negative post-IPO indicates that the share of low-income residents decreases overall after firms go public. Meanwhile, the coefficients of the interaction terms in panels (a2) and (b2) remain statistically insignificant until the IPO announcement, indicating that zip codes closer to IPO firms experience growth in income and loss of urban low-income residents after the IPO activity takes place. I also examine how going public affects the share of high-income individuals (gross personal income greater than \$200,000 per year). Column (3) in Table 4 suggests that the estimated effect of an IPO on the share of high-income individuals is positive but statistically insignificant and of small size. The second entry in column (5) shows that the share of individuals who earn more than \$200,000 per year increases by only 0.07 percentage point in a zip code compared with zip codes 1 mile farther from the corporate headquarters.

To further understand the household sorting in this area, I rerun the regression to investigate the local treatment effect in zones of different distance to the corporate headquarter. I plot the estimated coefficients of the interaction of spatial indicator variables and post-filing indicator in Figure 11. The pattern of the estimates by distance indicates that more households sorts into area within 1 to 3 miles from IPO firms driving up the income and housing prices in these area, while they also crowds out low-income residents. Panel (c) shows that there is small and insignificant increase of rich individuals, suggesting demographics changes

are not solely driven by the cash-out individuals after IPOs.

I now test whether there are more restaurants near IPO firms. The restaurant industry provides a good indicator of residential sorting and amenity shifts. If more people are moving into an area, and if they are richer than the average person, then it would be expected that the count of restaurants would increase over time in the treated areas. Column (3) in Table 10 reports the regression results for the number of restaurants by zip code. I control for year and zip-code fixed effects, and the standard errors are clustered by firms. In column (4), the coefficient of the post-IPO announcement and distance interaction term is negative and almost statistically significant at the 10% significance level. That is, if a zip code is one standard deviation from the IPO firm, the total number of restaurants in this area will decrease by 1.2% (about one establishment). In panel (c2) in Figure 10, I add interaction terms of year and distance from an IPO firm. The results show a slight upward trend in the number of restaurants. However, the time trend suggests that new restaurants are increasingly likely to open in nearby neighborhoods of corporate headquarters. Overall, the recent time trends in local resident income and restaurant count shows IPOs have caused local demographic changes and resulting amenity shifts.

2.6 Conclusions

The news media has talked about how the recent IPOs in Silicon Valley have boosted the local housing markets, and local residents have protested against Twitter's IPO because they are worried about affordable housing prices. However, there has been no academic work that systematically tests whether large IPOs like these reported tech companies have a causal impact on the local economy. The results presented in this paper show that firms going public have had a positive impact on the local economy. My analysis utilizes a difference-in-differences approach, comparing economic activities in areas very near firm headquarters with those in areas slightly farther away before and after the IPO. I then explored the channels through which IPOs might affect local housing prices, by investigating the effects of IPOs on total employment, agglomeration economies, and the share of high-income individuals. The

findings show that IPO firms increase employment and wages and attract firms in the same industry to establish nearby. These effects are stronger among IPO firms with above-median proceeds.

The results from the baseline hedonic pricing model suggest that an IPO announcement increases housing prices by 3.0%. An IPO's pricing and lockup expiration increase housing prices by approximately 3.3% and 1.3%, respectively. For the average-priced home in these areas, this translates into an approximate \$11,300 increase in the housing price during the IPO filing, and \$12,400 and \$4,900 after the pricing and lockup expiration, respectively. I further document that information on the final offering price adjustment has an important effect on housing price dynamics at the time of the IPO.

Finally, I examined the possibility that increased demand in the local real estate market crowds out low-income residents. The analysis finds evidence that neighborhoods that are close to the IPO firm headquarters experience some growth in income and a significant reduction in low-income residents, while the share of wealthy individuals does not change significantly post-IPO. Meanwhile, IPOs also shift the local amenities, as restaurant openings increase in neighborhoods close to IPO firms.

This paper shows that, beyond raising capital, going public brings in opportunities to the local economy by increasing investments, jobs, and property values. However, it also brings challenges, as rising housing prices and rents are likely to displace low-income residents. Recently, firms that have taken part in tax break deals and some other tech firms have teamed up with local governments to provide affordable housing, job training, and other assistance for local residents at risk of losing their homes.⁸ Therefore, my findings have important implications for local government policy on how to attract or retain emerging companies and at the same time provide affordable housing for local residents.

8

See for example, California Today: Silicon Valley, Housing Villain, Tries to Make Amends, *The New York Times*, 2016; Facebook Plans to Invest \$20m in Affordable Housing projects, *The Guardian*, 2016. S.F. Tax Break Tapped by Twitter Is Intended to Help Struggling Neighborhoods, *Next City*, 2017.

2.7 Figures and Tables

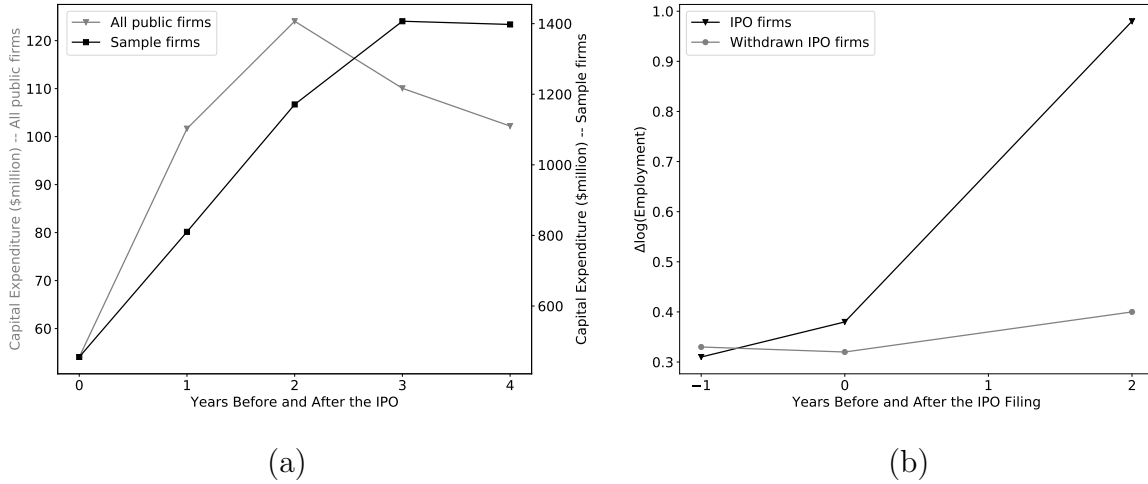


Figure 1: Post-IPO Capital Expenditures and Employment Growth

Note: Panel (a) of the figure shows the common logarithm of the average capital expenditures for all public firms and the sample firms from 2000 to 2012. Panel (b) of the figure depicts employment growth for the two kinds of firms in Borisov et al. (2015). IPO firms are the firms that complete an IPO during 1990-2010 with pre-IPO employment data. Withdrawn IPO firms are firms that file for an IPO during 1990-2010 but subsequently withdraw the offering and have pre-IPO employment information. Data: Capital Expenditure data is calculated from Compustat and employment data is from Borisov et al. (2015).

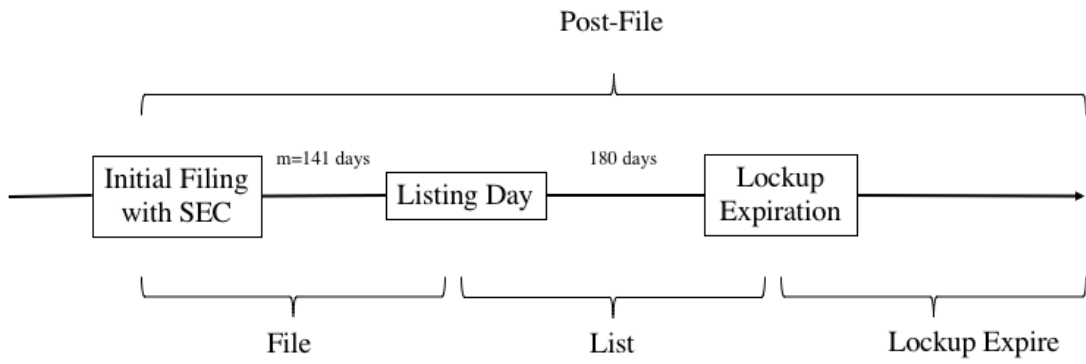


Figure 2: The IPO Process

Note: The number of days from IPO filing to the first day of trading is the mean among sample listed firms.

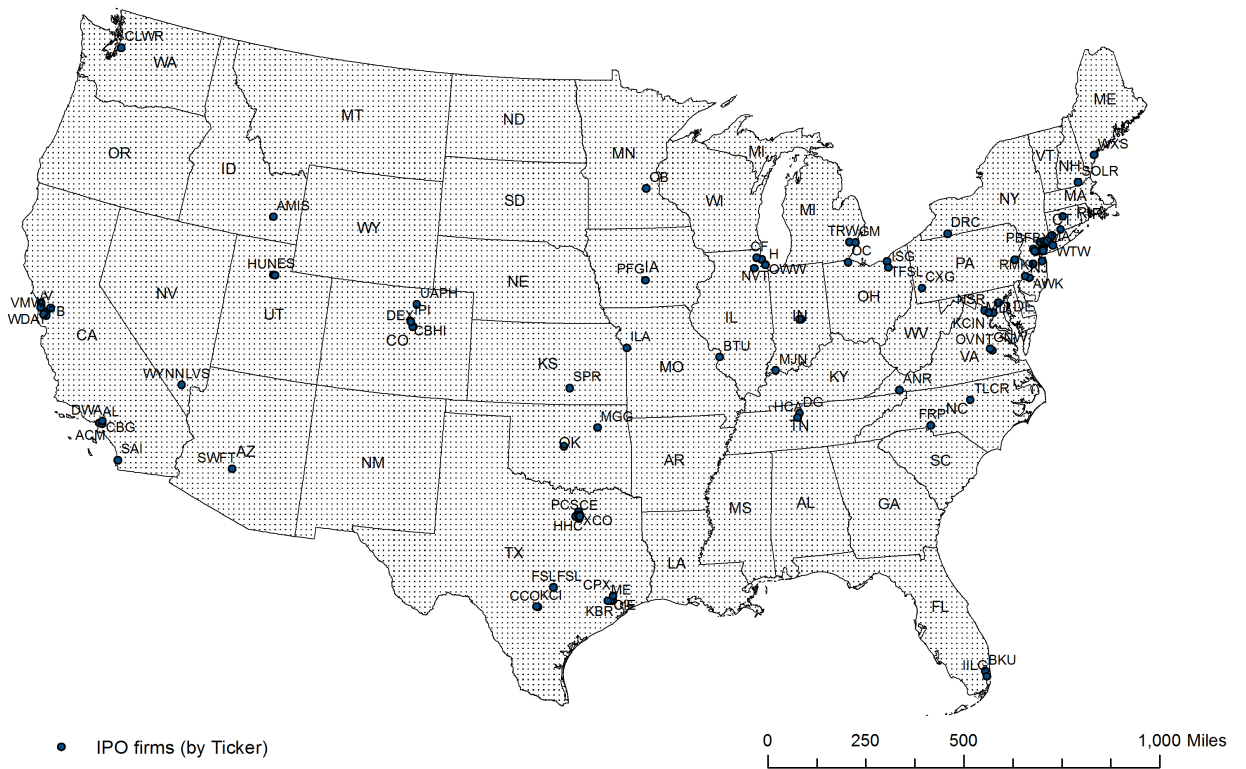
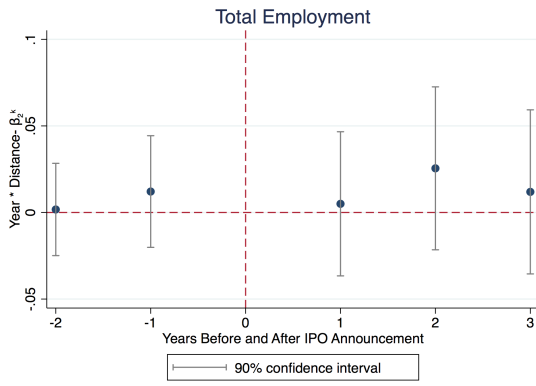
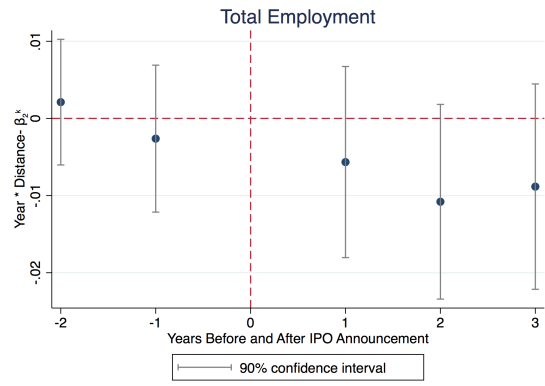


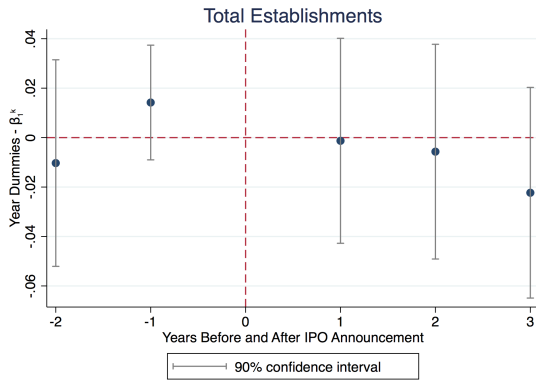
Figure 3: Corporate Headquarters of IPO Firms



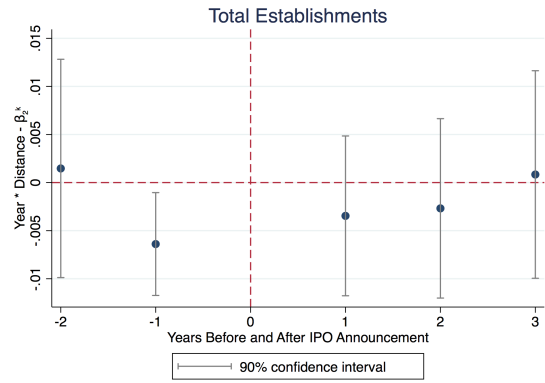
(a1)



(a2)



(b1)

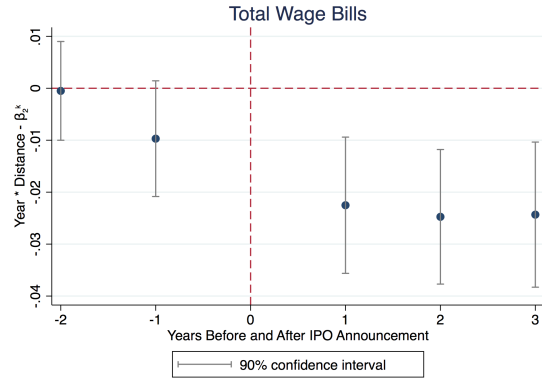


(b2)

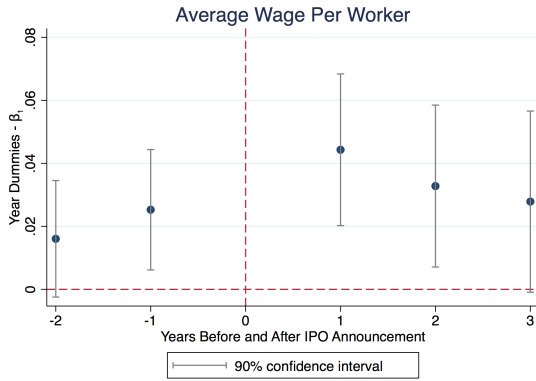
Figure 4: Effects of IPOs on Proximate Firms by Year



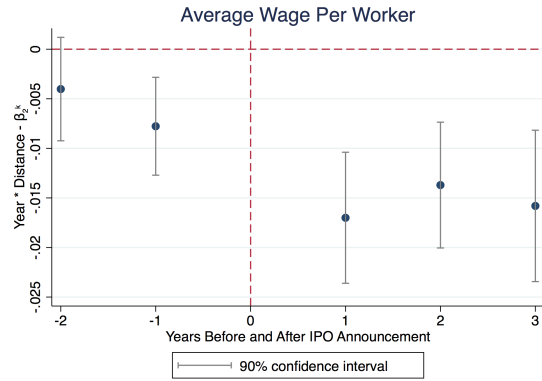
(c1)



(c2)



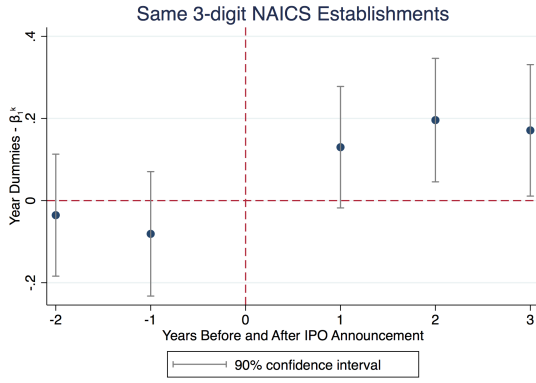
(d1)



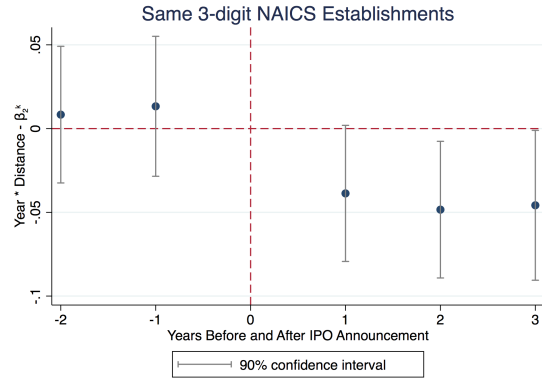
(d2)

Figure 5: Effects of IPOs on Wages by Year

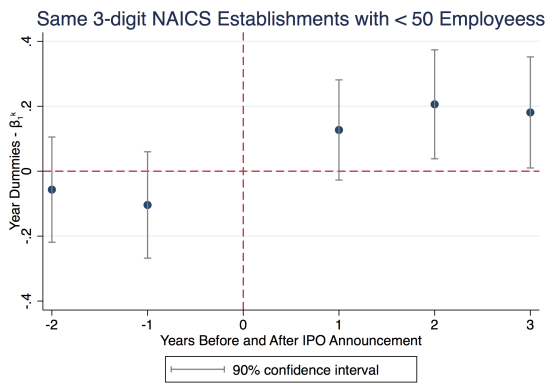
Note: I plot the estimated coefficients of the year dummies (β_1^k) and the distance-by-year interaction terms (β_2^k) in equation 2.4.1, taking as the dependent variable the local economic outcomes in each panel.



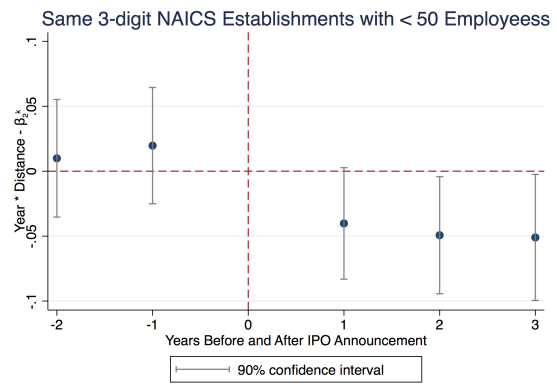
(a1)



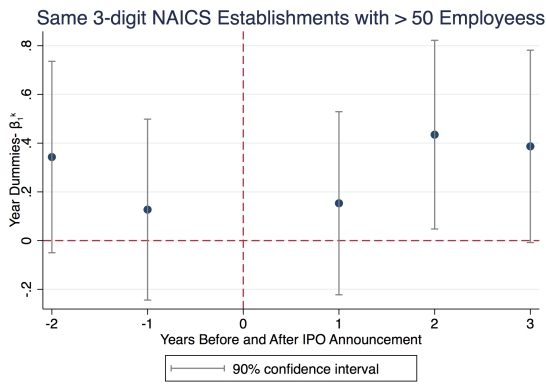
(a2)



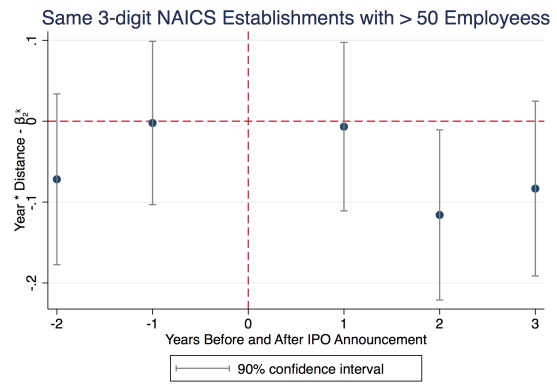
(b1)



(b2)



(c1)



(c2)

Figure 6: Effects of IPOs on the Same 3-Digit NAICS Industries by Year

Note: I plot the estimated coefficients of the year dummies (β_1^k) and the distance-by-year interaction terms (β_2^k) in equation 2.4.1, taking as the dependent variable the logarithm of the number of same 3-digit NAICS firms.

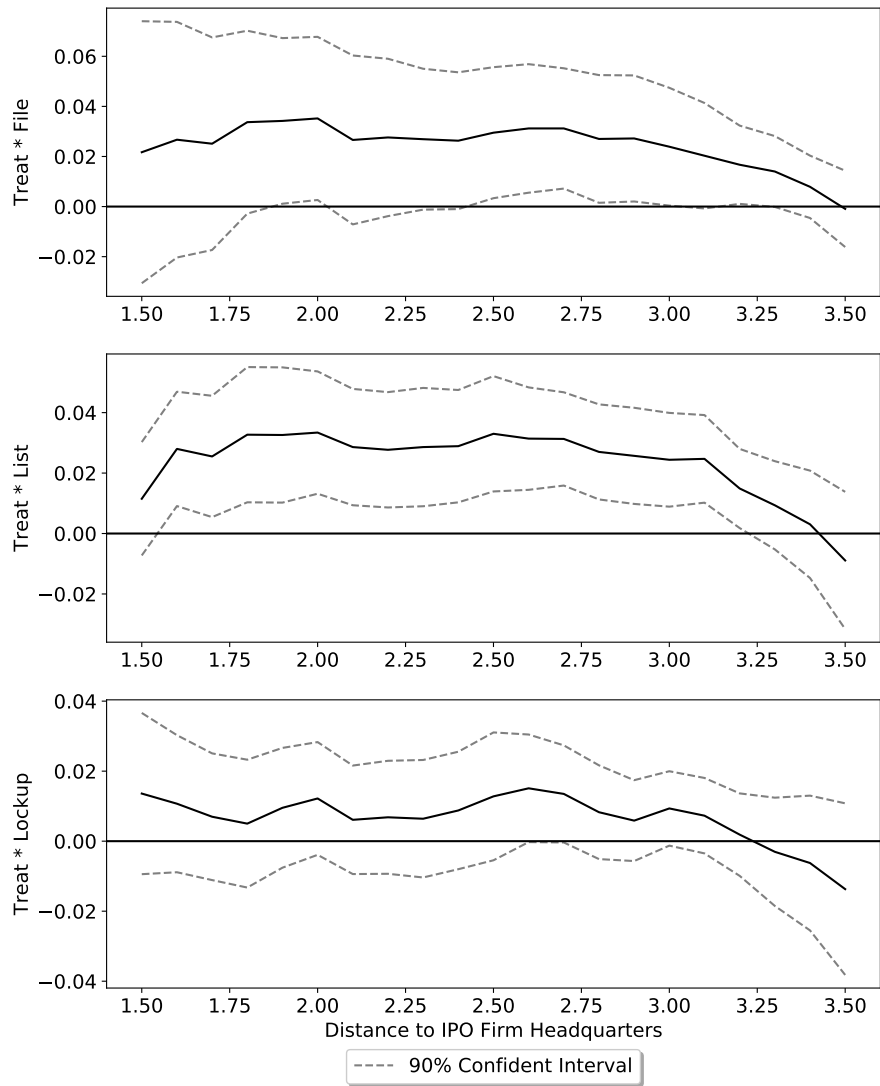


Figure 7: Treatment/Control Boundary Analysis

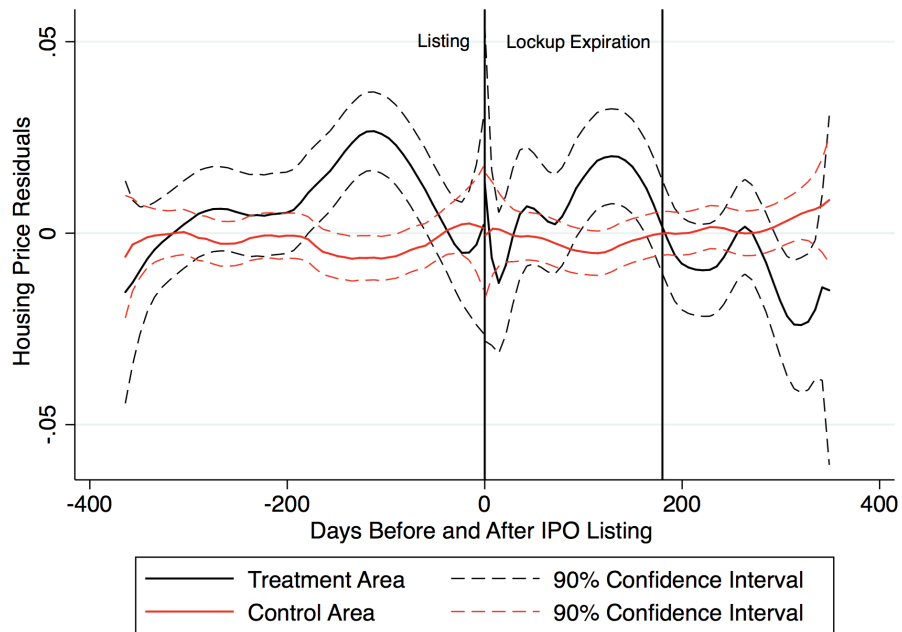
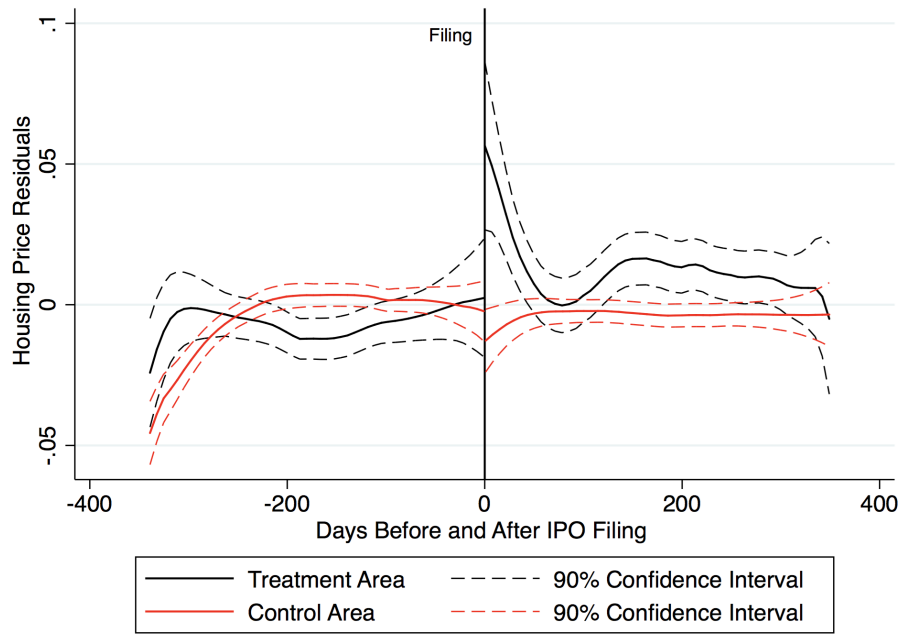
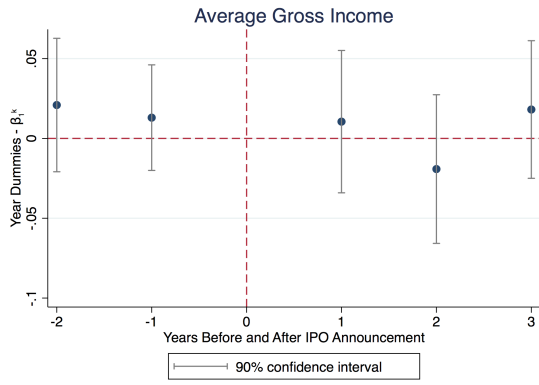
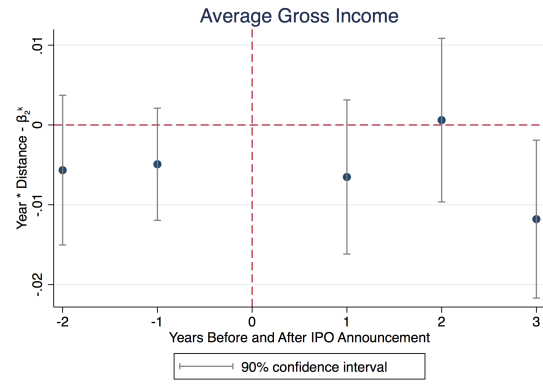


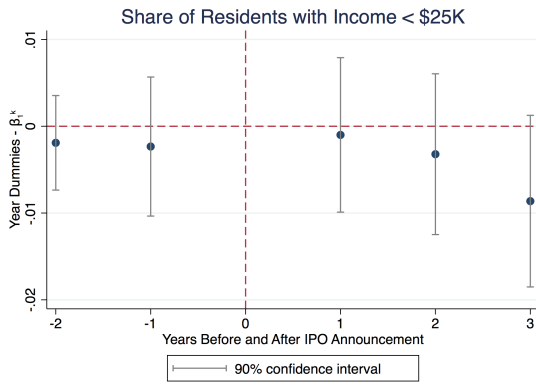
Figure 8: Housing Price Residuals Plots



(a1)



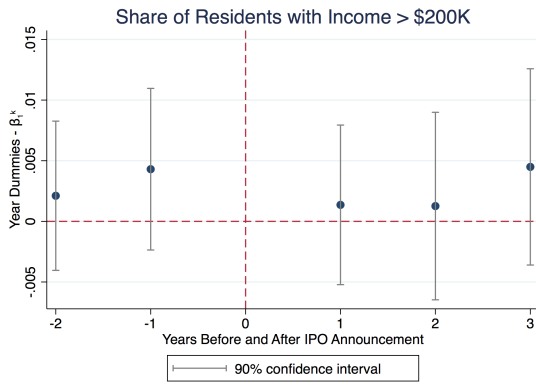
(a2)



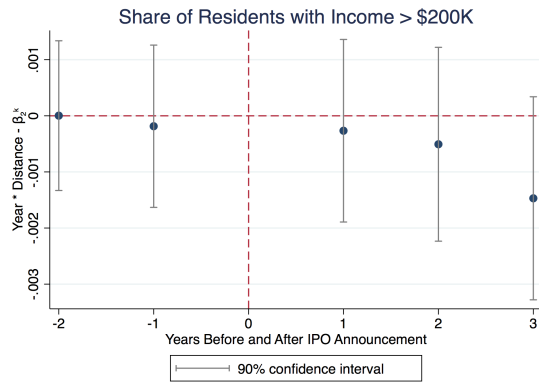
(b1)



(b2)



(c1)



(c2)

Figure 9: Effects of IPOs on Demographics by Year

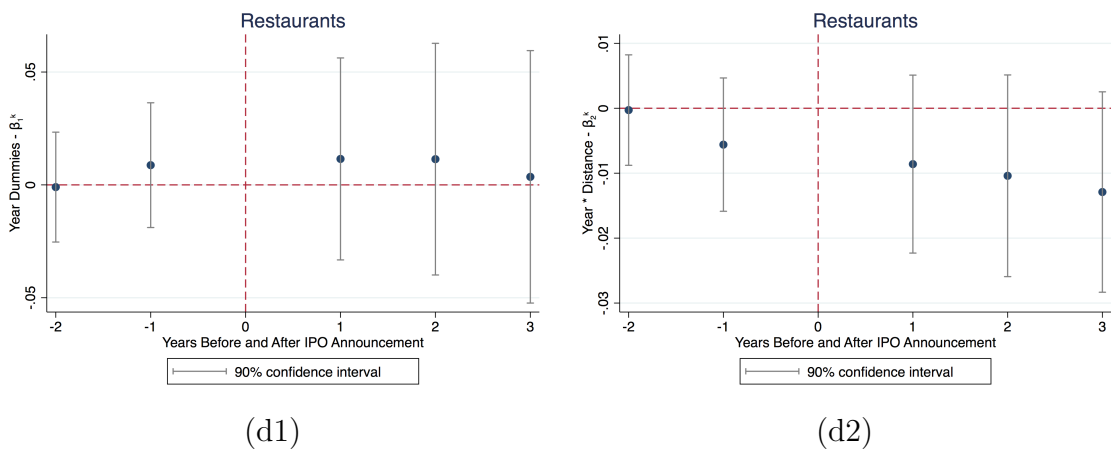


Figure 10: Effects of IPOs on Amenities by Year

Note: I plot the estimated coefficients of the year dummies (β_1^k) and the distance-by-year interaction terms (β_2^k) in equation (2.4.1) but taking as the dependent variable the logarithm of average resident income, share of residents with income less than \$25,000, share of residents with income greater than \$200,000, and logarithm of the restaurant count.

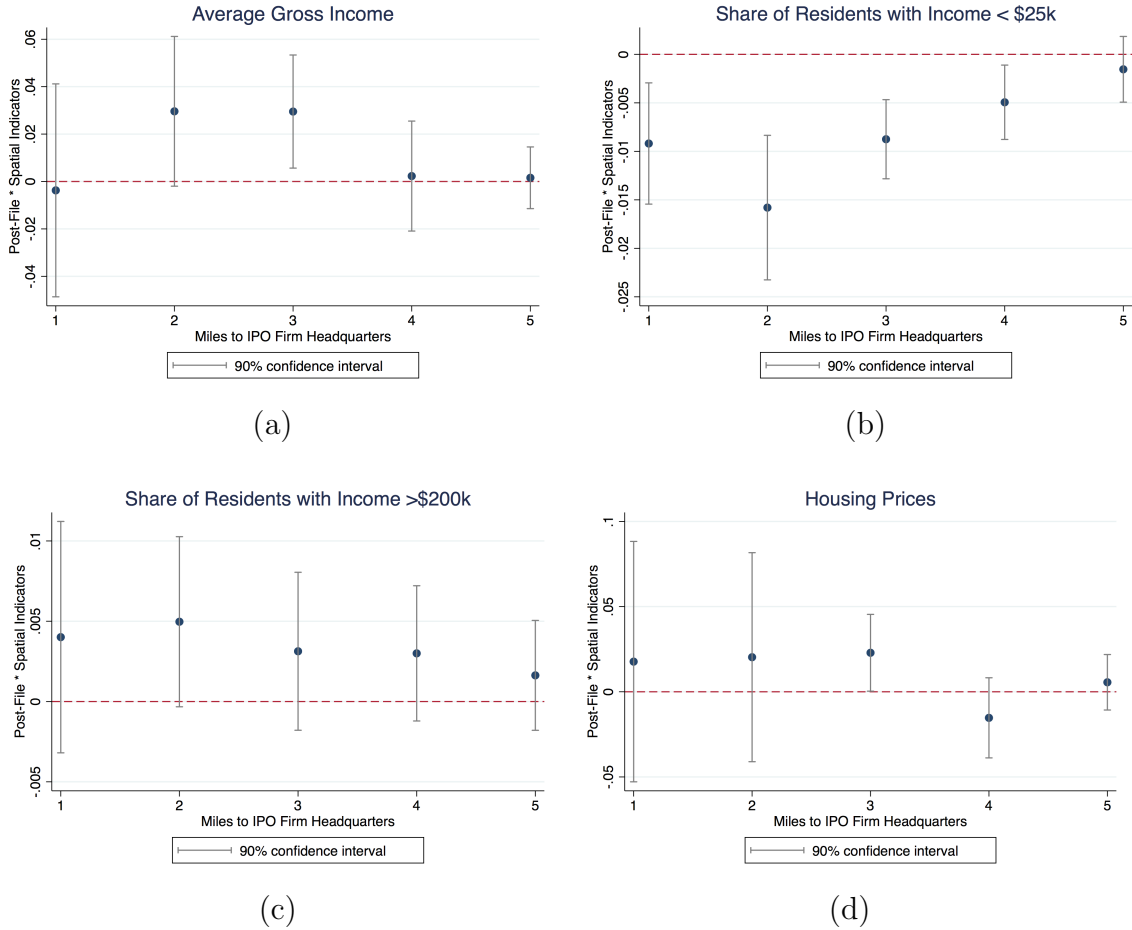


Figure 11: Effects of IPOs on Household Sorting

Note: I plot the estimated coefficients of the year dummies (γ^k) in section (2.4.2), taking as the dependent variable the logarithm of average resident income, share of residents with income less than \$25,000, share of residents with income greater than \$200,000, and logarithm of the housing prices.

Table 1: Summary of IPOs

PANEL A			PANEL B			PANEL C		
Year filed for IPO			Month filed for IPO			Industry by SIC code		
Year	Freq.	Percent	Month	Freq.	Percent	Industry	Freq.	Percent
2000	4	5.41	Jan.	2	2.70	Construction	1	1.35
2001	4	5.41	Feb.	8	10.81	Finance, Insurance and Real Estate	13	17.57
2002	3	4.05	Mar.	6	8.11	Manufacturing	17	22.97
2003	4	5.41	Apr.	7	9.46	Mining	7	9.46
2004	16	21.62	May	5	6.76	Retail Trade	1	1.35
2005	10	13.51	June	3	4.05	Services	21	28.38
2006	7	9.46	July	5	6.76	Transportation, Communications, Electric, Gas and Sanitary Services	14	18.92
2007	9	12.16	Aug.	10	13.51			
2008	2	2.70	Sept.	7	9.46			
2009	3	4.05	Oct.	4	5.41			
2010	5	6.76	Nov.	9	12.16			
2011	5	6.76	Dec.	8	10.81			
2012	2	2.70						
Sum	74	100.00	Sum	74	100.00	Sum	74	100.00

Table 2: Summary of Offering Proceeds by Expectation

		Above expectation	Below expectation	Within expectation
Median expected proceeds (\$million)	Min	603.75	910.11	695.98
	Max	656.25	1,026.94	754.22
Final proceeds (\$million)	Median	783.00	791.50	709.55
	Mean	2,838.55	938.82	1,056.51
Average change from expectation	Min	26.08%	-10.30%	8.55%
	Max	13.55%	-19.48%	-2.54%
Number of firms		29	18	24

Table 3: Summary Statistics of Housing Data

	Within 2.5 miles	2.5 to 5 miles	5 to 10 miles
Price	\$376,924 (399,268)	\$350,070 (369,995)	\$316,839 (311,569)
Log(price)	12.33 (1.09)	12.29 (1.02)	12.28 (0.92)
Age	48.68 (33.49)	46.75 (29.06)	37.98 (30.62)
Lot size	13,591 (441,838)	66,700 (10,200,000)	40,525 (5,342,221)
Bathrooms	1.90 (1.28)	2.01 (8.53)	2.13 (6.52)
Bedrooms	2.25 (1.67)	2.26 (1.59)	2.30 (1.64)
Stories	1.42 (0.68)	1.30 (0.62)	1.36 (0.60)
Square footage	1,752.80 (1,010.81)	1,741.47 (4,733.22)	1,769.41 (1,144.37)
Observations	98,190	321,016	1,076,590

Note: Summary statistics for houses sold one year before the IPO filing and one year after the lockup expiration.

Table 4: Impact of IPO Activity on the Local Economy

	(1)	(2)	(3)
Variables	All	IPOs with below median proceeds	IPOs with above median proceeds
Panel (a). Dependent variable: log (Total employment)			
Post-File	0.00874 (0.0206)	-0.0108 (0.0325)	0.0324 (0.0212)
Post-File×Distance	-0.00681 (0.0055)	-0.000602 (0.0092)	-0.0140** (0.0061)
Observations	5,462	2,669	2,793
R-squared	0.984	0.982	0.988
Panel (b). Dependent variable: log (Total establishments)			
Post-File	-0.00713 (0.0216)	-0.0325 (0.0275)	0.031 (0.0271)
Post-File ×Distance	-0.000509 (0.0053)	0.00666 (0.0075)	-0.0071 (0.0079)
Observations	5,685	2,707	2,978
R-squared	0.990	0.991	0.991
Panel (c). Dependent variable: log (Total wage bill)			
Post-File	0.0347* (0.0188)	0.0296 (0.0326)	0.0439** (0.0181)
Post-File ×Distance	-0.0194*** (0.0054)	-0.0147 (0.0097)	-0.0228*** (0.0053)
Observations	5,483	2,672	2,811
R-squared	0.983	0.982	0.988
Panel (d). Dependent variable: log(Average wages per worker)			
Post-File	0.0229** (0.0111)	0.0400** (0.0159)	0.00489 (0.0156)
Post-File ×Distance	-0.0117*** (0.0032)	-0.0141*** (0.0044)	-0.00708 (0.0047)
Observations	5,462	2,669	2,793
R-squared	0.932	0.937	0.934
Year FE	X	X	X
Zip Code FE	X	X	X

Note: Standard errors clustered by firm are in parentheses. All samples are restricted to three years pre- and post-IPO announcement. Models are limited to zip codes located within 5 miles of IPO firm headquarters.

* The estimate is significant at the 10% level.

** The estimate is significant at the 5% level.

*** The estimate is significant at the 1% level.

Table 5: Impact of IPO Activity on the Same 3-Digit NAICS Establishments

	(1)	(2)	(3)	(4)	(5)
Variables	All	IPOs with below median proceeds	IPOs with above median proceeds	Establishments with < 50 employees	Establishments with > 50 employees
Post-File	0.170*** (0.0556)	0.139* (0.0833)	0.196** (0.0787)	0.180*** (0.0621)	0.118 (0.1120)
Post-File \times Distance	-0.0479*** (0.0134)	-0.0245 (0.0209)	-0.0677*** (0.0175)	-0.0508*** (0.0149)	-0.038 (0.0314)
Observations	1,255	612	643	1,239	533
R-squared	0.977	0.972	0.982	0.973	0.918
Year FE	X	X	X	X	X
Zip Code FE	X	X	X	X	X

Note: Standard errors clustered by firm are in parentheses. All samples are restricted to three years pre- and post-IPO announcement. Models are limited to zip codes located within 5 miles of IPO firm headquarters.

* The estimate is significant at the 10% level.

** The estimate is significant at the 5% level.

*** The estimate is significant at the 1% level.

Table 6: Impact of IPO Activity on Property Values

	(1)	(2)	(3)	(4)	(5)	(6)
Sample restrictions	<5 miles 1 year pre& post	<5 miles 1 year pre& post	<10 miles 1 year pre& post	<5miles 2 years pre& post	<5 miles 1 year pre& post	<5 miles half years pre& post
File	0.0181 (0.0272)	0.0225 (0.0228)	-0.00221 (0.0104)	0.0213 (0.0226)	0.0192 (0.0220)	0.0219 (0.0236)
List	0.00103 (0.0309)	0.00435 (0.0291)	-0.0113 (0.0149)	0.00249 (0.0292)	-0.00284 (0.0278)	-0.000145 (0.0291)
Lockup	0.0308 (0.0298)	0.0371 (0.0282)	0.0192 (0.0162)	0.0307 (0.0288)	0.03 (0.0279)	0.0311 (0.0298)
Treat×File	0.0419 (0.0315)	0.0295* (0.0159)	0.0165 (0.0134)	0.0277** (0.0131)	0.0352* (0.0184)	0.0305 (0.0229)
Treat×List	0.0458*** (0.0135)	0.0330*** (0.0117)	0.0253** (0.0121)	0.0364*** (0.0131)	0.0548*** (0.0197)	0.0473** (0.0234)
Treat×Lockup	0.0281* (0.0160)	0.0128 (0.0112)	0.00801 (0.0120)	0.0239** (0.0102)	0.0367 (0.0267)	0.0317 (0.0340)
Observations	419,206	419,206	1,495,796	669,780	419,206	279,646
R-squared	0.667	0.676	0.638	0.669	0.677	0.686
Firm-level cluster	X	X	X	X	X	X
Year-Month-Firm FE	X	X	X	X	X	X
Firm-Treatment FE		X	X	X	X	X
Year-Month-Treatment					X	X

Note: Standard errors clustered by firm are in parentheses. Housing characteristics include building age, age square, lot size, square footage, number of bathrooms, number of bedrooms, number of total rooms, number of stories and indicators for housing conditions. All sample temporal restrictions refer to the years pre-IPO announcement and post-IPO stock lockup expiration. Models are limited to properties located within 5 or 10 miles of the nearest corporate headquarters.

* The estimate is significant at the 10% level.

** The estimate is significant at the 5% level.

*** The estimate is significant at the 1% level.

Table 7: Falsification Tests of the Effects of IPO Activity on Property Values

	(1)	(2)	(3)	(4)
	2 years earlier		3 years earlier	
Sample restrictions	1 year pre & post	2 years pre & post	1 year pre & post	2 years pre & post
File	0.00203 (0.0141)	0.000656 (0.0136)	0.0193 (0.0177)	0.0175 (0.0174)
List	-0.0386 (0.0277)	-0.0361 (0.0283)	0.0479* (0.0241)	0.0444* (0.0239)
Lockup	0.00328 (0.0263)	0.0028 (0.0252)	0.0428 (0.0295)	0.0359 (0.0297)
Treat×File	-0.0191* (0.0103)	-0.0129 (0.0103)	-0.0127 (0.0114)	-0.00373 (0.0117)
Treat×List	0.00594 (0.0107)	0.00671 (0.0108)	-0.0161 (0.0126)	-0.00265 (0.0136)
Treat×Lockup	-0.0186 (0.0146)	-0.00368 (0.0115)	-0.0166 (0.0143)	0.0118 (0.0131)
Observations	374,554	647,681	375,380	649,112
R-squared	0.672	0.678	0.667	0.666
Firm-level cluster	X	X	X	X
Year-Month-Firm FE	X	X	X	X
Firm-Treatment FE	X	X	X	X

Note: Standard errors clustered by firm are in parentheses. These are the results from difference-in-differences specifications that move the IPO filing date forward for a falsification test. The number of years the filing date is shifted refers to how many years the open date is shifted forward.

* The estimate is significant at the 10% level.

** The estimate is significant at the 5% level.

*** The estimate is significant at the 1% level.

Table 8: Housing Composition Regression Results

	(1)	(2)	(3)	(4)	(5)	(6)
Variables	Age	Lot size	Rooms	Bedrooms	Stories	Square ft
File	-0.913 (0.5880)	-30,979 (31782)	-0.011 (0.0629)	-0.024 (0.0179)	-0.018 (0.0187)	-9.659 (20.31)
List	-0.543 (0.8270)	-10,715 (12034)	-0.0606 (0.0604)	-0.0460* (0.0236)	-0.0292 (0.0185)	-38.92 (31.02)
Lockup	-1.296 (1.0310)	-11,430 (31692)	-0.00477 (0.0785)	-0.0342 (0.0332)	-0.0341 (0.0222)	-739.5 (709.30)
Treat×File	0.0818 (0.3000)	104,103 (109878)	0.0106 (0.0297)	-0.013 (0.0118)	-0.00821 (0.0091)	-4.012 (13.63)
Treat×List	-0.131 (0.4370)	8,990 (19931)	-0.00596 (0.0372)	0.00696 (0.0114)	0.00601 (0.0073)	-58.61 (53.32)
Treat×Lockup	-0.347 (0.3630)	-135,005 (100246)	-0.0358 (0.0349)	-0.013 (0.0107)	0.0018 (0.0072)	-13.97 (14.96)
Observations	419,206	419,206	419,206	419,206	419,206	419,206
R-squared	0.473	0.017	0.616	0.698	0.328	0.019
Firm-level cluster	X	X	X	X	X	X
Year-Month-Firm FE	X	X	X	X	X	X
Firm-Treatment FE	X	X	X	X	X	X

Note: Standard errors clustered by firm are in parentheses. These linear regressions put the housing characteristics on the left-hand side and interactions of the treatment indicator and post-IPO variable on the right-hand side as in the primary difference-in-differences estimation.

* The estimate is significant at the 10% level.

** The estimate is significant at the 5% level.

*** The estimate is significant at the 1% level.

Table 9: Heterogeneous Effects of IPO Activity on Property Values

	(1)	(2)	(3)	(4)	(5)
Sample	Above	Below	Within	Below median	Above median
restriction	expectation	expectation	expectation	proceeds	proceeds
File	-0.00963 (0.0206)	0.0796*** (0.0204)	-0.0164 (0.0207)	0.0112 (0.0230)	0.0296 (0.0199)
List	-0.00188 (0.0292)	0.0654** (0.0261)	-0.0321 (0.0332)	-0.0176 (0.0365)	0.0294 (0.0268)
Lockup	0.0397 (0.0354)	0.0588* (0.0304)	0.0145 (0.0412)	0.0262 (0.0384)	0.0432 (0.0319)
Treat×File	0.0151 (0.0122)	0.0656*** (0.0121)	0.0192 (0.0127)	0.0128 (0.0106)	0.0465*** (0.0109)
Treat×List	0.0559*** (0.0104)	0.0215** (0.0102)	0.0221* (0.0114)	0.0291** (0.0119)	0.0337*** (0.00913)
Treat×Lockup	0.0396*** (0.0088)	0.00135 (0.0085)	0.00262 (0.0095)	0.00501 (0.0130)	0.0263*** (0.00789)
Observations	146,129	124,602	132,886	220,734	198,471
R-squared	0.69	0.716	0.694	0.691	0.707
Firm-level cluster				X	X
Year-Month-Firm FE	X	X	X	X	X
Firm-Treatment FE	X	X	X	X	X
Year-Month-Treatment	X	X	X	X	X
P-value: Test $\gamma_2 - \gamma_1=0$	0.0029	0.0006	0.8363		

Note: Robust errors are in parentheses in columns (1)-(3) [each group include less than 30 firms], clustered standard error by firm are in parentheses in columns (4) -(5). Sample restriction refers to how the sample was split for each heterogeneity analysis. The temporal selection for each of these specifications uses housing data from one year pre-IPO announcement and post-IPO stock lockup expiration. Models are limited to properties located within 5 miles of the nearest IPO firm headquarters.

* The estimate is significant at the 10% level.

** The estimate is significant at the 5% level.

*** The estimate is significant at the 1% level.

Table 10: Impact of IPOs on Demographics and Amenities

Variables	Log(income)	Share of residents with income < 25k	Share of resident with income > 200k	log(Restaurants)
Post-File	-0.00009 (0.0199)	-0.00152 (0.0035)	0.000164 (0.0030)	0.0094 (0.0200)
Post-File×distance	-0.00348 (0.0053)	0.00210** (0.0010)	-0.000656 (0.0009)	-0.00851 (0.0059)
Observations	3,737	3,737	2,720	5,501
R-squared	0.982	0.978	0.986	0.980
Year FE	X	X	X	X
Zip Code FE	X	X	X	X

Note: Standard errors clustered by firm are in parentheses. All samples are restricted to three years pre- and post-IPO announcement. Models are limited to zip codes located within 5 miles of IPO firm headquarters.

* The estimate is significant at the 10% level.

** The estimate is significant at the 5% level.

*** The estimate is significant at the 1% level.

3.0 International Competition in the Race to Clean Technology

This chapter is coauthored with Douglas Hanley.

3.1 Introduction

Navigating the transition to low-emission energy infrastructure is one of the major challenges facing human civilization in the 21st century. Though few question the necessity of such a transition, it still took a decade of multilateral negotiation to reach the Paris Agreement. Under the agreement, countries determine their own carbon reduction targets with no binding commitment. Furthermore, the United States withdrawal from the Paris Agreement raises a great deal of uncertainty surrounding the nature and magnitude of the intervention required to lead the transition. How will these environmental policies affect firms' competitiveness and innovation in a global economy? How will the game-theoretic interactions in policies across countries change the speed of clean technology transition? These questions are critical for the future of climate change and for the structure of the optimal policy.

In a closed economy, the carbon tax effectively increases the cost of dirty goods, shifting demand to clean technologies and thus reducing emissions. However, such policies result in carbon leakage, as other countries benefit from production and innovation in dirty technologies via international trade, which leads to an increase in carbon emissions. A clean research subsidy can induce innovation in clean technologies. Over time, these technological advances lower the cost of clean products. However, international technological competition leads some countries to specialize in dirty sector. Therefore, a research subsidy may not prevent the associated environmental externality. One possible measure against carbon leakage is the introduction of carbon tariffs. With carbon tariffs, countries that have a stricter environmental policy would impose a tariff on dirty imports. However, carbon tariffs encourage dirty technologies innovation in domestic firms, may even generate large welfare loss when there is retaliation by the foreign country and reduce the gain from trade. To understand

effects of such international climate policies, a quantitative analysis necessitates an open-economy model of innovation and international technological competition in clean and dirty industries given the country-level environmental policies, and the direction of technological change is determined as a function of these policies.

In this paper, we build a two-country and two-sector endogenous growth model where clean and dirty technologies innovate to compete for global market leadership in final good production. Our framework builds on the micro-founded directed technology change model developed in Acemoglu et al. (2016a), which allows for a comprehensive quantitative evaluation. In both countries, the final good combines components produced using clean or dirty intermediates goods. The intermediate goods may be sourced from foreign or domestic producers. For each intermediate good, a home and a foreign firm compete for global market shares, and they improve the quality of their product through international knowledge spillover. The entrepreneurs in each country invest in R&D to enter the market. Meanwhile, clean and dirty sector are competing for market share in final good production with the dynamic evolution of technology. In addition to each country's choice of research subsidy and carbon tax levels, international trade opens up a new policy dimension in the form of tariffs on dirty goods. We parameterize the model to match key trade, innovation, climate and growth facts, with a specific focus on the US and China. Using standardized firm-level data on research and patenting in both the US and China, we quantify the incentives for both clean and dirty innovation faced by firms.

In *laissez-faire* and autarky, the allocation of innovation favors the leading technology and therefore reinforce technological lead over time. As in Acemoglu et al. (2016a), the allocation of innovation is path-dependent. If clean technologies are initially less advanced than dirty ones, they will have a smaller market share in the final good production, thus lower profitability. Therefore, the clean sector disappears completely, and the dirty sector takes over the entire economy. In an open economy, the total output increases because final good producers are able to import more productive intermediates overseas. Meanwhile, the innovation rates rise as the open economy allows for international knowledge spillover. However, the change in profits for each sector is ambiguous and depends on the initial distribution of the technology gaps between the two countries. While we observe a slower

transition to dirty technology in our model, the initial gap between clean and dirty technology is too big to overcome, and consequently, the economic growth is not sustainable in the long run.

Regarding policy evaluations, we first analyze the implications of unilateral carbon taxes. We focus on welfare and climate implications of this policy change on a 300 years horizon. The optimal carbon tax is determined by a rich set of externalities of carbon intermediate production. First, a high carbon tax increases the cost of domestic dirty goods, reducing the profitability of dirty intermediates producers on both domestic sales and exports. This decrease leads to a relative increase in clean intermediates profitability and innovation, securing a transition from dirty to clean technology for the home country. However, such policies generate a pollution haven effect, as the production of polluting intermediates moves to the foreign country with no such policies, which may lead to an increase in carbon emissions in the foreign country. Meanwhile, technology diffusion through international knowledge spillovers increases the competitiveness of clean technologies in the foreign country. We find that under the optimal unilateral carbon tax policies, the foreign countries slowly makes the transition from clean to dirty technologies but dirty technologies not necessarily converge to zero after the 300-year study period.

Next, we analyze the unilateral policies using clean R&D subsidies and carbon tariffs respectively. The optimal unilateral makes a heavy use of research subsidy because the social planner would like to direct R&D from carbon-intensive dirty technologies towards clean technologies in both countries as soon as possible. With the current estimate of international knowledge spillover rate, the clean technology in the foreign country will consequently catch up and increase the profitability of the clean sector relative to the dirty sector. A minimum of 46% research subsidy for either country can secure a transition from dirty to clean technology globally. As an alternative policy option to reduce carbon emission, we consider an increase in tariff on carbon imports. However, while the policy reduces the profitability of dirty intermediate goods in the foreign country, clean technologies are initially too much behind dirty technologies. The transition to dirty technology is slower comparing to laissez-faire but converges to zero in the long run.

This paper is related to several strands of research in the literature. First, our paper

is closely related to the literature on quantitative general equilibrium models on climate change. In addition to pure climate science, economic studies of climatic effects on utility and productivity, and microeconomic studies of the effects of policy on production and innovation decisions, there is a growing literature devoted to using macroeconomic models to synthesize the aforementioned results into assessments of the costs of climate change and measures intended to mitigate it, as well as the nature of the optimal policy response thereto. The literature started with the seminal work of Nordhaus (1994) and was extended by Nordhaus and Boyer (2000), Krusell and Smith Jr (2009) and Hassler and Krusell (2012), among many others. Golosov et al. (2014) formulate such an integrated assessment model (IAM) in a neoclassical setting and find conditions under which the optimal policy response depends upon the scale of potential climactic damages, but not on the current carbon concentration in the atmosphere. A major shortcoming of the existing IAM research is the assumption of a unified policy-making process, through the focus either on a single large country, such as the US, or the entire world. In reality, country-level segmentation of markets will affect both the incentives of firms to innovate and the optimal policy calculations of individual countries.

Our paper builds on the studies integrating directed technological change in the study of climate change policies. The endogenous and directed technological change framework we use is a model where producers choose between clean and dirty technologies as in Acemoglu (1998, 2002) and the latest developments by Acemoglu et al. (2012). This earlier work is mainly theoretical, and the models are generally not designed for quantitative analysis. Acemoglu et al. (2016a) develop a tractable microeconomics model in which the innovation decisions of firms are endogenized and quantitatively characterize the optimal path of research subsidy and carbon tax policy. However, they focus on a closed economy and abstract from cross-country variation in policies. Therefore, their characterized optimal policy makes heavy use of carbon taxes, while such taxes create negative externality by encouraging foreign countries to innovate in dirty technology. Hémous (2016) extend the framework developed by Acemoglu et al. (2012) with international trade. In Hémous (2016), there are two aggregated goods: polluting and non-polluting. Trade happens between the two countries at the level of these aggregated goods, not in intermediates, as we do here. This leads to two major differences. First, countries can specialize not just in clean or dirty technology,

but also in particular clean or dirty technologies, meaning output complementarities can be stronger across countries in our model. Second, countries directly compete in each product line in our model, and thus the distribution of productivities across product lines matters. This major differences makes the production structure more realistic and enabling us to use microdata on innovation and production.

We introduce directed technological change on the growing literature on the impact of international trade on firm dynamics. Analyzing various extensions of the canonical Melitz (2003) framework, Burstein and Melitz (2013) discuss how firms innovation responses determine transitional dynamics induced by trade liberalization. Akcigit et al. (2018) build a model where firm innovation endogenously determines the dynamics of technology, market leadership, and trade flows. They show that import tariffs generate at best short-term gains at the expense of long-term losses, whereas policies that encourage innovations directly (e.g., R&D subsidies) create substantial long-term gains. Buera and Oberfield (2016) and Sampson (2015) introduce diffusion of technologies into trade models with heterogeneous firms and show that the gains from trade increase substantially compared to the static counterparts of those models.

Finally, we contribute to the patent classification literature by analyzing the patent text using machine learning. Researchers in economics have made frequent use of patents, often in the form of patent count or patent citation (Hall et al., 2001; Abrams et al., 2013; Acemoglu et al., 2016b). Recent studies use patent classification codes to identify emissions reduction technologies (Aghion et al.,2016). Recognizing the importance of identifying such clean patents, The European Patent Office (EPO) employs experts to tag climate change mitigation technologies, but still heavily relies on International Patent Classification (IPC) or the European Patent Classification (ECLA) (Veefkind et al.,2012). Because patents relating to climate change mitigation technologies can be found in so many areas of technology, they do not fall under one single dedicated classification section. Both clean and dirty technologies could fall under the same the classification section, further complicating the classifying the relevant patents. Our approach differs as we do not specify a priori which IPCs to search for, but we classify patents as clean patents if their texts describe an invention that is a substitute for carbon-emitting technologies or that directly mitigates the emissions of carbon-emitting

tech.

The rest of the paper is organized as follows. Section 2 introduces our theoretical model and characterizes the equilibrium. Section 3 describes the data and method we use for classifying clean and dirty technology and outlines the calibration procedure. Section 4 discusses policy implications and optimal policies. Section 5 concludes.

3.2 Model

In this section, we present a two-country and two-sector (clean and dirty) Richardian model with international competition in technology. In each country, the final good combines components produced using clean or dirty intermediates. The productivity of the dirty or clean technologies for each intermediate is represented by a quality ladder. There is free trade in intermediate and no trade in assets. In each country, there is an active firm in each production line for clean/dirty intermediate goods, engaging in price competition to obtain monopoly power of production. Production is also subject to taxes, so profit-maximizing final good producers choose whether to import clean or dirty intermediates from foreign countries as a function of taxes, trade costs, tariffs and the productivity gap between the two countries. Research is conducted by only entrants, while incumbent firms improve the quality of production with technology diffusion through international knowledge spillovers. Finally, dirty technology contributes to carbon emissions, which create potential economic damage. We next describe each aspect of the model in turn and characterize the equilibrium.

3.2.1 Preferences and Endowments

Our economy is in continuous time and admits a representative household in each country i with a logarithmic instantaneous utility function and lifetime utility given by:

$$U_{i,0} = \int_0^{\infty} e^{-\rho t} \ln C_{i,t} dt$$

where $C_{i,t}$ is the representative household's consumption of country i at time t , and $\rho > 0$ is the discount factor.

There are two types of labor in the economy, skilled and unskilled. Unskilled workers are used in the production of the active products, while skilled workers perform R&D activities. In each period, the representative household has a fixed unskilled labor supply of measure normalized to one, and skilled labor measure of $L_{i,t}^S$. The representative household maximizes lifetime utility subject to the following budget constraint:

$$P_{i,t}C_{i,t} + \dot{A}_{i,t} \leq w_{i,t}^u + w_{i,t}^s L_{i,t}^S + R_{i,t}A_{i,t} - T_{i,t}$$

and the usual no-Ponzi condition. Here $w_{i,t}^u$ and $w_{i,t}^s$ denote unskilled and skilled wages, $P_{i,t}$ is the price of the consumption good, $R_{i,t}$ is the nominal return to asset holdings of the household, and $T_{i,t}$ is the net lump-sum tax/transfer used for balancing government budget. The household in country i own all the firms in the country; therefore, the asset market clearing condition requires that the asset holdings $A_{i,t}$ have to be equal to the sum of all domestic firm values.

3.2.2 Production

The final good, which is only used for consumption, is produced in each country through a combination of clean component C and dirty component D , with an elasticity of substitution $\varepsilon > 1$ (Papageorgiou et al., 2017). In addition, the final good production is negatively affected by the amount of carbon in the atmosphere, which we denote by S_t . The aggregation is given by

$$Y_t = \nu(S_t) \left(C_t^{\frac{\varepsilon-1}{\varepsilon}} + D_t^{\frac{\varepsilon-1}{\varepsilon}} \right)^{\frac{\varepsilon}{\varepsilon-1}} = \nu(S_t) \bar{Y}_t$$

where $\nu(S_t) = \exp(-\gamma(S_t - \bar{S}))$ as in Golosov et al. (2014) and Acemoglu et al. (2016a) and where $\bar{S} > 0$ is the preindustrial level of the atmospheric carbon concentration, $\gamma \geq 0$ is a scale parameter.¹

1

The current damage functional form assumes that the proportional cost of a unit increase in atmospheric carbon concentration is the same across countries. This is likely to be true because our quantitative exercise focuses on U.S. and China, which share similar climates.

These components are themselves composed from a continuum of intermediates $j \in [0, 1]$ with an elasticity of substitution equal to one:

$$\log X_t = \int_0^1 \log x_{j,t} dj$$

where $(x, X) \in \{(c, C), (d, D)\}$. The intermediates are aggregated into components then the final good competitively.² We will sometimes refer to clean and dirty “intermediates” as clean and dirty “product lines”.

Firms in both countries may potentially produce each intermediate j . Firms produce clean intermediates with linear production function as follows

$$c_{j,t} = q_{j,t}^c \ell_{j,t}^c$$

where $\ell_{j,t}^c$ is employment of production workers and $q_{j,t}^c$ is the labor productivity of the clean technology in product line $j \in [0, 1]$. The production function for dirty technology is similar, except that it also creates carbon emission $\epsilon_{j,t}$. Assume that production in dirty intermediates is Leontieff in labor and emissions

$$d_{j,t} = q_{j,t}^d \min\{\ell_{j,t}^d, \epsilon_{j,t}/\zeta\}$$

Here, intermediate firms using dirty technology pay a certain tax $\tau_t = \hat{\tau} w_t^u$ on emissions $\epsilon_{j,t} = \zeta \ell_{j,t}^d$.³

Intermediate goods are produced not only for sale domestically but also internationally. Firms with the most advanced technology for intermediate j in each country will compete for the global market leadership. However, because of trade and carbon taxes, it is not necessarily the country with the most advanced technology between these two will be able

²

It makes no differences whether this occurs in one or two stages.

³

The historical record indicates that the supply of fossil fuels has consistently increased over time and that their relative price advantage over low-carbon energy sources has not declined substantially over time (Covert et al., 2016). We simplify the discussion by not modeling the exhaustible resources.

to export its good abroad. Given these taxes, the marginal cost of intermediate j in country i is

$$MC_{i,j,t}^c = \begin{cases} \frac{w_{i,t}^u}{q_{i,j,t}^c}, & \text{if produced in country } i \\ \frac{\kappa w_{-i,t}^u}{q_{-i,j,t}^c}, & \text{if imported from country } -i \end{cases}$$

$$MC_{i,j,t}^d = \begin{cases} \frac{w_{i,t}^u(1+\zeta\hat{\tau}_i)}{q_{i,j,t}^d}, & \text{if produced in country } i \\ \frac{\kappa w_{-i,t}^u(1+\zeta\hat{\tau}_{-i})(1+b_i)}{q_{-i,j,t}^d}, & \text{if imported from country } -i \end{cases}$$

where κ is the iceberg trade cost and b_i is the carbon trade tax imposed by country i on dirty imports. In equilibrium, only the firms with the lower marginal cost inclusive of taxes and trade costs will choose to produce.

3.2.3 Innovation and the Quality Ladder

Labor productivity for each intermediate $q_{i,j}^x$ improves through two channels. The first is the entrants' innovation. Every period, a new entrepreneur in each product line and from each country invests in R&D to enter the market. If an entrepreneur is successful in her research, the entrant firm replaces the domestic incumbent; otherwise, the firm disappears. The second is knowledge diffusion, which occurs when a firm learns about ideas that have been developed in other countries. The productivity improvement in country i and technology $x \in (c, d)$ is incremental. The labor productivity advance by $\lambda > 1$ in quality ladder over the current domestic leading-edge technology of sector x . Hence, the labor productivity of technology x in intermediate j at time t is $q_{i,j,t}^x = \lambda^{N_{i,j,t}^x}$, where $N_{i,j,t}^x \in Z_+$ is the number of effective steps that this country has taken in this technology since the initial date $t = 0$. We assume the initial levels in both countries $q_{i,j,0}^x = 1$, for and $j \in (0, 1)$ and $x \in (c, d)$ that without loss of generality.

Given this specification, the relative productivity of country i to its foreign competitor in intermediate j in the clean or dirty sector can be written as

$$\lambda^{n_{i,j,t}^x} = \frac{q_{i,j,t}^x}{q_{-i,j,t}^x} = \frac{\lambda^{N_{i,j,t}^x}}{\lambda^{N_{-i,j,t}^x}}$$

where $n_{i,j,t}^x = N_{i,j,t}^x - N_{-i,j,t}^x$ is defined as the technological gap between two countries in product line j in sector $x \in (c, d)$. Let us next denote the tax-adjusted policy gap by $\bar{n}_{i,t}^x$ such that

$$\lambda^{\bar{n}_{i,t}^x} = \frac{w_{i,t}^u}{\kappa_i^x w_{-i,t}^u} \Rightarrow \bar{n}_{i,t}^x = \frac{\log(w_{i,t}^u/w_{-i,t}^u) - \log \kappa_i^x}{\log \lambda}$$

where

$$\kappa_i^x = \begin{cases} \kappa, & \text{if } x = c \\ \frac{1+\zeta\hat{\tau}_{-i}}{1+\zeta\hat{\tau}_i}(1+b_i)\kappa, & \text{if } x = d \end{cases}$$

The price-adjusted technology gap can, therefore, be written as:

$$\frac{q_{i,j,t}^x}{q_{-i,j,t}^x} \frac{\kappa_i^x w_{-i,t}^u}{w_{i,t}^u} = \lambda^{n_{i,j,t}^x - \bar{n}_{i,t}^x}$$

The leading-edge tax-adjusted technology in country i is domestic if $n_{i,j,t}^x > \bar{n}_{i,t}^x$; the two countries are neck and neck if $n_{i,j,t}^x = \bar{n}_{i,t}^x$; and country $-i$ is the leading technology otherwise. As we shall see, $n_{i,j,t}^x$ is sufficient statistic for describing line-specific values, and we will drop the subscript j thereafter when describing line-specific values. Let us denote $z_{i,t}^x$ the innovation rate of entrants in country i and α the rate of technology diffusion. Then the law of motion for the technology gap $n_{i,t}^x$ follows

$$n_{i,t+\Delta t}^x = \begin{cases} n_{i,t}^x + 1, & \text{with probability } (z_{i,t}^x + \alpha(-n_{i,t})) \Delta t + o(\Delta t) \\ n_{i,t}^x - 1, & \text{with probability } (z_{-i,t}^x + \alpha(n_{i,t})) \Delta t + o(\Delta t) \\ n_{i,t}^x, & \text{otherwise} \end{cases}$$

where $\alpha(n) = \alpha \cdot \mathbb{1}(n > 0)$ and $o(\Delta t)$ are second-order terms that disappear faster than Δt as Δt goes to zero.

3.2.4 Trade and Market Equilibrium

Prices and Profits From the perspective of intermediate producers, the revenue accrued is independent of price, so the state-of-the-art firm will prevail as a monopolist. In particular, we will have

$$\begin{aligned} p_{i,j}^x x_{i,j} &= \nu X_i^{\frac{\varepsilon-1}{\varepsilon}} \bar{Y}_i^{\frac{1}{\varepsilon}} P_i \\ &= \tilde{X}_i^{\frac{\varepsilon-1}{\varepsilon}} Y_i P_i \end{aligned}$$

where $\tilde{X} = \frac{X}{Y}$ and $p_{i,j}^x$ is the price of the good in product line j of sector $x \in (c, d)$.

With international trade, the intermediate-good producers are able to sell their goods both domestically and internationally. Without loss of generality, we plot in Figure 12 the two cutoffs that define three regions of product lines according to their relative technological gap in the trade. The intermediate-good producers face different demand schedules depending on the destination country. Therefore, the producer earns different levels of profits on these goods.

Let us denote the first index in the subscript as the identity of the producer and the second as the identity of the consumer. Assuming a Bertrand competition setting, the leading firms will set their price to their nearest competitors marginal cost. For any intermediates sold domestically, supposing there is a maximum markup of $\lambda^{\bar{m}}$ that is enforced by domestic competition, the markup is $\lambda^{\min\{\bar{m}, n_{i,j}^x - \bar{n}_i^x\}}$, $\forall n_{i,j}^x > \bar{n}_i^x$. Then prices and production are

$$\begin{aligned} p_{i,i,j}^c &= \lambda^{\min\{\bar{m}, n_{i,j}^c - \bar{n}_i^c\}} \frac{w_i^u}{q_{i,j}^c} \quad \text{and} \quad c_{i,i,j} = \lambda^{-\min\{\bar{m}, n_{i,j}^c - \bar{n}_i^c\}} \frac{q_{i,j}^c}{w_i^u} \tilde{C}_i^{\frac{\varepsilon-1}{\varepsilon}} Y_i P_i \\ p_{i,i,j}^d &= \lambda^{\min\{\bar{m}, n_{i,j}^d - \bar{n}_i^d\}} \frac{w_i^u}{\tilde{q}_{i,j}^d} \quad \text{and} \quad d_{i,i,j} = \lambda^{-\min\{\bar{m}, n_{i,j}^d - \bar{n}_i^d\}} \frac{\tilde{q}_{i,j}^d}{w_i^u} \tilde{D}_i^{\frac{\varepsilon-1}{\varepsilon}} Y_i P_i \end{aligned}$$

where we define the carbon tax price adjusted quality in dirty sector by $\tilde{q}_{i,j}^d = \frac{q_{i,j}^d}{1 + \zeta \tau_i}$. The labor utilization and profit for each product j following profit maximization is then

$$\begin{aligned} w_i^u \ell_{i,i,j}^c &= \lambda^{-\min\{\bar{m}, n_{i,j}^c - \bar{n}_i^c\}} \tilde{C}_i^{\frac{\varepsilon-1}{\varepsilon}} Y_i P_i \\ w_i^u \ell_{i,i,j}^d &= \lambda^{-\min\{\bar{m}, n_{i,j}^d - \bar{n}_i^d\}} \frac{1}{1 + \zeta \hat{\tau}_i} \tilde{D}_i^{\frac{\varepsilon-1}{\varepsilon}} Y_i P_i \\ \pi_{i,i,j}^x &= (1 - \lambda^{-\min\{\bar{m}, n_{i,j}^x - \bar{n}_i^x\}}) \tilde{X}_i^{\frac{\varepsilon-1}{\varepsilon}} Y_i P_i, \quad x \in (c, d) \end{aligned}$$

Intermediate firms will find it profitable to sell abroad when they when they have the leading technology after adjusting taxes and trade costs. The markup exporting intermediates will then be $\lambda^{\min\{\bar{m}, n_{i,j}^x + \bar{n}_{-i}^x\}}, \forall n_{i,j}^x > -\bar{n}_{-i}^x$. Given the demand from the other country, similar derivations as in the case of domestic sales lead to the following prices and quantities

$$p_{i,-i,j}^c = \lambda^{-\min\{\bar{m}, n_{i,j}^c + \bar{n}_{-i}^c\}} \frac{\kappa w_i^u}{q_{i,j}^c} \quad \text{and} \quad c_{i,-i,j} = \lambda^{-\min\{\bar{m}, n_{i,j}^c + \bar{n}_{-i}^c\}} \frac{q_{i,j}^c}{\kappa w_i^u} \tilde{C}_{-i}^{\frac{\varepsilon-1}{\varepsilon}} Y_{-i} P_{-i}$$

$$p_{i,-i,j}^d = \lambda^{-\min\{\bar{m}, n_{i,j}^d + \bar{n}_{-i}^d\}} \frac{\kappa w_i^u (1 + b_{-i})}{\tilde{q}_{i,j}^d} \quad \text{and} \quad d_{i,-i,j} = \lambda^{-\min\{\bar{m}, n_{i,j}^d + \bar{n}_{-i}^d\}} \frac{\tilde{q}_{i,j}^d}{\kappa w_i^u (1 + b_{-i})} \tilde{D}_{-i}^{\frac{\varepsilon-1}{\varepsilon}} Y_{-i} P_{-i}$$

And the optimal quantity of labor utilization and associated profits are

$$w_i^u \ell_{i,-i,j}^c = \lambda^{-\min\{\bar{m}, n_{i,j}^c + \bar{n}_{-i}^c\}} \frac{1}{\kappa} \tilde{C}_{-i}^{\frac{\varepsilon-1}{\varepsilon}} Y_{-i} P_{-i}$$

$$w_i^u \ell_{i,-i,j}^d = \lambda^{-\min\{\bar{m}, n_{i,j}^d + \bar{n}_{-i}^d\}} \frac{1}{\kappa (1 + \zeta \hat{\tau}_i) (1 + b_{-i})} \tilde{D}_{-i}^{\frac{\varepsilon-1}{\varepsilon}} Y_{-i} P_{-i}$$

$$\pi_{i,-i,j}^x = (1 - \lambda^{-\min\{\bar{m}, n_{i,j}^x + \bar{n}_{-i}^x\}}) \frac{1}{\kappa (1 + b_{-i})} \tilde{X}_{-i}^{\frac{\varepsilon-1}{\varepsilon}} Y_{-i} P_{-i}, \quad x \in (c, d)$$

As we can see, $n_{i,j}$ is a sufficient statistic for describing line-specific values, and we will therefore drop the subscript j when a line-specific value is denoted by n .

Production Allocation To determine the share of each component, We can aggregate at the intermediate in each country to find

$$\tilde{C}_i^{\frac{\varepsilon-1}{\varepsilon}} = \frac{(Q_i^c \Delta_i^c \Lambda_i^c)^{\varepsilon-1}}{(Q_i^c \Delta_i^c \Lambda_i^c)^{\varepsilon-1} + \left(\frac{1}{1+\zeta \hat{\tau}_i}\right)^{\varepsilon-1} (Q_i^d \Delta_i^d \Lambda_i^d)^{\varepsilon-1}}$$

$$\tilde{D}_i^{\frac{\varepsilon-1}{\varepsilon}} = \frac{\left(\frac{1}{1+\zeta \hat{\tau}_i}\right)^{\varepsilon-1} (Q_i^d \Delta_i^d \Lambda_i^d)^{\varepsilon-1}}{(Q_i^c \Delta_i^c \Lambda_i^c)^{\varepsilon-1} + \left(\frac{1}{1+\zeta \hat{\tau}_i}\right)^{\varepsilon-1} (Q_i^d \Delta_i^d \Lambda_i^d)^{\varepsilon-1}}$$

and hence

$$\left(\frac{w_i^u}{\nu P_i}\right)^{\varepsilon-1} = (Q_i^c \Delta_i^c \Lambda_i^c)^{\varepsilon-1} + \left(\frac{1}{1 + \zeta \hat{\tau}_i}\right)^{\varepsilon-1} (Q_i^d \Delta_i^d \Lambda_i^d)^{\varepsilon-1}$$

where we $\log Q_t^x = \int_0^1 \log q_{j,t}^x dj$, $x \in (c, d)$ is the productivity index of the economy by each sector at time t . Δ_i^x represent the productivity gains from trade for country i

$$\log(\Delta_i^x) = \log(\lambda) \sum_{n_i < \bar{n}_i^x} \mu_{i,n}^x (\bar{n}_i^x - n_i)$$

Λ_i^x is an inverse function of equilibrium markups following

$$\log(\Lambda_i^x) = -\log(\lambda) \sum_n \mu_{i,n}^x \min\{\bar{m}, |n - \bar{n}_i^x|\}$$

where $\mu_{i,n}^x$ is the fraction of product lines where the country i 's lead is exactly equal to n steps in sector $x \in (c, d)$. We also define the the product shares that sells domestically and imports abroad as

$$\bar{\mu}_{i,i}^x = \sum_{n_i^x > \bar{n}_i^x} \mu_{i,n}^x \quad \text{and} \quad \bar{\mu}_{-i,i}^x = \sum_{n_i^x < \bar{n}_i^x} \mu_{i,n}^x$$

Trade Balance Balance of trade requires that the (pre-tariff) value of imports by the home country must be equal to the value of imports by the foreign country:

$$\begin{aligned} & \int_0^1 \mathbb{1}(n_{-i,j}^c > -\bar{n}_{-i}^c) p_{-i,i,j}^c c_{-i,i,j} dj + \int_0^1 \mathbb{1}(n_{-i,j}^d > -\bar{n}_{-i}^d) p_{-i,i,j}^d d_{-i,i,j} dj \\ &= \int_0^1 \mathbb{1}(n_{i,j}^c > -\bar{n}_{-i}^c) p_{i,-i,j}^c c_{i,-i,j} dj + \int_0^1 \mathbb{1}(n_{i,j}^d > -\bar{n}_{-i}^d) p_{i,-i,j}^d d_{i,-i,j} dj \end{aligned}$$

Then combining with price and profit equations, the trade balance can be rewritten as

$$\left[\bar{\mu}_{-i,i}^c \tilde{C}_i^{\frac{\varepsilon-1}{\varepsilon}} + \bar{\mu}_{-i,i}^d \tilde{D}_i^{\frac{\varepsilon-1}{\varepsilon}} \right] Y_i P_i = \left[\bar{\mu}_{i,-i}^c \tilde{C}_{-i}^{\frac{\varepsilon-1}{\varepsilon}} + \bar{\mu}_{i,-i}^d \tilde{D}_{-i}^{\frac{\varepsilon-1}{\varepsilon}} \right] Y_{-i} P_{-i}$$

So that

$$\Psi_i = \frac{Y_i P_i}{Y_{-i} P_{-i}} = \frac{\bar{\mu}_{i,-i}^c \tilde{C}_{-i}^{\frac{\varepsilon-1}{\varepsilon}} + \bar{\mu}_{i,-i}^d \tilde{D}_{-i}^{\frac{\varepsilon-1}{\varepsilon}}}{\bar{\mu}_{-i,i}^c \tilde{C}_i^{\frac{\varepsilon-1}{\varepsilon}} + \bar{\mu}_{-i,i}^d \tilde{D}_i^{\frac{\varepsilon-1}{\varepsilon}}} = \frac{\bar{\mu}_{i,-i}}{\bar{\mu}_{-i,i}}$$

Labor Market Clearing Then the labor market clearing condition leads to

$$L^P = 1 = \int_0^1 \ell_{i,i,j}^c dj + \int_0^1 \ell_{i,-i,j}^c dj + \int_0^1 \ell_{i,i,j}^d dj + \int_0^1 \ell_{i,-i,j}^d dj$$

That is,

$$w_i^u = \left[\bar{\lambda}_{i,i}^c \tilde{C}_i^{\frac{\varepsilon-1}{\varepsilon}} + \frac{1}{1 + \zeta \hat{\tau}_i} \bar{\lambda}_{i,i}^d \tilde{D}_i^{\frac{\varepsilon-1}{\varepsilon}} \right] Y_i P_i + \frac{1}{\kappa} \left[\bar{\lambda}_{i,-i}^c \tilde{C}_{-i}^{\frac{\varepsilon-1}{\varepsilon}} + \frac{1}{(1 + \zeta \hat{\tau}_i)(1 + b_{-i})} \bar{\lambda}_{i,-i}^d \tilde{D}_{-i}^{\frac{\varepsilon-1}{\varepsilon}} \right] Y_{-i} P_{-i}$$

where

$$\bar{\lambda}_{i,i}^x = \sum_{n_i^x > \bar{n}_i^x} \mu_{i,n}^x \lambda^{-\min\{\bar{m}, n_i^x - \bar{n}_i^x\}} \quad \text{and} \quad \bar{\lambda}_{i,-i}^x = \sum_{n_i^x > -\bar{n}_i^x} \mu_{i,n}^x \lambda^{-\min\{\bar{m}, n_i^x + \bar{n}_i^x\}}$$

Now combining it with labor market clearing condition, we can get the following

$$\begin{aligned} \Omega_i &= \frac{w_i^u}{w_{-i}^u} \\ &= \frac{\left[\bar{\lambda}_{i,i}^c \tilde{C}_i^{\frac{\varepsilon-1}{\varepsilon}} + \frac{1}{1+\zeta\hat{\tau}_i} \bar{\lambda}_{i,i}^d \tilde{D}_i^{\frac{\varepsilon-1}{\varepsilon}} \right] Y_i P_i + \left[\bar{\lambda}_{i,-i}^c \tilde{C}_{-i}^{\frac{\varepsilon-1}{\varepsilon}} + \frac{1}{(1+\zeta\hat{\tau}_i)(1+b_{-i})} \bar{\lambda}_{i,-i}^d \tilde{D}_{-i}^{\frac{\varepsilon-1}{\varepsilon}} \right] Y_{-i} P_{-i}}{\left[\bar{\lambda}_{-i,-i}^c \tilde{C}_{-i}^{\frac{\varepsilon-1}{\varepsilon}} + \frac{1}{1+\zeta\hat{\tau}_{-i}} \bar{\lambda}_{-i,-i}^d \tilde{D}_{-i}^{\frac{\varepsilon-1}{\varepsilon}} \right] Y_{-i} P_{-i} + \left[\bar{\lambda}_{-i,i}^c \tilde{C}_i^{\frac{\varepsilon-1}{\varepsilon}} + \frac{1}{(1+\zeta\hat{\tau}_{-i})(1+b_i)} \bar{\lambda}_{-i,i}^d \tilde{D}_i^{\frac{\varepsilon-1}{\varepsilon}} \right] Y_i P_i} \\ &= \frac{\left[\bar{\lambda}_{i,i}^c \tilde{C}_i^{\frac{\varepsilon-1}{\varepsilon}} + \frac{1}{1+\zeta\hat{\tau}_i} \bar{\lambda}_{i,i}^d \tilde{D}_i^{\frac{\varepsilon-1}{\varepsilon}} \right] \Psi_i + \left[\bar{\lambda}_{i,-i}^c \tilde{C}_{-i}^{\frac{\varepsilon-1}{\varepsilon}} + \frac{1}{(1+\zeta\hat{\tau}_i)(1+b_{-i})} \bar{\lambda}_{i,-i}^d \tilde{D}_{-i}^{\frac{\varepsilon-1}{\varepsilon}} \right]}{\left[\bar{\lambda}_{-i,-i}^c \tilde{C}_{-i}^{\frac{\varepsilon-1}{\varepsilon}} + \frac{1}{1+\zeta\hat{\tau}_{-i}} \bar{\lambda}_{-i,-i}^d \tilde{D}_{-i}^{\frac{\varepsilon-1}{\varepsilon}} \right] + \left[\bar{\lambda}_{-i,i}^c \tilde{C}_i^{\frac{\varepsilon-1}{\varepsilon}} + \frac{1}{(1+\zeta\hat{\tau}_{-i})(1+b_i)} \bar{\lambda}_{-i,i}^d \tilde{D}_i^{\frac{\varepsilon-1}{\varepsilon}} \right] \Psi_i} \\ &= \frac{\bar{\lambda}_{i,i}^{-1} \Psi_i + \bar{\lambda}_{i,-i}^{-1}}{\bar{\lambda}_{-i,-i}^{-1} + \bar{\lambda}_{-i,i}^{-1} \Psi_i} \end{aligned}$$

Combining the equilibrium conditions, we can derive the total output as

$$\begin{aligned} \bar{Y}_i &= \frac{w_i}{Z P_i} \frac{1}{\bar{\lambda}_{i,i}^{-1} + \bar{\lambda}_{i,-i}^{-1} / \Psi_i} \\ &= \frac{\left[(Q_i^c \Delta_i^c \Lambda_i^c)^{\varepsilon-1} + \left(\frac{1}{1+\zeta\hat{\tau}_i} \right)^{\varepsilon-1} (Q_i^d \Delta_i^d \Lambda_i^d)^{\varepsilon-1} \right]^{\frac{1}{\varepsilon-1}}}{\bar{\lambda}_{i,i}^{-1} + \bar{\lambda}_{i,-i}^{-1} / \Psi_i} \end{aligned}$$

Carbon trade tax (rebate) for households will be:

$$T_{b,i} = \bar{\mu}_{-i,i}^d \frac{b_i}{1+b_i} \tilde{D}_i^{\frac{\varepsilon-1}{\varepsilon}} Y_i P_i - \bar{\mu}_{i,-i}^d \frac{b_{-i}}{1+b_{-i}} \tilde{D}_{-i}^{\frac{\varepsilon-1}{\varepsilon}} Y_{-i} P_{-i}$$

3.2.5 The Carbon Cycle

Recall that while clean intermediate production $c_{i,j}$ creates no carbon emission, dirty production $d_{i,j}$ emits ζ units of carbon per production labor. This implies that the total amount of carbon emission at time t is $\epsilon_t = \epsilon_{i,t} + \epsilon_{-i,t}$ where

$$\begin{aligned}\epsilon_{i,t} &= \zeta \left(\int_0^1 \ell_{i,i,j}^d dj + \int_0^1 \ell_{i,-i,j}^d dj \right) \\ &= \bar{\lambda}_{i,i}^d \frac{\zeta}{w_{i,t}^u + \zeta \tau_{i,t}} D_{i,t}^{\frac{\epsilon-1}{\epsilon}} Y_{i,t}^{\frac{1}{\epsilon}} P_{i,t} Z_t + \\ &\quad \bar{\lambda}_{i,-i}^d \frac{\zeta}{(w_{i,t} + \zeta \tau_{i,t})(1 + b_{-i})} D_{-i,t}^{\frac{\epsilon-1}{\epsilon}} Y_{-i,t}^{\frac{1}{\epsilon}} P_{-i,t} Z_t\end{aligned}$$

Assume that the atmospheric carbon concentration follows:

$$S_t = \int_0^{t-T} (1 - d_l) \epsilon_{t-l} dl$$

where $t = T$ is the first date when emission started and

$$1 - d_l = \varphi_p + (1 - \varphi_p) \varphi_0 e^{-\varphi l}$$

is the amount of carbon emitted l years ago still left in the atmosphere; $\varphi_p \in (0, 1)$ is the share of emission that remains permanently in the atmosphere; $(1 - \varphi_p) \varphi_0 \in (0, 1)$ is the fraction of the transitory component that remains in the first period; and $\varphi \in (0, 1)$ is the rate of decay of carbon concentration over time.

3.2.6 Value Functions

The value function for an incumbent will depend on the step differential for that particular product line. The value function of the firm, for $n_i^x > \bar{n}_i^x$, is then

$$\begin{aligned} RV_i^x(n) - \dot{V}_i^x(n) = & \pi_i^x(n) - z_i^x [V_i^x(n) - 0] + z_{-i}^x [V_i^x(n-1) - V_i^x(n)] \\ & + \alpha(n) [V_i^x(n-1) - V_i^x(n)] + \alpha(-n) [V_i^x(n+1) - V_i^x(n)] \end{aligned}$$

where $\pi_{x,i}(n)$ is the flow profit accrued from owning a product line given by

$$\pi_i^x(n) = (1 - \lambda^{-\min(\bar{m}, |n - \bar{n}_i^x|)}) \tilde{X}_i^{\frac{\varepsilon-1}{\varepsilon}} Y_i P_i + \frac{1}{1 + b_{-i}} (1 - \lambda^{-\min(\bar{m}, |n + \bar{n}_{-i}^x|)}) \tilde{X}_{-i}^{\frac{\varepsilon-1}{\varepsilon}} Y_{-i} P_{-i}$$

The first term on the right hand side is the operating profits generated from product line leading the technology from the foreign country by n steps. In addition, at the flow rate z_i^x , the incumbent will be replaced by a domestic entrepreneur in the same sector. If instead, the same product line experiences an innovation at a flow rate of z_{-i}^x in foreign country, the technology gap between the two countries declines by one step. With the international knowledge diffusion, there are two possibilities on technology improvement. First, if country i was leading in technology x ($n > 0$), then the foreign country $-i$ gain one step shorter from country i with probability α . Second, if country $-i$ was behind in technology x ($n < 0$), it will have free access to technology $n + 1$ with probability α . Let us denote the normalized value of a generic variable X as \tilde{x} . Using $R - \pi - g = \rho$, we will have

$$\begin{aligned} \rho \tilde{v}_i^x(n) = & \tilde{\pi}_i^x(n) - z_i^x [\tilde{v}_i^x(n) - 0] + z_{-i}^x [\tilde{v}_i^x(n-1) - \tilde{v}_i^x(n)] \\ & + \alpha(n) [\tilde{v}_i^z(n-1) - \tilde{v}_i^x(n)] + \alpha(-n) [\tilde{v}_i^x(n+1) - \tilde{v}_i^x(n)] \end{aligned}$$

This has a closed form solution in steady state, but for a general dynamic path we must leave it like this.⁴

4

See the proof in Appendix A.

3.2.7 Firm Entry and Innovation

Every period, a unit mass of entrepreneurs in each country attempt to innovate at individual product lines and enter the business (clean or dirty). A successful entrant improves on the active domestic incumbents technology. Therefore, the value to an entrant will be

$$\bar{v}_i^x = \sum_n \mu_{i,n}^x \tilde{v}_i^x(n+1).$$

Here all entrants will pay a fixed cost F for a chance at a successful innovation, regardless of which type they choose.

Thus the entrants' problem will be

$$\Pi_i^x = \max_{a_i^x} \{a_i^x \bar{v}_i^x - (1 - s_i^x) \tilde{w}_i^s c(a_i^x) - F\} \leq 0$$

where s_i^x is the subsidy rate that sector x receives from country i , a_i^x is innovation rate per entrepreneur and $c(a) = ca^\eta$ is the cost function of generating innovation rate a . The free entry condition holds as equality whenever $e_i^x > 0$, otherwise $\Pi_i^x < 0$. In order to smooth these results, it is also advantageous to add a little bit of type-dependent noise to the respective fixed costs, so that

$$F^x = \exp(\psi^x) F \quad \text{where} \quad (\psi^c, \psi^d) \sim \mathcal{N}(0, \sigma^2)$$

Conditional on entry, the optimal innovation rate is given by:

$$a_i^x = \left(\frac{\bar{v}_i^x}{(1 - s_i^x) c \tilde{w}_i^s \eta} \right)^{\frac{1}{\eta-1}}$$

Therefore, entrants will direct their R&D to the clean technology if $\bar{v}^c/(1 - s^c) > \bar{v}^d/(1 - s^d)$ and to the dirty technology if the reverse inequality holds.

Let us denote the endogenously determined mass of entrants performing R&D directed to technology x in country i by E_i^x . Then a unit mass of entrants implies that

$$1 = E_i^c + E_i^d \tag{3.1}$$

For each country, the labor market-clearing condition for skilled workers, combining demand from both clean and dirty industries, is

$$L_i^s = c(a_i^c)E_i^c + c(a_i^d)E_i^d$$

Therefore, the aggregate innovation rate is $z_i^x = E_i^x \times a_i^x$.

Finally, the evolution of the distribution of technology gaps represented by $\mu_{i,n,t}^x$ can be derived from the following differential equations (with some initial condition $\{\mu_{i,n,t}^x\}_{n=-\infty}^{\infty}$).

For any n , we have

$$\begin{aligned} \dot{\mu}_{i,n,t}^x &= (z_{i,t}^x + \alpha(-n))\mu_{i,n-1,t}^x + (z_{-i,t}^x + \alpha(n))\mu_{i,n+1,t}^x \\ &\quad - (z_{i,t}^x + \alpha(-n) + z_{-i,t}^x + \alpha(n))\mu_{i,n,t}^x \end{aligned}$$

Intuitively, the share of product lines $\mu_{i,n,t}^x$ changes when there is a difference in inflows into and outflows from the technology gap of n steps. The first line on the right-hand side refers to the inflows into position n from $n - 1$ due to domestic innovations and knowledge spillover if domestic technology is behind and from $n + 1$ due to foreign innovations and spillover effect if any. The second line refers to the outflows from $\mu_{i,n,t}^x$ due to any innovation and knowledge spillover in those lines with a technology gap of n steps. The total productivity of the intermediates with n -step gap $Q_{i,n,t}^x$, which is characterized in similar reasoning, evolves according to the following expressions:

$$\begin{aligned} \dot{Q}_{i,n,t}^x &= (z_{i,t}^x + \alpha(-n))\lambda Q_{i,n-1,t}^x + (z_{-i,t}^x + \alpha(n))Q_{i,n+1,t}^x \\ &\quad - (z_{i,t}^x + \alpha(-n) + z_{-i,t}^x + \alpha(n))Q_{i,n,t}^x \end{aligned}$$

We now summarize the dynamic equilibrium path using the equations we have derived in this section. For any given time path of policies $[\tau_{i,t}^x, s_{i,t}^x, b_{i,t}^x]_{x \in (c,d)}^{t \in [0,\infty)}$, a Markov Perfect Equilibrium of this world economy is an allocation

$$[x_{i,t}, p_{i,t}^x, a_{i,t}^x, E_{i,t}^x, Y_{i,t}, w_{i,t}^s, w_{i,t}^u, r_{i,t}, S_{i,t}, \{\mu_{i,n,t}^x, Q_{i,n,t}^x\}_{n=-\infty}^{\infty}]_{x \in (c,d)}^{t \in (0,\infty)}$$

such that [1] the sequences of $x_{i,t}, p_{i,t}^x$ maximize profits adjusting markup from domestic and international competition ; [2] The innovation rates $a_{i,t}^x$ is determined by entrants' profit maximization and $E_{i,x,t}$ clears the skilled labor market; [3] $w_{i,x,t}^u$ clears labor markets in each

country at every period t and $\frac{w_{i,t}^u}{w_{-i,t}^u}$ balance the trade; [4] the output $Y_{i,t}$ is given by combining labor market clearing condition, trade balance, and intermediate goods aggregation; [5] $w_{i,t}^s$ are determined from free-entry condition equation; [6] technology gap shares $\{\mu_{i,n,t}^x\}_{n=-\infty}^{\infty}$ and quality indices $\{Q_{i,n,t}^x\}_{n=-\infty}^{\infty}$ evolve as a result of entrants' innovation and knowledge spillover; [7] the interest rate $r_{i,t}$ solves the Euler Equation from household's optimization problem; [8] the atmospheric carbon concentration $S_{i,t}$ follows emission dynamics defined in section 3.2.5.

3.3 Data

In the calibrated model, we try to keep the least amount of heterogeneity across countries in order to focus solely on the effect of policy differences. Our model has 16 parameters to be determined:

$$\{\rho, g_n, L^s, \varepsilon, \lambda, \kappa, \alpha, c, \eta, \bar{S}, \varphi_p, \varphi_0, \varphi_p, \gamma, F, \sigma\}$$

initial gap between clean and dirty technologies, and the initial distribution of technology gaps between countries in clean and dirty industries.

We estimate these parameters in three steps. First, we choose from external sources. Second, we choose the initial distribution of technology gaps to match the distribution of clean and dirty patents in each country as we explain below. Finally, we estimate the remaining parameters using a simulated method of moments, with moments being selected to model the growth rates, entry rates, exporting behavior, and production labor allocation.

3.3.1 External Calibration

We take the time discount parameter $\rho = 1\%$ following Acemoglu et al. (2016a). Following the empirical R&D literature, we choose the elasticity of successful innovation with respect to scientists η as 2. We choose $L^s = 0.08$ to match the share of managers, scientists,

and engineers in the workforce. We set the domestic markup step $\bar{m} = 1$. Following (Papa-georgiou et al., 2017), we take the elasticity of substitution between clean and dirty to be $\varepsilon = 2.5$.⁵

We choose the set of parameters in the carbon cycle and damage function following Golosov et al. (2014) and Acemoglu et al. (2016a)’s approach. The pre-industrial stock of carbon dioxide is 581 gigatons of carbon (GtC). We choose the three parameters φ_p , φ_0 , and φ to model the dynamics of atmospheric carbon stock as follows. We set φ_p , the portion of any emission pulse that will stay in the atmosphere for thousands of years, to 0.2, according to the estimate in the 2007 Intergovernmental Panel on Climate Change report. The other two parameters φ_0 and φ models the excess carbon that does not stay the atmosphere forever. We identify these parameters by matching the carbon stock evolution using the world actual emissions data during the 1900 - 2012 period shown in Figure 13. We find a close fit at parameter values $\varphi_0 = 0.7491$ and $\varphi = 0.0231$.

As already noted, we assume the same damage function as in Golosov et al. (2014) and Acemoglu et al. (2016a), which has a scale parameter $\gamma = 5.3 \times 105^{-1}GtC^{-1}$.

Finally, we set carbon emission per unit labor $\zeta = 2.188GtC$ to link the current world emission levels to the baseline level of dirty sector labor demand. This formulation assumes that emissions grow at a constant rate with the labor share in the dirty sector. Table 11 lists these values.

3.3.2 Initial Patent Stock

3.3.2.1 Patent Data We rely on patent data for the characterization of the initial state of technology for both the US and China. To do this, we interpret patents as indicators of innovation, which in our model are proportional movements up the quality (productivity) ladder. Thus the initial technological state will be the aggregation of past patenting activity. To this end, our Chinese patent data spans from 1985 until the present day, while the US

5

Papageorgiou et al. (2017) finds that the estimates of the elasticity of substitution within the energy aggregate are significantly greater than unity around 2 for the electricity-generating sector and close to 3 for the non-energy industries. We set the baseline value of ε to 2.5, the midpoint within the range of estimates in different sectors.

patent data spans from 1976 to the present.

3.3.2.2 Patent Classification In order to properly map patents into our model, we must have some idea of whether they are pertinent to clean or dirty technology. This is a non-trivial exercise. Though existing patent classifications are rather detailed, even within the same industry or when producing the same products, there are both clean and dirty methods of production. For instance, energy generation can be done using coal or solar, among other options. Steel production can be undertaken using methods that limit emissions, and this is true for many other industrial processes as well. Additionally, on the consumer side, there are a variety of technologies that reduce emissions associated with the operation of automobiles, such as hybrid engines and catalytic converters.

To resolve this issue, we take a machine learning approach to the problem of patent classification. Each patent has text associated with it in the form of the invention title, an abstract describing the invention and its possible uses, formal claims related to the patent, as well as patent classification codes and associated definitions.⁶ Using this text, we can train a neural network classifier to predict whether patents are clean, dirty, or neither.

The trouble is finding a set of training data. There are no obvious existing candidates out there, so we resort to constructing one by hand. In particular, we could randomly choose 1000 patents from each country/language and classify them as clean or dirty by hand. We then train our classifier on this data and use the trained classifier to generate analogous predictions for the entire set of patents. In our case, there are roughly 5.7 million US patents and 5.5 million Chinese patents.

Hand classification of patents is, of course, a partially subjective exercise. In the end, our trained classifier will embody all of the errors and biases present in our human judgment. Nonetheless, we found that the classification decisions were a rather clean cut in the vast majority of cases. We use the following working definitions for each category:

- **Clean:** anything that is a substitute for carbon-emitting technologies or that directly mitigates the emissions of carbon-emitting tech.

6

There is also the full body text of the patent, however we find that the abstract contains most of the pertinent information needed for classification

- **Dirty**: anything that is or must be a complement to carbon-emitting technologies. For example, a device to facilitate fueling (US9222452) is **dirty**, but technology relating to car interiors (radio, display, etc) would be **neither**. Deep sea drilling is dirty (US4443000).
- **Neither**: aerospace not directly related to fuel and engines. Electricity distribution (but not storage).

There is also the issue of comparability between language/country. Each patent office may have slightly different standards for what should be included in abstracts, or even in what constitutes a valid patent. Furthermore, there are certain lexicographic and semantic issues that arise differentially in each language, such as the partial ambiguity of word boundaries in the case of Chinese and variable conjugation and stemming in the case of English. In the human classification, we attempted to maximize comparability in any dimension over which we had control.

Many of the design decisions for the neural network are standard from the machine learning (ML) and natural language processing (NLP) literature. We first convert each document (patent text) into vectorized form. That is, each document is represented by a vector in which each position indicates how many times a particular word appears. This vector will be of length D where D is the number of words in our vocabulary, which consists of any words that appear anywhere in the corpus two or more times.⁷ These vectors are then fed into a fairly complex neural network classifier.

We use a two-layer neural network with 128 units in the hidden layer. With a resulting vocabulary of about 3500, this results in a neural network with approximately half a million parameters. Given our training set size, this presents potentially large overfitting issues. We use two conventional techniques for dealing with this. One is to set aside a fraction (in our case 20%) of the data for validation. That is, we train only on the remaining 80% of the data, then use the validation set to ascertain whether overfitting has occurred (and potentially to optimally terminate the training midway through). The second is to use dropout, in which links in the neural network are randomly severed during the training process, forcing the optimizer to arrive at solutions that rely on many different dimensions of the data at once,

7

This minor restriction will help deal with issues of rare misspellings.

thus potentially limiting overfitting.

3.3.2.3 Patent to Step Distribution Now we map from patent counts into steps on the quality ladder in our model. To generate one aggregate step, we need innovation in each industry, of which there are N . One aggregate step increases productivity by a factor of λ . Let the total number of (climate related) patents be P , and the number of patents in an aggregate step be P_0 . Supposing we have 2% TFP growth ($g = 0.02$), we then need

$$g = \log(\lambda) \frac{P}{NP_0}$$

*

How to map from patent counts by industry into our initial conditions, which are:

1. Relative productivities between US and China in both clean and dirty industries
- 2.

The ratio of log-log aggregated productivities between clean and dirty for both US and China

The first can be got by directly simulating productivity evolution using patent data. Can include a deterministic type of knowledge diffusion. To deal with different industry “sizes,” scale all industries up to the average industry size.

The second can be gotten from patents as well, or somehow inferred from aggregates, like a fraction of energy that comes from renewable sources. This involves the elasticity of substitution ε as well.

Figure 14 plots the density of the resulting distribution of initial technology gaps in dirty and clean technologies between the two countries.

3.3.3 Simulated Method of Moments

We have five remaining parameters $\lambda, \kappa, C, \frac{Q_{i,0}^c}{Q_{i,0}^d}$ and σ . For the first four of these parameters, λ, κ, C , and $\frac{Q_{i,0}^c}{Q_{i,0}^d}$, we use the simulated method of moments (SMM) to calibrate them. This approach chooses the parameter vector to minimize the distance between data and model moments. We also choose the fixed cost heterogeneity parameter σ as 0.2 and verify that our results are not sensitive to this choice of parameter.

The first data moment we use is the average growth rates of total factor productivity in both countries, calculated in Feenstra et al. (2015). The next moment is the entry rate,

which we derive using USPTO and SIPO patent data. As a third target, we use the average export-to-GDP ratio to determine iceberg cost κ . The final moment is the dirty/clean sector employment ratio, which we obtained from the 2016 U.S. Energy and Employment Report. The targeted moments and the model performance in matching these moments are summarized in Table 12.⁸

Table 13 lists the internally calibrated parameters resulting from SMM. Our estimate of the innovation step size $\gamma = 1.091$, implies a gross profit markup of 1.08. The combination of the trade cost and the step size implies $\bar{n}_i^c = 2.6$. That is, a firm need to lead by at least three technological steps in our model to export. Our estimate shows that the total productivity of dirty technology is 1.348 times of that of clean technology, which implies an average of 3.7 technological steps leads by dirty technology.

3.4 Policy Analysis

3.4.1 Laissez-Faire

We start with the implied future equilibrium and atmospheric carbon paths of the model under laissez-faire (no carbon taxes, research subsidies nor tariffs). We then compare the results under autarky (and without knowledge spillovers). Given the initial distribution of the technology gap between the two countries, dirty technology is more advanced relative to clean technology in both countries. As shown in Figure 15, more of R&D is initially targeted to the dirty technology for both open and closed economies. Moreover, with higher innovation rates, technology gaps and the profitability of the dirty technologies increase relative the those of clean technologies. As a result, the share of clean intermediates in the final output drops rapidly, and clean R&D eventually converges to zero. In the long run, dirty technology completely takes over the final good production. This time path of innovation will lead to unbounded grow emissions. Figure 16 shows an increase in temperature of an additional 4°C in the next 250 years.

⁸

The computational algorithm is described in Appendix B.

However, in a world with open economy, the transition to complete dirty technology is slower, as the clean sector gains more profit relative to the dirty sector. This also leads to a lower emission level and temperature increase in the long run. In the open economy, trade not only allows more productive intermediate-goods producers to sell to the final good producers in both countries but also increase the innovation rates allowing knowledge spillover. The total welfare increases significantly by 28.6% and 25.1% for the U.S. and China respectively.

3.4.2 Unilateral Policy

3.4.2.1 Carbon Tax First, we compute the optimal carbon tax policies for each country. Precisely, we compute the carbon tax rates that maximize the present discounted value of welfare in a 300-year horizon from now on and calculate the welfare gains from the optimal policy under autarky and from laissez-faire. Table 14 reports the results for the optimal unilateral policy for each country.

Table 14 shows that the optimal unilateral carbon tax is 45% for a unilateral policy taken by the U.S. while 29% when taken by China. This is because the dirty technologies in China is less advantageous in China than it is in the U.S. In our model, the optimal carbon tax is determined by a rich set of externalities of carbon intermediate production. First, a high carbon tax increases the cost of domestic dirty goods, reducing the profitability of dirty intermediates producers on both domestic sales and exports. This decrease leads to a relative increase in clean intermediates profitability and innovation, securing a transition from dirty to clean technology for the home country. However, such policies generate a pollution haven effect, as the production of polluting intermediates moves to the foreign country with no such policies, which leads to an increase in carbon emissions in the foreign. Figure 17 - 20 show the transition paths of innovation and temperature under optimal unilateral carbon tax policies in the U.S. and China.

3.4.2.2 Research Subsidy Next, we analyze the unilateral policies using clean R&D subsidies respectively. The optimal unilateral makes a heavy use of research subsidy because the social planner would like to direct R&D from carbon-intensive dirty technologies

towards clean technologies in both countries as soon as possible. With the current estimate of international knowledge spillover rate, the clean technology in the foreign country will consequently catch up and increase the profitability of the clean sector relative to the dirty industry. A minimum of 46% research subsidy for either country can secure a transition from dirty to clean technology globally. Figure 21 - 24 show the transition paths of innovation and temperature under optimal unilateral clean research subsidies in the U.S. and China.

3.4.2.3 Carbon Tariffs

3.4.2.4 Carbon Tariffs As an alternative policy option to reduce carbon emission, we consider an increase in tariff on carbon imports. However, while the policy reduces the profitability of dirty intermediate goods in the foreign country, clean technologies are initially too much behind dirty technologies. The transition to dirty technology is slower comparing to laissez-faire but converges to zero in the long run. As an alternative policy option to reduce carbon emission, we consider an increase in tariff on carbon imports. However, while the policy reduces the profitability of dirty intermediate goods in the foreign country, clean technologies are initially too much behind dirty technologies. The transition to dirty technology is slower comparing to laissez-faire but converges to zero in the long run. Figure 25 and 26 show the transition paths of innovation under optimal unilateral carbon tariffs in the U.S. and China.

3.5 Conclusion

One of the biggest challenges facing the world economy is reducing carbon emissions, which may only be feasible if a successful transition to clean technology is induced. This paper has investigated the nature of a transition to clean technology considering cross-country variation in policies and knowledge diffusing from international knowledge spillover. We build a two-country and two-sector endogenous growth model where clean and dirty technologies innovate to compete for global market leadership in final good production, which

allows for a comprehensive quantitative evaluation. If clean technologies are initially less advanced than dirty ones, they will have a smaller market share in the final good production, thus lower profitability. Therefore, the clean sector disappears completely, and the dirty sector takes over the entire economy. In a closed economy model, the optimal policy heavily relies on both subsidies and carbon taxes. However, carbon taxes may create environmental externality as the production of dirty intermediates shifts to the foreign country where there are no carbon taxes. The paper argues that unilateral environmental policies should make heavy use of clean research subsidies, which have the potential to reduce domestic emissions, but also overseas either through technology diffusion or by slowing down the movement of polluting industries there.

Our paper also left several questions unanswered, and we hope to tackle it in the future. First, we have abstracted from finding the optimal policy path using a combination of carbon taxes, research subsidies, and carbon tariffs, which is likely to improve the efficiency of optimal unilateral policy using a single policy tool. Second, we have also abstracted from optimal bilateral policies, especially game-theoretic interactions in policies between the two countries. Finally, we hope to extend our analysis to multiple countries in both theory and data work, allowing for a richer set of interactions across countries.

3.6 Figures and Tables

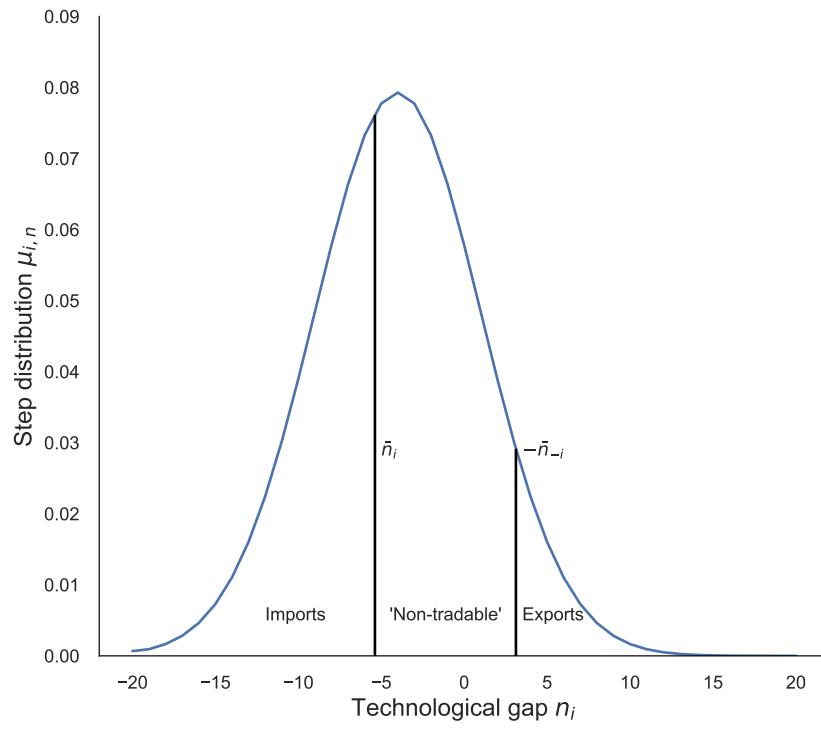
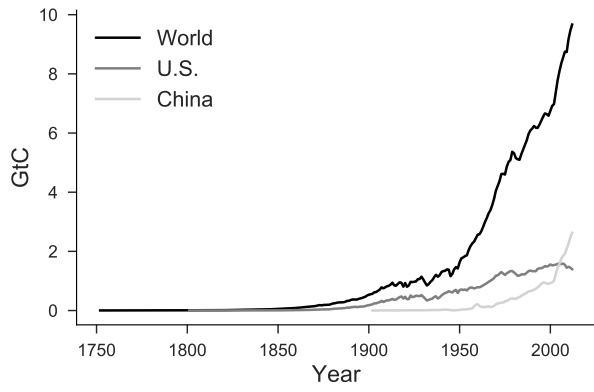
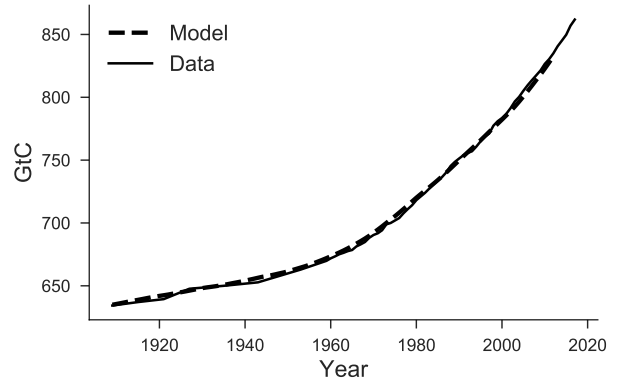


Figure 12: The Trade Flow

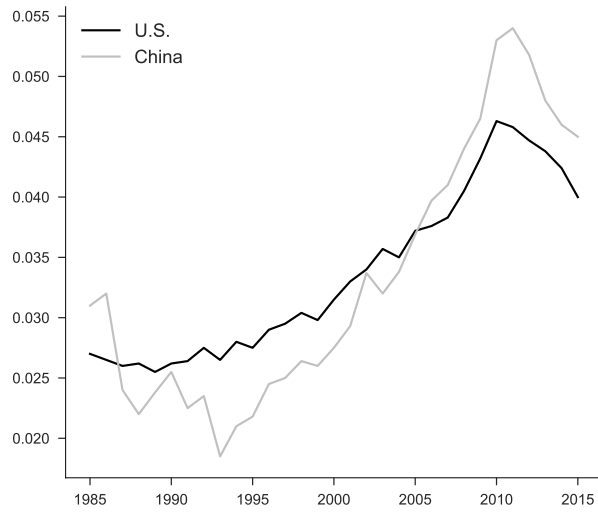


(a) Carbon Emissions

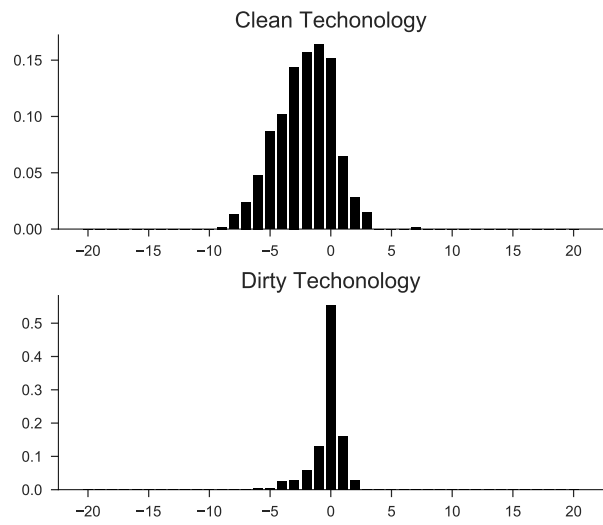


(b) Atmospheric Carbon Concentration

Figure 13: Carbon Emission and Concentration: Data and Model Implications



(a) Clean Patents: 1985 - 2015



(b) Initial Step Distribution

Figure 14: Patents Classification

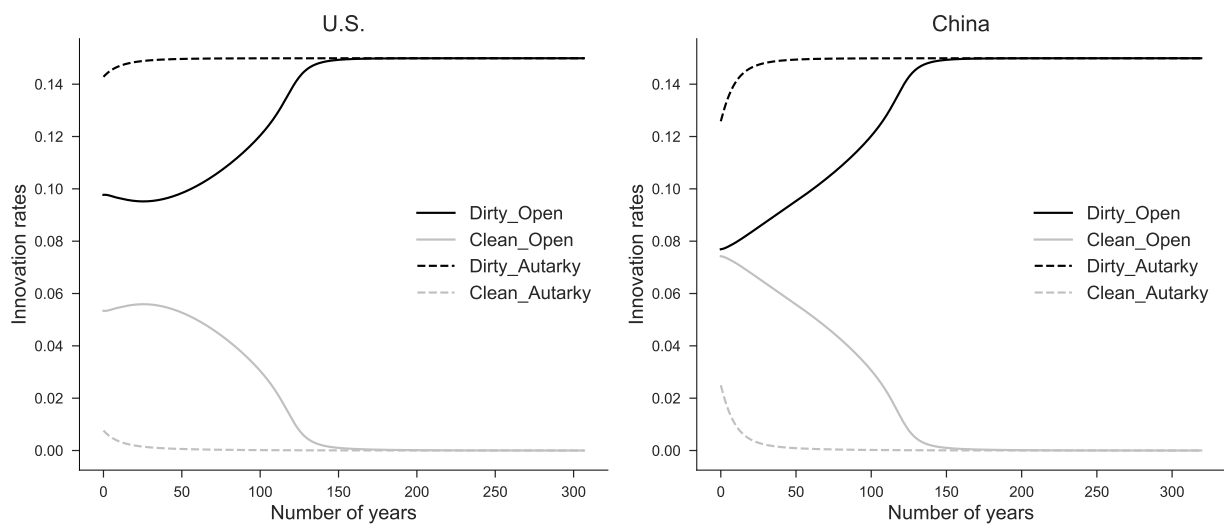


Figure 15: Laissez-Faire

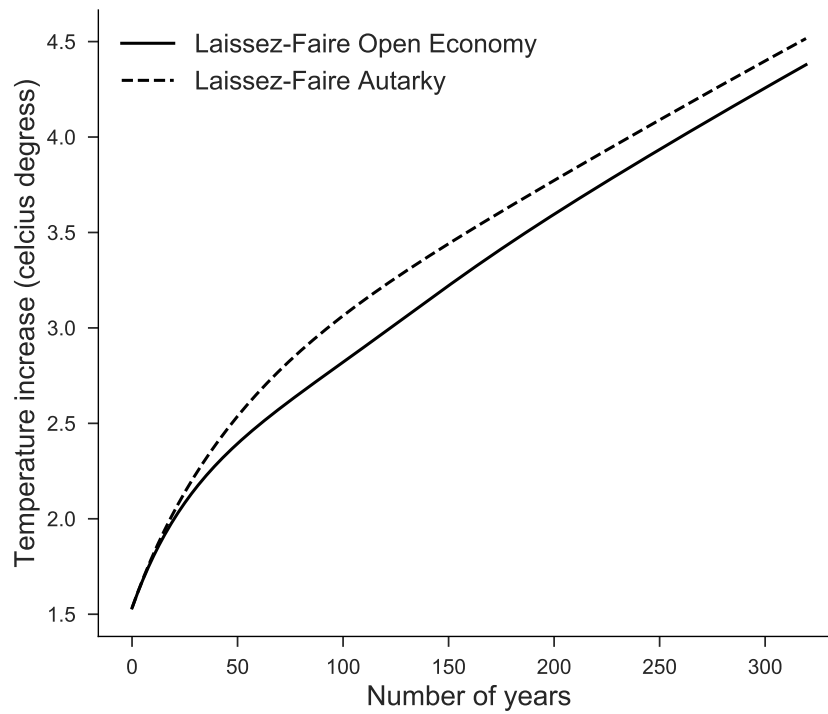


Figure 16: Time Path of Temperature Under Laissez-Faire

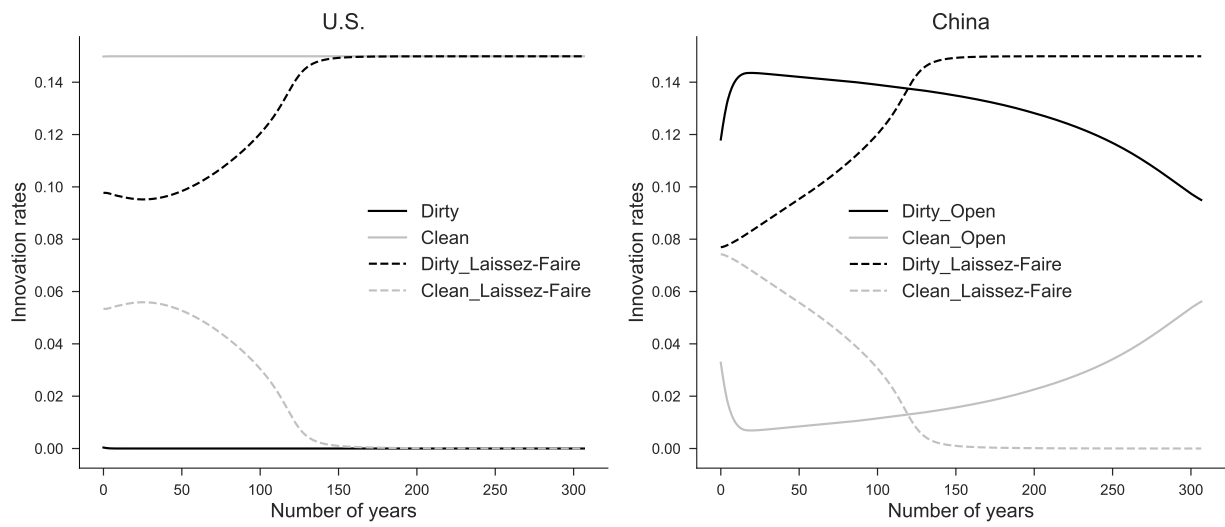


Figure 17: Optimal Unilateral Carbon Tax - US

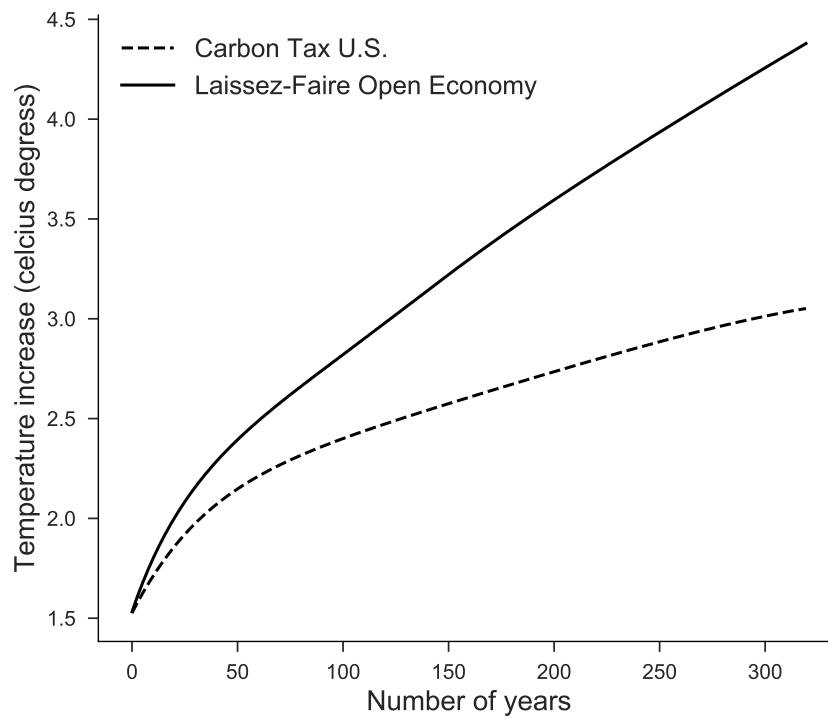


Figure 18: Time Path of Temperature Under Optimal Unilateral Carbon Tax - US

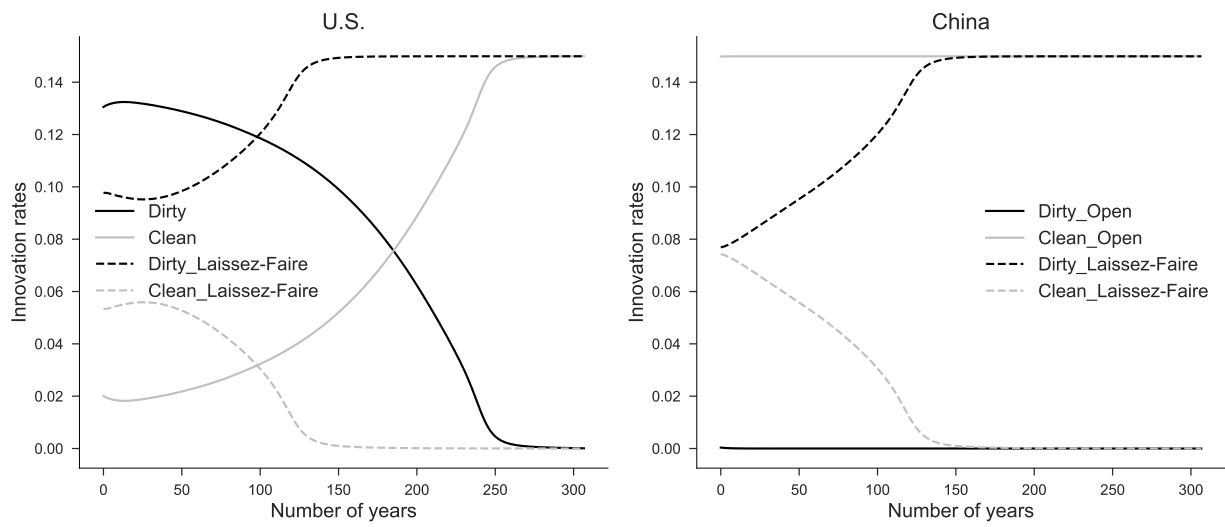


Figure 19: Optimal Unilateral Carbon Tax - CN

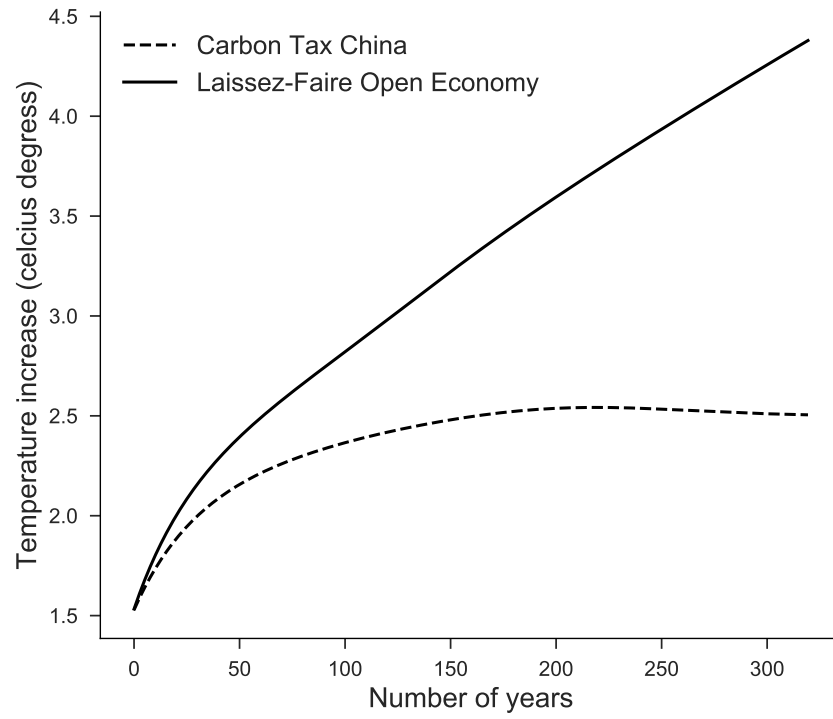


Figure 20: Time Path of Temperature Under Optimal Unilateral Carbon Tax - CN

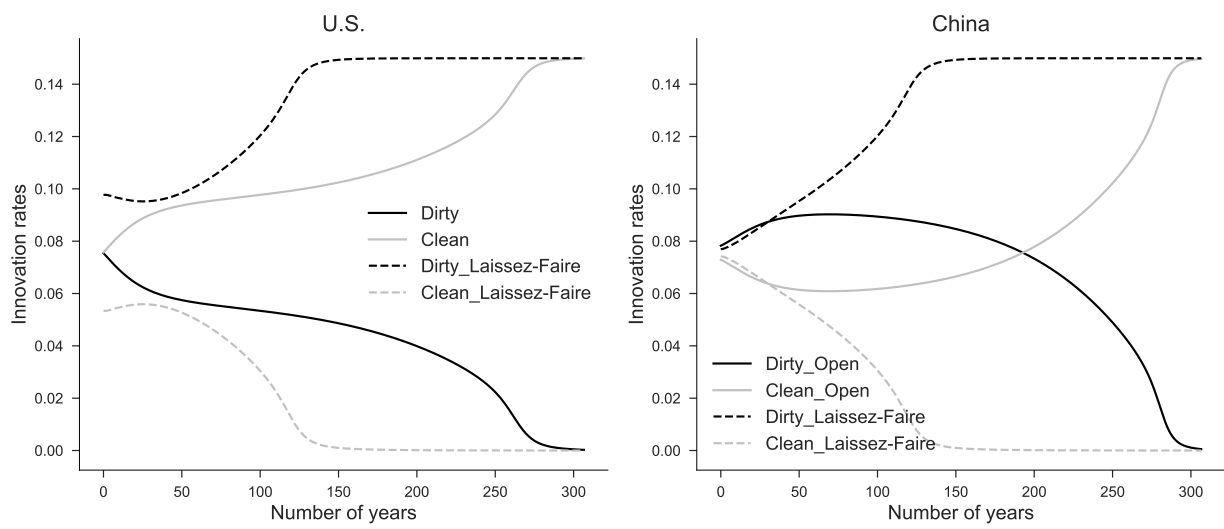


Figure 21: Optimal Unilateral Research Subsidy - US

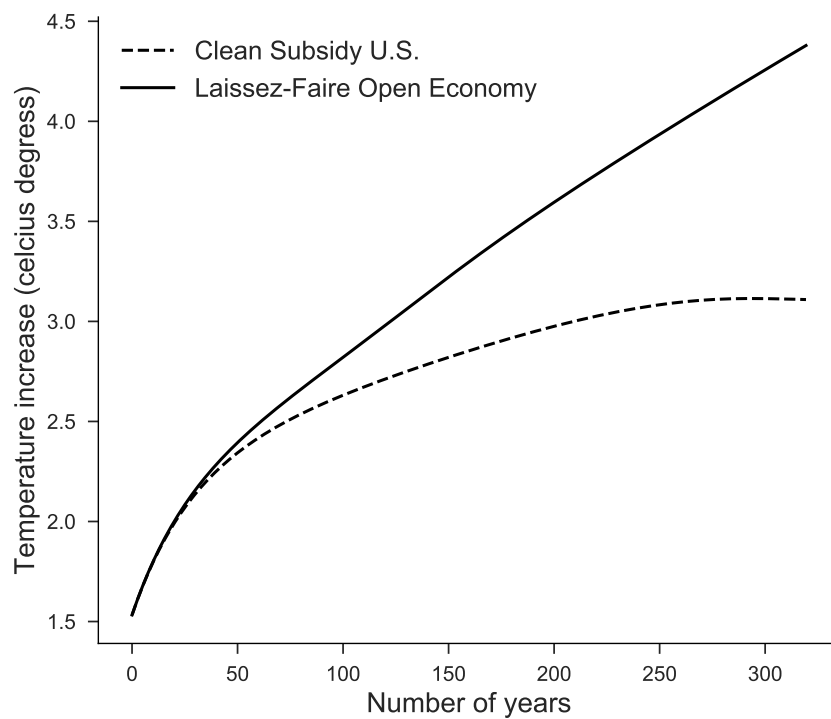


Figure 22: Time Path of Temperature Under Optimal Unilateral Research Subsidy - US

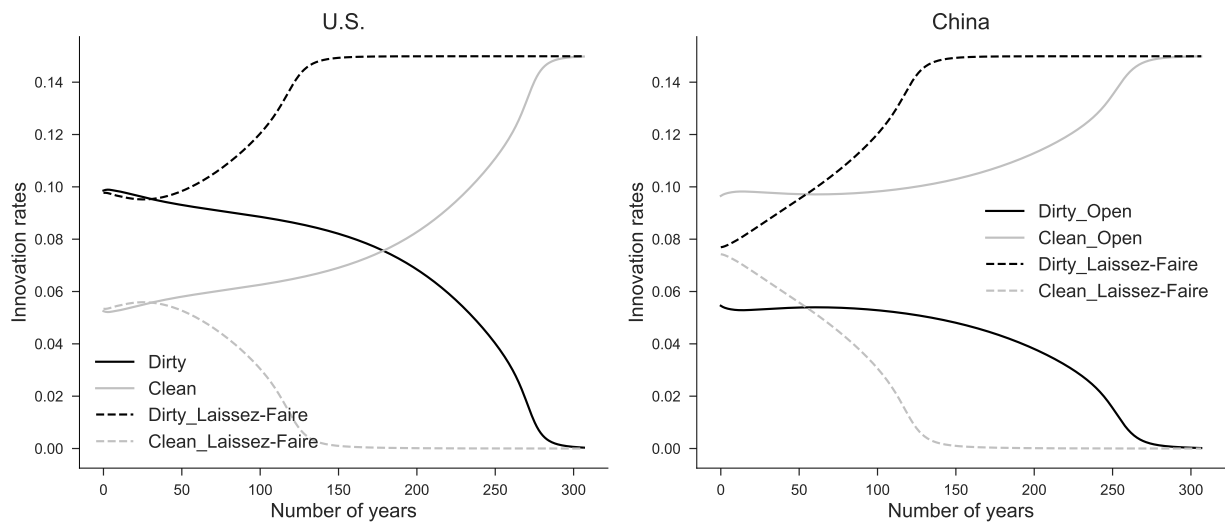


Figure 23: Optimal Unilateral Research Subsidy - CN

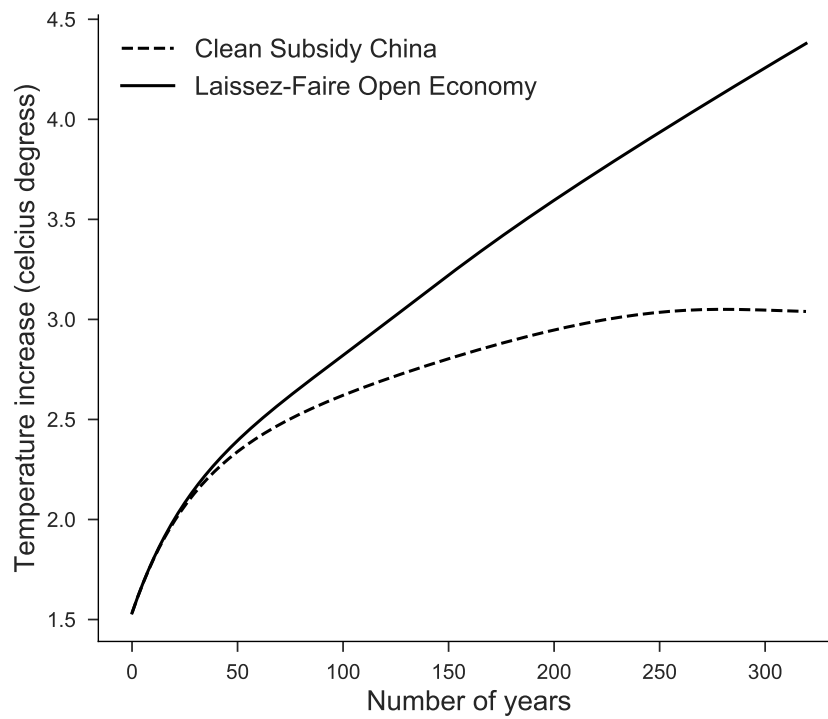


Figure 24: Time Path of Temperature Under Optimal Unilateral Research Subsidy - CN

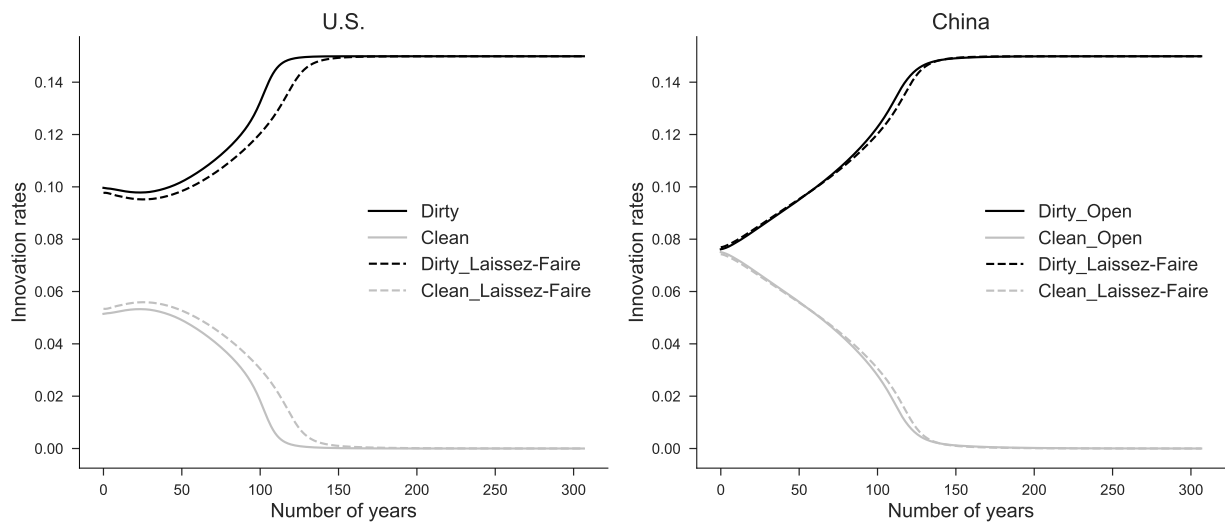


Figure 25: Optimal Unilateral Carbon Tariffs - US

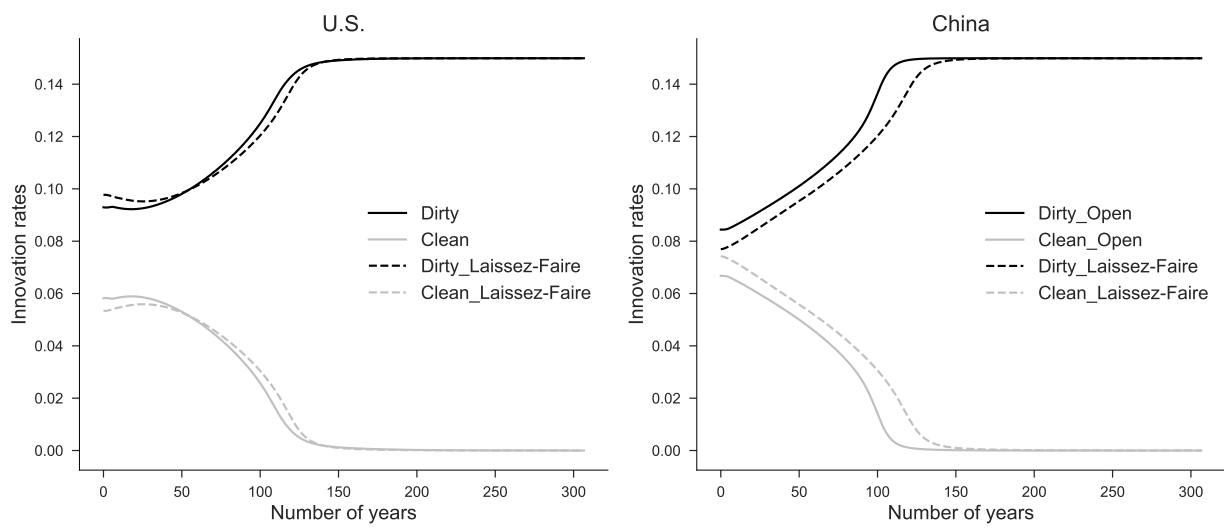


Figure 26: Optimal Unilateral Carbon Tariffs - CN

Table 11: Externally Calibrated Parameters

Parameter	Meaning	Estimate
ρ	Discount parameter	1%
L^s	Mass of Scientists	0.08
\bar{m}	maximum domestic markup	1
ε	Elasticity of substitution	2.5
α	International knowledge spillover	0.149
η	R&D elasticity with respect to scientists	2
φ_p	Carbon cycle	0.2
φ_0	Carbon cycle	0.7491
φ	Carbon cycle	0.0231
\bar{S}	Pre-industrial Carbon Concentration	581 GtC
γ	Scale parameter in damage function	$5.3 \times 105^{-1} GtC^{-1}$
ζ	Carbon emission per unit labor in dirty sector	2.188 GtC

Table 12: Model Fit

Moment	Target	Estimate	Source
TFP Growth Rate	1.01%	1.02%	Fed.
Entry Rate	15.12%	15.11%	USPTO/SIPO
Export Share	15.16%	15.26%	World Bank 2016
Dirty/Clean Labor Ratio	1.97	1.98	U.S. Energy and Employment Report 2015-2016

Table 13: Internally Calibrated Parameters

Parameter	Meaning	Estimate
γ	Innovation step size	1.091%
C	Scale parameter of the R&D cost function	3.50
κ	Iceberg cost	1.256
$\frac{Q_{i,0}^c}{Q_{i,0}^d}$	Initial gap between clean and dirty sector	1.348

Table 14: Optimal Unilateral Carbon Tax Policies

Optimal Carbon Tax Rate		Welfare Gains from Laissez-Faire		Welfare Gains from Autarky	
		US	China	US	China
US	45%	- 3.77%	13.41 %	23.79%	41.91%
China	29%	22.99%	15.04 %	44.99%	45.35%

4.0 Consumer Reviews and Employment Decisions: Evidence from Yelp.com

4.1 Introduction

With recent technology advancement, online consumer reviews have become increasingly popular, as consumers can easily read ratings and reviews from platforms such as Yelp and TripAdvisor, and make informed decisions about products and services (Anderson and Magruder, 2012; Luca, 2016). The rising popularity and credibility of online review platforms put business owners under growing pressure to maintain a good online reputation. While consumers can acquire information from countless other consumers about product quality, business owners also frequently read or respond to consumer reviews to improve products and services (Proserpio and Zervas, 2017; Xie et al., 2016). Moreover, business owners may use the information from consumer reviews to monitor their employee's performance and even fire employees who have been criticized on the site.¹ In this way, the online reviewers not only help other consumers but function as unpaid managers for the business.

Although the importance of consumer reviews is widely acknowledged, it is unclear how business owners and managers respond to consumer reviews in their managerial decisions on employment and wages. There are two primary channels through which consumer reviews could affect managerial labor decisions. First, online reviews inform consumers about product quality and thus shaping consumer demand (Anderson and Magruder, 2012; Luca, 2016). Higher demand requires local businesses to hire more workers and thus increase their wage bills. Second, consumer reviews also inform business owners about their employees' performance, helping them monitor and increase the worker productivity. However, on the one hand, customer reviews can be biased and not credible (Chevalier and Mayzlin, 2006; Luca and Zervas, 2016). On the other hand, consumer criticism does not necessarily lead to labor discipline. For example, a long wait for lunch is easily blamed on a server, not on owners decision to reduce the afternoon staff and thus lower cost by giving the server more

1

For example, <https://www.yelp.com/topic/chicago-i-was-just-fired-for-a-1star-yelp-review>; <https://www.yelp.com/topic/boston-getting-fired-over-a-yelp-review>.

work than they can handle.

In this paper, I study the relationship between online consumer reviews and managerial labor decision, focusing on the key question of whether consumer reviews exert a causal effect on businesses' employment and wage bills. Having found a significant impact on labor decisions, I then investigate the channels through which consumer reviews might affect management decisions. Specifically, I study whether this increase is attributable to the consumer reviews that mention customer service by employees in a business and its quality. I use a newly assembled database that includes the information and consumer reviews of all local businesses on Yelp.com in the city of Pittsburgh, combined with administrative data of wage and employment for all establishments in Pittsburgh between 2009 and 2014. Figure 27 displays the geographical locations of all local businesses on Yelp.com in Pittsburgh Jan 2017. There was a substantial increase in businesses and consumer reviews on Yelp.com since Yelp entered the market in Pittsburgh, as shown in Figure 28. The rich observations in this data set allow me to measure the impact of consumer reviews on labor decisions while controlling for individual fixed effects.

My empirical analysis exploits a key feature that Yelp.com round the average star rating to the nearest half star. For example, a restaurant with an average rating of 4.24 displays a 4-star average rating while a restaurant with an average rating of 4.26 displays a 4.5-star average rating. I employ a regression discontinuity design that compares the number of employees and the total wage bill of local businesses with a rating just above the discontinuity points and those with a rating just below the discontinuity points. I find that in the foodservice industry one-star increase in Yelp rating leads to around a 3.5 increase in employment and a \$2,800 increase in total wage, but it has no effect on average wage per worker. These effects on employment and total wage are also significant in the overall service industry.

Next I investigate whether consumer reviews on customer services has a direct impact on the managerial decision. I extract the texts of all consumer reviews from 2005 to 2017 and train a machine learning algorithm on a sample of 1500 manually classified reviews to sort reviews into service mentioned (bad or good) and service not mentioned reviews. I find that most of the increase in employment and total wage bill arise from review counts, which help attract more traffic to business pages on Yelp, rather than through reviews contents

on services. The results suggest that business owners or managers may not use consumer review contents as a significant indicator of managerial decisions.

This paper is related to a growing body of literature investigating how consumer reviews, more specifically, quality disclosures affect consumer purchase behavior. Chevalier and Mayzlin (2006) examine the effect of consumer reviews on book sales. They find that an improvement in a book's reviews leads to an increase in book sales. They also show that customers read review texts rather than relying only on summary statistics. Luca (2016) studies whether online consumer reviews influence the way that reputation is formed. He has shown that a one-star increase in Yelp ratings results in a 5 to 9 percent increase in revenue. He also finds that while consumers do not use all available information, they respond more strongly when a rating contains more information. Anderson and Magruder (2012) finds that an extra half-star rating causes restaurants to sell out 49% more frequently, with larger impacts when other information is more scarce. Vermeulen and Seegers (2009) and Ye et al. (2011) examine the impact of online reviews on consumer decision-making in the travel context. They show that online travel reviews increase consumer awareness of lesser-known hotels and thus increase online sales.

This paper contributes to the literature on management responses to online reputation. Because online reviews play an important role in consumer decision-making, firms actively manage or respond to customer reviews. For example, to manage unfavorable reviews, firms tend to post fake reviews (Mayzlin et al., 2014; Luca and Zervas, 2016), solicit positive reviews in exchange for perks, threaten legal action against negative reviewers, and use nondisparagement clauses in sales contracts that stipulate fines if consumers write negative reviews. With technological advancement in detecting fake reviews (Ott et al., 2011), managers now frequently use public responses to consumer reviews as an alternative reputation management strategy. Substantial previous research investigates the effects of a firm's use of management responses on its online reputation and performance (see, for example, Proserpio and Zervas, 2017; Wang and Chaudhry, 2018; Xie et al., 2016). However, previous literature has not examined the extent to which business management decisions and labor market outcomes respond to customer reviews. Using data on employment and wage at each local business, I examine the relationship between online ratings and factors in reviews which may

increase or decrease labor demand.

This paper is organized as follows. Section 2 describes data and sentiment analysis on text reviews. I discuss the estimating methodology regression discontinuity design in Section 3, and then in Section 4, I present regression results and robustness checks. Finally, I conclude in Section 5.

4.2 Data

To estimate the effect of Yelp ratings on business management, I combine two independent data sources. The first data set consists of the universe of Yelp reviews for all businesses in Pittsburgh, Pennsylvania, as of June 2014. The second data set consists of wage and employment data from the Quarterly Census of Employment and Wages (ES202).

4.2.1 Yelp

Yelp.com is a major crowd-sourced review platform that contains more than 100 million reviews for millions of shops, restaurants, and home and local services. Yelp users can submit a review of any product or service with which they have dealt using a one to five star rating system, and enter a text review. Businesses can also update contact information, hours and other basic listing information or add special deals. In addition to writing reviews, users can react to reviews, plan events, and make reservations. Yelp aggregates all reviews for a given business and displays the average rating. Key to this paper is that when Yelp computes the average rating, they round off to the nearest half-star. When a user browses or searches Yelp.com, Yelp presents them with a list of businesses that meet their search criteria or fall within the category of interest. For example, users can look for restaurants that exceed a specified star rating (say 3.5 stars). Businesses are sorted according to relevance and rating, and for each business, the average rating is displayed and rounded to the nearest half-star.

Yelp expanded its business to Pittsburgh in 2005, but very few online reviews were available back then. During the past decade, Yelp has received over 180,000 reviews for

about 8,000 businesses in Pittsburgh.

4.2.1.1 The Content of Consumer Review on Yelp.com Although Yelp rating reflects an overall experience of customers, the star ratings on Yelp do not provide any insight into various aspects of a business such as environment, service or flavor. To understand whether the business owners read the consumer reviews and use it to manage its employees, I directly explore the service content of the customer text reviews. To answer such questions in the past would have required a great deal of effort to read and categorize the text reviews. Modern machine learning techniques, however, allow me to extract the relevant service content of customer reviews classifieds directly from the text.

I obtain all 75,993 text reviews for all businesses in Pittsburgh on Yelp.com from 2005 to 2014. I examine the text of 1,500 randomly chosen reviews and classify them as good service, bad service or neither by hand. I classify text reviews as good (bad) service reviews if (1) The review clearly mentions good (bad) service; (2) The reviewer is satisfied (dissatisfied) with the businesses in the following five dimensions in the SERVQUAL model first proposed by Parasuraman et al. (1988): Reliability (the ability to perform the promised service dependably and accurately); responsiveness (the willingness to help customers and provide prompt service); tangibles (the physical facilities, equipment, and appearance of personnel); assurance (the knowledge and courtesy of employees and their ability to inspire trust and confidence); and empathy (the caring, individualized attention the firm provides its customers). I classify reviews as neither if a review does not mention service or is directly related to customer service.

I then train a convoluted neural network classifier on this data and use the trained classifier to generate analogous predictions for the entire set of text reviews. Many of the design decisions for the neural network are standard from machine learning (ML) and natural language processing (NLP) literature. First, I pre-process the patent text so that only the words (or parts of words) with the highest amount of useful information are retained. I then convert each processed document into vectorized form. That is, each review is represented by a vector in which each position indicates how many times a particular word appears. These vectors are then fed into a relatively complex neural network classifier.

I use a two-layer neural network with 128 units in the hidden layer. We end up with a vocabulary of about 5,500. To limit potentially large overfitting issues, I use two conventional techniques for dealing with this. One is to set aside a fraction (in this case 20%) of the data for validation. That is, I train only on the remaining 80% of the data, then use the validation set to determine whether overfitting has occurred (and potentially to terminate the training midway through optimally). The second is to use dropout, in which links in the neural network are randomly selected during the training process, forcing the optimizer to arrive at solutions that rely on many different dimensions of the data at once, thus potentially limiting overfitting.

Table 15 summarizes the performance of the classifier in the test data. The confusion matrix provides information about where the manual coding and the machine learning algorithm agreed and disagreed about the classification of different types of customer reviews in the test data. Of the 300 test reviews, the manual and algorithm classifier agreed on 218 (133+19+66) reviews, giving an accuracy rate of $218/300 = 72.3\%$. The classifier is particularly good at identifying “Neither” reviews, with a sensitivity rate (or the conditional probability that the classifier assigns a ”Neither” review correctly) is 84.7 percent. The classifier has a decent sensitivity rate of 68.8 percent at identifying good service reviews. While some share of misclassified reviews remains, it is important to reemphasize that I have only analyzed a small sample of text reviews. Nevertheless, this type of textual analysis is an important first step in any attempt to understand what yelp star rating measures and which types of customer review may be read by business owners and managers.

4.2.2 Employment and Wage Data

The Covered Employment and Wages Program, commonly referred to as the ES-202 program, is a cooperative program involving the Bureau of Labor Statistics (BLS) of the U.S. Department of Labor and the State Employment Security Agencies (SESAs). The ES-202 program produces a comprehensive tabulation of employment and wage information for workers covered by State unemployment insurance (UI) laws and Federal workers covered by the Unemployment Compensation for Federal Employees (UCFE) program. It includes

95.3 percent of civilian wage and salary employment across the United States.

I obtain all local businesses in the city of Pittsburgh in the confidential ES202 data. The data contains every business that reported monthly employment and wage at any point between January 2010 and June 2014. This dataset includes business from restaurants to shopping malls to dentists.

I manually merged the employment data with the Yelp reviews, inspecting the two datasets for similar or matching names. When a match is unclear, I referred to the address from ES202 data. The final dataset is at the quarterly business data. The mean rating is 3.6 stars out of 5. On average, a business receives one review per month. Figure 29 presents the unrounded and rounded average Yelp rating distribution in the Pittsburgh area.

4.3 Empirical Methodology

I first implement a regression discontinuity approach to investigate whether consumer reviews have a causal impact on business. A key feature of consumer reviews on Yelp is that it displays the average rating for each restaurant. Users can limit searches to restaurants with a given average rating. These average ratings are rounded to the nearest half a star, as in Figure 30. This schedule provides variation in the rating that is displayed to consumers that is exogenous to the business quality.

The regression discontinuity design is as follows:

$$y_{it} = \beta T_{it} + \gamma rating_{it} + \eta_i + \delta_t + \varepsilon_{it}$$

where y_{it} is the outcome of interest, number of employees and wage, for a business i in month t ; $rating_{it}$ is the unrounded average rating for a business i in month t , η_i and δ_t are individual and time fixed effects. I define T as a binary variable taking a value of 1 if the rating of a business is just above a rounding threshold (so the rating is rounded up) and a value of 0 if rating falls just below a rounding threshold (so the rating is rounded down). The coefficient of interest is β , indicating the impact of moving from just below a discontinuity to just

above a discontinuity. The baseline results only include a pooled sample with a bandwidth of 0.01 stars. To show that the result is not being driven by choice of bandwidth, I vary the bandwidth. In alternative results. I also allow for non-linear response to the rating.

To understand whether the business owners read the consumer reviews and use it to manage its employees, I test whether consumer reviews regarding employee services has any impact on employment decisions. Specifically, I estimate

$$y_{it} = \beta_1 rating_{it} + \beta_2 rating_{it} \times reviews_{it} + \gamma rating_{it} \times reviews_on_service_{it} + \eta_i + \delta_t + \varepsilon_{it}$$

where $reviews_{it}$ is the number of reviews for business i at time t ; $reviews_on_service_{it}$ is the number of reviews that mention employee service. The coefficient of interest is then γ . All specifications will include individual and year-quarter fixed effects.

4.4 Empirical Results

4.4.1 Cross-Section Results

I first describe the results from estimating a traditional cross-sectional analysis. The observations in this regression are from all 1,446 restaurants matched to ES202 employment and wage data in Pittsburgh. The regression includes year-by-quarter fixed effects and the individual restaurant fixed effects. The year-by-quarter fixed effects provide the regression with over time, while the individual fixed effect control for individual characteristics. This is important since I have pooled observations of all Yelp star ratings to conduct the analysis and the fixed effects force identification to come from rating change within an individual restaurant over time. Table 17 provides the coefficients and their standard errors for the three outcome variables. The coefficients on Yelp rating in columns (2) and (3) suggest that one-star increase the total wage bill by approximately \$116.3 and increase the average wage per worker by a little more than 5.4% (statistically significant at the 10% level). Of course, the concern with interpreting these estimates as the causal impact of Yelp on labor outcomes is that they are likely to suffer from omitted variable bias, that is, changes in a restaurants rating may be correlated with other changes in a restaurant s reputation.

4.4.2 RDD Results

To help mitigate the concern of omitted variable bias in the analysis, I implement a regression discontinuity design. The observations used in this regression are restricted to those restaurants whose yelp rating is within 0.01 stars bandwidth of rounding thresholds. The regression again includes year-by-quarter fixed effects and the individual restaurant fixed effects. Besides the Yelp unrounded underlying rating that was included in the cross-sectional analysis, an indicator for ratings just above the discontinuity is also included. The coefficient estimates on the indicator are of primary interest in the regression discontinuity analysis.

Table 18 presents coefficient estimates of baseline regression. I find that a one-star improvement leads to a roughly 3.6 (12.8%) increase in employment and \$ 2,880 (11.5%) increase in total wage. However, it does not affect the average wage per worker. The results are robust when controlling for the quadratic star rating. Figure 31 provides a graphical analysis of demeaned employment, total wages and average wage per worker for restaurants just above and just below a rounding threshold. There are discontinuous jumps in employment and total wage bills, but not in average wage per worker.

In the main specification, I include only the restricted sample of restaurants that are less than 0.01 stars away from a discontinuity. To show that the result is not being driven by choice of bandwidth, I allow for alternative bandwidths. Table 19 displays the regression results varying with bandwidth in the food service business. I find that the results are robust to the bandwidth choice. I also explore the lagged impact of consumer reviews on employment and wages by regression the outcome variables at $t + 1$ on ratings at t . While there is no significant impact on employment and total wages, the average salary per worker drop by a significant \$ 53 (1.0%).

I have so far been using restaurants as my sample. One could also potentially expand to the whole service industry. I redo the regression discontinuity design with a larger sample - all service businesses in Table 20. The results suggest that a one-star improvement leads to a roughly 2.4 (11.5%) increase in employment and \$3,130 (12.5%) increase in total wage. The results are consistent if I only include non-food service businesses in my sample as

shown in Table 21. The result provides support to the claim that Yelp has a causal effect on employment and total wage. In particular, the impact on restaurant and accommodations industry is lower than the service industry due to the limited flexibility in labor discipline.

4.4.3 Reviews on Employee Services and Management Decision

One issue with how to interpret the results I have found has to do with whether the results are driven by the shift in demand or online reviews informing the quality of employees' customer services. If the business owners or managers care about the service content of reviews, then I should observe employment or wage changes driven by the good or bad services mentioned in the text reviews.

To explore the mechanism of the observed impact, I run a series of linear regressions, using the same data as in the cross-section analysis, with the employment and wage variables on the left-hand side and the Yelp rating and interactions with No. reviews on the right-hand side. In these regressions, I continued to control for year-by-quarter fixed effects and business-specific fixed effects. The coefficients on interaction terms are of primary interest as they will signal if there were substantial changes in employment or wages after the number of text reviews on customer services changes. Table 23, 24 and 25 provide the results from these regressions. Column (1)s shows the results where we analyze the relationship between employment decisions and number of reviews on Yelp.com in a quarter, Column (2)s shows the results where we include the interaction of customer reviews and underlying yelp rating, and Column (3)s shows the results where we decompose the service reviews to good or bad services. Of all the interaction coefficients that are estimated these tables, only the interaction of yelp rating and the number of quarterly reviews is statistically significant (all at the 1% level) suggesting that the number of reviews has a positive impact on employment decisions. However, none of the interaction coefficients of yelp rating and the number of customer reviews on service are statistically significant. Overall, these regressions do not seem to suggest that business owners use customer reviews to measure their employees performance and then adjust their employment decisions.

4.5 Conclusion

While online reviews become increasingly popular on the internet, there has been no academic work that attempted to understand its implication on managerial labor decisions. Online reviews not only help other customers understand more of the business itself, but it also serves as a “hidden manager” to the companies. In this paper, I studied the customer reviews of all business on Yelp.com in Pittsburgh. Using a regression discontinuity design, I find that in the restaurant industry a one-star increase in Yelp rating leads to a 3.5 increase in employment and a \$2,800 increase in total wage, but it has no effect on wage per worker. These effects also hold in the overall service industry. This paper shows that the service industry is responsive to consumer reviews. By analyzing consumer reviews regarding services with a text-mining approach, my results show that consumer reviews on employees services do not seem to change employment decisions significantly.

4.6 Figures and Tables



Figure 27: Businesses on Yelp in Pittsburgh

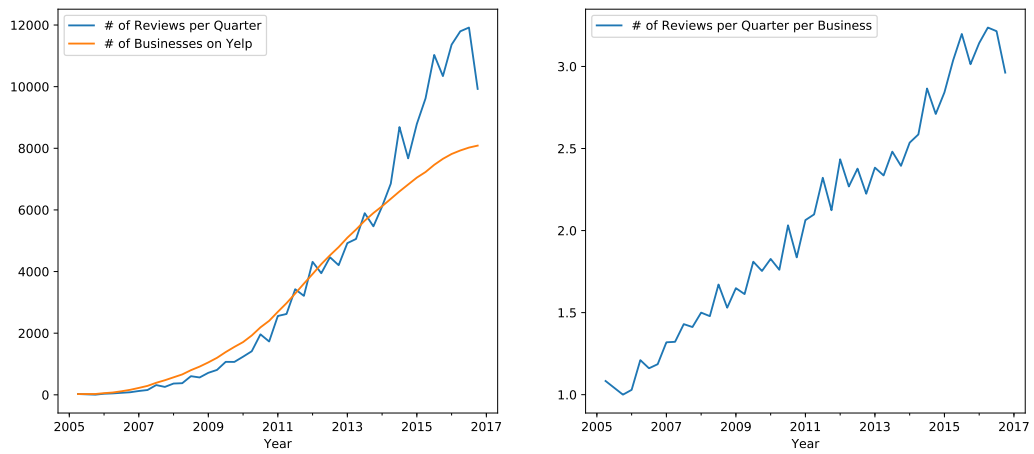


Figure 28: Yelp Review Trend

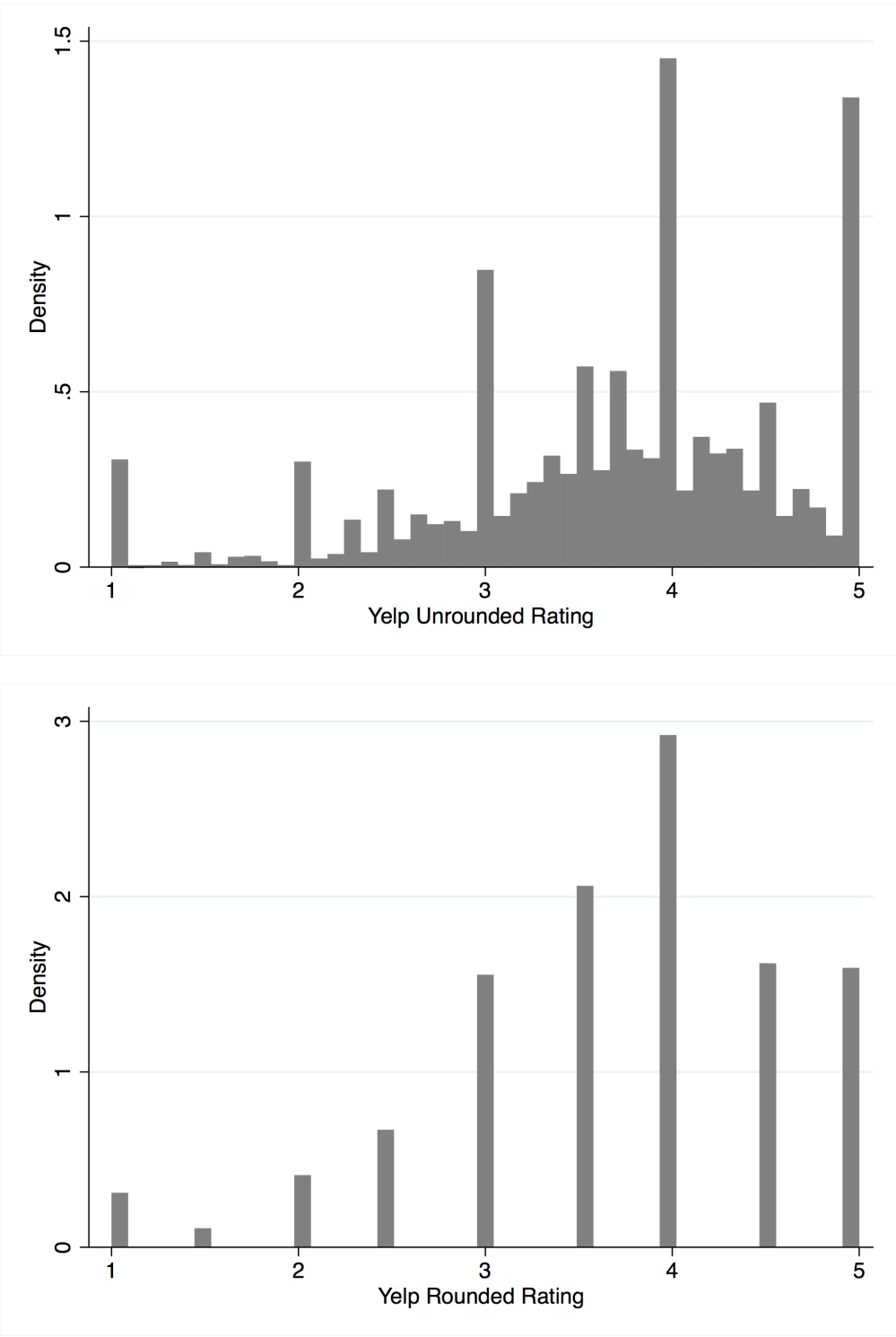


Figure 29: Yelp Rating Distribution

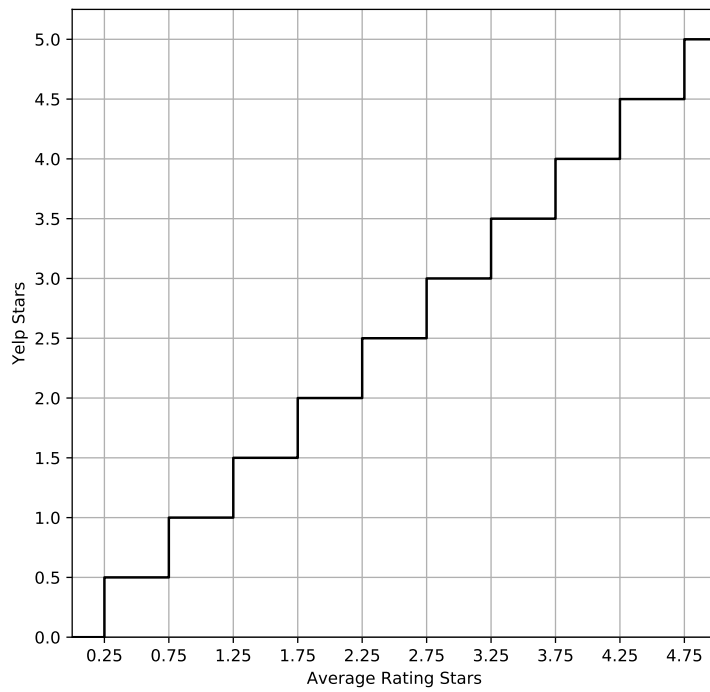


Figure 30: Yelp Rating Schedule

Note: Yelp prominently displays a restaurant's rounded average rating. Each time a restaurant's rating crosses a rounding threshold, the restaurant experiences a discontinuous increase in the displayed average rating.

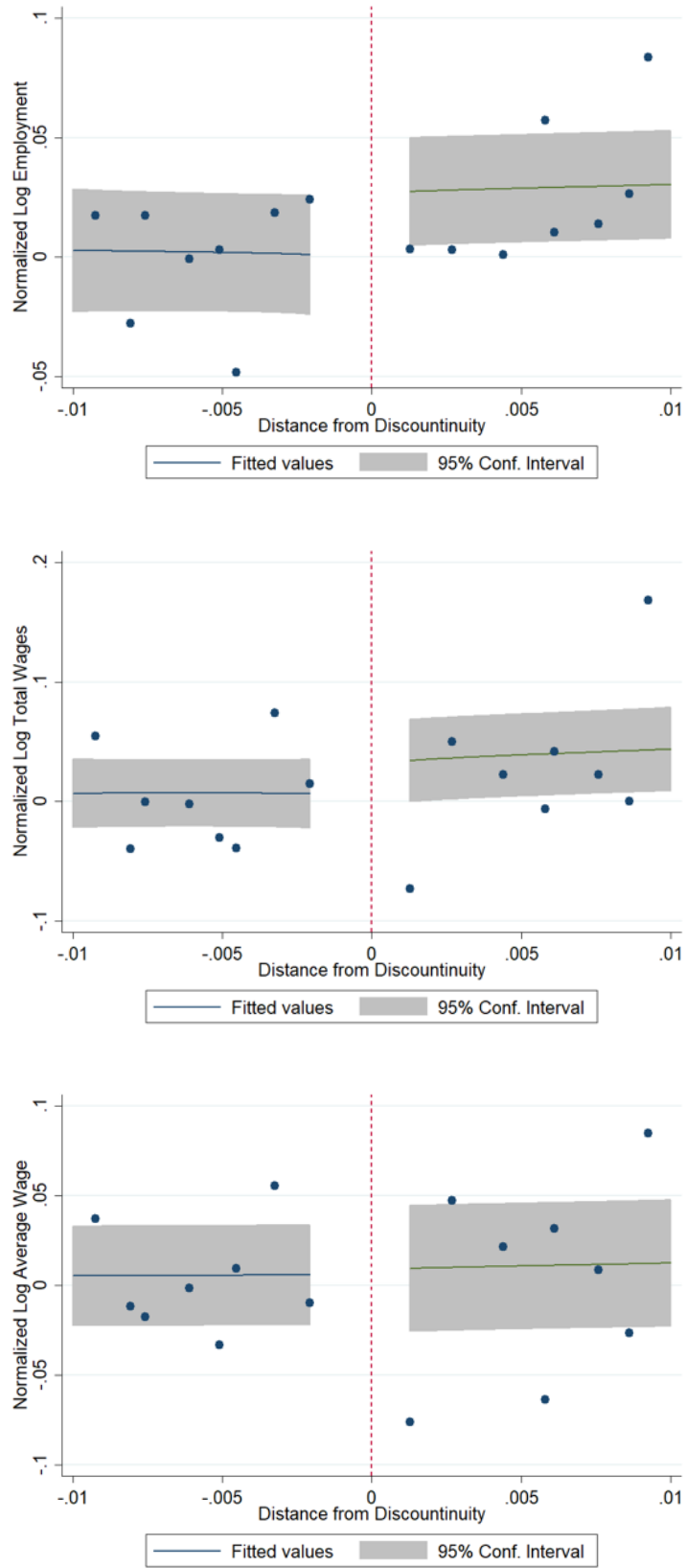


Figure 31: Discontinuous Changes in Rating

Table 15: Confusion Matrix for Predictions on the Test Data

Test Data		Prediction		
		Neither	Bad Service	Good Service
Manual	Neither	133	1	23
	Bad Service	14	19	14
	Good Service	30	0	66

Table 16: Summary Statistics of Businesses on Yelp in Pittsburgh

	Variables	Obs.	Mean	Std. Dev
	Employment	23,346	36	153
All Businesses	Total wage	\$23,346	\$82,779	\$679,158
	Wage per worker	\$23,346	\$1,587	\$1,326
	Employment	18,031	26	32
Restaurants	Total wage	\$18,031	\$38,724	\$68,895
	Wage per worker	\$18,031	\$1,329	\$657

Note: All statistics are per quarter per business.

Table 17: Impact of Yelp Rating On Employment and Wage

Dependent Variables	(1) Employment	(2) Total wage	(3) Wage per worker
Rating	-0.00167 (0.131)	116.3 (74.79)	5.433* (2.83)
Individual FE	X	X	X
Year Quarter FE	X	X	X
Observations	18,031	18,031	18,031
R-squared	0.979	0.98	0.696
Businesses	1446	1446	1446

Note: Rating is the star rating on Yelp. Robust standard errors in parentheses.

* The estimate is significant at the 10% level.

** The estimate is significant at the 5% level.

*** The estimate is significant at the 1% level.

Table 18: RD Estimates - Restaurants (bandwidth: 0.01 stars)

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent Variables	Employment	Employment	Total Wage	Total Wage	Average Wage	Average Wage
Discontinuity	3.576*** (1.231)	3.513*** (1.187)	2,880** (1,155)	2,870** (1,159)	11.19 (23.17)	10.6 (23.13)
Dependent Variables	Lg(Employment)	Lg(Employment)	Lg(Total Wage)	Lg(Total Wage)	Lg(Average Wage)	Lg(Average Wage)
Discontinuity	0.128* (0.0668)	0.127* (0.0662)	0.115 (0.0829)	0.112 (0.0821)	-0.0129 (0.0452)	-0.0147 (0.0450)
Rating	X	X	X	X	X	X
Rating Quadratic		X		X		X
Individual FE	X	X	X	X	X	X
Year Quarter FE	X	X	X	X	X	X
Observations	1,086	1,086	1,086	1,086	1,086	1,086
Businesses	530	530	530	530	530	530

Note: Rating is the star rating on yelp. Robust standard errors in parentheses.

* The estimate is significant at the 10% level.

** The estimate is significant at the 5% level.

*** The estimate is significant at the 1% level.

Table 19: RD Estimates - Difference Bandwidths

Dependent Variables	(1) Employment	(2) Total wage	(3) Average Wage	(4) Employment	(5) Total Wage	(6) Average Wage
Discontinuity	1.216** (0.596)	1,318** (592.7)	-5.677 (19.05)	0.248 (0.332)	569.9* (314.6)	1.343 (11.93)
Rating	X	X	X	X	X	X
Rating Quadratic	X	X	X	X	X	X
Individual FE	X	X	X	X	X	X
Year Quarter FE	X	X	X	X	X	X
Observations	1,373	1,373	1,373	1,804	1,804	1,804
Businesses	609	609	609	723	723	723
Bandwidth (Stars)	0.02	0.02	0.02	0.03	0.03	0.03

Note: Rating is the star rating on yelp. Robust standard errors in parentheses.

* The estimate is significant at the 10% level.

** The estimate is significant at the 5% level.

*** The estimate is significant at the 1% level.

Table 20: RD Estimates - All Services Business (0.01 stars)

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent Variables	Employment	Employment	Total Wage	Total Wage	Average Wage	Average Wage
Discontinuity	2.358* (1.247)	2.362* (1.228)	3,130* (1,839)	3,132* (1,843)	20.32 (23.35)	20.41 (23.51)
Dependent Variables	Lg(Employment)	Lg(Employment)	Lg(Total Wage)	Lg(Total Wage)	Lg(Average Wage)	Lg(Average Wage)
Discontinuity	0.115** (0.0571)	0.115** (0.0572)	0.125* (0.0685)	0.125* (0.0682)	0.0108 (0.0422)	0.0110 (0.0424)
Rating	X	X	X	X	X	X
Rating Quadratic		X		X		X
Individual FE	X	X	X	X	X	X
Year Quarter FE	X	X	X	X	X	X
Observations	1,584	1,584	1,584	1,584	1,584	1,584
Businesses	726	726	726	726	726	726

Note: Rating is the star rating on yelp. Robust standard errors in parentheses.

* The estimate is significant at the 10% level.

** The estimate is significant at the 5% level.

*** The estimate is significant at the 1% level.

Table 21: RD Estimates - Non Restaurants (Bandwidth: 0.05 stars)

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent Variables	Employment	Employment	Total Wage	Total Wage	Average Wage	Average Wage
Discontinuity	3.891** (1.808)	4.050** (1.839)	4,488 (2,942)	4,636 (2,970)	24.08 (33.11)	24.08 (33.16)
Dependent Variables	Lg(Employment)	Lg(Employment)	Lg(Total Wage)	Lg(Total Wage)	Lg(Average Wage)	Lg(Average Wage)
Discontinuity	0.0406* (0.0230)	0.0425* (0.0229)	0.0533** (0.0270)	0.0548** (0.0268)	0.0127 (0.0230)	0.0122 (0.0230)
Rating	X	X	X	X	X	X
Rating Quadratic		X		X		X
Individual FE	X	X	X	X	X	X
Year Quarter FE	X	X	X	X	X	X
Observations	1,088	1,088	1,088	1,088	1,088	1,088
Businesses	322	322	322	322	322	322

Note: Rating is the star rating on yelp. Robust standard errors in parentheses.

* The estimate is significant at the 10% level.

** The estimate is significant at the 5% level.

*** The estimate is significant at the 1% level.

Table 22: Regression Discontinuity Estimates - Restaurants (Lagged Dependent Variables)

	(1)	(2)	(3)
Dependent Variables	Employment	Total Wage	Average Wage
Discontinuity	-0.183 (2.342)	-1,908 (2,134)	-53.15** (25.83)
Dependent Variables	Lg(Employment)	Lg(Total Wage)	Lg(Average Wage)
Discontinuity	0.0324 (0.0991)	-0.0635 (0.1010)	-0.0958** (0.0470)
Rating	X	X	X
Rating Quadratic	X	X	X
Individual FE	X	X	X
Year Quarter FE	X	X	X
Observations	1,021	1,021	1,021
Businesses	499	499	499

Note: Rating is the star rating on yelp. Robust standard errors in parentheses.

* The estimate is significant at the 10% level.

** The estimate is significant at the 5% level.

*** The estimate is significance at the 1% level.

Table 23: Response to Reviews on Services - Employment

	(1)	(2)	(3)
Dependent Variables	Lg(Employment)	Lg(Employment)	Lg(Employment)
Rating	-0.0157*** (0.00538)	-0.0157*** (0.00538)	-0.0155*** (0.00540)
Rating × No. of reviews	0.00306*** (0.00036)	0.00309*** (0.00042)	0.00308*** (0.00036)
Rating× No. of reviews on services		-0.000619 (0.00066)	
Rating× Share of reviews on bad services			0.000218 (0.00619)
Rating×Share of reviews on good services			-0.000799 (0.00145)
Observations	18,031	18,031	18,031
R-squared	0.964	0.964	0.964
Individual FE	X	X	X
Year Quarter FE	X	X	X
Businesses	1430	1430	1430

Note: Rating is the star rating on Yelp. Robust standard errors in parentheses.

* The estimate is significant at the 10% level.

** The estimate is significant at the 5% level.

*** The estimate is significant at the 1% level.

Table 24: Response to Reviews on Services - Total Wage

	(1)	(2)	(3)
Dependent Variables	Lg(Total Wage)	Lg(Total Wage)	Lg(Total Wage)
Rating	-0.0176** (0.00717)	-0.0174** (0.00717)	-0.0170** (0.00718)
Rating × No. of reviews	0.00401*** (0.00051)	0.00442*** (0.00058)	0.00409*** (0.00052)
Rating × No. of reviews on services		-0.001 (0.00083)	
Rating × Share of reviews on bad services			-0.00282 (0.00658)
Rating × Share of reviews on good services			-0.00260 (0.00183)
Observations	18,031	18,031	18,031
R-squared	0.961	0.961	0.961
Individual FE	X	X	X
Year Quarter FE	X	X	X
Businesses	1430	1430	1430

Note: Rating is the star rating on Yelp. Robust standard errors in parentheses.

* The estimate is significant at the 10% level.

** The estimate is significant at the 5% level.

*** The estimate is significant at the 1% level.

Table 25: Response to Reviews on Services - Average Wage

	(1)	(2)	(3)
Dependent Variables	Lg(Average Wage)	Lg(Average Wage)	Lg(Average Wage)
Rating	-0.00183 (0.00611)	-0.00165 (0.00611)	-0.00147 (0.00612)
Rating × No. of reviews	0.000954*** (0.000327)	0.00134*** (0.000417)	0.00101*** (0.000329)
Rating× No. of reviews on services		-0.000939 (0.000603)	
Rating× Share of reviews on bad services			-0.00304 (0.00460)
Rating×Share of reviews on good services			-0.00180 (0.00151)
Observations	18,031	18,031	18,031
R-squared	0.778	0.778	0.778
Individual FE	X	X	X
Year Quarter FE	X	X	X
Businesses	1430	1430	1430

Note: Rating is the star rating on Yelp. Robust standard errors in parentheses.

* The estimate is significant at the 10% level.

** The estimate is significant at the 5% level.

*** The estimate is significant at the 1% level.

Appendix A

Proofs and Additional Theoretical Results

Proof of Lemma 1 Substituting $V_i^x = \tilde{v}_i^x \times P_i Y_i$ into value functions, we get:

$$\begin{aligned} & R\tilde{v}_i^x(n)P_i Y_i - \dot{\tilde{v}}_i^x(n)P_i Y_i - \tilde{v}_i^x(n)\dot{P}_i Y_i - \tilde{v}_i^x(n)P_i \dot{Y}_i = \\ & \pi_i^x(n) - z_i^x [\tilde{v}_i^x(n)P_i Y_i - 0] + z_{-i}^x [\tilde{v}_i^x(n-1)P_i Y_i - \tilde{v}_i^x(n)P_i Y_i] \\ & + \alpha(n) [\tilde{v}_i^x(n-1)P_i Y_i - \tilde{v}_i^x(n)P_i Y_i] + \alpha(-n) [\tilde{v}_i^x(n+1)P_i Y_i - \tilde{v}_i^x(n)P_i Y_i] \end{aligned}$$

Dividing all sides by $P_i Y_i$, we derive the following result:

$$\begin{aligned} (R - \pi_i - g_Y)\tilde{v}_i^x(n) + \dot{\tilde{v}}_i^x(n) &= \tilde{\pi}_i^x(n) - z_i^x [\tilde{v}_i^x(n) - 0] + z_{-i}^x [\tilde{v}_i^x(n-1) - \tilde{v}_i^x(n)] \\ &+ \alpha(n) [\tilde{v}_i^x(n-1) - \tilde{v}_i^x(n)] + \alpha(-n) [\tilde{v}_i^x(n+1) - \tilde{v}_i^x(n)] \end{aligned}$$

where

$$\tilde{\pi}_i^x(n) = \frac{\pi_i^x(n)}{P_i Y_i} = \left(1 - \lambda^{-[n-\bar{n}_i^x]_0^{\bar{m}}}\right) \tilde{X}_i^{\frac{\varepsilon-1}{\varepsilon}} + \frac{1}{(1+b_{-i})\Psi_i} \left(1 - \lambda^{-[n+\bar{n}_{-i}]_0^{\bar{m}}}\right) \tilde{X}_{-i}^{\frac{\varepsilon-1}{\varepsilon}}$$

Applying Euler Equation $R - \pi_i - g_Y = g$, we obtain the desired results.

Static Effects of Openness

Autarky: Supposing said competitor is behind by the ratio $\lambda^{\bar{m}}$ so that prices and production are

$$\begin{aligned} p_{j,t}^c &= \frac{\lambda^{\bar{m}} w_t^u}{q_{j,t}^c} \quad \text{and} \quad c_{j,t} = \frac{q_{j,t}^c}{\lambda^{\bar{m}} w_t^u} \tilde{C}_t^{\frac{\varepsilon-1}{\varepsilon}} Y_t P_t \\ p_{j,t}^d &= \frac{\lambda^{\bar{m}} (w_t^u + \zeta \tau_t)}{q_{j,t}^d} \quad \text{and} \quad d_{j,t} = \frac{q_{j,t}^d}{\lambda^{\bar{m}} (w_t^u + \zeta \tau_t)} \tilde{D}_t^{\frac{\varepsilon-1}{\varepsilon}} Y_t P_t \end{aligned}$$

This will result in labor utilization of

$$\ell_{j,t}^c = \frac{1}{\lambda^{\bar{m}} w_t^u} \tilde{C}_t^{\frac{\varepsilon-1}{\varepsilon}} Y_t P_t \quad \text{and} \quad \ell_{j,t}^d = \frac{1}{\lambda w_t^u} \left(\frac{1}{1 + \zeta \hat{\tau}} \right) \tilde{D}_t^{\frac{\varepsilon-1}{\varepsilon}} Y_t P_t$$

The profit for each product line j in either industry then is

$$\pi_{j,t}^x = (1 - \lambda^{-\bar{m}}) \tilde{X}_t^{\frac{\varepsilon-1}{\varepsilon}} Y_t P_t$$

To determine the shares of each component in autarky, we can integrate the intermediates to find

$$\tilde{C}_t = \left(\frac{Q_t^c}{\lambda^{\bar{m}} w_t^u} \right)^\varepsilon P_t^\varepsilon Z_t^\varepsilon \quad \text{and} \quad \tilde{D}_t = \left(\frac{1}{1 + \zeta \hat{\tau}} \right)^\varepsilon \left(\frac{Q_t^d}{\lambda^{\bar{m}} w_t^u} \right)^\varepsilon P_t^\varepsilon Z_t^\varepsilon$$

where we define the productivity index of the economy by each sector at time t as $\log Q_t^x = \int_0^1 \log q_{j,t}^x dj$, $x \in (c, d)$. In what follows, we drop the time subscripts when this causes no confusion.

From the final good production function we have the component share as

$$\tilde{C} = \left[\frac{(Q^c)^{\varepsilon-1}}{(Q^c)^{\varepsilon-1} + \left(\frac{1}{1+\zeta\hat{\tau}} \right)^{\varepsilon-1} (Q^d)^{\varepsilon-1}} \right]^{\frac{\varepsilon}{\varepsilon-1}} \quad \text{and} \quad \tilde{D} = \left[\frac{\left(\frac{1}{1+\zeta\hat{\tau}} \right)^{\varepsilon-1} (Q^d)^{\varepsilon-1}}{(Q^c)^{\varepsilon-1} + \left(\frac{1}{1+\zeta\hat{\tau}} \right)^{\varepsilon-1} (Q^d)^{\varepsilon-1}} \right]^{\frac{\varepsilon}{\varepsilon-1}}$$

and

$$\left(\frac{\lambda^{\bar{m}} w^u}{PZ} \right)^{\varepsilon-1} = (Q^c)^{\varepsilon-1} + \left(\frac{1}{1 + \zeta \hat{\tau}} \right)^{\varepsilon-1} (Q^d)^{\varepsilon-1}$$

In the static equilibrium, the labor market clearing, with a unit mass of production labor, leads us to

$$\begin{aligned} 1 &= \int_0^1 \ell_j^c dj + \int_0^1 \ell_j^d dj \\ \Rightarrow \bar{Y} &= \frac{\lambda w^u}{PZ} \frac{1}{\tilde{C}^{\frac{\varepsilon-1}{\varepsilon}} + \left(\frac{1}{1+\zeta\hat{\tau}} \right) \tilde{D}^{\frac{\varepsilon-1}{\varepsilon}}} \\ \Rightarrow \bar{Y} &= \frac{\left[(Q^c)^{\varepsilon-1} + \left(\frac{1}{1+\zeta\hat{\tau}} \right)^{\varepsilon-1} (Q^d)^{\varepsilon-1} \right]^{\frac{\varepsilon}{\varepsilon-1}}}{\left[(Q^c)^{\varepsilon-1} + \left(\frac{1}{1+\zeta\hat{\tau}} \right)^\varepsilon (Q^d)^{\varepsilon-1} \right]} \end{aligned}$$

This implies

$$C = \frac{(Q^c)^\varepsilon}{\left[(Q^c)^{\varepsilon-1} + \left(\frac{1}{1+\zeta\hat{\tau}} \right)^\varepsilon (Q^d)^{\varepsilon-1} \right]} \quad \text{and} \quad D = \frac{\left(\frac{1}{1+\zeta\hat{\tau}} \right)^\varepsilon (Q^d)^\varepsilon}{\left[(Q^c)^{\varepsilon-1} + \left(\frac{1}{1+\zeta\hat{\tau}} \right)^\varepsilon (Q^d)^{\varepsilon-1} \right]}$$

Since $C = Q^c L^c$ and $D = \frac{1}{1+\zeta\hat{\tau}} Q^d L^d$, this also means that

$$L^c = \frac{(Q^c)^{\varepsilon-1}}{\left[(Q^c)^{\varepsilon-1} + \left(\frac{1}{1+\zeta\hat{\tau}}\right)^\varepsilon (Q^d)^{\varepsilon-1}\right]} \quad \text{and} \quad L^d = \frac{\left(\frac{1}{1+\zeta\hat{\tau}}\right)^\varepsilon (Q^d)^{\varepsilon-1}}{\left[(Q^c)^{\varepsilon-1} + \left(\frac{1}{1+\zeta\hat{\tau}}\right)^\varepsilon (Q^d)^{\varepsilon-1}\right]}$$

Let the ratio of aggregated productivity be $S = Q^c/Q^d$. We can express the component share as

$$\tilde{C} = \left[\frac{S^{\varepsilon-1}}{1 + \left(\frac{1}{1+\zeta\hat{\tau}}\right)^{\varepsilon-1} S^{\varepsilon-1}} \right]^{\frac{\varepsilon}{\varepsilon-1}} \quad \text{and} \quad \tilde{D} = \left[\frac{\left(\frac{1}{1+\zeta\hat{\tau}}\right)^{\varepsilon-1}}{S^{\varepsilon-1} + \left(\frac{1}{1+\zeta\hat{\tau}}\right)^{\varepsilon-1}} \right]^{\frac{\varepsilon}{\varepsilon-1}}$$

and

$$L_c = \frac{S^{\varepsilon-1}}{1 + \left(\frac{1}{1+\zeta\hat{\tau}}\right)^\varepsilon S^{\varepsilon-1}} \quad \text{and} \quad L_d = \frac{\left(\frac{1}{1+\zeta\hat{\tau}}\right)^\varepsilon}{S^{\varepsilon-1} + \left(\frac{1}{1+\zeta\hat{\tau}}\right)^\varepsilon}$$

Two important qualitative conclusions follow from equations above: First, carbon taxes increase production cost of dirty intermediates, thus lowering dirty component share in final good production. Second, more importantly, clean/dirty market size depends on the aggregate technology gap between these two sectors. Then the allocation of innovation exhibits path-dependence because of the market size effect: a more advanced technology has a larger market which increases the profits of subsequent innovators.

Now consider a simplified open economy without iceberg trade cost. Case 1 - No Carbon Taxes ($\hat{\tau}_i = \tau_{-i} = 0$)

$$\bar{Y}_i^O = \left[(Q_i^c \Delta_i^c)^{\varepsilon-1} + (Q_i^d \Delta_i^d)^{\varepsilon-1} \right]^{\frac{1}{\varepsilon-1}}$$

$$\bar{Y}_i^C = \left[(Q_i^c)^{\varepsilon-1} + (Q_i^d)^{\varepsilon-1} \right]^{\frac{1}{\varepsilon-1}}$$

where Δ_i^x represent the productivity gains from trade for country i

$$\log(\Delta_i^x) = \log(\lambda) \sum_{n_i < \bar{n}_i^x} \mu_{i,n}^x (\bar{n}_i^x - n_i)$$

Because $\Delta_i^x > 1$ as long as there is productivity different across the two countries, we have $\bar{Y}_i^O > \bar{Y}_i^C$.

The product shares now becomes

$$\tilde{X}_i^{\frac{\varepsilon-1}{\varepsilon}} = \frac{(Q_i^x \Delta_i^x)^{\varepsilon-1}}{(Q_i^c \Delta_i^c)^{\varepsilon-1} + (Q_i^d \Delta_i^d)^{\varepsilon-1}}$$

So $\tilde{C}_i^O > \tilde{C}_i^C$ and $\tilde{C}_{-i}^O < \tilde{C}_{-i}^C$, if $\Delta_i^c > \Delta_i^d$; $\tilde{C}_i^O \leq \tilde{C}_i^C$ and $\tilde{C}_{-i}^O \geq \tilde{C}_{-i}^C$, if otherwise.

The profits for clean and dirty intermediates in the open economy i are

$$\Pi_i^{x,O} = \mu_{i,i}^x (1 - \lambda^{\bar{m}}) \tilde{X}_i^{\frac{\varepsilon-1}{\varepsilon}} Y_i P_i + \mu_{i,i}^x (1 - \lambda^{\bar{m}}) \tilde{X}_{-i}^{\frac{\varepsilon-1}{\varepsilon}} Y_{-i} P_{-i}$$

while in autarky,

$$\Pi_i^{x,C} = (1 - \lambda^{\bar{m}}) \tilde{X}_i^{\frac{\varepsilon-1}{\varepsilon}} Y_i P_i$$

However, the impact of openness on profits is not obvious. In contrast to the state of autarky, the open economy allows relatively more productive firms to sell to a larger market by providing the opportunity to export. Yet, at the firm level the selection channel implies that less productive domestic firms lose their profits to foreign competitors, which they would earn otherwise in autarky, causing a decline in aggregate profit income. As a result, the net effect of openness on total profits remains ambiguous. As a result, the net effect of openness on total profits remains ambiguous.

Case 2 - Unilateral Carbon Tax Only

Now consider this economy only subject unilateral carbon taxes. If country i raise carbon tax of τ_i , then the total output becomes

$$\bar{Y}_i = \frac{\left[(Q_i^c \Delta_i^c)^{\varepsilon-1} + \left(\frac{1}{1+\zeta\hat{\tau}_i} \right)^{\varepsilon-1} (Q_i^d \Delta_i^d)^{\varepsilon-1} \right]^{\frac{\varepsilon}{\varepsilon-1}}}{(Q_i^c \Delta_i^c)^{\varepsilon-1} + \left(\frac{1}{1+\zeta\hat{\tau}_i} \right)^{\varepsilon} (Q_i^d \Delta_i^d)^{\varepsilon-1}}$$

$$\bar{Y}_{-i} = \left[(Q_{-i}^c \Delta_{-i}^c)^{\varepsilon-1} + (Q_{-i}^d \Delta_{-i}^d)^{\varepsilon-1} \right]^{\frac{1}{\varepsilon-1}}$$

To understand the impact of carbon taxes on technological change, we focus on the profit change in clean and dirty sectors. A large carbon tax could lead to a decrease in $\frac{\Delta_i^d}{\Delta_i^c(1+\zeta\hat{\tau}_i)}$. As a result shares of dirty intermediates in both countries drops. Meanwhile, imposing carbon tax make it hard for the home country to produce and export dirty intermediates ($\mu_{i,i}^d$

becomes smaller). However, while the rising clean sector shares make it more profitable to produce and export clean intermediates. As a result, the home country who implement the unilateral carbon tax policy will secure a shift from dirty technology to clean technology. However, the foreign country are now encouraged to produce more dirty intermediates, resulting in the pollution heaven effect. A unilateral carbon tax cannot generally secure a transition to clean technology.

Appendix B

Computational and Estimation Algorithms

Because the theoretical analysis shows that the key firm decisions are independent of climate dynamics, we therefore start with solving for wage ratios, value functions, innovation rates, and distributions first, then use those to first the time path for the carbon stock, temperature, and other variables of interest.

We construct a fixed point method to solve this model and find the transition dynamics. The algorithm is a forward backward solution method, in which we first update the product line distribution (μ_x) in the forward direction and the value functions (V_i^x) in the backward direction, using the long-term (clean or dirty) steady state as the terminal condition.

To solve for the fixed point of the sequence of value functions, We discretize time into $N = 500$ steps and set a terminal period $T = 400$. Due to the symmetry between the two countries inherent in this model (knowledge spillover), when a single type of technology is dominant in the sense that the technology gap distribution is heavily skewed to either clean or dirty technology one can compute value functions and innovation rates in the steady state. We use these values as terminal conditions, though we do not know in advance which technology (clean or dirty) will be dominant eventually. In addition, we set the upper and lower bounds on the step gap distribution space to 20. The algorithm proceeds as follows:

1. Start iteration $h = 0$ with the guess on long-term steady state dominant technology (clean or dirty) and assume the terminal value functions to be the true value function. Instantiate the technology gap distribution using the patent data in subsection 3.3.2.

$$\{\tilde{v}_{i,t}^x\}^{h=0} = \tilde{v}_{i,T}^x \quad \text{and} \quad \{\mu_t^x\}^{h=0} = \mu_0^x, \forall t$$

2. At iteration h , take value function and product distributions guesses at time $t + 1$, $\{\tilde{v}_{i,t+1}^x, \mu_t^x\}^h$ as given and solve innovation rates z_i^x by forward iteration. Using these

innovation rates, update the time $t + 1$ product distribution μ_{t+1}^x using discrete time versions of the flow equations.

3. At iteration h , take value function and product distributions guesses at time $t + 1$, $\{\tilde{v}_{i,t+1}^x, \mu_t^x\}^h$ as given and solve innovation rates z_i^x by forward iteration. Using these innovation rates, update the time $t + 1$ product distribution μ_{t+1}^x using discrete time versions of the flow equations.

4. Repeat steps 2-4 and check if the convergence criterion

$$\max |\{\tilde{v}_{i,t}^x\}^{h+1} - \{\tilde{v}_{i,t}^x\}^h| < \epsilon$$

is met. We use $\epsilon = 10^{-4}$

5. Find the implied dominant technology at the terminal period by determining which technology type has a higher aggregate innovation rate as some late stage period $T - T_P$ (we use $T_P = 40$). Repeat steps 1 - 4 with implied dominant technology until the dominant strategy is same as the initial guess.

In order to avoid any instability, particularly when one is close to a threshold where the asymptotically dominant technology switches over, we also introduce heterogeneity in entrant's fixed costs as explained in the text.

All code of our solution algorithm is written in standard Python 3, and depends only on common numerical and scientific modules such as numpy, scipy, pandas, statsmodels, patsy, and matplotlib. The parameter estimation and optimal policy calculations are done using either the Nelder-Mead algorithm or simulated annealing.

Bibliography

- Alexander Borisov, Andrew Ellul, and Merih Sevilir. Access to public capital markets and employment growth. Technical report, CEPR Discussion Paper No. DP10521., 2015.
- Shai Bernstein. Does going public affect innovation? *The Journal of Finance*, 70(4):1365–1403, 2015.
- Casey Dougal, Christopher A Parsons, and Sheridan Titman. Urban vibrancy and corporate growth. *The Journal of Finance*, 70(1):163–210, 2015.
- Stuart S Rosenthal and William C Strange. Geography, industrial organization, and agglomeration. *Review of Economics and Statistics*, 85(2):377–393, 2003.
- Mohammad Arzaghi and J Vernon Henderson. Networking off madison avenue. *The Review of Economic Studies*, 75(4):1011–1038, 2008.
- Gabriel M Ahlfeldt, Stephen J Redding, Daniel M Sturm, and Nikolaus Wolf. The economics of density: Evidence from the berlin wall. *Econometrica*, 83(6):2127–2189, 2015.
- Martin Kenney, Donald Patton, and Jay R Ritter. Post-IPO employment and revenue growth for US IPOs, June 1996-2010. *Report for the Kauffman Foundation*, 2012.
- David Weild, Edward Kim, and Lisa Newport. Making stock markets work to support economic growth. *OECD Publishing*, 2013.
- David Card, Kevin F Hallock, and Enrico Moretti. The geography of giving: The effect of corporate headquarters on local charities. *Journal of Public Economics*, 94(3):222–234, 2010.
- Michael Greenstone and Enrico Moretti. Bidding for industrial plants: Does winning a million dollar plant increase welfare? *Mimeograph*, 2004.
- Michael Greenstone, Richard Hornbeck, and Enrico Moretti. Identifying agglomeration spillovers: Evidence from winners and losers of large plant openings. *Journal of Political Economy*, 118(3):536–598, 2010.
- Holger Sieg, V Kerry Smith, H Spencer Banzhaf, and Randy Walsh. Estimating the general equilibrium benefits of large changes in spatially delineated public goods. *International Economic Review*, 45(4):1047–1077, 2004.
- Siqi Zheng and Matthew E Kahn. Does government investment in local public goods spur gentrification? Evidence from Beijing. *Real Estate Economics*, 41(1):1–28, 2013.

- Stephen B Billings, Eric J Brunner, and Stephen L Ross. Gentrification and failing schools: The unintended consequences of school choice under NCLB. *Review of Economics and Statistics*, 100(1):65–77, 2018.
- Alexander W Butler, Larry Fauver, and Ioannis Spyridopoulos. Local economic consequences of stock market listings. 2016.
- Jess Cornaggia, Matthew Gustafson, and Kevin J Pisciotta. Public ownership and the local economy. 2018.
- Jay R Ritter and Ivo Welch. A review of IPO activity, pricing, and allocations. *The Journal of Finance*, 57(4):1795–1828, 2002.
- Michelle Lowry. Why does IPO volume fluctuate so much? *Journal of Financial Economics*, 67(1):3–40, 2003.
- Karl E Case and Robert J Shiller. The efficiency of the market for single-family homes. *The American Economic Review*, 79(1):125–137, 1989.
- Karl E Case and Robert J Shiller. Forecasting prices and excess returns in the housing market. *Real Estate Economics*, 18(3):253–273, 1990.
- Richard Meese and Nancy Wallace. Testing the present value relation for housing prices: Should I leave my house in San Francisco? *Journal of Urban Economics*, 35(3):245–266, 1994.
- Michelle Lowry and G William Schwert. Is the IPO pricing process efficient? *Journal of Financial Economics*, 71(1):3–26, 2004.
- Jos Van Bommel and Theo Vermaelen. Post-ipo capital expenditures and market feedback. *Journal of Banking and Finance*, 27(2):275–305, 2003.
- Atif Mian and Amir Sufi. The consequences of mortgage credit expansion: Evidence from the US mortgage default crisis. *The Quarterly Journal of Economics*, 124(4):1449–1496, 2009.
- Louis S Jacobson, Robert J LaLonde, and Daniel G Sullivan. Earnings losses of displaced workers. *The American Economic Review*, pages 685–709, 1993.
- Sandra E Black. Do better schools matter? Parental valuation of elementary education. *The Quarterly Journal of Economics*, 114(2):577–599, 1999.
- Kenneth Y Chay and Michael Greenstone. Does air quality matter? Evidence from the housing market. *Journal of Political Economy*, 113(2):376–424, 2005.
- Kevin Haninger, Lala Ma, and Christopher Timmins. The value of brownfield remediation. Technical report, National Bureau of Economic Research, 2014.

- Devin G Pope and Jaren C Pope. When Walmart comes to town: Always low housing prices? Always? *Journal of Urban Economics*, 87:1–13, 2015.
- José Azar, Ioana Marinescu, and Marshall I Steinbaum. Labor market concentration. Technical report, National Bureau of Economic Research, 2017.
- Efraim Benmelech, Nittai Bergman, and Hyunseob Kim. Strong employers and weak employees: How does employer concentration affect wages? Technical report, National Bureau of Economic Research, 2018.
- Kevin Rinz. Labor market concentration, earnings inequality, and earnings mobility. Technical report, CARRA Working Paper Series, 2018.
- Daron Acemoglu, Ufuk Akcigit, Douglas Hanley, and William Kerr. Transition to clean technology. *Journal of Political Economy*, 124(1):52–104, 2016a.
- William D Nordhaus. *Managing the global commons: the economics of climate change*, volume 31. MIT press Cambridge, MA, 1994.
- William D Nordhaus and Joseph Boyer. *Warming the world: economic models of global warming*. MIT press, 2000.
- Per Krusell and Anthony A Smith Jr. Macroeconomics and global climate change: Transition for a many-region economy. 2009.
- John Hassler and Per Krusell. Economics and climate change: integrated assessment in a multi-region world. *Journal of the European Economic Association*, 10(5):974–1000, 2012.
- Mikhail Golosov, John Hassler, Per Krusell, and Aleh Tsyvinski. Optimal taxes on fossil fuel in general equilibrium. *Econometrica*, 82(1):41–88, 2014.
- Daron Acemoglu. Why do new technologies complement skills? directed technical change and wage inequality. *The Quarterly Journal of Economics*, 113(4):1055–1089, 1998.
- Daron Acemoglu. Directed technical change. *The Review of Economic Studies*, 69(4):781–809, 2002.
- Daron Acemoglu, Philippe Aghion, Leonardo Bursztyn, and David Hemous. The environment and directed technical change. *American Economic Review*, 102(1):131–66, 2012.
- David Hémous. The dynamic impact of unilateral environmental policies. *Journal of International Economics*, 103:80–95, 2016.
- Marc J Melitz. The impact of trade on intra-industry reallocations and aggregate industry productivity. *Econometrica*, 71(6):1695–1725, 2003.

- Ariel Burstein and Marc Melitz. Trade liberalization and firm dynamics. In *Advances in Economics and Econometrics Tenth World Congress. Applied Economics*, volume 2, pages 283–328, 2013.
- Ufuk Akcigit, Sina T Ates, and Giammario Impullitti. Innovation and trade policy in a globalized world. Technical report, National Bureau of Economic Research, 2018.
- Francisco J Buera and Ezra Oberfield. The global diffusion of ideas. Technical report, National Bureau of Economic Research, 2016.
- Thomas Sampson. Dynamic selection: an idea flows theory of entry, trade, and growth. *The Quarterly Journal of Economics*, 131(1):315–380, 2015.
- Bronwyn H Hall, Adam B Jaffe, and Manuel Trajtenberg. The nber patent citation data file: Lessons, insights and methodological tools. Technical report, National Bureau of Economic Research, 2001.
- David S Abrams, Ufuk Akcigit, and Jillian Popadak. Patent value and citations: Creative destruction or strategic disruption? Technical report, National Bureau of Economic Research, 2013.
- Daron Acemoglu, Ufuk Akcigit, and William R Kerr. Innovation network. *Proceedings of the National Academy of Sciences*, 113(41):11483–11488, 2016b.
- Philippe Aghion, Antoine Dechezleprêtre, David Hemous, Ralf Martin, and John Van Reenen. Carbon taxes, path dependency, and directed technical change: Evidence from the auto industry. *Journal of Political Economy*, 124(1):1–51, 2016.
- Victor Veefkind, J Hurtado-Albir, S Angelucci, K Karachalios, and N Thumm. A new epo classification scheme for climate change mitigation technologies. *World Patent Information*, 34(2):106–111, 2012.
- Chris Papageorgiou, Marianne Saam, and Patrick Schulte. Substitution between clean and dirty energy inputs: A macroeconomic perspective. *Review of Economics and Statistics*, 99(2):281–290, 2017.
- Thomas Covert, Michael Greenstone, and Christopher R Knittel. Will we ever stop using fossil fuels? *Journal of Economic Perspectives*, 30(1):117–38, 2016.
- Robert C Feenstra, Robert Inklaar, and Marcel P Timmer. The next generation of the penn world table. *American economic review*, 105(10):3150–82, 2015.
- Michael Anderson and Jeremy Magruder. Learning from the crowd: Regression discontinuity estimates of the effects of an online review database. *The Economic Journal*, 122(563):957–989, 2012.
- Michael Luca. Reviews, reputation, and revenue: The case of Yelp. com. 2016.

- Davide Proserpio and Georgios Zervas. Online reputation management: Estimating the impact of management responses on consumer reviews. *Marketing Science*, 36(5):645–665, 2017.
- Karen L Xie, Zili Zhang, Ziqiong Zhang, Amrik Singh, and Seul Ki Lee. Effects of managerial response on consumer ewom and hotel performance: Evidence from tripadvisor. *International Journal of Contemporary Hospitality Management*, 28(9):2013–2034, 2016.
- Judith A Chevalier and Dina Mayzlin. The effect of word of mouth on sales: Online book reviews. *Journal of Marketing Research*, 43(3):345–354, 2006.
- Michael Luca and Georgios Zervas. Fake it till you make it: Reputation, competition, and yelp review fraud. *Management Science*, 62(12):3412–3427, 2016.
- Ivar E Vermeulen and Daphne Seegers. Tried and tested: The impact of online hotel reviews on consumer consideration. *Tourism Management*, 30(1):123–127, 2009.
- Qiang Ye, Rob Law, Bin Gu, and Wei Chen. The influence of user-generated content on traveler behavior: An empirical investigation on the effects of e-word-of-mouth to hotel online bookings. *Computers in Human behavior*, 27(2):634–639, 2011.
- Dina Mayzlin, Yaniv Dover, and Judith Chevalier. Promotional reviews: An empirical investigation of online review manipulation. *American Economic Review*, 104(8):2421–55, 2014.
- Myle Ott, Yejin Choi, Claire Cardie, and Jeffrey T Hancock. Finding deceptive opinion spam by any stretch of the imagination. In *Proceedings of the 49th Annual Meeting of the Association for Computational Linguistics: Human Language Technologies-Volume 1*, pages 309–319. Association for Computational Linguistics, 2011.
- Yang Wang and Alexander Chaudhry. When and how managers responses to online reviews affect subsequent reviews. *Journal of Marketing Research*, 55(2):163–177, 2018.
- Ananthanarayanan Parasuraman, Valarie A Zeithaml, and Leonard L Berry. Servqual: A multiple-item scale for measuring consumer perc. *Journal of Retailing*, 64(1):12, 1988.