Essays on the Macroeconomic Consequences of Market Frictions

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Abstract of the Dissertation

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This thesis studies the implications of firms' and households' decisions on macro and environmental aggregates in economies with market frictions using quantitative macroeconomic methods. The thesis consists three chapters. In each chapter, I study respectively the effects of product market frictions on firms' emission decisions, the effects of financial frictions on firms' hiring decisions, and those on households' consumption-saving choices.

In Chapter 2, I study the effects of product market frictions on firm size distribution and its subsequent impact on aggregate output and industrial pollution in China. Using a unique micro-level manufacturing census, I find that larger firms generate and emit less pollutants per unit of production. Furthermore, I provide evidence suggesting the existence of size-dependent product market frictions that disproportionately affect more productive firms. Using a model with firms heterogeneous in productivity and an endogenous choice of pollution treatment technology, I show that these frictions limit the expansion of productive firms, allowing small unproductive firms to continue operating. This results in lower aggregate output and higher industrial pollution.

In Chapter 3, I study the effects of financial frictions on firms' hiring decisions and their implications on the job finding rates of service and manufacturing occupations. Using CPS data, I document three novel facts. First, the job finding rates of the service occupations in the long-run are higher than those of the manufacturing occupations. Second, in recessions driven by productivity shocks, the job finding rates of both occupations decline in parallel. Third, in recessions originated from financial sectors, the job finding rates of the service occupations decrease more than those of the manufacturing occupations. I use a search and matching model featuring training costs and credit market frictions to account for these observations simultaneously.

In Chapter 4, I study the role of financial frictions—down payment requirement associated with housing investment—in resolving the household life-cycle portfolio choice puzzle. I show that by introducing housing investment with down payment requirement and permanent income shocks, the standard model implies a life-cycle profile of the share of risky assets that is comparable with the data.

Chapter 2 is a joint work with Ji Qi and Xican Xi. Xican Xi initially proposed the project, and we discussed continuously about the direction to explore. Ji Qi provided the data. The execution of the project, including data cleaning, computation of results, and final writing of the paper, is due to me.

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I always consider myself to be extremely lucky to be part of a great cohort of students. I have benefitted enormously from years of discussions of research with my classmate, friend, and future colleague Yan Liu. Memories with my classmates Bruno D. Badia, Biligbaatar Tumendemberel, Qian Li and Abhinav Anand will certainly not fade away as time goes by. Lunan Jiang from the senior year has offered me countless help both in research and in life. I am sure Tamara Gurevich suffered through proof-reading many of my horrendous English. I am also greatly appreciate for her and Dr. Xinyun Chen's continued support to me morally when I am stuck in my research, and for helping me dress professionally for the job market. My Stony Brook life is also blessed by many friends, among whom I should mention specially (in alphabetical order): Anju Bhandari, Bo Li, Yupeng Li, Zhi Li, Ryan McKenna, Zhenning Wang, Xiaoxi Zhang, and Chang Zhao.

Some of my old friends are also an important part of my unforgettable Ph.D life. I have been benefitting from discussions with Xican Xi from Arizona State University about research ever since 2007, when he was the TA of one of the class I am taking. We have worked together on the research presented in Chapter 2, and I believe we will continue to work on important research projects in the future. It has to be mentioned that that project is simply impossible without Ji Qi, whom I have known since 2005, providing and explaining to us the research data.

Last, but most importantly, I am deeply indebted to my parents for their great love. This thesis is dedicated to them.

Chapter 1

Introduction

Market frictions leading to efficiency losses in resource allocations exist widely in the economy. Examples include local protectionism and trade barriers which impede the inter-regional flow of goods, borrowing constraints under limited enforcement, amongst others. Empirical evidence shows that such frictions are found both in the developing economies, and in the developed economies. From a theoretical perspective, these frictions prevent the economy from allocating resources in the most efficient way. Moreover, these frictions also have important environmental consequences. In order to evaluate these effects and subsequently design policies to remedy them, a better understanding of how market frictions interact with firms and households from a quantitative perspective is needed.

This dissertation is organized as follows. The first two chapters focus on the firm's side. Chapter 2 studies the effects of product market frictions on the output, pollutant emission, and the size distribution of manufacturing firms in China. This chapter is based on my job market paper, and is a joint efforts with Xican Xi from Arizona State University and Ji Qi from the Chinese Academy of Environmental Protection. Chapter 3 investigates the role of credit shocks in explaining the differential responses of job finding rates of the low-skill service and manufacturing occupations at the business cycle frequency. This chapter is based on a research project supported by the U.S Department of Labor from May 2013 to December 2014. In Chapter 4, we change our focus to the decisions of the household. More specifically, we study how incomplete financial market shapes the household portfolio choice decisions over the life-cycle. Chapter 5 concludes.

In Chapter 2, "The Size Distribution of Firms and Industrial Pollution", we study the effects of product market frictions on firm size distribution and their impact on aggregate output and industrial pollution in China. Using a unique micro-level manufacturing census, we find that larger firms generate and emit less pollutants per unit of production. Furthermore, we provide evidence suggesting the existence of size-dependent product market frictions that disproportionately affect more productive firms. Using a model with firms heterogeneous in productivity and an endogenous choice of pollution treatment technology, we show that these frictions limit the expansion of productive firms, allowing small unproductive firms to continue operating. This results in lower aggregate output and higher industrial pollution.

To assess the effects of product market frictions on output and industrial pollution quantitatively, we calibrate the model to the Chinese data by requiring the model to generate firm size and employment distributions that are comparable with those obtained from the data. Using the calibrated model, we conduct two quantitative experiments where we contrast the results from a policy that removes the frictions in economy with those from a policy that increases the environmental regulation. The results show that elimination of frictions increases output by 30%. At the same time, the fraction of firms using clean technology increases by 27% and aggregate pollution decreases by 20%. Furthermore, we show that 80% of the reduction in pollution can be achieved by removing the size-dependent feature of frictions. In addition, we compare these results with those from a regulatory policy which increases the clean technology adoption rate by the same 27%. We find that under this scenario, aggregate output does not change and pollution decreases by only 10%. Theoretically, this is because that while reducing the frictions improves the resource allocation on both the extensive (who are the firms that are producing) and intensive margin (how is production allocated among the active firms), stringent regulation acts as another size-dependent distortions which worsens the allocation on the intensive margin.

In Chapter 3, "Job Training, Financial Frictions and Unemployment Outflows", I study the effects of credit market frictions on firms' hiring decisions and their implications on the job finding rates of service and manufacturing occupations. Using the U.S Current Population Survey data, I document three novel facts. First, the job finding rates of the service occupations in the long-run are higher than those of the manufacturing occupations. Second, in recessions driven by productivity shocks, the job finding rates of both occupations decline in parallel. Third, in recessions originated from financial sectors, the job finding rates of the service occupations decrease more than those of the manufacturing occupations. I use a search and matching model featuring training costs and credit market frictions to account for these observations simultaneously. Credit market frictions are modeled as borrowing constraints under limited enforcement. The job finding rates of service occupations in the long-run are higher because the new hires of these occupations require lower training costs. When facing credit shocks tightening the borrowing constraints, the job finding rates of service jobs decrease more because these jobs are usually associated with little value-added and therefore less collateral value. Since training costs are fixed costs, firms with mostly service jobs are more likely to have difficulties raising funds for training new workers when hit by credit shocks. As a result, the firms are forced to cut down deeper on new employment, which leads to a larger decrease in service job finding rates than in manufacturing jobs. The model is calibrated to the U.S economy. Impulse responses show that while the job finding rates of both occupations decrease by the same magnitude in response to a one standard deviation productivity shock, the decline of job finding rates of service occupations is three times of that of manufacturing occupations in response to a one standard deviation credit shock.

In Chapter 4, "Housing Investment and the Household Life-cycle Portfolio Choice Puzzle", I study the role of credit market frictions—down payment requirement associated with housing investment—in resolving the household life-cycle portfolio choice puzzle. The life-cycle portfolio choice puzzle refers to the fact that the mean risky assets share of young workers predicted by the standard models is almost 100% while that in the data never exceeds 40%. I show that by introducing housing investment with down payment requirement and permanent income shocks, the standard model implies a life-cycle profile of the share of risky assets that is comparable with the data. Housing investment creates incentives for young workers to accumulate wealth for the down payment. Permanent income shocks prevent young workers from taking too much risk in the financial markets. As a result, young workers allocate a large proportion of their financial wealth to risk free assets.

In Chapter 5, a conclusion to the dissertation is provided. The three main chapters of this thesis show that market frictions have significant influences over the economic and environmental performances of both the developing and developed economies. The thesis shows the importance to continue devoting efforts in researches that identify, measure, and provide insights on how to cope with market frictions of various forms. A brief discussion of several important directions in the future is provided in offered in this chapter.

CHAPTER 2

THE SIZE DISTRIBUTION OF FIRMS AND INDUSTRIAL POLLUTION

1 INTRODUCTION

Rapid economic growth in China has successfully pulled hundreds of millions of people out of poverty in the last few decades. However, the public has been concerned with the environmental consequences of economic growth, as both the pace of industrialization and urbanization accelerate.[1] In recent years, major metropolitan cities across the country suffered from atmospheric haze pollution. A large number of the country's population is threatened by frequent incidents of emergent and cumulative water contamination.[2] As stated in the *Report on the Work of the Government 2014*, the Chinese government has vowed to undertake a campaign to fight against environmental pollution. For this purpose, the State Council has allocated about $600 billion of special funds for controlling air and water pollution.[3] The primary target of the campaign is to reduce industrial pollution. In order to provide effective policy prescriptions, the key question is then what is the driving force behind the heavy industrial pollution by Chinese manufacturing firms? Although there is a growing literature examining the determinants of pollution discharge by Chinese manufacturing firms [Wang and Wheeler (2005) and Jiang, Lin, and Lin (2014) among others], much of this area needs better understanding.

We show that firm size is an important factor in explaining the high industrial pollution emission problem in China. There are two observations that motivate our inquiry into firm size:

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[1] For general surveys of the current situation of China's environmental pollution see Vennemo, Aunan, Lindhjem, and Seip (2009), Zheng and Kahn (2013) and the references therein. For media press coverage, see for example the Symposium "Choking on growth — Examining the Impact of China's Epic Pollution Crisis" in *The New York Times* in late 2007 and more recently special coverage by *CCTV News Weekly* (05/14/2014) on industrial water pollution.

[2] A wealth of literature has since investigated the causal relationship between pollution and various aspects of human's well-being. For health consequences of water pollution, see for example Economy (2004), Ebenstein (2012), Zhang (2012) and Yang and Zhuang (2014). Graff Zivin and Neidell (2013) provides an excellent survey of the related literature. For a general survey on environmental pollution and food safety, see Lam, Remais, Fung, Xu, and Sun (2013).

[3] The funds are CNY 1.6 trillion ($260 billion) under *Air Pollution Prevention and Control Plan* and CNY 2 trillion ($320 billion) under *Water Pollution Prevention and Control Plan*.

(i) Small firms have much higher pollution intensity (pollutants discharged per unit of production) than large firms, indicating that firm size differences can potentially have large effect on measured aggregate industrial pollution. Using firm-level data from *the First National General Survey of Pollution Sources*, we find that the elasticity between pollution intensity and output value in the top-5 polluting industries in China is -0.37.[4] More specifically, we find that large firms pollute less because they use production technologies that are more environmentally friendly and pollutant treatment technologies that are more advanced. Put differently, large firms not only generate less pollutants, but also remove larger proportion of them from the discharged wastewater.

(ii) Small firms account for a larger fraction of production in manufacturing sectors in China than in the U.S. Using data from *the First China National Economic Census* and *the Statistics of U.S Businesses*, we document that for the top-5 polluting industries in China, firms with more than 400 employees account for 40% of the total employment, while for their American counterparts the number is close to 70%.[5]

We investigate the role of product market frictions in shaping the firm size distribution in China and subsequently assess quantitatively their impacts on aggregate industrial pollution and other macro aggregates, as well as their interactions with environmental policies. We use wedges of average factor product to measure implicitly the level of product market frictions [Hsieh and Klenow (2009) and Restuccia and Rogerson (2013)]. Examples of such product market frictions include local protectionism and trade barriers which impede the inter-regional flow of goods, various administrative costs and others. We find that product market frictions affect disproportionately large productive firms, which limits the expansion of these productive firms. Therefore, unproductive firms are allowed to survive, which results in output loss. Since the adoption of advanced pollution treatment technology requires fixed installation costs, product market frictions affect aggregate pollution via two channels. First, less firms are willing to install clean technologies because firms earn less profits in a market with frictions. Second, firms using clean technologies account for less market share. As a result, output is lower while pollution level is higher.

To guide our analysis, we use a neoclassical growth model with heterogeneous production units (*a lá* the Lucas (1978) span-of-control model) featuring product market frictions, imperfect environmental monitoring and endogenous pollution treatment technology choice (clean and dirty). In our model, there is a stand-in representative household with a continuum of members that are endowed with different managerial talents. Household members make occupational choice decisions

[4]Other studies using either data from other countries or from a selective group of Chinese firms also point to the negative correlation between firm size and pollution intensity (see, for instance Shapiro and Walker (2015) for the U.S; Dasgupta, Lucas, and Wheeler (1998) for Brazil and Mexico; and Bloom, Genakos, Martin, and Sadun (2010) for energy use in the UK).

[5]See Axtell (2001), Luttmer (2007) and Rossi-Hansberg and Wright (2007) for theories and evidence regarding the heavy right tail of U.S. firm distribution.

based on their talents before entering the economy. The novelty of our model lies in that upon entering the market, the entrepreneurs have to make decisions on which treatment technology to install. The installation of clean technology requires some fixed costs, however, firms with clean technology will not be punished by the environmental agencies. In this paper, we focus mainly on firms' choices of treatment technologies and capture the decrease of pollution intensity during the production stage in a reduced-form way. The optimal scale of operation of a firm is determined by the managerial talent of the entrepreneur and the frictions that the firm faces. Therefore, for a given distribution of managerial talents and market frictions, the model implies a distribution of firm sizes and employment. Environmental policies change the cost and benefit of the two technologies, and subsequently affect the treatment technology firms use.

To discipline our quantitative analysis, we require that our benchmark model with product market frictions matches the firm size and employment distributions observed in China. We then conduct two counterfactual experiments: in the first one we eliminate the product market frictions completely, while in the second we increase the regulation such that the fraction of firms adopting clean treatment technology is the same as in the first experiment. We subsequently calculate and compare measures of output, consumption, productivity and aggregate pollution among other variables in these steady states.

Our quantitative results show that elimination of product market frictions increases output by 30%, increases the fraction of firms using clean technology by 27% and decreases pollution by 20%. The improvement in output is expected, since the elimination of frictions in the model yields the first best solution. The cut in pollution comes from both the reduction in pollutants generated during the production stage and the increase in adoption rate of clean treatment technologies at the treatment stage. Each stage contributes to about 50% of the total reduction. The expansion of productive firms is key to both channels. On the other hand, environmental policy which strengthens the regulation reduces pollution by only about 10% and has very little effect on output. The environmental policy improves resource allocation on the *extensive* margin by driving small unproductive firms out of the economy. However, the allocation worsens at the *intensive* margin in the sense that among the remaining active firms, the production of medium sized firms expands more at the expense of large firms.

To assess quantitatively the importance of the size-dependency of these frictions, we solve a version of the model where all firms in the economy face the same level of frictions. In our model, the size-dependency of the frictions do not imply large output loss. However, size-dependency of the frictions assumes a center role in determining the pollution level. This finding is consistent with Hopenhayn (2014). The author shows that it is the total amount of resources that are affected that determines the effects of the frictions as opposed to who are affected. Our results complement his findings by demonstrating that while which firms produce does not hold a decisive role in determining the aggregate output, it matters a lot in pinning down the pollution level.

Our findings call for a change in the ways of addressing the pollution issue pairing urbanization and industrialization. The literature has blamed the GDP-oriented promotion scheme as the source of aggravated industrial pollution [Jia (2014) and Jiang, Lin, and Lin (2014)]. In this paper we emphasize on the roles of product market frictions and firm size distribution. From a policy perspective, we urge for policies that target reducing economic frictions which prevent talented entrepreneurs from operating their business at efficient scale necessary for the adoption of environmentally friendly technologies. In fact, one implication of our results is that GDP-oriented promotion scheme does not necessarily lead to increased environmental pollution. In such circumstances, a double-dividend is possible [Goulder (1994)].

Related Literature.—Our paper contributes to several strands of literature. First, we contribute to a broad literature analyzing the environmental consequences of economic activities. Modern discussions in this area are usually traced back to the seminal work by Grossman and Krueger (1993, 1995) where the two authors documented an inverse U-shaped relationship between various metrics of pollution levels and output per capita. This relationship, due to its resemblance of the famous Kuznets curve [Kuznets (1955)], is thus referred to as the *environmental Kuznets Curve* (EKC) in subsequent literature. The trade community has devoted considerable efforts to studying the underlying economic mechanisms of the EKC. Copeland and Taylor (2004) provide a thorough and complete survey of the early contributions. Most of those studies focused on decomposing the pollution to the scale, technology and industry composition effects using reduced-form methods. There is however, a very recent growing literature on CO_2 emissions in the trade community where heterogeneous firms models are involved theoretically [Barrows and Ollivier (2014a,b) and Shapiro and Walker (2015)]. We view our approach as complementary to that work. In this paper, we build a macroeconomic model with rich quantitative implications which facilitates the investigation of policy related questions. Our focus on the firm size distribution and treatment technology adoption also distinguishes our paper from that literature, which studies the roles of product mix, consumer preference, etc. In connection with literature focusing on the cross-country comparison of firm size distributions [Poschke (2014)], our paper is also a candidate of structural interpretations of the EKC.

There is also a growing literature studying the causes of China's industrial pollution. In accordance with the views widely covered by the media and these studies almost universally reach the conclusion that political issues like the GDP-oriented political objectives [Wang, Webber, Finlayson, and Barnett (2008), Jia (2014)] and differential policy treatment due to firms' ownership rights structures [Jiang, Lin, and Lin (2014)] are to be held responsible for the massive pollutant discharge. In this paper, we argue that at the micro level, the effects of economic frictions also play a major role. In fact, we think political factors are more likely acting as amplifying the effects of economic frictions. Policy prescriptions aiming at reducing such economic frictions are thus more likely to overcome the problems of poor implementations and quick rebound that are constantly disturbing policy makers. Another difference between our paper and these studies is that we have access to a universal coverage database which contains information on *directly observed* firm-level discharge of various pollutant.

Furthermore, our paper is closely related to an important and growing literature on misallocation of resources across heterogeneous production units and its implications on macroeconomic aggregates. The early contributions along this branch are seminal work from Hopenhayn (1992) and Hopenhayn and Rogerson (1993).[6] Our paper relates particularly to Guner, Ventura, and Xu (2008) and Adamopoulos and Restuccia (2014) where the role of size-dependent policies is examined. We contribute to this literature in two ways. First, we provide empirical evidence on the potential role of product market frictions in generating differences in size distributions between China and the U.S, using the *indirect* approach by Hsieh and Klenow (2009, 2014). Second, we extend the discussion of implications of size distribution on aggregate output and TFP to aggregate pollution.

Lastly, our paper also connects to the literature on technology adoption in macroeconomics. The seminal work by Parente and Prescott (1994) introduces frictions in technology adoption as a candidate for generating the cross-country productivity difference. A number of papers were dedicated to understanding technology diffusion since then. This paper investigates in particular the role of product market frictions and size distribution in impeding the adoption of clean production technology. Along this line, our paper inherits some intuitions from two early studies in economic history about tractors in U.S—Clarke (1991) with the role of market frictions and Olmstead and Rhode (2001) with the role of size distribution. We also view our study as complementary to the paper by Acemoglu, Aghion, Bursztyn, and Hemous (2012). There the authors primarily analyze the optimal policies to promote the advancement of clean production technology while our paper answers the related question of under what circumstances will these newly invented technologies eventually be installed by firms.

The article proceeds as follows. The next section documents facts pertaining to pollution intensity differences across firms and the comparison of firm size distributions between China and the U.S. We describe the model in Section 3 and calibrate its benchmark version in Section 4. In Section 5 we perform various quantitative experiments to study the interaction between product market frictions and environmental policies. We conclude in Section 6.

2 Empirical Evidence

In this section, we document the key empirical findings regarding the size-intensity relationship and the comparison of size distributions between China and the U.S that motivate our study. We start with a brief introduction of the data that we use. We then move on to explain the empirical findings. Using an accounting exercise, in the last section, we show that size distribution has a

[6] See Restuccia and Rogerson (2008), Guner, Ventura, and Xu (2008), Hsieh and Klenow (2009) and Adamopoulos and Restuccia (2014) for recent discussions amongst others.

sizable effect on aggregate pollution.

2.1 *Data Sources*

There are three major data sources that we draw upon in this paper: (i) the First National General Survey of Pollution Sources, (ii) the First China National Economic Census and (iii) the Statistics of U.S. Businesses. These three data sources are used to calculate the pollution intensity of Chinese manufacturing firms and the size and employment distributions of manufacturing firms in China and in the U.S. They are referred to in the remainder of this paper respectively by their acronyms NGSPS, CNEC and SUSB.

National General Survey of Pollution Sources.—The NGSPS is a joint effort of multiple national ministries in China including Ministry of Agricultural, Environmental Protection, Commerce, etc, led and coordinated by the State Council. The survey records data for year 2007. It is designed to cover all entities and self-employed households which have pollution sources within the borders of the People's Republic of China. The complete survey consists of four components: industrial pollution sources, agricultural pollution sources, domestic pollution sources and facilities for centralized treatment of pollution. For the purpose of this paper, we use only information from the industrial pollution sources. The variables we use are: quantity of major pollutant generated and discharged, total value of production, book value and annual operating costs of pollutant treatment equipments, type of treatment equipments, firm's industry (four-digit GB/T4574-2002), ownership classification and province. Specifically, the NGSPS contains information on discharges of air and water pollutant and solid waste. For measurement accuracy, here we focus on water pollution only. However, we expect that the main results of this paper could be applied to other pollution sources as well. The raw data contain over 900 thousand firms.

China National Economic Census.—The CNEC is conducted by the National Bureau of Statistics (NBS, henceforth) in year 2004. It is designed to cover all legal entities, industrial entities and privately-owned businesses which undertake economic activities in secondary and tertiary industries within the borders of the People's Republic of China. For our purpose we use observations which belong to the manufacturing sector. The variables we use are: total value of production, labor compensation, book value of capital stock, number of employees, firm's industry (four-digit GB/T4574-2002), ownership classification and province. [7] The number of firms covered in NGSPS

[7] We emphasize here that it is important that we use the CNEC rather than the *Annual Surveys of Industrial Production* for which data of year 2007 is available (the same year that the NGSPS covers). The reason is that CNEC surveys firms of all scales as opposed to only firms with revenue more than CNY 5 million in the case of the annual surveys. Put in 2004 scale, the number of firms and employees covered by the annual survey are respectively 276,410 and 66,725,059 while those covered in the census are 1,375,148 and 93,541,923. Therefore we will be missing 28.6% employment and 79.9% firms had we used only the annual survey. However, basic features like variable definitions are essentially the same in these two datasets. Therefore we strongly encourage the readers to read Brandt, Biesebroeck, and Zhang (2012), which did a magnificent job in describing the annual surveys.

TABLE 2.1
PERCENTAGE OF FIRMS WITH POSITIVE EMISSION BY POLLUTANTS

	Waste	COD	Petro	NH_4^+	BOD	CN	Cr^{6+}	Phenol	As	Cr	Total
Key	76.2	73.2	31.4	25.2	17.5	4.90	4.86	2.42	2.27	2.01	106,067
Reg	35.2	28.3	7.91	6.49	2.56	0.13	N/A	0.04	0.07	N/A	814,937

† Data Source: National General Survey of Pollution Sources. The acronyms are respectively referring to: Wastewater, Chemical Oxygen Demand, Petrochemicals, Ammonian, Biochemical Oxygen Demand, Cyanidium, Hexavalent Chromium, Volatile Phenols, Arsenium and Chromium.

and CNEC, 900 thousand and 1.3 million are broadly consistent given that NGSPS further requires that a production entity to have pollution sources in order to be included.

Statistics of U.S. Businesses.—The SUSB is conducted by the U.S Census Bureau and is an annual series that provides national and subnational data on the distribution of economic data by enterprise size and industry. It contains the number of firms and total employment by sector (up to six-digit 2002 NAICS) and enterprise size groups which we utilize among other variables.

2.2 *Firm-level Pollution Intensity*

It is well established in environmental science that industrial waste is typically concentrated in only several sectors. Furthermore, even within narrowly defined manufacturing sectors, pollutant emissions are usually concentrated among firms that engage in some particular manufacturing processes. To address this issue, the NGSPS divide the complete sample into two large groups—*key sources* and *regular sources*—where firms identified as "key sources" are broadly speaking those that are most polluting. We use only the key firms in this article because the inclusion of regular firms introduces a large number of firms that are not closely related to industrial pollution and will contaminate the quality of our estimates. In addition, among all the pollutants covered, for brevity consideration we use *Chemical Oxygen Demand* (COD, henceforth) as an example in the main text. COD is the amount of oxygen consumed when a chemical oxidant is added to a sample of water. It is an indirect measure indicating the overall quantity of contaminants that will eventually cause oxygen loss and thus death of living creatures. We choose COD because it allows us to keep most observations from the data. Other pollutants are discharged by significantly less number of firms which raises sample selection issue. These two points can be seen in Table 2.1, which lists the percentage of firms that have positive emissions of different pollutants. Finally, we focus on the *measured* end-of-pipe discharges and present results for the top-5 polluting industries (see Figure 2.1 for their relative contributions).

Table 2.2 contains basic statistics about these industries. We see from it that the key firms in the top-5 polluting industries are fairly representative of China's industrial polluting situation: in particular, these industries combined contribute to 77% of the total industrial COD emission; the

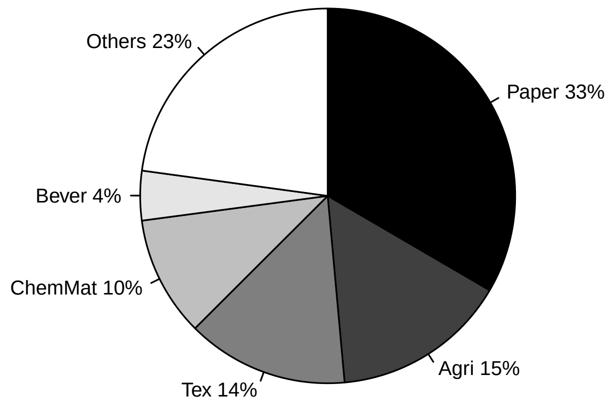

FIGURE 2.1.—COD EMISSION BY SECTORS

key firms are responsible on average for more than 90% of the within sector emission and for more than 80% of the within sector output.

We define pollution intensity per unit value of production as

$$\text{Intensity} = \frac{\text{Total COD Emission}}{\text{Total Value of Production}}$$

The scatter plots along with the least square lines of the logarithm of intensity against that of the total value of production for the top-5 polluting industries are presented in Figure 2.2 (except the bottom-right one).

As is shown in Figure 2.2, for all the five industries, there exists negative correlation between log-intensity and log-production in the data.[8] We then regress the log-intensity (y_i) on the log-production (V_i) including a complete set of provincial ($\mathbf{X_p}$) and ownership rights ($\mathbf{X_o}$) dummies for each industry:

$$y_i = \beta_0 + \beta_1 V_i + \mathbf{X_p}\beta_2 + \mathbf{X_o}\beta_3 + \varepsilon_i \tag{2.1}$$

[8]One exception is Chemistry Materials, the middle right panel. Further investigation into the data reveals that the reason that we do not observe a negative correlation in the Chemistry Material industry as clear as in the other industries is because there are many sub-industry level heterogeneities pooled at the two-digit level. To show that this is indeed the case, we repeat the exercise for the top polluting four-digit industry within the Chemistry Material industry, Nitrogen Fertilizer (C2621) which ranks the sixth among all four-digit industries. The result is shown in the lower right panel of Figure 2.2, where the negative correlation is clear. Put differently, the "circle" we see in the Chemistry case is in fact a combination of several "ellipses", each with a downward sloping transverse diameter. We have also plotted these figures using the residuals from regressions (2.1) and (2.2). The results are almost the same. This is confirmed by including four-digit industry dummy in the regression for Chemistry industry specified below. After introducing four-digit industry dummies, the magnitude estimates for β_1 increases to -0.21 and the R^2 increases to 0.26. Both numbers are now of comparable magnitudes with the other industries.

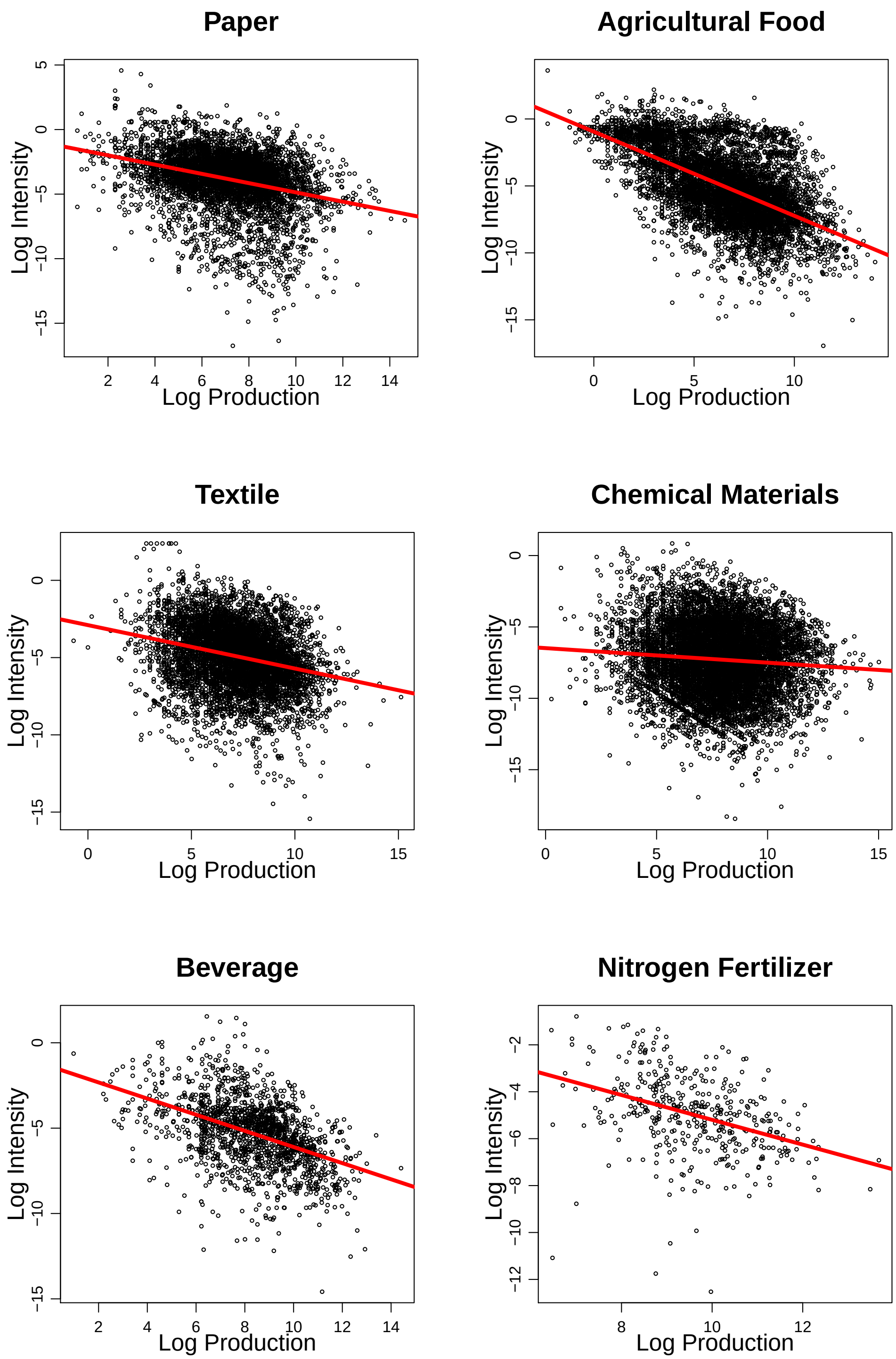

FIGURE 2.2.—INTENSITY AGAINST PRODUCTION

Source: National General Survey of Pollution Sources. Dots: Pollution intensity against total production; Lines: Least square fit. See notes under Table 2.2 for the reference of the acronyms.

TABLE 2.2
STATISTICS OF TOP-10 POLLUTING INDUSTRIES BY COD

	Paper	Agri	Tex	Chem	Bever	Med	Fer	Petro	Food	Fib
Frac[a]	33.4	15.2	14.0	10.4	4.27	2.98	2.49	2.32	2.30	2.15
% Emi[b]	99.6	91.8	91.1	99.7	65.1	92.9	99.9	99.9	96.4	97.8
% Pro[c]	87.2	69.3	48.3	98.6	88.1	95.7	99.3	99.7	98.5	91.9

† Data Source: National General Survey of Pollution Sources. The acronyms are respectively referring to (with two-digit GB/T4547-2002 classification code in the parentheses): Paper and Paper Products (C22); Processing of Food from Agricultural Products (C13); Textile (C17); Raw Chemical Materials and Chemical Products (C26); Beverages (C15); Medicines (C27); Mining, Smelting and Pressing of Ferrous Metals (C32); Processing of Petroleum, Coking, Processing of Nuclear Fuel (C25); Foods (C14); Chemical Fibers (C28).

[a] Relative contribution to total COD emissions by sectors.

[b] Percentage of total COD emissions accounted for by key firms.

[c] Percentage of total production accounted for by key firms.

We then run a pooled regression with two-digit industry dummy specified by $\mathbf{X_s}$:

$$y_i = \beta_0 + \beta_1 V_i + \mathbf{X_p}\beta_2 + \mathbf{X_s}\beta_3 + \mathbf{X_o}\beta_4 + \epsilon_i \tag{2.2}$$

Regression results from (2.1) and (2.2) are shown in Table 2.3. Estimation results in Table 2.3 confirm observations in Figure 2.2. The intensity-production elasticities β_1 are all accurately estimated to be negative and they are also of economic significance. The R^2 shows that a fair amount of variation observed in the intensity is changing with production scale. As a crude calculation, the coefficient -0.37 on $\log V_i$ for the pooled case implies that by doubling the production scale, the COD discharged per unit production will decrease by 37%.

2.3 *Firm Size and Treatment Technologies*

The negative size-intensity relationship we document in Section 2.2 does not explain why larger firms pollute with less intensity. To answer this question, we exploit the detailed information in the NGSPS on the *end-of-pipe* wastewater treatment equipment that firms use. The NGSPS groups wastewater treatment technologies in five categories: *physical, chemical, physio-chemical, biological* and *combined* technologies. In the subsequent analysis, we drop physio-chemical technologies because less than 0.5% firms adopt this type of equipments. The combined technologies are different combinations of biological technology with other technologies. They demonstrate very similar features as biological technologies. We therefore further group them with biological technologies. Several examples of the actual technologies attributed to the three base categories (physical, chemical and biological) are provided below:

(i) Physical: Filtering, Centrifuging, Precipitation Separation, etc.

TABLE 2.3
OLS REGRESSION RESULTS

Parameters	Paper	Agri	Textile	Chem	Bever	Pooled
β_0	-4.25^{***}	-2.23^{***}	-3.73^{***}	-7.17^{***}	-2.82^{***}	-2.50^{***}
	(0.56)	(0.26)	(0.57)	(0.33)	(0.38)	(0.17)
β_1	-0.30^{***}	-0.61^{***}	-0.31^{***}	-0.13^{***}	-0.45^{***}	-0.37^{***}
	(0.01)	(0.01)	(0.01)	(0.01)	(0.02)	(0.01)
R^2	0.22	0.46	0.14	0.08	0.29	0.37
N	5626	6883	6281	8672	1557	29019

† Note: All regressions include complete sets of provincial and ownership rights dummies. The pooled regression includes in addition two-digit industry dummies. OLS standard errors are reported in parentheses. Regressions with robust standard errors clustered on provinces (industry level regression) and industries (pooled regression) yield very similar results are reported only in the online appendix for brevity. Statistical significance code: *** $p < 0.001$.

TABLE 2.4
TREATMENT EFFICIENCIES AND ADOPTION RATES

Technology	25%	Median	75%	Mean	Adoption Rates
Physical	39.54%	77.81%	87.83%	63.37%	25.79%
Chemical	74.96%	81.29%	86.78%	69.77%	34.50%
Biological	78.87%	86.77%	91.27%	80.90%	39.71%

† Note: The numbers reported are for the Paper and Paper Product (C22) industry. Treatment Efficiencies is defined as $1 - \text{COD Emitted}/\text{COD Generated}$.

(ii) Chemical: Oxidation-reduction, neutralization, etc.

(iii) Biological: Aerobic Biological Treatment, Activated Sludge Process, etc.

We are interested in the following features of these technologies: processing efficiency, designed processing capacity and installation costs. We do not include the annual operating costs in our analysis because on average, the ratio of operating costs of the treatment equipments on the annual value of production is about 1.5%. Furthermore, the median of this ratio is less than 0.5%, suggesting that operating costs are almost negligible for more than 50% of the firms. To control for potential heterogeneities in production processes across different industries, we use the Paper and Paper Product industry (C22) as an example. Pooling all polluting industries together yields very similar results and in the interest of space we do not include them in the main text. We proxy the processing efficiency using one minus the ratio of emitted COD to generated COD. Table 2.4 shows the quartiles of processing efficiencies and percentage of firms adopting each type of technology. The designed processing capacity (in tons) and actual installation costs (in 2007 CNY) that are needed for the equipments to function properly can be retrieved directly from the data.

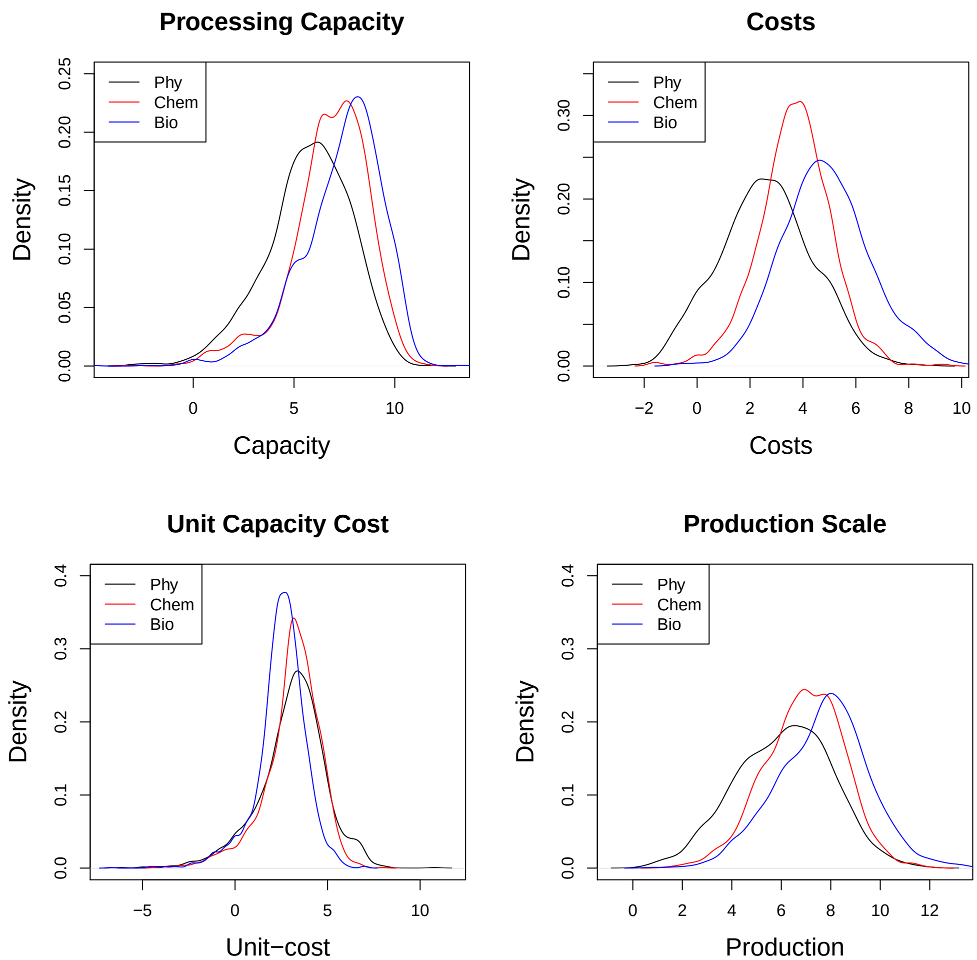

FIGURE 2.3.—TECHNICAL FEATURES OF DIFFERENT TREATMENT TECHNOLOGIES

Source: National General Survey of Pollution Sources. In all panels, the horizontal axes are in log-scale.

We then calculate the unit capacity costs by dividing the installation costs by capacity. We use the unit capacity costs as an indicator of returns to scale of treatment equipment. In Figure 2.3, in clockwise order we plot the density functions of processing capacity, installation costs, total value of industrial output and unit capacity cost by technology types. For all panels, log-scale is used in the horizontal axes.

Broadly speaking, biological technologies have the best processing efficiency, the largest processing capacity, the highest installation costs but the lowest unit capacity cost. More specifically, the mean (median) processing efficiency of biological technology is 17% (10%) higher than the physical technology. The evidence points to a fixed costs type of mechanism behind the less pollution intensity by large firms. In particular, although biological technologies are more advanced in terms of processing capacity and efficiency, they are also more costly. Therefore, small firms lack the profit margins that are needed to take advantage of the returns to scale exhibited by biological technologies, thus large firms are more likely to adopt these more advanced technologies.

Notice that the above results are all about the *end-of-pipe* treatment technologies and we made no statement about factors that could lead to less COD *generated*. In fact, in the data the COD generated per unit of production is also decreasing in total value of output. It is possible that more productive technologies are also more energy-efficient and environment-friendly. An example from the *Handbook of Emission Coefficients* by the *Chinese Academy of Sciences* is as follows. Two technologies in paper pulp manufacturing use different inputs: bagasse and wood. While bagasse is used mostly by firms with annual production of less than 100 k-tons with COD generation of 140-180 kg per ton, wood is used mostly by firms with annual production more than 100 k-tons with COD generation of 30-55 kg per ton. In this paper, we focus on firms' decisions on treatment equipments adoptions. Discussions about the intensity reduction during the production process are beyond the scope of the current paper. Using data of more than 300 manufacturing firms in UK, Bloom, Genakos, Martin, and Sadun (2010) show that better management practices are associated with both improved productivity and lower greenhouse gas emissions.

2.4 *Firm-Size Distributions*

The negative correlation between the pollution intensity and production scale implies that, ceteris paribus the relative contribution to total output by large and small firms could significantly affect the industrial pollution at the aggregate level. Therefore, for our purpose, it is pivotal to understand the industrial structure—the number, size and employment of firms—in China. To gauge our comparison, we look at size and employment data in the U.S as a yardstick. We choose the U.S to be a benchmark of the comparison for two reasons. First, it is generally agreed among macroeconomists that among all the economies in the world, the U.S economy is perhaps the closest counterpart to an undistorted market economy. Firms in many European countries are subject to various labor market restrictions and hence their distributional properties are less likely to be representative of a frictions-free benchmark. Second, China and U.S are both gigantic economies with complete sets of industrial sectors. For disaggregated studies like ours, it is important that we find comparable counterparts in the benchmark country. Contrasting the industries in China with those in European advanced economies, it would be problematic to find comparable counterparts, or the corresponding industries are of significantly smaller production scale on aggregate.

The distribution of employment by firms of different sizes is the closest related concept to our analysis. Ultimately, what is crucial to the quantity of pollutants discharged is how much production is produced by small and large firms respectively, not how many of them there are in the economy. Employment is a nice proxy for production share because it has been firmly established that labor compensation is strongly correlated with total production. Nevertheless, we provide evidence on both the size and employment distributions in this section for the ease of connection of our results with those in previous studies. We use the *International Standard*

Industrial Classification of All Economic Activities, Rev.3.1 (ISIC Rev 3.1) published by the United Nations to bridge different industrial classification systems adopted by China (GB/T4574-2002) and the U.S (NAICS 2002). More specifically, crosswalks of GB/2002 at four-digit level and those of NAICS/2002 at six-digit level are issued by China's NBS and the U.S Census Bureau. The results presented in this section are from matching at the disaggregated level (four-digit GB with six-digit NAICS). However, those from matching at a more aggregated level (two-digit GB with three-digit NAICS) yields very similar results.

The SUSB organizes data according to enterprise size group rather than firm or establishment size which relates closer to what we want. In particular, for each size bin, the SUSB reports the total number of firms, establishments and employees along with other variables summed up across all enterprises that fall in that size bin. We cannot use the size and share distribution of the enterprises because according to the definition in SUSB, a large enterprise could consist of firms and establishments in different locations, of different sizes and even in different sectors. However, the number of firms includes only those firms that are categorized as belonging to one particular industry. Therefore, we approximate the firm size distribution using the average firm size of a particular size group, which is calculated by dividing the total employment by the number of firms. We then assign groups of firms to different size bins according to their average size. Such imputation introduces approximation errors in a complex way. However, we argue that most approximation errors lie in the upper tail of the distribution since it is less common for enterprises with less than 200 employees to have multiple firms or establishments. To further reduce the approximation noise, we group the size bins into four main groups: 1–19, 20–99, 100–399 and 400+. We drop firms with less than 19 employees when plotting the size distribution because we think many of them may not be engaged in the actual production process but will significantly change the shape of the *size distribution*. Including or dropping these firms does *not* change the employment distribution because the calculation is essentially a weighted average with the number of employees as the weight. These small firms are thus weighted much less compared to the large ones. However, the firm size distributions are affected because the sheer amount of these firms.[9]

The employment distributions for each of the top polluting industries and all industries pooled together are shown in Figure 2.4. Similarly, those of the firm size distributions are contained in Figure 2.5.

For all panels in Figure 2.4, we see that the number of workers employed by firms with more than 400 employees in the U.S are significantly higher than those in China. More specifically, for the paper manufacturing industry, more than 90% of the workers in the U.S are hired by firms with more than 400 employees while in China, the number is less than 40%. Overall, looking at these

[9]We choose not to use establishment as the unit of our analysis because more noise is likely to be introduced by the approximation procedure that we adopt. However, results regarding the employment distributions, which are our ultimate interest here, is quite robust across variations. What is less robust is the firm size distribution, which by itself is less relevant to our conclusions.

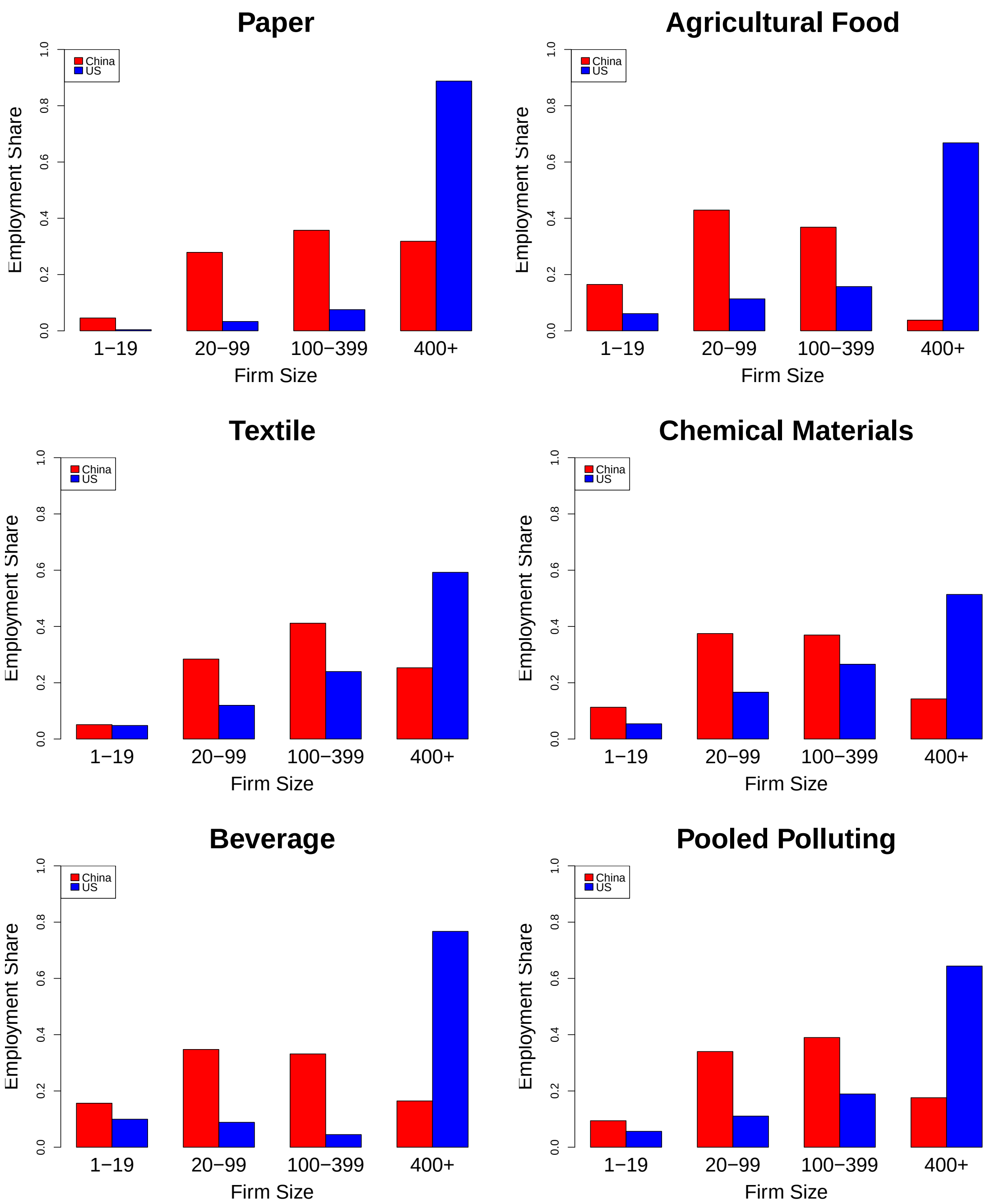

FIGURE 2.4.—EMPLOYMENT DISTRIBUTION

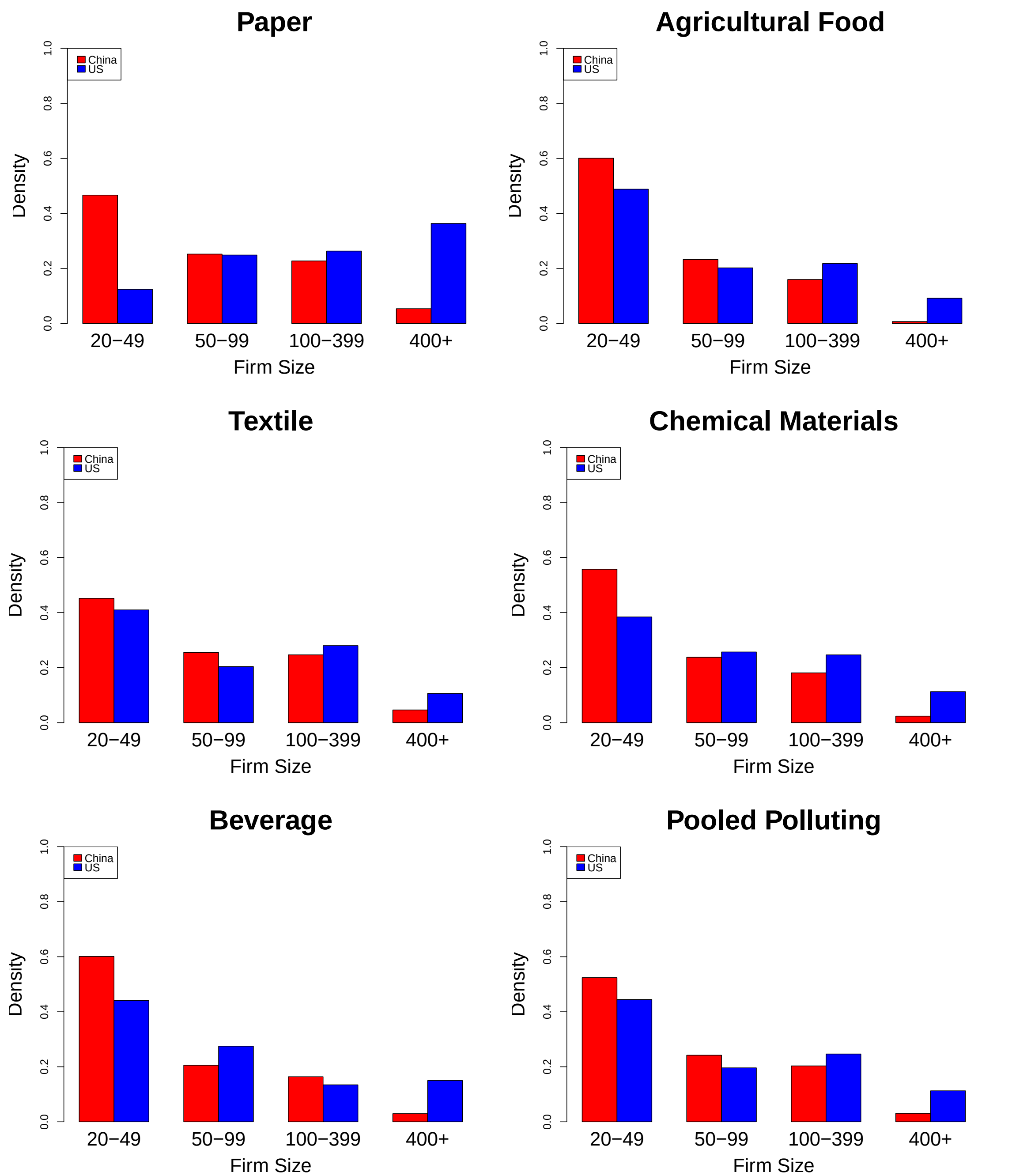

FIGURE 2.5.—FIRM SIZE DISTRIBUTION

industries together, approximately 70% employment is in the large firms in the U.S while in China the number is only 20%.[10] These features of the data are consistent with Wang and Whalley (2014) where the authors compare the manufacturing concentration ratio (the share of market occupied by the largest firms) between China and the U.S. According to Table 1 in their paper, the ratios of the concentration indicators of U.S over China for all five top polluting industries are higher than the overall average.

These findings indicate that comparing to China, much larger portion of production is done by firms with large production scale in the U.S. Hence the underlying industry structure difference could be a candidate for explaining the high industrial pollution emissions in China.

2.5 *Size Distribution and Aggregate Pollution*

To gain an understanding of the size of the quantitative effect of employment distribution on aggregate pollution, in this section we conduct an accounting exercise. In this exercise, for each polluting industry in China, we fix the level of total industrial production, but replace the employment distribution (which we use as a proxy for production share distribution) with that from the U.S and calculate the subsequent implied level of aggregate industrial pollution. This simple exercise is complicated by the fact that NGSPS only reports the firm-level total value of production but not the number of employees. We use CNEC to overcome this issue. There are many ways to construct the employment-production relationship using CNEC and each method has its own advantages and disadvantages. In this section, we report results where the employment-production relationship is constructed by linear regression. We provide the details of the calculation and results of two alternative estimation methods in Appendix A.

The results are shown in Table 2.5. The numbers reported are the ratio of the aggregate pollution level produced with the U.S employment share distribution over that with the original Chinese distribution. The results imply that by changing the employment share distribution to that of the U.S, while keeping production at the same level, the aggregate discharge in the Paper and Paper Product industry reduces to 43.5% of the original level. The size of such reductions decreases as the overall contributions (i.e., row one in Table 2.2) decrease. The scale of the reduction for each industry is broadly proportional to the industry's contribution to the aggregate pollution. On average, for the top-5 polluting industries, the effect of change in size distribution is reduction of discharge to 67% of the original level. Changing the size distributions of the five industries together will achieve a reduction in total discharge by about 25.5%. Although the exercise here is a crude approximation, it nevertheless shows that size distribution could have a significant impact on the level of aggregate industrial pollution.

[10] The contrast is less stark in Figure 2.5, where firm size distributions are presented. For the most polluting industry, paper manufacturing, the difference is still apparent with around 40% of the U.S firms with more than 400 employees, but less than 10% of those in China. But the pattern is less pronounced for other industries and all polluting industries combined.

TABLE 2.5
SIZE DISTRIBUTION ON POLLUTION

	Paper	Agri	Tex	Chem	Bever	Avg	Reduc
Average Intensity	43.5%	61.1%	97.5%	101.2%	89.0%	67.0%	25.5%

† Note: Please see notes of Table 2.2 for acronyms of industries. For individual industries, the numbers reported are the aggregate pollution from the artificial U.S production structure as percentage from that of China. Column 6 (Ave) calculates the weighted average of these ratios using the percentage contribution in row one of Table 2.2 as weights. Column 7 (Reduc) reports the aggregate reduction, which is simply the average without normalization.

3 THE MODEL

We consider a one sector neoclassical growth model with heterogeneous production units featuring product market frictions, imperfect environmental monitoring and endogenous treatment technology choice. There is a stand-in representative household with a continuum of members in the economy. Each period household members make occupational choices on whether to work as a wage-earner or to become an entrepreneur based on their comparative advantages. Without loss of generality, we assume there are two types of treatment technologies—dirty and clean. An entrepreneur has to choose between the two upon starting business. The two technologies could be interpreted as the physical and biological technology we discussed in Section 2.3. We use physical/dirty and biological/clean interchangeably in the rest of the paper. The environmental regulator imperfectly monitors the installation of clean technology which requires fixed installation costs. If a firm is inspected and is found to be using dirty technology, it receives a penalty.

3.1 *Setup*

Household.—Assuming that there is perfect risk sharing within the household, the preference of the household could then be characterized by

$$\sum_{t=0}^{\infty} \beta^t U(C_t) \tag{2.3}$$

where C_t is the consumption at time t and β is the discount factor. Each household member is endowed with z units of managerial talent, $z \sim G(z)$ with support $Z \triangleq [0, \overline{z}]$, where $G(z)$ is the cumulative density and $g(z)$ is the probability density. We assume the support and distribution of z are exogenous. Further we assume that z is fixed once drawn. Household members face an occupational choice decision between worker and entrepreneur. A worker supplies one unit of labor inelastically in exchange for wage income and an entrepreneur rents capital and labor to run a neoclassical firm and earns profits. Let the final product be the numeraire and R and W be the capital and labor rental price respectively. Firms and capital are owned by the household.

Firms.—Firms combine managerial talent z, capital k and labor n to produce output y according to technology

$$y = F(z, k, n) = z^{1-\gamma}(k^{\alpha}n^{1-\alpha})^{\gamma}$$

where $\gamma < 1$ is the span-of-control parameter. The assumption of decreasing returns to scale with respect to k and n supports a non-degenerate distribution of firms.[11]

The production process generates pollutants e as by-products. The total emission depends on the production scale y and the treatment technology firms use

$$e = E(i, y) \tag{2.4}$$

where $i = 1$ indicates the adoption of clean technology and $i = 0$ otherwise. The installation of the clean equipment incurs fixed costs k_E. The benefit associated with the equipment is that firms will not be subject to potential penalties from the regulating agency for using dated treatment technologies.[12]

Regulators.—We assume that the environmental authority monitors the adoption of clean technology by firms with probability p. When a firm that uses dirty production technology gets caught, we assume that a fraction ξ of its total profits is confiscated by the regulating agency. The confiscated profits are distributed to the household as lump-sum transfers so they do not affect the decision problem of household members. This reduced-form way of modeling monitoring policy could for instance be rationalized by a mixed strategy Nash Equilibrium of a behind-the-scenes "monitoring game".

The current industrial pollution management and control framework in China consists primarily of economic incentives and command-and-control instruments.[13] The pollution levy system is the most widely used economic instrument in China. However, it has been widely documented that it places very limited constraint on the pollution emission of the firms because the penalty imposed is very low. Firms only have to pay for the pollutant discharges that go beyond the national standard. The pollutant discharges are self-reported and the truthfulness of the reported discharges is imperfectly examined by the regulators. Further, for firms that discharge multiple pollutants and more than one of the pollutants discharged are above the national standards, firms only have to pay for the one that leads to the highest penalty. We calculate from the CNEC the pollution fees levied on firms as a fraction of total value of output and labor compensation. We

[11] We build our model based on Lucas (1978) here. However, all the qualitative properties of our model remain valid if we instead use a model with monopolistic competition [Melitz (2003)] since the two models are isomorphic [Appendix I of Hsieh and Klenow (2009)]. In the Melitz model, the decreasing returns to scale come from the concavity in the utility function.

[12] We choose to model the installation costs as one-time fixed costs as opposed to fixed costs plus operating costs or size-dependent fixed costs because the latter two are not supported by empirical evidence. We also assume that the fixed costs are only associated with clean technology.

[13] See Chapter 5 of World Bank (2001) for a detailed description.

find that for firms with strictly positive emission fees, these fees only account for 0.8% (median) and 3.1% (mean) of the labor compensation. The corresponding median and mean are respectively 0.06% and 0.3% when evaluated as a fraction of output.

Therefore in practice, the environmental agencies rely mostly on the command-and-control instruments. To implement the regulation, field inspections are done by the staff of local environmental agencies. Using data from the Environmental Protection Bureau in Zhenjiang, Dasgupta, Laplante, Mamingi, and Wang (2001) showed that at the firm level, compared to variations in pollution levies, variations in the number of field inspections better explains the variations in pollution levels. At the firm level, field staff typically check the type of treatment equipment firms installed and test emission intensity of major pollutants. Firms that are found at fault during the field inspection are usually suspended from production for an extended period of time until the issues are resolved. In cases of serious pollution accidents which lead to grave consequences, criminal charges are imposed on the owner of the firm. In our model, the fraction ξ of the profits confiscated is used to approximate these situations. Since according to Table 2.4, the treatment technology used by firms is highly correlated with the pollution intensity, without loss of generality we assume that the regulator in our model checks only the treatment technologies. Although the local environmental agencies also monitor the total amount of discharges, these regulations are usually done at more aggregated level, in most cases based on the provincial-level aggregation. They thus are less relevant to the firm-level decision that we study here.[14]

3.2 *Product Market Frictions*

Chinese firms face large frictions on both the product market and factor markets [Hsieh and Klenow (2009), Brandt, Tombe, and Zhu (2013) and Song and Wu (2013)] and these frictions could have sizeable effects on the size and employment distributions of firms as well as other macro aggregates [Guner, Ventura, and Xu (2008), Restuccia and Rogerson (2008) and Adamopoulos and Restuccia (2014)]. In this section, we provide evidence on the identification of these frictions and subsequently our modeling choice of the prevailing market frictions.

We follow Hsieh and Klenow (2014) by inferring factor and product market frictions from the average factor products. In particular, if we let τ_{y_i}, τ_{k_i} and τ_{l_i} be respectively the wedges firms face

[14] Firm level inspections in the U.S are also targeted mainly on the adopted treatment technologies. For example, as is stated in the 1977 Amendment of the Clean Air Act, each July every county in the U.S will be classified as either an attainment or a non-attainment county according to their overall pollutants emissions level. Firms in non-attainment counties are subject to substantially stronger environmental regulations. For instance, newly established firms in these counties are required to meet the standard of Lowest Achievable Emission Rate (LAER) which demands the installation of the cleanest possible technology supposedly regardless of costs. While on the other hand, in attainment counties only Best Available Control Technology (BACT) which incorporates cost considerations is required. Similarly, existing firms are also subject to stricter regulations on production and end-of-pipe treatment technologies in non-attainment counties than in the attainment counties. See Becker and Henderson (2000) and the references therein for more details.

on the product, capital and labor market, the profit maximization problem of firm i is

$$\pi_i = \max_{k_i, l_i} \left\{ (1-\tau_{y_i}) z_i^{1-\gamma} (k_i^{\alpha} l_i^{1-\alpha})^{\gamma} - (1+\tau_{k_i}) R k_i - (1+\tau_{l_i}) W l_i \right\}$$

Substituting in the first order conditions, the average product of capital ϕ_k, labor ϕ_l and the capital-labor ratio κ could be expressed as

$$\phi_k = \frac{y}{k} = \frac{(1+\tau_{k_i})R}{\alpha\gamma(1-\tau_{y_i})} \tag{2.5}$$

$$\phi_l = \frac{y}{l} = \frac{(1+\tau_{l_i})W}{(1-\alpha)\gamma(1-\tau_{y_i})} \tag{2.6}$$

$$\kappa = \frac{k}{l} = \frac{\alpha}{1-\alpha} \cdot \frac{(1+\tau_{l_i})W}{(1+\tau_{k_i})R} \tag{2.7}$$

The above equations show that in absence of any market friction ($\tau_y = \tau_k = \tau_l = 0$), ϕ_k, ϕ_l and κ should be equalized across all firms. Equations (2.5) and (2.6) say that firms that face higher capital (labor) and/or product market frictions will demonstrate higher average product of capital (labor). In addition, according to equation (2.7), the capital-labor ratio increases with the relative size of labor to capital market wedge. Using firm-level data on total value of production, book value of capital stock and labor compensation from the CNEC, we calculate z, ϕ_k, ϕ_l and κ for each firm in our sample. Figure 2.6 shows in log scale the scatter-plots of ϕ_k, ϕ_l and κ against firm-level productivity z for the Paper industry.

Two patterns can be observed from Figure 2.6. First, from the two upper panels, we see that both ϕ_k and ϕ_l are positively correlated with z, which shows that more productive firms have higher average product of both capital and labor. Expressed in wedges, this means both $(1+\tau_k)/(1-\tau_y)$ and $(1+\tau_l)/(1-\tau_y)$ are higher for more productive firms. It could be because more productive firms are subject to higher capital or product market frictions or both. Second, from the lower panel, we see that the capital-labor ratio is at best weakly negatively correlated with z. Least square fitness estimates the elasticity to be -0.0057 and the R^2 is only 0.053. This indicates that the relative wedges firms face on the capital and labor markets do not exhibit systematic patterns on the idiosyncratic productivity of firms, which in the context of our model implies $1+\tau_k \approx 1+\tau_l$. Since we cannot separately identify the three wedges, for simplicity, we assume $\tau_k = \tau_l = 0$ and attribute all the changes in the average product of factors to wedges in the product market τ_y.[15] Different assumptions on the distribution of frictions across the three markets will not affect our results, but the interpretations need to be changed accordingly.[16]

[15] For example, we cannot distinguish between the data generating process we use here and another process where τ_k and τ_l increase simultaneously while τ_y is equal to zero.

[16] We cannot rule out the possibility that the results is driven by measurement error. However, we argue that this does not seem to be the case here. In particular, if y is measured with extreme measurement error, the regression coefficient of ϕ_k over z will be $1-\gamma$. Similarly, if instead k is measured with extreme measurement error, the regression coefficient will be $(1-\gamma)/\gamma$. We calculate calculate ϕ_k and z using different values of γ and the regression coefficients do not vary as predicted by either case.

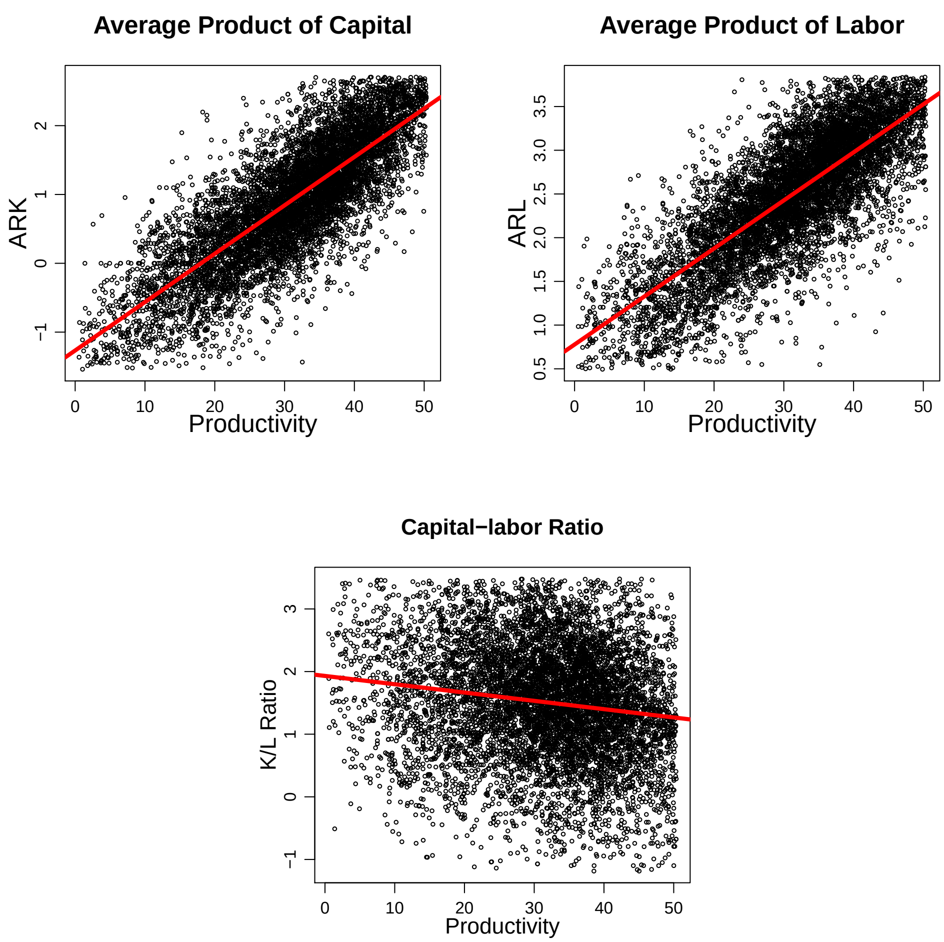

FIGURE 2.6.—FACTOR AND PRODUCT MARKET FRICTIONS

Source: China National Economic Census. All panels are plot in log scale. Lines are least square fit.

In the spirit of Restuccia and Rogerson (2008) and Adamopoulos and Restuccia (2014), we implement these idiosyncratic wedges in the model by positing a generic "tax" function that specifies the wedges as a function of firm's productivity z:

$$\tau_z = \max\left\{0, 1 - \phi_0 z^{\phi_1}\right\} \tag{2.8}$$

From now on, we use τ_z instead of τ_y to denote the product market frictions. We again assume the taxes collected are returned to household as lump-sum transfers. Anticipating the benchmark calibration in the next section, the wedge function specified in equation (2.8) is increasing and concave in z, with the lower and upper bounds being 0 and 1 respectively. The shape of the function captures the size-dependency of the product market frictions where the wedges are higher for larger firms.

There is one difference between (2.8) and the tax function used by Adamopoulos and Restuccia (2014). To model the size dependency, in their specification, the authors use an exponential function as opposed to the power function here. We choose the power function because it is consistent with the log-linearity of ϕ_k (ϕ_l) and z while the exponential function implies a tax scheme that increases much sharper with respect to productivity than the empirical counterpart. We rule out subsidies ($\tau_z < 0$) because $\lim_{z \downarrow 0} \tau_z = -\infty$ which leads to unrealistic solutions.

The idiosyncratic τ_z is meant to capture a variety of policies and institutions affecting the profits and, subsequently, the size of the firm. For example, it could be that more productive firms face transportation costs [Adamopoulos (2011)] or local protectionism and trade barriers that impede the inter-regional flow of goods [Young (2000)] when attempting to deliver their products to wider range of areas. It could be that smaller firms are subject to preferential tax treatments. For instance, the value added taxes for firms with annual value of industrial output that is less than CNY 1 million is 3% while firms with production scale larger than CNY 1 million are subject to a 13% tax rate. It is also consistent with a sheer amount of anecdotal evidence where Chinese entrepreneurs complain about higher administrative costs associated with increasing production scale. Finally, in the language of the trade community, τ_z could also be interpreted as different markups. Melitz and Ottaviano (2008) show that a linear demand yields a demand elasticity that is decreasing in firm size, which subsequently translates into markups that increase with firm size.[17]

In summary, the purpose of τ_z is to capture the empirical regularities in Figure 2.6 in a parsimonious way. We do not intend to evaluate the role of any particular observable product or factor market frictions. To this extent, methodologically we are following the indirect approach as opposed to the direct approach (cf. Restuccia and Rogerson (2013)).

[17] For the markup interpretation, we have to write a monopolistic competition version of our model [Melitz (2003)], instead of the Lucas model we use here.

3.3 *Firms' Problem*

Entrepreneurs first decide on which type of treatment technology to use and then on how much to produce. The business profits of a type-z entrepreneur $\pi(z)$ is the maximum over the profits of producing using dirty technology $\pi_0(z)$ and those of using clean technology $\pi_1(z)$:

$$\pi(z) = \max_{i \in \{0,1\}} \{\pi_0(z), \pi_1(z)\} \tag{2.9}$$

where $i(z)$ is the treatment equipment choice decision.

Firms that produce using clean technology are not subject to environmental penalties, hence their profits are just revenues less costs:

$$\pi_1(z) = \max_{k,n} \left\{(1-\tau_z) z^{1-\gamma} (k^\alpha n^{1-\alpha})^\gamma - Wn - R(k + k_E)\right\} \tag{2.10}$$

Notice that here the treatment equipment k_E cannot be used to produce the final product. This is consistent with the empirical finding by Shadbegian and Gray (2005).

On the other hand, firms that produce using dirty technology will be inspected by the environmental authority with probability p. Under such circumstances, a fraction ξ of their annual profits will be confiscated. Hence, the profit function is

$$\pi_0^C(z) = (1-\xi)\left[(1-\tau_z) z^{1-\gamma} (k^\alpha n^{1-\alpha})^\gamma - Wn - Rk\right]$$

where the superscript C indicates "caught". While if the firm succeeds in evading the inspection, the profit function is

$$\pi_0^E(z) = (1-\tau_z) z^{1-\gamma} (k^\alpha n^{1-\alpha})^\gamma - Wn - Rk$$

where the superscript E indicates "evaded". Because we assume perfect risk sharing within the household, these entrepreneurs will not have precautionary motive and will simply maximize the expected profits over π_0^C and π_0^E:

$$\pi_0(z) = \max_{k,n} \left\{(1-p)\pi_0^E(z) + p\pi_0^C(z)\right\}$$

A little bit algebra yields

$$\pi_0(z) = \max_{k,n} \left\{(1-p\xi)\left[(1-\tau_z) z^{1-\gamma} (k^\alpha n^{1-\alpha})^\gamma - Wn - Rk\right]\right\} \tag{2.11}$$

3.4 *Product Market Frictions and Technology Adoption*

To clarify the basic mechanics of the model, in this section we analyze firms' optimization problem when R and W are fixed as given. We prove two results in this section. First, we show that there exists a threshold $\tilde{z}$ such that firms with $z > \tilde{z}$ adopt the clean technology while firms with $z \leq \tilde{z}$ do not. Second, if we denote the previous threshold in environments with and without product market frictions to be respectively $\tilde{z}_n$ and $\tilde{z}_f$, we show that $\tilde{z}_f > \tilde{z}_n$. The first result says that there are returns to scale embedded with clean treatment technologies that are only exploited when firms are large enough. The second result says that by introducing product market frictions, a positive measure of firms that adopt clean technology when there is no frictions do not have the profits margin to benefit from the clean technologies and hence choose to enter the market with dirty technology. Throughout, we assume $0 < \alpha < 1$, $0 < \gamma < 1$, $\phi_0 = 1$ and $1 - \gamma + \phi_1 > 0$. We impose the last inequality because the product market tax specified in (2.8) is imposed on talent z. In order for the benefits of higher talent z (the elasticity of profits to talents $1 - \gamma$) to always outweight the costs (the elasticity of taxes to talents ϕ_1), $1 - \gamma + \phi_1 > 0$ must be satisfied. This also rules out the counterfactual prediction of our model where the most talented individuals choose to become workers. All proofs are left for Appendix B.

Lemma 2.1 characterizes firms' profit functions in absence of product market frictions.

Lemma 2.1. *In an economy with no product market frictions, $\pi_0(z)$ and $\pi_1(z)$ are both increasing and linear with respect to z. In addition, the slope of $\pi_1(z)$ is steeper than that of $\pi_0(z)$:*

$$\frac{\partial \pi_0(z)}{\partial z} = (1 - p\xi)\frac{\partial \pi_1(z)}{\partial z}, \qquad \forall z \in Z \tag{2.12}$$

Lemma 2.1 highlights the core trade-off of adopting clean technology in our model. Although the up-front fixed costs shift the overall profit function down by Rk_E, firms with clean technology are not subject to the ξ proportion of profits being confiscated. With constant elasticity between capital and labor, the optimizing capital to labor ratio is constant in absence of factor market frictions, therefore entrepreneurs reap economic rents from managerial talents z. These economic rents increase linearly because we assume a constant returns to scale production function.

Since the tax in (2.8) is size-dependent in the sense that more talented entrepreneurs are subject to higher frictions, it is straightforward to show that in an economy with product market frictions, both $\pi_0(z)$ and $\pi_1(z)$ are concave. $\pi_0(z)$ and $\pi_1(z)$ will remain linear if the frictions are uniformly imposed.

Corollary 2.1. *Suppose the product market frictions are specified as $\max\{0, 1 - z^{\phi_1}\}$ with $1 - \gamma + \phi_1 > 0$, then $\pi_0(z)$ and $\pi_1(z)$ are both increasing and concave with respect to z. In addition, the slope of $\pi_1(z)$ is steeper than that of $\pi_0(z)$:*

$$\frac{\partial \pi_0(z)}{\partial z} = (1 - p\xi)\frac{\partial \pi_1(z)}{\partial z}, \qquad \forall z \in Z$$

Since the wage income associated with being a worker is fixed at W, the monotonicity of the profit functions implies that there is a threshold $\hat{z}$ for which all household members with talents higher than $\hat{z}$ choose to become entrepreneurs. Put differently, household members choose their occupations according to their comparative advantages.

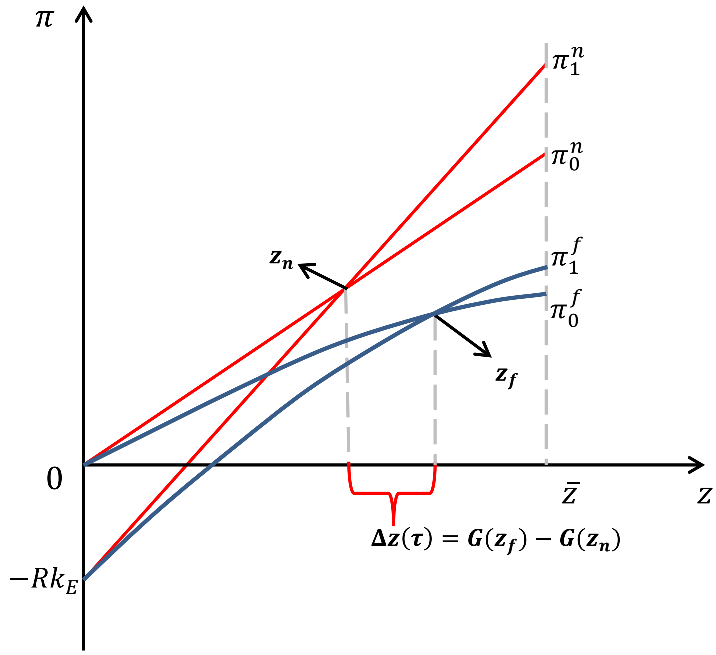

FIGURE 2.7.—THE EFFECT OF PRODUCT MARKET FRICTIONS

Proposition 2.1. *There exists a unique threshold $\hat{z}$ such that all household members with $z < \hat{z}$ choose to be workers and those with $z \geq \hat{z}$ become entrepreneurs. Further, $\hat{z}$ is the solution of $W = \pi(\hat{z})$*

Finally, Proposition 2.2 summarizes the main result of this section: larger firms adopt more advanced treatment technology and the existence of product market frictions impedes the technology upgrade.

Proposition 2.2. *Given k_E, W, τ_z and R, there exist unique thresholds $\tilde{z}_n$ and $\tilde{z}_f$ such that:*

(i) In the economy with no product market frictions, entrepreneurs with $z \leq \tilde{z}_n$ produce using dirty technology while those with $z > \tilde{z}_n$ produce using clean technology.

(ii) In the economy with product market frictions, entrepreneurs with $z \leq \tilde{z}_f$ produce using dirty technology while those with $z > \tilde{z}_f$ produce using clean technology.

(iii) $\tilde{z}_n < \tilde{z}_f$, that is, product market frictions impede the technology upgrade.

A graphical illustration of Proposition 2.2 is shown in Figure 2.7. There are four curves in the figure, $\pi_0^n, \pi_0^f, \pi_1^n$ and π_1^f where superscripts n and f represent whether there are product market frictions and subscripts 0 and 1 represent firms using dirty or clean technology respectively. The elasticity of profits to managerial talents is $1 - \gamma$ when clean technology is adopted which is larger than that with dirty technology $1-\gamma+\phi_1$. Therefore, although for less talented entrepreneurs the fixed installation costs of clean technology is not justified, for highly talented entrepreneurs using more advanced treatment technologies will eventually pay off. Whether it is worthwhile for firms to pay the installation costs is determined by contrasting the costs with potential profits loss from inspections by the regulator. Since the product market frictions shrink the profit margin by ϕ_1, for some firms their "after-tax" profits do not permit them to exploit the benefits from adopting more advanced technologies, although the "pre-tax" profits do. The ultimate result is that a positive measure $\Delta z(\tau) = G(z_f) - G(z_n)$ of firms that with no frictions would produce using clean technology, in the existence of product market frictions produce using dirty technology.

3.5 *General Equilibrium*

We specify the household problem and define the general equilibrium to close the model.

Household Optimization.—Household engages in a simple consumption saving problem:

$$\max_{C_t, K_{t+1}} \sum_{t=0}^{\infty} \beta^t U(C_t) \tag{2.13}$$

$$s.t.$$

$$C_t + K_{t+1} - (1-\delta)K_t = I_t$$

where δ is the depreciation rate and I_t is household income which we will specify in details shortly. We assume that household does not value environmental quality, but values consumption. The solution to (2.13) is the standard intertemporal Euler equation

$$U'(C_t) = \beta U'(C_{t+1})(1 + R_{t+1} - \delta) \tag{2.14}$$

which pins down the equilibrium interest rates in steady state.

Household income I_t comes from three sources: wage income, firms' profits and lump-sum transfers associated with product market frictions τ_z and environmental penalties ξ. To characterize I_t, we need some additional notations. We denote $Z_0 = \{z \in [\hat{z}_t, \overline{z}] | \pi_0(z) \geq \pi_1(z)\}$ as the set of firms operating under dirty technology and $Z_1 = \{z \in [\hat{z}_t, \overline{z}] | \pi_0(z) < \pi_1(z)\}$ as the set of firms using clean technology. Notice that for the intermediate case where $0 < \hat{z} < \tilde{z} < \overline{z}$, Proposition 2.2 implies $Z_0 = [\hat{z}, \tilde{z})$ and $Z_1 = [\tilde{z}, \overline{z}]$. Since the "taxes" are distributed to household as lump-sum transfers, in the budget constraint taxes and transfers cancel each other out. Equation (2.11) and Proposition 2.1 then yield:

$$I_t = R_t K_t + W_t G(\hat{z}_t) + \int_{z \in Z_0} \pi_0(z) dG(z) + \int_{z \in Z_1} \pi_1(z) dG(z)$$

where the four terms are capital rental income, wage income and profits from dirty and clean firms. Law of Large Numbers here guarantees the ex ante probability of being inspected equals the ex post number of firms that in fact get inspected.

General Equilibrium.—Now we are ready to characterize the general equilibrium.

Definition 2.1. General Equilibrium
The general equilibrium in this model is sequences of prices $\{W_t, R_t\}_0^\infty$*, allocations* $\{C_t, K_{t+1}, Y_t\}_0^\infty$*, firms policy functions* $\{k(z), n(z), y(z), \pi(z)\}$*, household occupational choices* $\{\hat{z}_t\}_0^\infty$*, firms' technology adoption choices* $\{\tilde{z}_t\}_0^\infty$ *and aggregate pollutants emission* E_t *such that:*

(i) Given factor prices $\{W_t, R_t\}_0^\infty$*,* $\{C_t, K_{t+1}, \hat{z}_t\}_0^\infty$ *solve the household optimization problem.*

(ii) Given factor prices $\{W_t, R_t\}_0^\infty$*,* $\{k(z), n(z), y(z), \pi(z)\}_0^\infty$ *and* $\{\tilde{z}_t\}_0^\infty$ *solve firms' optimization problems.*

(iii) Factor prices $\{W_t, R_t\}_0^\infty$ *clear all markets.*

- *Labor Market:*
$$G(\hat{z}_t) = \int_{\hat{z}_t}^{\overline{z}} n(z) dG(z)$$
- *Capital Market:*
$$K_t = \int_{\hat{z}_t}^{\overline{z}} k(z) dG(z) + k_E \int_{z \in Z_1} dG(z)$$
- *Product Market:*
$$C_t + K_{t+1} - (1-\delta) K_t = \int_{\hat{z}_t}^{\overline{z}} y(z) dG(z)$$

(iv) The aggregate pollutants discharges are

$$E_t = \int_{z \in Z_0} e\left(0, y(z)\right) dG(z) + \int_{z \in Z_1} e\left(1, y(z)\right) dG(z)$$

4 Calibration

We calibrate our model to the Chinese data. The model period is set to be one year.

Parameterizations.—Motivated by the empirical evidence in Section 2.2 and Section 2.3, we assume that the functional form of the pollution intensity functions of firms with treatment technology i and production level y are log-linear:

$$\log \iota = \psi_0^{(i)} + \psi_1^{(i)} \log y \tag{2.15}$$

where $\iota = e/y$ is the pollution intensity. This specification implies that conditional on treatment technology adopted, there is still "within group" intensity reduction as production scale increases. Since our model includes only the choices of firms on the end-of-pipe treatment technologies, in the quantitative exercises, we capture the decrease in pollution intensity in a reduced-form way. Equation (2.15) implies that the actual discharge is

$$e = E(i, y) = \mathrm{e}^{\psi_0^{(i)}} y^{1+\psi_1^{(i)}} \tag{2.16}$$

Our model features only two broad categories of treatment technologies as opposed to five in the data. We interpret the clean technology in our model as biological technology and dirty technology as the remaining types. Since the aggregated installation costs of the physical equipments are less than 9% of those of the biological equipment, we assume only the installation of biological technology incurs the fixed cost k_E.

Because firm size distribution in the model is affected by both the talent distribution $G(\cdot)$ and the product market frictions τ_z, our identification assumption is such that parameters governing τ_z are assigned according to the empirical regularities and given τ_z, $G(\cdot)$ is set to match the firm size and employment distribution in China. We choose the pooled polluting industries as our calibration targets. The employment and firm size distributions of these industries pooled together are shown in the lower-right panels of Figures 2.4 and 2.5. The firm size distribution resembles a log-normal distribution, but also demonstrates a considerable degree of employment concentration at very large firms. It is well documented in the literature that the commonly used log-normal distribution does a reasonably good job at matching the distribution of the bulk of small and medium-sized firms, but does not support the concentration of employment. The heavy right tail is crucial to our evaluation because these are the firms that are producing with clean technology. Since τ_z is levied based on the productivity z, we assume the distribution of after-tax talents z' to be a combination of two components. The first is a log-normal distribution with mean μ, standard deviation σ and total probability mass $1 - g_{max}$ that accounts for the bulk of small and medium firms. The second is an atomic with value z'_{max} and measure g_{max} which accounts for the very large firms.[18] The talent z is then calculated by

$$z = \left(z' \phi_0^{1/(\gamma-1)}\right)^{\frac{1-\gamma}{1-\gamma+\phi_1}}$$

which gives us $G(z)$.

Therefore, we are left with total of 17 parameters to calibrate: preference β, production technology parameters $\{A, \delta, \alpha, \gamma\}$, treatment technology parameters $\{\psi_0^{(0)}, \psi_1^{(0)}, \psi_0^{(1)}, \psi_1^{(1)}, k_E, p\xi\}$, product market frictions $\{\phi_0, \phi_1\}$ and distributional parameters $\{\mu, \sigma, z'_{max}, g_{max}\}$. The general strategy of our calibration involves assigning values to some parameters based on a priori information in the data and calibrate the rest jointly such that the distance between the moments from the model and the data is minimized.

Eight of the seventeen parameters can be determined exogenously. We set the depreciation rate δ to 10% [Song, Storesletten, and Zilibotti (2011)]. To get estimates of $\{\psi_0^{(0)}, \psi_1^{(0)}, \psi_0^{(1)}, \psi_1^{(1)}\}$, we

[18] This strategy follows Guner, Ventura, and Xu (2008) and is quite popular among macroeconomic studies on wealth distribution, see for example Castańeda, Díaz-Giménez, and Ríos-Rull (2003).

repeat the exercises in Section 2.2 for firms using physical and biological equipment separately. The estimates are $\psi_0^{(0)} = -3.5795$, $\psi_1^{(0)} = -0.4149$, $\psi_0^{(1)} = -4.4270$ and $\psi_1^{(1)} = -0.3410$. In the context of our model, these estimates suggest that on average, for two firms with the same level of production but different treatment technologies, the firm that uses biological technology discharges 40% to 60% less pollutants than the firm equipped with physical technology. We use information on the average factor products to calibrate the tax function. Equation (2.5) suggest that the elasticity of ϕ_k to $1-\tau_z$ is equal to unity. Therefore ϕ_1 is equal to the elasticity of ϕ_k to z. Given ϕ_1, we then calibrate ϕ_0 such that the average tax burden in the economy equals 13% value added tax imposed on Chinese manufacturing firms. Since, as is shown in Proposition 2.2, the gains from the liberalization, which eliminates the product market friction are increasing in both the average level and the degree of size-dependency of frictions, we make both choices conservatively. As a result, $\phi_0 = 1.15$ and $\phi_1 = -0.03$. We set $A = 1$ as normalization.

The rest of the parameters have to be calibrated jointly. The calibration involves two layers: an outer layer loops over the parameterizations of $G(z)$ and an inner layer solves the model given $G(z)$. In the inner layer, first we approximate $G(z)$ with 5,000 grid points. We then choose β and α to match respectively the capital-output ratio of 1.65 and capital share of 0.5 (both are taken from Bai, Hsieh, and Qian (2006)) in China. We set $p\xi$ and k_E such that the total treatment equipment investment is equal to 1% of the total output and the fraction of firms adopting biological equipment equals the empirically observed level of 57%. The value of γ is set such that the distance between the employment and firm size distribution generated by the model and those in the data is minimized. In the outer layer, we then launch a multi-dimensional search process to choose the combination of $\{\mu, \sigma, z_{max}, g_{max}\}$ that minimizes the distance from the inner layer. The model parameters along with their targets and calibrated values are listed in Table 3.3.

Discussion.—The calibrated model matches very well the capital share, capital-output ratio, the fraction of treatment equipment in total output and the fraction of firms adopting biological equipment. The implied discount rate β is less than the values commonly used in the literature. The reason is that we calibrate our model to the steady state as opposed to the balanced growth path. If we assume that the household has log-utility function and the secular growth rate equals to 8%, the counterpart of the discount rate in this situation is equal to 0.95. We choose to calibrate the model to the steady state because we do not have to make additional assumptions on the functional form of the utility function. Nevertheless, all of the qualitative and quantitative results in this paper hold in the balanced growth path calibration. The implied value of returns to scale γ also lies within the empirically estimated range.[19] The calibrated value of $p\xi$ means that in expectation, the penalty to firms using less advanced treatment technology is equal 20.5% of their annual output

[19]The values previously used in the macro literature range from 0.85 [Atkeson and Kehoe (2005)] at the lower end to 0.95 [Bartelsman, Haltiwanger, and Scarpetta (2013)] at the upper end. Estimations from micro-level data yield similar results, for example Olley and Pakes (1996) estimated the value to be between 0.8 to 0.9 for the U.S telecommunications equipment industry, depending on the particular econometric specifications.

TABLE 2.6
PARAMETERIZATION

Parameter		Value	Targets
Production	A	1	Normalization
	δ	0.1000	Depreciation Rate
	α	0.5376	Capital Share 0.5
	γ	0.9300	Size Distribution†
Treatment	$\psi_0^{(0)}$	-3.5795	Physical Intensity-output Elasticity
	$\psi_1^{(0)}$	-0.4149	
	$\psi_0^{(1)}$	-4.4270	Biological Intensity-output Elasticity
	$\psi_1^{(1)}$	-0.3410	
	k_E	4.1500	Envir.capital-output ratio 1%
	$p\xi$	0.205	Frac.Firms Use Bio 57%
Frictions	ϕ_0	1.15	Average Value Added Tax 13%
	ϕ_1	-0.03	Avg.Factor.Prod-Prod Elasticity
Preference	β	0.8750	Capital-output Ratio 1.65
Talents	μ	-2.4567	Size Distribution†
	σ	4.0020	
	z_{max}	10820.4	
	g_{max}	0.00048	

† Note: Jointly calibrated.

value.[20]

Figure 2.8 shows graphically the model fit of the firm size (left panel) and employment share distributions (right panel). While not perfect, overall the model does a reasonable job in matching the two distributions given that there are five degrees of freedom. The mean (59.27) and median (22.95) of the firm size distribution, which are not targeted in the calibration, also match well with their empirical counterparts, where the mean and median are equal to 59.05 and 20 respectively. The challenges of calibrating the model to simultaneously match the employment and size distributions are as follows. First, in order to create the large firms in the model, we need not only very talented entrepreneurs who are willing to hire a lot of employees, but also the wage these entrepreneurs face has to be kept at a low level to make them able to actually hire the desired amount of workers. Therefore, the average talent in the economy must be low. If we have a wide range of employment level to cover, the properties of the distributions at the right tail of the log-normal are difficult to control. It is for this particular reason that we introduce an atom to the distribution.

[20] While empirical counterpart of the value is difficult to find, the number lies within the range of percentage of plants inspected reported in Becker and Henderson (2000). In particular, Becker and Henderson (2000) report the percentage of firms inspected in four industries in the U.S: Plastics, Wood Furniture, Industrial Organic Chemicals and Metal Containers. The numbers are respectively 2.4%, 6.8%, 20% and 27%.

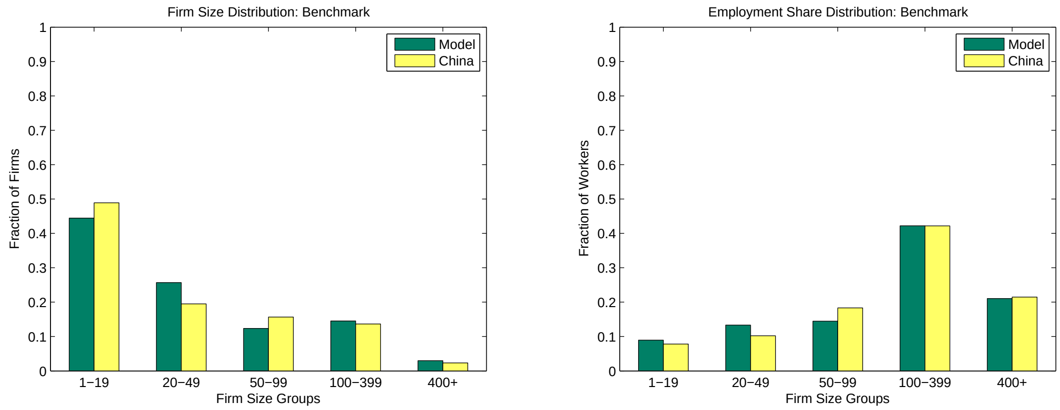

FIGURE 2.8.—MODEL FIT: BENCHMARK

Second, since for the five industries we are studying in this paper the employment concentration level is very high, to generate comparable level of concentration, the returns to scale (γ) must also be high given that the average talent is low as we just discussed. This will significantly jeopardize the firm size distribution as the big firms enjoy too many technological advantages. The fit of our model is thus the compromise of these two forces.[21]

The identification assumption of our benchmark calibration is that given taxes τ_z, the talent distribution is identified by the size distribution in the data. Another commonly used calibration strategy in the literature takes the U.S as an undistorted economy (in the context of our model this means $\tau_z = 0$) and calibrates $G(z)$ by matching the size distribution from the tax-free economy to the U.S data. Taxes are then introduced such that certain moments of the size distribution of the country in interest are matched [Guner, Ventura, and Xu (2008), Hsieh and Klenow (2009, 2014), Adamopoulos and Restuccia (2014), etc]. If we calibrate our model in this way, the underlying assumption would be that the talent distribution of the entrepreneurs in China is the same as that in the U.S and all the differences between the size distributions of China and the U.S result from taxes.[22] From our perspective, both strategies have their strength and weakness and compromise to data limitations in different ways. The quantitative results of our paper are to a large extent driven by size and shape of τ_z. Therefore, as long as the latter calibration implies a tax scheme that is similar to what we use in our benchmark parameterizations, the quantitative aspects of our results will hold as well.[23] We choose to calibrate our model to the Chinese economy directly because

[21]Models where these two forces are not very antagonistic to each other usually have much better fit. For instance, Guner, Ventura, and Xu (2008) study the whole U.S business sector which has narrower employment span and lighter employment concentration. In particular, the largest group they are targeting is firms with more than 100 employees. On the contrary, the largest group we are targeting is 400+ employees, which is significantly larger. In another paper, Adamopoulos and Restuccia (2014) assume away the selection mechanism in the model which, put differently, mutes the general equilibrium feedback through wages. This relaxes the restriction on the average talents considerably.

[22]The evidence regarding this point is mixed, see Figure 2 in Bloom and Van Reenen (2010).

[23]In an earlier version of the paper where endogenous treatment technology choice is not explicitly modeled this is

better empirical evidence (Section 3.2) is available to us.

5 Quantitative Results

We use the calibrated model as a framework for understanding the implications of firm size distribution on industrial pollution. We do two experiments here. In experiment (i), we eliminate all the product market frictions by setting $\tau_z = 0$. The experiment could be interpreted as reductions in inter-regional trade barriers, improvements in transportation infrastructure, decreases in tax burdens, etc. Since we are following the *indirect* approach, we do not have empirical evidence of how much improvements on observable frictions such as transportation infrastructure reduces τ_z by how much. The size of the policy could be assessed by changes in the average firm size across steady states as is done in Guner, Ventura, and Xu (2008). In experiment (ii), we increase the monitoring $p\xi$ such that the fraction of firms using biological equipment reaches the same level as in experiment (i). With this experiment, we approximate the current environmental policy that punishes firms using less advanced treatment technology. We contrast results from the two experiments to illustrate different effects of these two types of policies.

5.1 *Less Frictions versus Stronger Regulation*

In this section, we compare the effects of the two types of policies, namely reducing frictions and intensifying regulation. We start by describing the results of the two experiments. Table 2.7 contains results that characterize the steady states. Columns labeled (i) and (ii) refer respectively to experiments (i) and (ii).

Elimination of Frictions.—The core mechanism that generates the results of experiment (i) is the change of size distribution that is driven by the general equilibrium wage effect. Since the tax scheme τ_z is assumed to be size-dependent, which imposes larger frictions over more productive firms, in the benchmark economy the market share of these highly productive firms is severely restrained. The elimination of τ_z removes these constraints. As a result, the previously suppressed factor demand increases considerably. In column (i) of Table 2.7, this shows up as a 61% increase in aggregate capital and a 28% increase in wage (output per worker). The size-dependency of τ_z also implies that the situation of small unproductive firms improves by a lesser extent than that of the large productive ones. Many small unproductive firms that previously survived because of the low prevailing wage now lose the profit margins. The owners of these firms therefore find it more profitable to work for the more productive firms. This selection mechanism explains the 125% increase in average talent of active entrepreneurs, the 57% decrease in the number of active firms, the three-fold increase in output per firm and the increase in the mean and median size of the firms. Notice that the selection mechanism works in two-ways. Beyond the increase in the

indeed the case.

TABLE 2.7

AGGREGATE AND PRODUCTIVITY EFFECTS

Statistics	Benchmark	(i)	(ii)
Aggregate Output	100.00	129.72	100.12
Capital	100.00	161.25	100.14
Consumption	100.00	123.45	100.11
Output per Worker	100.00	128.49	99.97
Output per Firm	100.00	298.78	109.76
Average Talent	100.00	224.67	109.49
TFP	100.00	102.00	100.14
Number of Firms	100.00	43.42	91.22
Mean Size	59.27	137.81	65.07
Median Size	22.95	41.83	26.72
Aggregate Pollution	100.00	78.95	90.75
Average Intensity	100.00	60.86	90.65
Biological Share	57.40	85.29	85.15
Monitoring	20.50	20.50	32.50

† Note: All values reported are in percentage points except mean and median size, which are numbers of workers in absolute term.

TABLE 2.8

OUTPUT SHARE BY DIFFERENT MANAGERIAL TALENTS QUINTILE

Economy	QU_1	QU_2	QU_3	QU_4	QU_5
Benchmark	2.69	4.19	7.29	16.55	69.28
Case (i)	1.50	2.83	6.34	18.06	71.27
Case (ii)	2.93	4.47	7.77	17.37	67.46

† Note: QU_1 to QU_5 represent respectively the first to the fifth quintile.

cutoff we just described, among the remaining firms, production is also more concentrated at firms with high productivity. We define the *extensive* margin as the selection of active entrepreneurs and the *intensive* margin as the production distribution among the active firms. The first two rows of Table 2.8, which report the output share accounted for by firms with productivity in different quantiles, show this intensive margin. The overall changes of the size and employment distribution can be seen from the left two panels of Figure 2.9. We see clearly that firms in the top group expand considerably at the expense of firms in the bottom three groups. Therefore, elimination of τ_z improves resource allocation on both the extensive and intensive margin. Consistent with the findings in Guner, Ventura, and Xu (2008), size distribution in models with firm selection exerts very limited influence over TFP, which is defined as the Solow residual following standard growth

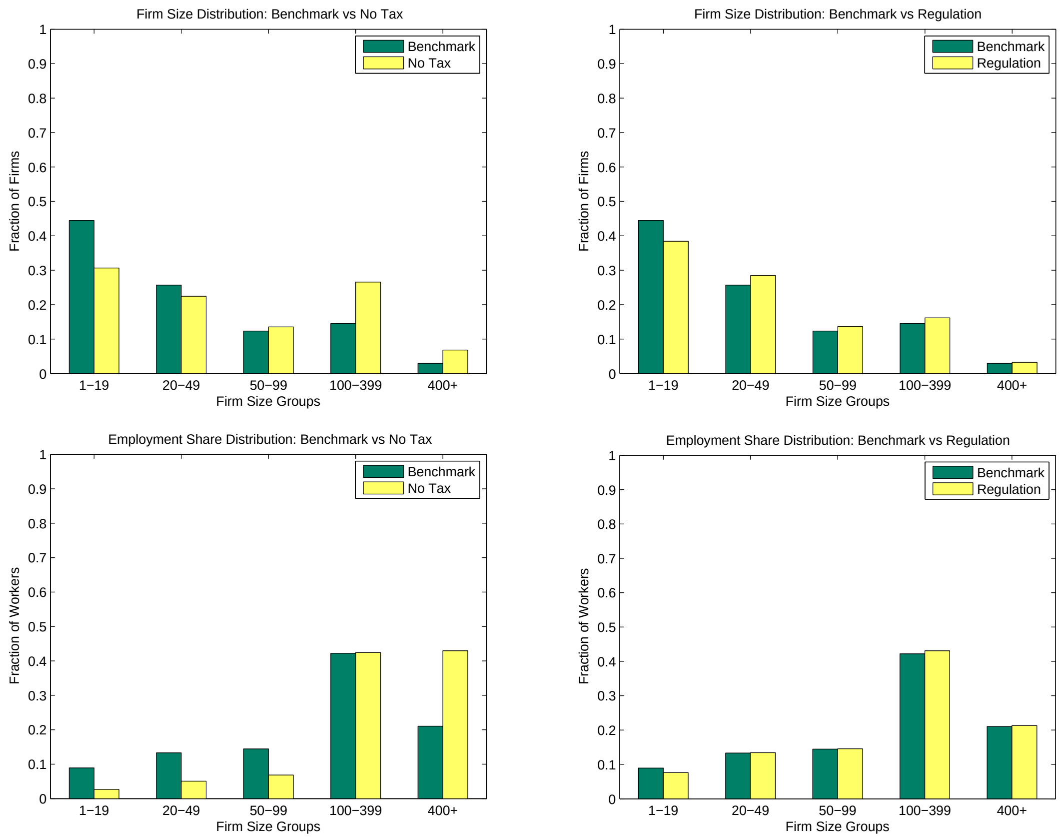

FIGURE 2.9.—SIZE AND EMPLOYMENT DISTRIBUTION: LESS FRICTIONS VERSUS STRONGER REGULATIONS

accounting literature [Hall and Jones (1999)]

$$\text{TFP} = \frac{Y}{K^{\gamma\alpha} N^{1-\gamma\alpha}}$$

Although the aggregate output increases by 30%, due to the average pollution intensity decreasing more (by 40%), the aggregate pollution in fact decreases by 20%. The decline in average intensity enters in both the production stage and the treatment stage. In both stages, changes in the size distribution assume a key role. Since the production in the no friction economy shows higher degree of concentration in large productive firms, the fact that the two within group elasticities $\psi_1^{(0)}$ and $\psi_1^{(1)}$ are negative implies a mechanical decrease in pollution intensity. The effect of size distribution on a firm's choice of the end-of-pipe treatment technology works exactly as is described in Proposition 2.2. The elimination of τ_z increases significantly the profits of firms, which strengthens the economic incentive of adopting more advanced treatment technology. It is important to bear in mind that both the elimination of τ_z itself and the subsequent decrease of wages contribute to the strengthening of the economic incentive.

To evaluate the relative contribution of reduction in the production stage and in the treatment stage, we assume artificially that $\psi_0^{(0)} = \psi_0^{(1)}$ and $\psi_1^{(0)} = \psi_1^{(1)}$ which means the biological equipment has the same technical features as the physical equipment. We apply this modification to both the benchmark case and the no tax case. We set the pollution intensity and aggregate pollution in the first case to be the new benchmark. The difference between the above two cases shows the effect from purely changing the size distribution, which is equal to 61% for the intensity and 79% for the aggregate pollution. We interpret these numbers as reduction of industrial pollution in the production stage, which is incorporated into our model in a reduced-form way. We then express the intensity and pollution in case (i) as a percentage of the new benchmark. The numbers are respectively 45% for intensity and 58% for aggregate pollution. Therefore, in the context of our model, about 30% of the decrease in pollution intensity and 50% of the decrease in aggregate pollution are from the treatment stage.

Strengthening of Regulation.—The intensification of regulation affects the decisions of firms directly through technology adoption requirement and indirectly through the general equilibrium wage feedback. Unlike in experiment (i), these two effects do not affect the size and employment distributions in equilibrium by too much, as can be seen from the two right panels in Figure 2.9. There are two reasons behind this. First, large firms that already have adopted the clean technology in the benchmark are not affected by the changes in the policy. Second, the installation cost of the clean technology in our benchmark calibration is small, which does not affect too many of the firms' resources from productive use and therefore does not affect the optimal operating scale of firms by much. As a result, in column (ii) of the top panel of Table 2.7, the macro aggregates barely change comparing to the benchmark case.

However, despite a tiny decrease (0.03%) in wages, there is selection which to some extent increases the average size and productivity of active firms. The underlying mechanics here are that an increase in the regulations decreases the expected returns from being an entrepreneur, which drives out the least productive firms that cannot afford the installation of a clean technology.[24] These household members then choose to become workers, which increases the labor supply and suppresses equilibrium wage rates. The remaining more productive and hence larger firms benefit from the reduction in wage rates and expand their operating scale, which explains the increases in size and productivity. Graphically this is reflected in Figure 2.9 as a contraction of group "1-19" both in the size and employment distributions and expansion in other four groups.

Firms in the four expanding groups are not affected equally though. To see this, we refer to row (ii) in Table 2.8. As is shown in the experiment (i), the most efficient way of allocating the talents

[24]This prediction matches well the policy practice in China. For example, during 2004 to 2008, the emission of major air pollutants together with industrial production have declined significantly. The reduction of per unit GDP emission for these pollutants are 35% for SO_2, 29% for Black Carbon and 31% for CO [Lin, Pan, Davis, Zhang, He, Wang, Streets, Wuebbles, and Guan (2014)]. During that period of time, 34 million kW coal-burning electric generating sets were directly shut down, which amounts to 6.18% of the total electric production in 2013 (*National Development and Reform Commission* [2009] Decree 4).

is to shift the production to most productive firms, increasing the share of output accounted for by firms with productivity in the top quantiles. However, row (ii) says the opposite. Comparing with the benchmark case, the proportion of production accounted for by the lower quantiles increase while that of the top quantile decreases. Therefore, although strengthening the monitoring improves the allocation of managerial talents on the extensive margin, the allocation on the intensive margin worsens. Both effects are small here because in our benchmark calibration k_E is small. In Section 5.3, we discuss the case where k_E is set to a higher level.

Since the aggregate output only increases slightly, quantitatively the decreases in aggregate pollution and intensity are almost the same. In this experiment, they decrease by about 10%. Since the size distributions do not change much here, most of the decrease comes from the treatment stage. In fact, if we repeat the decomposition exercise we did for experiment (i), 92% of the reductions in both intensity and aggregate pollution stem from by the adoption of more advanced technologies.

Comparing the Two Policies.—The elimination of τ_z moves the economy to the first best solution, which dominates intensified regulations. The lesson we learn from the quantitative exercise is that if resources are devoted to smoothing the frictions in the economy instead of being used to intensify regulations, reductions of pollution in both the production and treatment stage arise naturally as equilibrium outcomes. In fact, the effect of regulation policies such as government campaigns are notorious for their ease of rebound. Since the reduction of pollution could be achieved even with less regulations under the case of no frictions, directing resources at improving economic efficiency is more likely to be effective in the context of China. Put differently, because elimination of τ_z increases output and decreases pollution simultaneously, our results actually suggests that economic development and environmental protection are not necessarily in sharp conflict with each other.

Partial Equilibrium Interpretations.–Some readers may be concerned that in reality, reduction of labor demand in one industry does not necessarily cause a decline of wages across the whole economy, thereby challenging the main mechanism of our model. We argue that the general logic carries well onto other model environments. First, what eventually matters in our model is not the wage per se, but the profits which are revenue less factor costs. In a partial equilibrium version or a Melitz (2003)-style version of our model where the wage and demand are both fixed, τ_z will push up the equilibrium price that the firms could charge. This is because with size-dependent τ_z, the supply from the large productive firms is suppressed, where competition among consumers bids up the equilibrium price. Much of the quantitative results are still maintained in these situations. We choose to work with a general equilibrium Lucas model because it enables us to discuss the changes in output level. In fact, the results we present in the general equilibrium setting are stronger than those in the partial equilibrium counterparts. A decrease in the average intensity could well be accompanied by an increase in aggregate pollution if the output increases by too much. Second, if the labor markets in different industries are segmented, then a decrease in labor demand will in

TABLE 2.9
THE EFFECT OF SIZE DISTRIBUTION

Statistics	Benchmark	(i)	(i')
Aggregate Output	100.00	129.72	105.33
Capital	100.00	161.25	106.38
Consumption	100.00	123.45	105.12
Output per Worker	100.00	128.49	104.34
Output per Firm	100.00	298.78	242.61
Aggregate Pollution	100.00	78.95	70.60
Average Intensity	100.00	60.86	67.02
Biological Share	57.40	85.29	72.21

† Note: All values reported are in percentage points.

fact trigger a wage drop. Third, the nature of our comparison is to contrast economies with and without frictions as a whole, not any particular industry. Therefore, as long as the product market frictions exist at the aggregate level, wages will be lower in cases with frictions.

5.2 *The Effect of Size Distribution*

To further isolate the effect of size distribution, we solve a version of the model where the product market frictions are imposed uniformly over all firms in the economy. More specifically, in these exercises, we set values of τ_z such that the total amount of taxes collected is the same as in the benchmark case with size-dependent τ_z. To this end, the experiments resemble those in the taxation literature, where progressive taxes are compared with flat taxes. If we interpret τ_z literally as a tax, it would be unwise to suggest eliminating the whole tax system on manufacturing sector. This exercise could be interpreted as a counterfactual on policies that remove the size-dependent feature of current taxation policies in China. The implied tax rate $\tau_z = 18\%$ is higher than the average tax rate in the size-dependent case, 13%. The results of the experiment are summarized in Table 2.9. Columns benchmark and (i) are results of the benchmark calibration and those from setting $\tau_z = 0$ respectively. We label the uniform tax case as (i'). By comparing benchmark with (i'), we are able to assess the effect of the size-dependency of τ_z. Similarly, a comparison of (i) with (i') shows the effect from levying a flat tax. First notice that a uniform τ_z imposed on all firms does not change the extensive margin comparing to the zero τ_z situation, therefore measures of average talents, number of firms, mean/median size of firms and TFP are not affected [Guner, Ventura, and Xu (2008)].

Aggregate output, capital, consumption, output per worker and output per firm in case (i') all increase comparing to the benchmark case, which is consistent with findings about size-dependent distortions in the literature. What is different here is that since the uniform tax rate needed to generate the same tax revenue is relatively high (the tax rate for the largest firm in the size-dependent case is 25%), tax itself still results in a considerable amount of output loss. The source of output loss in our model is the misallocation of the entrepreneurial talent z. However, for the average pollution intensity, much of the reduction is achieved through the elimination of the size-dependency of τ_z. The adoption rates of the clean technology increase by 15 percentage points in case (i'), which is 53% of the total increase comparing to the complete elimination of τ_z. 84% of the total decline in aggregate pollution in the zero τ_z case is achieved by simply removing the size-dependent feature of τ_z.

Discussion.—The finding that size-dependency of τ_z affects the economic efficiency moderately, but the average pollution intensity considerably could be well explained by the theory established in Hopenhayn (2014). In particular, he shows that size-dependency of the policy does not necessarily imply large distortions. What matters for the size of the distortion is the total amount of resources that are affected, not these resources belong to which firms. Studies like Restuccia and Rogerson (2008) and Guner, Ventura, and Xu (2008) find that size-dependent policies affect economic efficiency more than their size-independent counterparts because those size-dependent policies happen to lead to large amount of resources being affected . The fact that in the flat tax case we impose a fairly large τ_z explains why removing size-dependency of τ_z does not improve the efficiency of the economy by much. However, for the sake of industrial pollution, size distribution does matter. Since larger firms produce in a cleaner way, if the majority of the production is done by large as opposed to small firms, pollution will in fact decrease. Since the size distribution of the firm is purely affected by the size-dependency of τ_z and not by the size of the distortions (in the definition of Hopenhayn (2014)), although size-dependency does not necessarily imply significant efficiency loss, it necessarily results in aggravation of pollution.

5.3 *Environmental Policy and Size Distribution*

In our benchmark calibration, we choose a relatively small k_E at about 2.5 times of the equilibrium wage of a typical worker. This limits the extent to which environmental policy could affect the real economy. In this section, we show that when k_E is increased to ten times the value used in the benchmark calibration, environmental policy has sizable effect on the allocation of talents. In particular, we show that although environmental policy improves the efficiency through selection at the extensive margin (occupational choice), the allocation at the intensive margin (production distribution among active firms) worsens. To show this, we consider two scenarios. In the first case, we solve the model again with all parameters remaining at the benchmark calibration level, but increase k_E to 41.5. With no changes in the regulation intensity, the adoption rate of clean technology decreases. Therefore, in the second case, we increase $p\xi$ such that the adoption rate in the benchmark case (57%) is restored. We label these two experiments by (iii) and (iv).

The results of experiments (iii) and (iv) are shown in Table 2.10. First we notice that the size distribution as well as the efficiency of the economy stay virtually the same as the benchmark case. The clean technology adoption rate falls to 9%, since a large number of firms now find it

TABLE 2.10
AGGREGATE AND PRODUCTIVITY EFFECTS: HIGHER k_E

Statistics	Benchmark	(iii)	(iv)
Aggregate Output	100.00	100.00	100.41
Capital	100.00	100.28	101.45
Consumption	100.00	99.94	100.21
Output per Worker	100.00	100.00	99.63
Output per Firm	100.00	100.00	187.70
Average Talent	100.00	100.00	184.14
TFP	100.00	100.00	100.81
Number of Firms	100.00	100.00	53.50
Mean Size	59.27	59.27	111.65
Median Size	22.95	22.95	63.24
Aggregate Pollution	100.00	125.64	87.56
Average Intensity	100.00	125.64	87.20
Biological Share	57.40	8.89	57.06
Monitoring	20.50	20.50	73.50

† Note: All values reported are in percentage points except mean and median size, which are numbers of workers in absolute term.

unprofitable to use more advanced treatment technology. Higher level of pollution follows. This result suggests that subsidies to treatment technology upgrading work as a substitute to stronger regulation.

If we increase the regulation to the level such that the original technology adoption rate is restored, as opposed to the results of case (ii) where size distributions and the allocation of resources are only mildly affected, the changes in experiment (iv) are enormous. The size and employment distributions for case (iv) are shown in Figure 2.10. In contrast to the size and employment distributions in the benchmark case, all firms in the first group are driven out. This is also reflected in column (iv) of Table 2.10 as increases in average talent and mean/median size of the firms. Therefore environmental policy improves resource allocation at the extensive margin by forcing small unproductive firms to quit the market. However, the gains from these improvements are limited because the allocation of resources at the intensive margin worsens. Table 2.11 shows the allocation of resources at the intensive margin. The efficient allocation at the intensive margin is achieved in the no size-dependent τ_z case, which is shown again here in row (i). Instead of an allocation of production toward larger firms, as in the efficient case, here the production of firms in the bottom four quantiles expands significantly at the expense of production share of the most productive firms. As a result, much of the gains in economic efficiency are offset by the worsening of resource allocations at the intensive margin. Although the level of industrial pollution gets lower, the reduction could be much larger if the allocation at the intensive margin was also improved, as

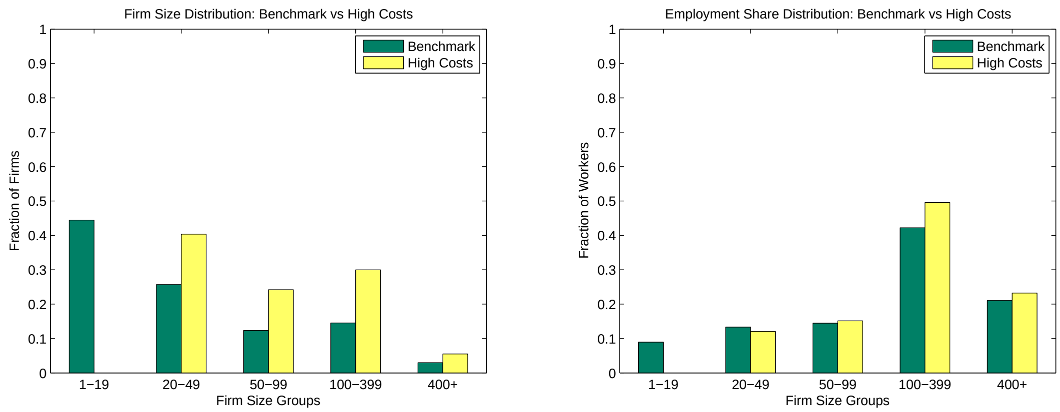

FIGURE 2.10.—ENVIRONMENTAL POLICY AND SIZE DISTRIBUTION

TABLE 2.11
ALLOCATION OF PRODUCTION AT THE INTENSIVE MARGIN: HIGH k_E

Economy	QU_1	QU_2	QU_3	QU_4	QU_5
Benchmark	2.69	4.19	7.29	16.55	69.28
Case (iv)	4.44	6.63	10.98	21.86	56.10
Case (i)	1.50	2.83	6.34	18.06	71.27

† Note: QU_1 to QU_5 represent respectively the first to the fifth quintile.

is in the case of elimination of τ_z.

6 CONCLUSIONS

In this paper, using a unique micro-level manufacturing census, we find a strong negative correlation between firm size and the pollution intensity in production. We also document substantial differences in firm size distribution between China and the U.S. Furthermore, we find empirical evidence which suggests that size-dependent product market frictions contribute significantly to these observed differences. We use a quantitative framework to organize these empirical regularities and to study the implication of firm size distribution on industrial pollution at the aggregate level. Quantitative analysis shows that firm size distribution has a sizable impact on industrial pollution. Our results imply that traditional productivity-oriented measures of the costs of size dependent policies underestimate the true costs because industrial pollution, which arguably affects households' welfare to a lare extent, is not accounted for in previous studies. Furthermore, our results suggest a new way to reduce the industrial pollutants discharge, by focusing on elimination of the economic frictions.

GDP-oriented promotion scheme is often blamed as the cause of China's heavy industrial pollution [Jia (2014)]. Our paper shows that growth-enhancing policies that smooth the frictions in the market could foster economic growth and reduce pollutant discharge at the same time. To this end, identifying observable factors that generate the product market frictions and designing optimal policies are very important directions to pursue in future studies. Our model is constructed to facilitate steady states comparisons and, as a result, abstracts from features that could be pertinent in analysis of short-run policy effects. Extending our model to allow for short-run dynamic path and firm's life-cycle analysis is important to further our understanding of the costs and benefits of certain pollution reduction policies.

In our paper, we focus on industrial water pollution (more specifically Chemical Oxygen Demand) and the case of China. However, the conclusions in our paper could be generalized to other pollutants and cross-country comparisons that involve more countries. For instance, small capacity coal-burning plants are widely acknowledged to be the main source of the emission of sulfur dioxide resulting in acid rain that affects a wide range of areas in China.

There are studies using micro-level manufacturing census of firms' production and emissions of other countries [Barrows and Ollivier (2014a,b), Shapiro and Walker (2015) and Dardati (2014 Forthcoming)], cross-country comparisons are therefore important directions to pursue. It is also interesting to study the geographical concentration of firms and pollution using a macroeconomic framework. We leave these extensions to future research.

Appendix for Chapter 2

A Accounting Exercises

This appendix provides robustness calculations of the accounting exercises.

Estimation Strategies.—Ideally, we would like to have the pollution intensity over firm size. However, such data do not exist since the NGSPS only reports total value of production and total amount of pollution. Therefore, we would need to construct pollution intensity over the number of employees. We use the CNEC for this purpose. In particular, we estimate the corresponding bins for production for each employment bin from the U.S data.

SUSB reports firm size in 22 bins. For the U.S size bins, we construct the corresponding production bins to be used in NGSPS. CNES is used to bridge the employment bins (SUSB) to the production bins (NGSPS).

1. *Non-parametric*:
   - For each U.S employment bin, we compute the 1st quartile and 3rd quartile production levels for Chinese firms within that employment bin. The two quartiles are used as the lower and upper bounds for the production bins in NGSPS.
   - We then use the median pollution intensity of firms within the newly defined production bins as the average pollution intensity for those bins.
   - Lastly, we calculate the aggregate pollution by assigning to each bin the corresponding share of production. The NGSPS production bins are used for China and the employment bins are used for U.S.
2. *Piecewise Linear*:
   - For each U.S employment bin, we regress log-product on log-employment using the subset of Chinese firms within that employment bin. The lower and upper bounds for the production bins in this case are calculated as the predicted value of the above regression.
   - We then run piecewise log-linear regression of pollution intensity on production within each new production bin. The average pollution intensity is chosen to be the predicted intensity at the midpoint of the new log-production bin.
   - Lastly, the average intensity is applied to the production share distributions. The U.S distribution does not change, however, a new distribution for China is calculated since the endpoints of the production bins are different.
3. *Parametric*:

TABLE A1

SIZE DISTRIBUTION ON POLLUTION

Methods	Paper	Agri	Tex	Chem	Bever	Avg	Reduc
Non-parametric	39.8%	60.7%	81.6%	102.5%	103.7%	63.5%	28.2%
Piecewise-linear	34.8%	69.4%	93.5%	180.1%	N/A[a]	75.4%	19.0%
Parametric	43.5%	61.1%	97.5%	101.2%	89.0%	67.0%	25.5%

[†] Note: Please see notes of Table 2.2 for acronyms of industries. For individual industries, the numbers reported are the aggregate pollution from the artificial U.S production structure as percentage from that of China. We use the 1st and 3rd quartile in the non-parametric calculation. Column 6 (Ave) calculates the weighted average of these ratios using the percentage contribution in row one of Table 2.2 as weights. Column 7 (Reduc) reports the aggregate reduction, which is simply the average without normalization.

[a] Since the beverage industry has a lot fewer firms than the others, there are employment size bins with no corresponding firms in China, which invalidates the method. We set the ratio to 100% in the calculation of the last two averages.

- Using CNEC, we regress log-production on log-number of workers, which yields a parametric relationship between the number of workers and production.

- Using NGSPS, we regress log-intensity on log-production, which yields a parametric relationship between intensity and production. From these two relationships, we can subsequently construct a new *parametric* relationship between intensity and number of employees. The average intensity is chosen to be the midpoint of each U.S employment bin. Notice that in this case we have a direct functional form for employment and intensity).

- Lastly, the average intensity is applied to the production share distributions. The U.S distribution does not change, but a new distribution for China is calculated since the endpoints of the production bins are different. Notice that this distribution for China is the one we use in Section 2.4.

The estimation results are shown in Table A1. Each of these three methods has its own advantages and disadvantages. The two non-parametric methods capture more of the variation at the local level, which could be washed out in a parametric estimation across the whole state space. However, this local nature also introduces a lot of instability on the estimations. Further, there are situations when there are gaps not covered by adjacent production bins and situations when these production bins overlap with each other. Under these conditions, some information will be lost while other is used for multiple times. Nevertheless, the results are robust across different estimation strategies.

B PROOFS

In this section we provide formal proofs to the results in Section 3.4. For convenience, we state those results here again.

PROOF OF LEMMA 2.1:

Lemma 2.1. In an economy with no product market frictions, $\pi_0(z)$ and $\pi_1(z)$ are both increasing and linear with respect to z. In addition, the slope of $\pi_1(z)$ is steeper than that of $\pi_0(z)$:

$$\frac{\partial \pi_0(z)}{\partial z} = (1-p\xi)\frac{\partial \pi_1(z)}{\partial z}, \qquad \forall z \in Z \tag{B1}$$

Proof. Since k_E is sunk-cost, it does not affect firms' decision once is paid. The factor demand decisions for the two types of firms are therefore the same. The first order conditions for capital and labor are respectively

$$\frac{\partial \pi_i(z)}{\partial k}: \qquad \alpha\gamma z^{1-\gamma} k^{\alpha\gamma-1} n^{(1-\alpha)\gamma} = R \tag{B2}$$

$$\frac{\partial \pi_i(z)}{\partial n}: \qquad (1-\alpha)\gamma z^{1-\gamma} k^{\alpha\gamma} n^{(1-\alpha)\gamma-1} = W, \qquad i = 0, 1 \tag{B3}$$

Dividing (B2) with (B3) yields constant capital to labor ratio h

$$h = \frac{k}{n} = \frac{\alpha W}{(1-\alpha)R} \tag{B4}$$

which says more capital is demanded when technology is capital intensive (higher α) or when capital rental price R low. Notice that the system of equations (B2) with (B3) is log-linear and thus has closed-form solution. With some algebra, the solutions are characterized by

$$n(z) = \Phi_1 R^{\frac{\alpha\gamma}{\gamma-1}} W^{\frac{1-\alpha\gamma}{\gamma-1}} \cdot z, \qquad \Phi_1 = \left[\frac{(1-\alpha)^{\alpha\gamma}}{(1-\alpha)\gamma\alpha^{\alpha\gamma}}\right]^{\frac{1}{\gamma-1}} \tag{B5}$$

$$k(z) = \Phi_2 R^{\frac{1+\gamma(\alpha-1)}{\gamma-1}} W^{\frac{\gamma(1-\alpha)}{\gamma-1}} \cdot z, \qquad \Phi_2 = \frac{\alpha}{1-\alpha}\Phi_1 \tag{B6}$$

Substitute the optimal solutions (B5) and (B6) back to the definition of profits functions (2.10) and (2.11), we have

$$\pi_0(z) = (1-p\xi)\left(\Omega - \frac{1}{1-\alpha}\Phi_1\right)\kappa z, \qquad \Omega = \left(\frac{\alpha}{1-\alpha}\right)^{\alpha\gamma}\Phi_1^{\gamma} \text{ and } \kappa = W^{\frac{\gamma(1-\alpha)}{\gamma-1}} R^{\frac{\alpha\gamma}{\gamma-1}}$$

$$\pi_1(z) = \left(\Omega - \frac{1}{1-\alpha}\Phi_1\right)\kappa z - Rk_E$$

where it is clear that both functions are increasing and linear in z and (B1) is true. □

PROOF OF COROLLARY 2.1:

Corollary 2.1. Suppose the product market frictions are specified as $\max\left\{0, 1 - z^{\phi_1}\right\}$ with $1-\gamma+\phi_1 > 0$, then $\pi_0(z)$ and $\pi_1(z)$ are both increasing and concave with respect to z. In addition, the slope of $\pi_1(z)$ is steeper than that of $\pi_0(z)$:

$$\frac{\partial \pi_0(z)}{\partial z} = (1-p\xi)\frac{\partial \pi_1(z)}{\partial z}, \qquad \forall z \in Z$$

Proof. The proof is straightforward given Lemma 2.1. Substituting in the tax function, $\pi_0(z)$ and $\pi_1(z)$ now becomes

$$\begin{aligned}
\pi_0(z) &= (1-p\xi)\left(\Omega - \frac{1}{1-\alpha}\Phi_1\right)\kappa z^{\frac{1-\gamma+\phi_1}{1-\gamma}} \\
\pi_1(z) &= \left(\Omega - \frac{1}{1-\alpha}\Phi_1\right)\kappa z^{\frac{1-\gamma+\phi_1}{1-\gamma}} - Rk_E
\end{aligned}$$

where Ω, Φ_1 and κ are defined as in Lemma 2.1.

Assumption $1-\gamma+\phi_1 > 0$ guarantees the monotonicity of the profits functions. Concavity is easily verified by taking second order derivatives. □

PROOF OF PROPOSITION 2.1:

Proposition 2.1. There exists a unique threshold $\hat{z}$ such that all household members with $z \leq \hat{z}$ choose to be workers and those with $z \geq \hat{z}$ become entrepreneurs. Further, $\hat{z}$ is the solution of $W = \pi(\hat{z})$

Proof. Since the overall profit function $\pi(z)$ is the upper envelope of $\pi_0(z)$ and $\pi_1(z)$, from Lemma 2.1 and 2.1 we know $\pi(z)$ is monotonic increasing. It is easy to verify that $\pi(0) = 0$. Therefore, as long as $0 < W < \pi(\overline{z})$, we can find a unique $\hat{z}$ such that $\pi(\hat{z}) = W$, where uniqueness follows from monotonicity. The condition $0 < W < \pi(\overline{z})$ is guaranteed in the general equilibrium version of our model by Inada condition on the production function. □

PROOF OF PROPOSITION 2.2:

Proposition 2.2. Given k_E, W, τ_z and R, there exist unique thresholds $\tilde{z}_n$ and $\tilde{z}_f$ such that:

(i) In the economy with no product market frictions, entrepreneurs with $z \leq \tilde{z}_n$ produce using dirty technology while those with $z > \tilde{z}_n$ produce using clean technology.

(ii) In the economy with product market frictions, entrepreneurs with $z \leq \tilde{z}_f$ produce using dirty technology while those with $z > \tilde{z}_f$ produce using clean technology.

(iii) $\tilde{z}_n < \tilde{z}_f$, that is, product market frictions impede the technology upgrade.

Proof. Uniqueness follows from

$$\frac{\partial \pi_0(z)}{\partial z} = (1 - p\xi)\frac{\partial \pi_1(z)}{\partial z}, \qquad \forall z \in Z$$

and monotonicity under both the case with and without frictions.

We can solve for analytical expression for z_n:

$$z_n = \frac{Rk_E}{p\xi\left[\Omega\kappa^\gamma - \frac{1}{1-\alpha}\kappa\right]} \tag{B7}$$

where z_n is simply the "distance" (Rk_E) over "speed" ($p\phi\left[\Omega\kappa^\gamma - \frac{1}{1-\alpha}\kappa\right]$). The "distance" in both cases are the same, so eventually whether z_f lies left or right to z_n depends on the "speed" of convergence.

Using expressions of the profits functions with frictions, we can show that

$$z_n = \frac{Rk_E}{p\xi\left[\Omega - \frac{1}{1-\alpha}\right]\kappa} < \left(\frac{Rk_E}{p\xi\left[\Omega - \frac{1}{1-\alpha}\right]\kappa}\right)^{\frac{1-\gamma}{1-\gamma+\phi_1}} = z_f^* \tag{B8}$$

which proves the proposition.

One caveat is that the second inequality holds only if the number in the parentheses is greater than 1. We verify this in our quantitative analysis but restrain ourselves from discussing extreme cases where the condition is not hold. □

Chapter 3

Job Training, Financial Frictions and Unemployment Outflows

1 Introduction

Evaluated according to civilian unemployment rate, two of the ten postwar recessions hit the U.S. labor market extremely strong: the back-to-back 1980 recession (later in this paper referred to as the Second Oil Shock) and the Great Recession. In both recessions, the civilian unemployment rate doubles from around 5% to 10%. Figure 3.1 shows this graphically.

With this resemblance being said, it has been widely acknowledged in the literature that the sources of the two recessions are different. While the Second Oil Shock is more of a traditional total factor productivity (TFP) driven recession [Chari, Kehoe, and McGrattan (2007)], many researchers attribute the origination of the Great Recession to the turmoil of the financial markets [Jermann and Quadrini (2009, 2012)].[1] Whether this difference in origination affects the performance of the labor market at a disaggregate level is thus called for examination. In this paper, we made two contributions, one empirical and the other theoretical. Empirically, we document some novel evidences on job finding rates at the occupational (we use jobs and occupations interchangeably later in this paper) disaggregate level which is overlooked by the literature that typically implementing the disaggregation according to education attainment. Theoretically, we propose a combination of Kiyotaki and Moore (1997) credit cycle model and Pissarides (2009) search and matching model with differential hiring cost and credit shocks and show that calibrated to the U.S. economy, the model is able to generate these empirical patterns. We then use our model as a laboratory to conduct various counterfactual analysis. These quantitative exercises shed light on the potential effects of expanding current U.S. active labor market policies, the programs we have in mind are the *WIA Dislocated Worker Program* and the *Wagner-Peyser Employment Service*.

In particular, regarding our empirical contribution, we find two facts with respect to the job finding rates of the low/middle-skill jobs that are not documented in previous literature.[2] First, disaggregated along occupation groups, the service jobs *on average* enjoy higher job finding rates

[1] In fact as reported in Petrosky-Nadeau (2013), the TFP actually increases by 3.35% from 2008Q3 to 2009Q4.

[2] By low/middle-skill jobs we mean service jobs, operators and laborers, construction workers and manufacturing production workers, see Appendix D for details.

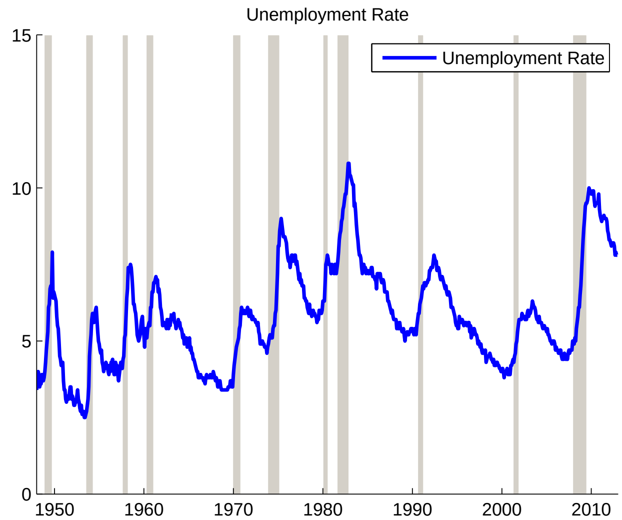

FIGURE 3.1.—SEASONALLY ADJUSTED U.S. CIVILIAN UNEMPLOYMENT RATE

Data Source: Bureau of Labor Statistics, series LNS14000000. Shaded areas indicate NBER recessions.

(approximately 15 percentage point) comparing to other manufacturing based low/middle-skill jobs, meaning there exists a *level difference*. Second, the job finding rates of these occupations decreased in parallel during the Second Oil Shock while the difference in levels disappears in the Great Recession, indicating that there exists a *business cycle response difference*. More specifically, while the job finding rates of both occupations respond similarly to productivity shocks, service jobs are more responsive to negative credit shocks. The left panel of Figure 3.2 shows a graphical demonstration.

These findings contribute to the recent empirical discussion of the cyclical behavior of unemployment rate.[3] Elsby, Hobijn, and Sahin (2010) relates most closely to our work. The authors also attempt to investigate the cyclical behavior of labor market flows by different labor force groups. However, they use education attainments as proxies for the average skill levels of different labor force groups and conclude that "reductions in the outflow rate that accompany recessions, from both a qualitative and a quantitative perspective, are truly an aggregate phenomenon". This can be seen from the right panel of Figure 3.2, which is a replication of their left bottom panel of Figure 8. Therefore our findings complements their paper by revealing that the job finding rates are a disaggregate phenomenon, both in terms of level and cyclical variation.

Theories are then called upon to explain our findings in Figure 3.2. Specifically, we need a theory that could explain the level and the cyclical variation *simultaneously*. An immediate candidate for the explanation of the level difference is the difference of hiring and training costs

[3]See for example Fujita and Ramey (2009), Elsby, Michaels, and Solon (2009) and Shimer (2012a).

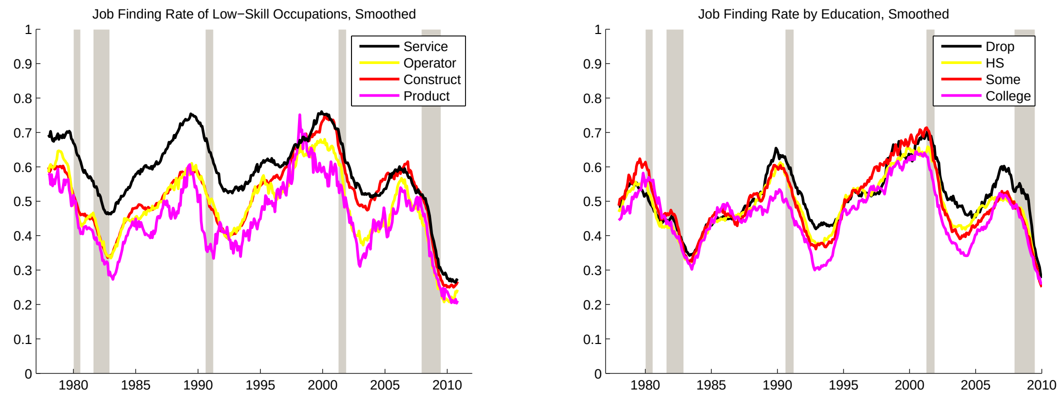

FIGURE 3.2.—SMOOTHED JOB FINDING RATES BY MAJOR OCCUPATIONAL GROUPS AND EDUCATIONAL ATTAINMENTS

Data Source: Calculated from CPS Monthly Basic using duration method, smoothed using 13-month symmetric moving average filter. Shaded areas indicate NBER recessions. Left panel: by occupational groups; Right panel: by educational attainments.

across different occupational groups. Using data from the *Dictionary of Occupational Titles 1991*, we found that service jobs on average requires three months less *special vocational preparation* time than the manufacturing based jobs. Therefore, the intuition for the *level* difference is that ceteris paribus, lower hiring costs means lower opportunity costs for firms in service occupations to create jobs.

On the cyclical variation, the fact that the shrinkage of the difference in job finding rates across occupations only happens at the current recession leads us to suspect the role played by the financial shocks. Indeed when we look at the job finding rates and net issuance of debt in the business sector together, we find a significant comovement and positive correlation for the period after 1985 but not during the Second Oil Shock. Similar correlations between firms' job creation behaviors and the issuance of debt in the business sector have also been documented by Davis, Faberman, and Haltiwanger (2013) and Garin (2013), using the micro and macro level *Job Openings and Labor Turnover Survey* (JOLTS) data respectively. Recall that our empirical findings show that the service jobs creation is affected to a larger extent comparing to the manufacturing based jobs in periods of credit shocks, we therefore ask the question that which feature of the service occupations makes it more vulnerable to credit shocks. There are two distinct characteristics of firms with more service jobs comparing to those with more manufacturing jobs: size and capital share in production. We argue that these are the exact reasons that service jobs are hit harder in an recession originated from the financial sector. The mechanism is the celebrated credit channel [a là Kiyotaki and Moore (1997)]. To illustrate this mechanism, we build a simple search and matching model with credit shocks and training costs. Down to the bare essential, the model is a combination of Pissarides

(2009) and Kiyotaki and Moore (1997). The intuition goes as follows. Since firms operating primarily on service jobs are smaller and have less capital which could serve as collateral to ask for loans from banks, therefore in periods of tightened credit standard, their financing of working capital is more likely to run into shortage compared to larger manufacturing firms who not only have better access to bank loans (because their capital equipment could serve as collateral assets to borrow against) but also could rely on other sources to finance their liquidity demand (for example issuing corporate bonds). Put differently, although service jobs still have a lower opportunity cost in hiring a new worker, the fact that such costs are fixed costs makes them more likely to surpass firms' credit availability. Inspected with the parallel decreasing of job finding rates across occupations in the Second Oil Shock recession, we conclude that TFP shocks affect *the willingness* of firms to hire new employees while financial shocks affect the *ability* of firms to make new hires. Therefore, although the effects of aggregate productivity shocks to firms' willingness to create jobs are similar for different occupations, those of aggregate credit shocks are different, mainly due to the difference in firms' collateral values.

Several empirical studies lend support to our hypothesis above. In particular, Buera, Kaboski, and Shin (2011) reported that the average number of workers per establishment in the manufacturing sector is 47 while that of the service sector is only 14. Also, Valentinyi and Herrendorf (2008) reports that the capital equipment share in service sectors is 13% while that in the manufacturing sector is 25%. Empirical studies demonstrate that both features leave the service sectors susceptible to credit constraints. First, using the data from *Quarterly Financial Report for Manufacturing Corporations* (QFR), Gertler and Gilchrist (1994) shows that within manufacturing sectors, small firms are affected disproportionately by liquidity constraints because of their shortage of collateral capital, lack of financing channels and limited amount of retained earnings. Similar finding is recently confirmed by Becker and Ivashina (2014) in other sectors using firm level data from the *Reuters' DealScan* database. They show that the bond-to-bank substitution (an indicator of banks lending standards) has significant predictive power over the borrowing behavior of small firms both statistically and economically. Moreover, evidences that the growth of *small businesses* is significantly affected by the availability of home equity lines is also found in micro studies. For example, using micro data on franchising, Fan, Kuhn, and Lafontaine (2013) found that a 30% decline in average collateralizable housing wealth leads to a 10% reduction in regional employment growth.

The theoretical part of our paper contributes to an emerging literature studying the interaction between the credit market and the labor market. Two notable examples are Petrosky-Nadeau (2014) and Chugh (2013). Specifically, these papers use different modeling strategy for the financial market friction (the Bernanke and Gertler (1989) agency cost mechanism versus the trade-off between internal and external finance) but both result in an amplification effect of financial *friction* to productivity shock. However, the main theme of these papers is the amplification of the *financial frictions*, not the effect of *financial shocks*. Put differently, in these models if we shut down the TFP shock, the economy will not demonstrate any fluctuation. The model closest to our is

Monacelli, Quadrini, and Trigari (2011) where they also have a textbook search and matching with credit shocks. The key feature distinguishes our paper with theirs is that we introduced training costs and we also explore the differential response of different occupations to the TFP shocks and credit shocks while they focus on the wage dynamics (and subsequently employment dynamics) at an aggregate level. This latter feature also distinguishes our paper with that of Garin (2013) where the latter has a Merz (1995) business cycle model with Kiyotaki and Moore (1997) credit channel. Another related paper is Mueller (2012) where the author also explicitly highlights the role of credit shocks, however the focus of that paper is on the cyclical behavior of job separation rates rather than job finding rates.

Since our evidences and theory have different diagnosis of the labor market compare to the literature, the prescriptions following our model predictions are also different. Recall that our evidence led us to conclude that the difference between the effect of TFP shocks and credit shocks on firms' hiring decisions is that TFP shocks affect firms' *incentive* to post jobs while credit shocks mainly affect firms' *ability* to post jobs. In other words, in the current recession, the reason that job rationing happens is not because firms do not want to create jobs but rather because there are frictions in the credit market that hold firms from exploiting potential economic opportunities. Our policy suggestion is thus calling for efforts to smooth the severe credit frictions firms facing during the current recession. Although our model is abstract from particular designs of policy instruments, two of the current U.S. active labor market programs map closest to the counterpart in the model: the *Workforce Investment Act Dislocated Worker Program* (WIA henceforth) and the *Wagner-Peyser Employment Service* (ES henceforth). Broadly speaking, in the model we mimic WIA as reduction of training cost and implement ES as reduction of vacancy posting cost. Our quantitative results show that evaluated according to job finding rates, active labor market policy is more effective when targeted at service jobs as opposed to manufacturing jobs. A per-job subsidy equals to 10% of the training cost for service occupations restores the job finding rates by 8 percentage points while the same amount of subsidy only brings the job finding rates for manufacturing jobs by 4 percentage points. It is slightly more effective when the economy is hit by credit shocks and implemented as expansions of ES.

On the policy implications, we view our paper as a complement to the existing discussion along three dimensions. First, our focus here is active labor market policy rather than the passive labor market policies (i.e. unemployment insurance) that prevails in the literature. Second, in our model credit shocks serve as another important exogenous driving force and they operate through a different channel than the usual productivity shock. Third, not only do we have two different shocks in the current environment, we also analyze the difference in the effects of policies on different occupations, thereby giving more accurate suggestions.

Relationship to the Literature.—Before we move on, we briefly discuss the relationship between our theory and some alternative competing hypotheses in the literature. In order that the *normative* prescriptions implied by our theory stand firmly, we need to make sure that first *pos-*

itively our hypothesis is correct. This is the reason why we need to spend some time and space on building a coherent theory. It is important as different theories usually deliver different policy suggestions. An immediate example would be the completely opposite policy suggestions made by Mitman and Rabinovich (2015) and Landais, Michaillat, and Saez (2015). Mitman and Rabinovich (2015) calls for a *pro-cyclical* unemployment insurance payment scheme because in their model an increase in the unemployment insurance raises workers' reservation value, reduces the matching surplus firms could snatch and thus further discourages firms' job creation on top of the negative aggregate shocks. On the other hand, in Landais, Michaillat, and Saez (2015) the rationing of the jobs in the recessions mainly comes from decreasing marginal productivity and wage rigidity where the value of the unemployment insurance does not enter firms' job creation decisions.[4] They then advocate a *counter-cyclical* unemployment insurance payment scheme because UI's function of consumption smoothing dominates its negative externality on unemployed workers' search intensity in recessions.

Possible explanations to explain the differential behaviors of the job finding rates of service and manufacturing occupations in the Great Recession and the Second Oil Shock in general fall into two categories: workers' or firms' behaviors. On workers' side, as of the current recession, the literature more or less reaches consensus that lack of search intensity is not the key to explain the poor labor market performances. However, the job polarization literature seems a natural candidate that will deliver predictions that are consistent with our empirical evidences. In particular, Jaimovich and Siu (2015) points to a cleansing effect of business cycle where workers leave the withering routine based occupations (here manufacturing occupations) and reallocate themselves to the prospering non-routine occupations (here the service occupations). Therefore one possible explanation that the job finding rates of the service occupations decline more is that more unemployed workers are lining at service occupations, which is a general equilibrium conjestion effect and as a result financial shocks is of limited or no effect at all. If this hypothesis is true, we should observe in the data that in recessions the number of people that changes their occupations increases dramatically comparing to regular time. To test this, we exploited the limited panel dimension of CPS Monthly Basic to check whether a disproportionate occupational switch during the recessions could be observed and the results do not seem to support this hypothesis.[5] Another evidence in support of our story is that Jaimovich and Siu (2015) found the sector reallocation (and the resulting jobless recovery) also in 1990-91 recession and the 2001 recession, where the convergence of

[4]This *de facto* mutes the channel at operation in Mitman and Rabinovich's paper, see Michaillat (2012) for more discussions.

[5]However the results should be interpreted with caution. The fact that only about 50% of the total observations could be merged leads to a significant reduction in the number of remaining observations. For a disaggregated analysis like ours, it is difficult to make strong quantitative statements because the sampling variance worsens, which yields very noisy estimates. Nevertheless, even with the magnified sampling variance, we observe on average around 3.5% people switch occupational groups and this number does not seem to vary across business cycles. Further restricting our concentration on the unemployed workers does not change the scenario significantly.

the job finding rates only occurs in the Great Recession according to our evidence. Therefore we argue that although the Jaimovich and Siu (2015) story accounts for the change in *relative employment levels* across occupations brilliantly, the convergence of the job finding rates in the Great Recession does not seem to root from this origin.

The break down of the Beveridge curve in the Great Recession [Elsby, Hobijn, and Sahin (2010) and Davis, Faberman, and Haltiwanger (2013)] indicates strongly the central role of firms in explaining the labor market performance in the current recession. Hagedorn, Karahan, Manovskii, and Mitman (2013) empirically identifies that the persistent increase in unemployment rate could largely be attributed to the extensions of unemployment benefit duration using the variation of state unemployment policy discontinuity across boarder. They use a standard search and matching model to show that the reason behind this is that the extended unemployment insurance raises the value of workers' outside options, and hence discourages firms' incentives to create jobs. This is in line with Mitman and Rabinovich (2015). Ravenna and Walsh (2012) points to increased screening of job candidates by firms. The reason that screening is intensified in recessions is because the share of low-efficiency workers in the unemployment pool rises under such occasions, therefore as a result firms take more effort to filter out those low-efficiency workers. In this sense, the mechanism shares the similar taste as Pries and Rogerson (2005). A take away message here is that it is not necessary the case (we actually think that it is highly implausible the case) that one single theory stands behind what we observe in the data, rather there are multiple channels that things could work and each mechanism contributes to a certain fraction of the variation we observe in the data. In fact, the way we view our findings in Figure 3.2 is that the differential response of service occupations and manufacturing based occupations in the Great Recession and the Second Oil Shock provides a variation that helps us to identify the differential effects of TFP shocks and credit shocks to firms' job creation behavior. This way we view our proposed mechanism as a complements rather than substitutes to the existing literature by providing another potential explanation to the current labor market situation.

The rest of the paper is organized as follows. In Section 2, we provide more information and analysis on the empirical evidences in support of our quantitative theory. We then build and analyze our model in Section 3. The model is calibrated and simulated in Section 4, which also contains the main quantitative results of our paper. We then conduct some simple counterfactual analyses in Section 5. Section 6 concludes the paper. All technical details are collected in the appendices.

2 Empirical Evidence

This section describes the empirical evidences that this paper builds on. We first describe our data source and briefly discuss the way we calculate the job finding rates in Figure 3.2. We then discuss evidence in support of the two building blocks of our model, the training costs and the relationship between job creation and credit availability. Limitations to our empirical analysis are discussed in Appendix E.

2.1 *Occupational Job Finding Rates*

For the disaggregated occupational level analysis of labor market dynamics, large size high frequency data is essential. Our main data source draws from the *Current Population Survey Basic Monthly Data*. Our analysis covers the period between January 1978 and December 2010. An observation is included in our sample if his/her age is greater than 16, reports his/her occupation and is in the labor force. This way we are left with approximately 80,000 valid observations for each month. So in total, we have 32 years $\times$ 12 months $=$ 384 cross sections, each with about 80,000 observations.

From these data, we collect information on labor force status, unemployment durations and Census occupational classification code for each observation. We then merge each cross section with the occupational codes crosswalk used in Autor and Dorn (2013).[6]. After that, we generate time series of total number of employed, unemployed and short-term unemployed (less than one month, the sampling frequency of CPS) for each occupational group. We seasonally adjust these time series using The X-12-ARIMA Seasonal Adjustment Program developed and maintained by the Census Bureau.[7] We use *indirect* seasonal adjustment as suggested by the CPS staffs of BLS [Tiller and Evans (2013)] because each of the time series may bear different seasonal pattern. Our later analysis is thus based on these time series. In all calculations, we use the CPS sampling weight. Of the six occupational groups used in Autor and Dorn (2013), from now on we only focus on the four low/middle skill occupations: service jobs, operator and laborers, construction and transportation workers and manufacturing production workers. Measured according to educational attainments, these occupations are predominantly held by high school dropouts and high school graduates. Before we move on, it is important to clarify that by low-skill service job we mean "food preparers", "waiters", "guides" or "gardeners", etc. We are *not* referring to the broad *service sector* where many decently or very well paid jobs belong to.

To calculate the labor market flows, we use seasonally adjusted time series on numbers of unemployed and short-term unemployed (less than 4 weeks) people. Let U_t and U_t^s represent the two sequences respectively.[8] Our estimation follows Shimer (2012a). We therefore only sketch through the calculation, the readers are encouraged to read Shimer's original exposition. Assuming that the arrival rates of job offers follow a Poisson process with arrival rate $f_t = -\log(1 - F_t)$

[6]The crosswalk is initially issued by the Bureau of Labor Statistics (Meyer and Osborne (2005), modified slightly by Dorn (2009))

[7]Our calculation directly calls the Census Fortran implementation (version 0.3). The source codes and releases for multiple operating systems are available from the Census website (`http://www.census.gov/srd/www/x12a/`). The Census maintains excellent technical support for X-12 method, among all documents mentioned on the Census' webpage, we find Findley, Monsell, Bell, Otto, and Chen (1998) and Ladiray and Quenneville (2001) of especial help.

[8]As in the literature, we correct for the discontinuity in short-term unemployment caused by the CPS 1994 Redesign (details explained in Appendix C).

TABLE 3.1
DIFFERENCES IN JOB FINDING RATES

Data Periods	Mean	Std.dev	Min	Max
1978.01 – 1992.12	14.02%	2.74%	7.95%	21.54%
2003.01 – 2007.06	9.96%	3.22%	3.62%	16.12%
2007.07 – 2009.12	5.75%	1.61%	3.51%	10.33%

Data Source: CPS Monthly Basic. Calculated following Shimer (2012a).

where F_t is the cumulative probability. Hence the number of total unemployment and short-term unemployment follows first-order difference equation:

$$U_{t+1} = (1 - F_t)U_t + U^s_{t+1} \tag{3.1}$$

The intuition behind equation (3.1) is rather straight forward. It says the total number of people unemployed period $t + 1$ equals those of period t that fails to find a job in $[t, t + 1)$ plus the newly unemployed at $t + 1$. We fit in (3.1) the series U_t and U^s_t that we recovered from CPS, this gives us a sequence of F_t. The sequence of f_t then follows naturally. Figure 3.2 is plotted using f_t for each occupational groups.

From a quantitative perspective, the size of the differences in job finding rates (in percentage points) between the service occupations and the manufacturing based occupations in different time periods are shown in Table 3.1. A direct comparison between the periods right before and in the financial crisis, we see all the three statistics (mean, standard deviation and maximum) indicate a dramatic closure of the difference.

2.2 *Occupational Training Costs*

To support our hypothesis, two pieces of evidences regarding occupational level training costs are needed. First, the evidence should reveal that the training costs are indeed higher for the manufacturing based low/middle skill occupations comparing to low skill service jobs. Second, at least a certain fraction of the human capital accumulated throughout these training is firm specific and is thus not transferable if the worker experiences an unemployment interval. We provide empirical evidence on both perspectives. Before we move on, we would like to emphasize that the training costs we refer to throughout our paper is the training offered by the private sector. The reason is that the expenditures of these programs amount to approximately only 0.1% to 0.2% annual GDP and further they only amount to 3% to 6% of the cost training provided by private employers [LaLonde (2003)].

Differential Training Costs.—Despite the data limitation, the existence of on-the-job training is well established in the literature. An immediate example is Lerman, McKernan, and Riegg (2004) which reports that according to the 1995 Survey of Employer-Provided Training (SEPT),

TABLE 3.2
MEAN AND MEDIAN OF SVP FOR MAJOR OCCUPATIONAL GROUPS

	Product	Construct	Operator	Service
Mean	6.35	4.79	3.66	3.92
Median	6.85	4.83	3.60	3.46

Data Source: U.S. Department of Labor, Dictionary of Occupation Titles, Revised Fourth Edition. Weighted according to CPS Monthly Basic. Details regarding the scale are explained in Appendix D.

95% of workers in establishments with 50 or more employees receive some training provided by the employers. Similarly, in the 1994 National Employment Survey (NES), 97% of establishments with 20 or more employees provide some training. From a more quantitative perspective, using the *1982 Employment Opportunity Pilot Project Survey* (1982 EOPP), Cairo and Cajner (2011) shows that on average it takes 13.4 weeks for a newly hired worker to become fully productive and the percentage productivity gap between a new trainee and an average incumbent worker is 39.1%. Cairo and Cajner (2011) did a disaggregated analysis of the EOPP survey according to education attainment and with the information in EOPP, we could in principle do a similar disaggregation according to occupational groups. However we pursue a different route mainly because our occupational system adopted from Autor and Dorn (2013) is not directly comparable with that in the EOPP survey and we would like to avoid spurious results because of mismatch in the occupational categorical system. Also the information contained in the 1982 EOPP is a little bit dated given that there is a large amount of literature documenting the skill-biased technological progress and job polarization.[9] Instead, we use the information on *special vocational preparation* (SVP) contained in the U.S. Department of Labor's *Dictionary of Occupational Titles* (DOT) to infer the occupational level training cost for our purpose.[10] The DOT fits our purpose in particular because BLS issued a modified version of it in companion with the occupational system we are using. The results are shown in Table 3.2.

In general, the numbers in Table 3.2 is consistent with our intuition. Service jobs require much shorter training time compares to manufacturing based occupations. The comparison between Operators and Service jobs may seem at odds with our story, as they have very similar SVP time. However, we argue that training time is just one dimension of the total training cost, the cost per hour also makes contribution. According to Autor and Dorn (2013), the average wage across our data span for service jobs is \$8.91, while that for the Operators is \$12.19. Therefore although Service jobs and Operators have similar training time, the actual training cost could differ signifi-

[9]See for example, Autor, Levy, and Murnane (2003), Acemoglu and Autor (2011), Autor and Dorn (2013) and Jaimovich and Siu (2015).

[10]SVP refers to "the amount of lapsed time required by a typical worker to learn the techniques, acquire the information, and develop the facility needed for average performance in a specific job-worker situation." See Appendix D for more details.

cantly.

Is the Training General or Specific?—In order that our proposed mechanism works, a conceptual issue must be addressed. That is, whether the training costs we documented in the previous section refers to *general* human capital (which is broadly transferable across jobs) or *job specific* human capital (which loses its value completely after job transition)? If the human capital accumulated in previous jobs can be transferred smoothly from one job to another, then it is not necessarily the case that training costs are the primary cause of hiring frictions. More specifically, we cannot comfortably assume that every time when a firm tries to hire a new worker, it has to bear some training costs as we do in later sections of the paper. As a results we would have to look for other alternatives in explaining why on average service workers enjoy a higher job finding rates comparing to their manufacturing counterpart. Moreover we need to make sure whatever mechanism we find is not in confliction with our observed business cycle difference.

Before we move on, we would like to make some clarifications. The question we are trying to answer is *not* whether firms or labor market intervention programs should provide general or specific training. Nor are we trying to estimate whether vocational training provided by firms and intervention programs is general or specific in its nature.[11] All that we need for our proposed mechanism and its policy implication to function is that there is some fraction of the human capital workers accumulated on their jobs has some specific nature and firms on average need to provide training whenever they are hiring new workers. Put differently, all we need is a fixed cost functioning as a friction that interacts differently with TFP shocks and credit shocks.

Two papers by Lisa Lynch provided us with some evidences. She used data in *National Longitudinal Survey of Youth 1979* (NLSY) and found that on-the-job training in the U.S. is mostly not transferrable between employers [Lynch (1991)]. She also found that past experience of on-the-job training has no predictive power over respondents' current wages [Lynch (1992)]. These evidences go against what we would expect to see if on-the-job training by firms has more of a general taste. Since if this is the case, we would expect a strong predictive power of past training experience to current wages. Another dimension to examine this is that if human capital accumulated through employment is general, we would expect to observe less people among the older cohorts or those with longer relevant labor market experience to report receiving on-the-job training or subjecting to productivity gap upon changes of employers. This is also not supported by the literature. Cairo and Cajner (2011) documented that as reported by employers participating in the EOPP, newly hired workers with at least 5 years of relevant labor market experience still suffers from a 25% productivity gap comparing to an incumbent average worker. The number is smaller but still economically significant (recall in last section we have 39.1% for all samples). The authors also checked the formal training data contained in NLSY 1979 and failed to find notable decline in training incidence as people age.

[11] Although the optimal design of training programs over the business cycles is interesting per se, it is beyond the scope of the current paper.

Although there are some evidence supporting the argument that the private sectors provide training in general human capital, logically it does not mean that the human capital accumulated on-the-job has *no* specific component.[12] Also, the SVP in DOT is explicitly designed to measure the initial training in order that a newly hired worker becomes productive as opposed to human capital development programs in later periods of the employment relationship, we argue that this kind of training is more likely to bear a firm or job specific nature. After all, all that we need for our mechanism to carry over is the existence of a non-trivial part of the difference in the firm specific training costs across occupations, we believe that this claim is very difficult to reject statistically even using the data adopted by those literature supporting the existence of general human capital training.

2.3 *Credit Shocks and Job Finding Rates*

In this section, on top of those mentioned in the introduction, we provide more evidence regarding the connection between credit constraints and job finding rates. Figure 3.3 shows the comovement between net debt issuance of the business sector and aggregate job finding rates.[13] The scale of figure is adjusted such that the two curves could be placed in the same figure.

It is quite evident that there is strong positive comovement between net debt issuance and job finding rates after 1984. A very important observation is that in support of our hypothesis is that we see a significant drop in the net debt issuance in the current recession which is observed nowhere before. The patterns in Figure 3.3 are broadly consistent with the findings in Jermann and Quadrini (2009) that the U.S. economy has experienced substantial changes in the volatility of the real variables (the so-called Great Moderation) and more related to us liberalization in the financial market. Of particular interest to us is the banking liberalization and the subsequent increase in the competition in the lending market happened in the 1980s. As claimed in Jermann and Quadrini (2009), "this has been especially important for firms more directly dependent on bank loans, namely small and medium size firms." Along the business cycle dimension, using the data from *Senior Loan Officer Opinion Survey* (SLOOS), Liu (2013) in an unpublished manuscript tests empirically the hypothesis that banks competition over the business cycle drives the tightening of lending policies and increasing in the interest spread during recessions (the opposite holds for expansions).[14] The effect of bank loans accessibility on job creation has been tested and verified by micro level data, see for example Fan, Kuhn, and Lafontaine (2013), Schmalz, Sraer, and Thesmar (2013) and the references therein. Ultimately, how fast a worker is able to find a job is to a large extent determined

[12]See for example, Acemoglu and Pischke (1998, 1999) and Autor (2001). Interestingly, viewing workers' health condition as a particular kind of general human capital, Fang and Gavazza (2011) applied the mechanism in Acemoglu and Pischke (1998) to argue for the under-provision and dynamic inefficiency in the employment-based health insurance system prevailing in the U.S.

[13]The net debt issuance is the summation of the issuance from nonfinancial corporate sector and non-corporate sector. We take the data from the FRED maintained by St.Louis Federal Reserve.

[14]See also Lown and Morgan (2006) for an earlier contribution.

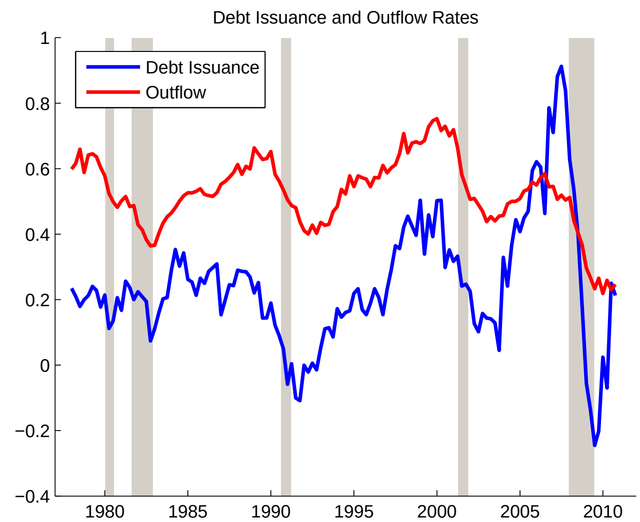

FIGURE 3.3.—NET DEBT ISSUANCE OF BUSINESS SECTOR AND JOB FINDING RATES

Data Source: Job finding rates are calculated from CPS Monthly. Net debt issuance is taken from the Flow of Funds Accounts of the Federal Reserve Board. Shaded areas indicate NBER recessions.

by the total number of jobs available in the economy.

So far we have presented evidence in support of our two core assumptions in this paper, the difference in training costs and the correlation between job finding rates and the credit conditions. Some readers may argue that the evidences we provide regarding the credit market lacks the occupational dimension. The reason is because of the lack of occupational level financial data. It is understandable because no matter establishment or firm is used as sampling units, it is very likely the case that multiple occupations are pooled together (it is not difficult to find a firm with a manager and a couple of janitors). And it is for this reason that the disaggregated financial data are usually presented according to sectors. Since the importance of occupational disaggregation has just recently gained attention, to the best of our knowledge, direct publicly available evidence does not seem to exist. Nevertheless, we argue that the combined discussion of firm size, capital utilization, financial market accessibility as well as various micro evidence in the literature could at least serves as a reasonable first pass.[15]

3 THE MODEL

We present our model in this section. Unlike in the textbook version of the search model where vacancy posting cost has to be paid whenever a position is maintained, in our model besides the regular vacancy posting cost, a training cost is incurred only when a match is formed. So to put it

[15]Recall the papers we mentioned in the introduction, we do not list them again here in the interests of space.

in another way, vacancy cost needs to be paid whenever the firm is willing to attract future workers. But in order to make an attracted worker productive, a further training cost must be paid. There are other ways of modeling training cost [for example, Cairo and Cajner (2011)]. We choose to model training here in such a parsimonious way in principal because we want to keep the tractability of the model and the transparency of the mechanism. We start with a narrative description about the economic environment of the story, we then formally set up and analyze the model.

The Environment.—We give a narrative description of the timing of our model. Time is discrete and is denoted by $t = 1, 2, 3, \ldots$. There are three kinds of agents in the model: workers, new firms and incumbent firms. Workers have two identities, unemployed and employed workers. Unemployed workers search for job with inelastic search intensity and employed workers work in exchange for wages. New firms borrow money from the financial intermediaries and post vacancies, meet unemployed workers searching for jobs on a frictional labor market and train a worker once it meets one. Incumbent firms borrow money from the financial intermediaries to finance their working capital, repay the existing debt if any and pay the workers their wages. The remaining residual is consumed by firm owners. There are two aggregate shocks in this economy, TFP shocks and credit shocks. At the beginning of period t, both firms and workers observe the realization of the two shocks. New firms start with zero debt make decide whether to enter the market. If they decide to enter, then they borrow to pay the vacancy posting costs and training costs. Incumbent firms bargain wages with workers, organize production, borrow new debt to repay existing debt and wage bills and consume the residuals. At the end of the period, incumbent firms are subject to an exogenous separation shock which destroys the matched pair. It is at this moment that the firms make decisions on whether to default on existing debt. If firm defaults, the financial intermediary takes over the ownership rights of the firm and liquidate the firm on the market. After liquidation, the financial intermediary gets a certain fraction (depending on the realization of the credit shocks at period t) of the market value of the firm. If the firm decides to respect the debt, all agents move to period $t + 1$, observe the realization of the two shocks at $t + 1$ and the environment moves forward recursively.

3.1 *The Labor Market*

The labor market is characterized using a discrete time directed search model with segmented markets for each occupation. Labor markets for different occupations are indexed by $h \in \mathcal{H} = \{h_1, \cdots, h_{max}\}$. There is no heterogeneity within each market, therefore we have a collection of markets with representative workers and firms in our model. Different occupations are characterized by different production technology and matching technology. All the endogenous variables in the model will depend on the level of human capital h and should thus have the subscript h. Since the markets are essentially segmented, it will not cause confusion if we suppress the subscript h for these variables in later discussion. This will greatly simplify the notation. However, we will *not* omit the subscription of any of the exogenous variables.

Workers have a trivial role in this model. There is a continuum of mass 1 workers in each market. They share the same preference of maximizing the lifetime utility $\mathbb{E}_0 \sum_{t=0}^{\infty} \beta^t c_t$. Linear preference implies the interest rates in the model is constant, given by $r = 1/\beta - 1$ and the timing of the consumption stream is not important in this model. Therefore we do not have to worry about the consumption saving decision of the worker.[16] In any period, the worker is either employed or unemployed. Employed workers produce products according to the production technology to be specified shortly after and get their wage payments. Employed workers are subject to an exogenous separation shock λ_h. The labor market status of the workers hit by the shock will change to unemployed. They unemployed workers search costlessly on the labor market. Search takes up one period and the probability that a job offer arrives depends on the unemployment rate u_t, vacancies posted by firms v_t and the frictional matching process $m(u_t, v_t)$. We deviate a little bit here from the standard practice of the textbook model by assuming the functional form of $m(\cdot)$ to be:

$$m(u_t, v_t) = \frac{u_t v_t}{(u_t^l + v_t^l)^{1/l}} \tag{3.2}$$

This is the functional form adopted in den Haan, Ramey, and Watson (2000). The primary merit of such functional form is that the job finding rates is bounded above from one.[17] Without loss of generality, the matching technology is assumed to be the same across all labor markets.[18] Let $\theta_t = v_t/u_t$ stands for labor market tightness, then the vacancy filling rate $q(\theta_t)$ and the job finding rate $p(\theta_t)$ are defined respectively as:

$$q(\theta_t) = \frac{m(u_t, v_t)}{v_t} = \frac{1}{(1 + \theta_t^l)^{1/l}} \tag{3.3}$$

$$p(\theta_t) = \frac{m(u_t, v_t)}{u_t} = \frac{\theta_t}{(1 + \theta_t^l)^{1/l}} \tag{3.4}$$

We assume that a newly formed match is immune to the separation shock λ_h.

We assume the production technology is linear

$$y_t = A_t h$$

[16] Recall that in the literature review section we documented that it is widely accepted in the literature that the workers are not the main character in driving the variations in the labor market in the Great Recessions.

[17] It is a common issue in search and match model with the canonical Cobb-Douglas matching function that the job finding rates will sometimes exceed one. Under our underlying assumption, since there is no search decisions on the workers' side, therefore in this model the probability that an unemployed worker receives an offer is equivalent to the probability of moving out of the unemployment pool. Under plausible matching efficiency, job finding rates could be higher than one if there is a positive realization of productivity shock, which conceptually does not make sense. This is not an issue for continuous version of the model [Shimer (2005)] as any Possion intensity would be weighted by the length of the time interval Δt. Some researchers propose to address this issue under discrete time horizon by *ex post* truncating the job finding rates. However, the resulting discontinuity complicates the numerical solution of the model.

[18] This also allows us to highlight the role of hiring costs and collateral values. If we allow different matching functions in different markets, not only the mechanisms would be seriously contaminated, but also we cannot identify the parameters in the model without occupational level labor market tightness data.

where y_t is the actual production level, A_t is the aggregate TFP shock which is universal across all markets. Its law of motion follows an AR(1) process:

$$\log A_t = \rho_A \log A_{t-1} + \varepsilon_{A,t} \tag{3.5}$$

Therefore the TFP shocks in different markets only differ in their *average level*, the stochastic component of the processes are the same. Before the technology could be actually put into production, entrepreneurs need to post vacancies, hire workers and borrow to finance the financing need.

New Firm.—We start with a new firm. In order to get a worker matched with the technology, the firm owner has to first post a vacancy, waiting for a worker to be attracted and then train the worker to become productive. Of course all these need money. We assume entrepreneurs borrow all money that is needed in running the business from a frictional financial market (to be explained in details in the next section). This way we do not capture the precautionary behavior of entrepreneurs described in Shimer (2012b). In particular, to maintain a position on the labor market, a flow cost of κ is incurred. Once a worker comes to the vacancy, to train her, an occupational specific fixed cost H_h is required. We assume away the randomness in the matching process on the firms' side, this means by posting $1/q(\theta_t)$ vacancies, one match will form *with certainty*. Thus this means the total expected cost of *posting one vacancy* is:

$$\kappa + q(\theta_t)H_h$$

or equivalently, the expected cost of *preparing a productive worker* is:

$$\frac{\kappa}{q(\theta_t)} + H_h$$

The entrepreneur then turns to the financial market to borrow and finance the above cost. Since the interest rate is $1 + r$, if we denote the debt liability next period to be b_{t+1}, then the actual money borrowed is then $b_{t+1}/(1 + r)$. Notice they could potentially borrow more than the needed for the cost if it is within the borrowing limits and we show later they indeed will because this improves their bargaining position on the table. We assume that the entrepreneurs also have a linear preference over the consumption stream. Given the constant interest rate, again the timing of the consumption stream will not affect entrepreneurs' decisions.

Incumbent Firm.—When a trained worker is in position, the firm starts the regular production. The information set consists the realization of the two aggregate shocks, productivity shock A_t and credit shock ϕ_t; and the inherited debt liability b_t. The information is public. Based on the information, the entrepreneur sits down with the worker to discuss the wage payment. Upon the agreement, the worker produces output $A_t h$ in exchange for wage w_t. At the same time, the entrepreneur goes to the financial market to borrow working capital b_{t+1}. Using the working capital b_{t+1} and the remaining product after wage payment, the firm pays back liability b_t and distribute the rest as dividend d_t. The objective of the firm is thus to maximize the discounted value of dividend stream $\{d_t\}_{t=0}^{\infty}$ (recall the linearity assumption):

$$d_t = A_t h - w_t - b_t + \frac{b_{t+1}}{R_h}$$

R is the gross interest rate the firm has to pay to the financial intermediary. As we will see soon, because there exists a positive probability that the firm defaults, a surcharge is usually included in R on top of the competitive risk free rate $1 + r$. The default happens because before move to the next period, the match is subject to an exogenous separation shock λ_h. At the time the shock hits the firm, debt b_{t+1} is not yet repaid and upon separation the value of the firm immediately falls to zero and the debt will not be paid at all. If the match is not destroyed by λ_h, firm decides whether to default *endogenously*. We will show later that in equilibrium, the financial contract guarantees that firm never defaults *endogenously*. Firm then moves to the next period, observe $A_{t+1}, \phi_{t+1}, b_{t+1}$ and repeats the above decisions again.

Notice that the timing of the model is actually rather flexible. All that we need is that w_t is determined with b_t in the information set. This is a convenient flexibility we buy by making the linearity assumption.

3.2 *The Financial Market*

The financial market consists of a continuum of financial intermediaries and is perfect competitive. This means in the equilibrium, the prevailing gross interest rate R will be actuarially fair. We already explained in the previous section that upon separation of the match, the value of the firm is zero and hence the lender recovers nothing from such situation. On the other end, if the match is not separated and the firm decides to default, we assume that the financial intermediary takes the ownership of the firm and sells it on the market. The credit situation of the economy is then characterized by an exogenous variable χ_t ($0 \leq \chi_t \leq 1$), which represents the fraction of the equity value of the firm the lender is able to recover. There are many ways to rationale the mechanism behind the reduced form, the probability of finding a proper buyer [Jermann and Quadrini (2012)] and costly states verification [Bernanke and Gertler (1989)] are just two examples. We abstract from the details on this end as it is not the focus of our paper. With this given, the financial intermediary sets the borrowing limits such that the outstanding debt could always be recovered by selling the firm when λ_h does not hit the firm and thus the firm will never choose to default *endogenously*. This is because in the event of default entrepreneur gets zero out of the action while if he or she sticks to the debt contract, he or she carries a positive value of the firm into the next period. Equation (3.6) writes this out explicitly. Therefore, actually the only financial decision the firm is making is how much debt to raise. More specifically, if we assume the equity value of a firm with outstanding liability b_t denoted by $J(b_t; A_t, \chi_t)$ (later we suppress the exogenous variables and simply writes this to be $J_t(b_t)$), then the borrowing limits of the firm in present value form could be written as

$$\frac{b_{t+1}}{1+r} \leq \chi_t \Big[\frac{b_{t+1}}{1+r} + \beta \mathbb{E}_t J_{t+1}(b_{t+1})\Big] \tag{3.6}$$

Inside the square bracket of the r.h.s of (3.6), there is the term $b_{t+1}/(1+r)$ again. This is because $J_t(b_t)$ is the equity value of the firm after it has paid back b_t. Therefore the value of the firm to the financial intermediary, the creditor of the debt, is $J_t(b_t)$ adding the outstanding liability back. This will become more clear when we write out explicitly the functional form of $J_t(b_t)$. Rearranging terms and substitute in $\beta(1+r) = 1$ in (3.6), we get

$$b_{t+1} \leq \phi_t \mathbb{E}_t J_{t+1}(b_{t+1}) \tag{3.7}$$

where $\phi_t = \chi_t/(1-\chi_t)$. This ϕ_t is the very same one we referred to in Section 3.1. We again assume the credit shock follows an AR(1) process:

$$\log \phi_t = \rho_\phi \log \phi_{t-1} + \varepsilon_{\phi,t}$$

Remember that the situation characterized by (3.7) happens only with probability λ_h for occupation h, therefore the occupational specific actuarially fair gross interest rate R_h is determined by

$$R_h(1-\lambda_h) = (1+r) \tag{3.8}$$

3.3 *Wage Bargaining*

Now we discuss the policy functions for the participants in this economy.

Workers' Problem.—The workers have a passive role in this model, their main function is to pin down the general equilibrium "prices". Let $W_t(b_t)$ be the value of an employed worker matched to a firm with debt level b_t and U_t be the value of an unemployed worker, then

$$W_t(b_t) = g(b_t) + \beta \mathbb{E}_t[(1-\lambda_h)W_{t+1}(b_{t+1}) + \lambda_h U_{t+1}] \tag{3.9}$$

and

$$U_t = a_h + \beta \mathbb{E}_t[p_t W_{t+1}(b_{t+1}) + (1-p_t)U_{t+1}] \tag{3.10}$$

where a_h is flow of unemployment income (both explicit and implicit, like home production). Since in our model, both firms and workers are representative, the values of individual variables coincide with their aggregate counterpart. We used this feature in (3.10). Also here wage $w_t = g(b_t)$ is *endogenously* solved from a Nash Bargaining problem specified later. Since the only endogenous state variable is b_t, the wage bargaining solution could without loss of generality be represented by a function $w_t = g(b_t)$. Notice that this specification fully allows the possibility that b_{t+1} and w_t are jointly determined, although we will demonstrate that they are not later in this section.

Firms' Problem.—Recall that the equity value a matched productive vacancy is denoted by $J_t(b_t)$, formally:

$$J_t(b_t) = \max_{b_{t+1}} \left\{ A_t h - g(b_t) - b_t + \frac{b_{t+1}}{R_h} + \beta(1-\lambda_h)\mathbb{E}_t J_{t+1}(b_{t+1}) \right\} \tag{3.11}$$
$$s.t.$$
$$b_{t+1} \leq \phi_t \mathbb{E}_t J_{t+1}(b_{t+1})$$

Write down the Lagrangian of (3.11) and taking the first order condition w.r.t b_{t+1}, applying the Envelop Theorem of w_t w.r.t b_{t+1} immediately reveals to us that the choice of b_{t+1} is independent of b_t. To further pin down b_{t+1}, we need to know $dJ_{t+1}(b_{t+1})/db_{t+1}$, which from the Envelop Theorem calls for dg/db_t. Therefore we first take a detour to characterize the bargaining solution g.

Wage Bargaining.—So now the problem becomes what is $g(b_t)$. g is the solution to a two-person cooperative game between the firm and the worker. Here they cannot take the bargaining results as given but have to behave strategically because each party's decision has non-negligible effect on the other party. We follow the standard practice since Myerson (1991) by solving for the *Markovian Perfect Equilibrium*. In particular, let

$$\hat{J}_t(b_t, w_t) = \max_{b_{t+1}} \left\{ A_t h - w_t - b_t + \frac{b_{t+1}}{R_h} + \beta(1-\lambda_h)\mathbb{E}_t J_{t+1}(b_{t+1}; g) \right\} \tag{3.12}$$
$$s.t.$$
$$b_{t+1} \leq \phi_t \mathbb{E}_t J_{t+1}(b_{t+1})$$

Therefore, $\hat{J}_t$ is the equity value of a firm when wage is *exogenously* set to be an arbitrary value w_t and all future wages are determined through function g. Notice here we have made the dependence of J (not $\hat{J}$) in the expectation operator explicit. Similarly, the counterpart of (3.12) on the workers' side is

$$\hat{W}_t(b_t, w_t) = w_t + \beta\mathbb{E}_t[(1-\lambda_h)W_{t+1}(b_{t+1}; g) + \lambda_h U_{t+1}] \tag{3.13}$$

Again, the dependence of W on g is made explicit on purpose.

Suppose the bargaining power of the worker on the table is η, the prevailing wage is then the solution to the problem

$$\max_{w_t} \{(\hat{W}_t(b_t, w_t) - U_t)^{\eta} \hat{J}_t(b_t, w_t)^{1-\eta}\} \tag{3.14}$$

If the solution to this problem is $w_t = \hat{g}(b_t, g)$ (notice the dependence on g again), then a *Rational Expectation Equilibrium* is characterized by the fixed point $\hat{g} = g$.

A great convenience of the fact that b_{t+1} is independent of w_t and b_t is the textbook solution of (3.14) could be directly applied here [Myerson (1991)]. Therefore under the equilibrium wage, if we denote the total bargaining surplus $S_t = J_t + W_t - U_t$

$$J_t(b_t) = (1-\eta)S_t(b_t) \tag{3.15}$$

$$W_t(b_t) = \eta S_t(b_t) \tag{3.16}$$

The intuition is straight forward, each party gets the share of the cake according to their bargaining power.

3.4 *Financial Decision*

Substitute (3.15) into (3.11), the firms' problem is equivalent to

$$J_t(b_t) = \max_{b_{t+1}} \left\{ A_t h - g(b_t) - b_t + \frac{b_{t+1}}{R_h} + \beta(1-\lambda_h)(1-\eta)\mathbb{E}_t S_{t+1}(b_{t+1}) \right\} \tag{3.17}$$

$$s.t.$$

$$b_{t+1} \leq (1-\eta)\phi_t \mathbb{E}_t S_{t+1}(b_{t+1})$$

Combining (3.11) and (3.9), apply (3.15) and (3.16) repeatedly, we get the expression for S_t

$$S_t(b_t) = A_t h - a_h - b_t + \frac{b_{t+1}}{R_h} + (1-\lambda_h)\beta\mathbb{E}_t S_{t+1}(b_{t+1}) - \eta\beta p_t \mathbb{E}_t S_{t+1}(b_{t+1}) \tag{3.18}$$

This is the law of motion for the surplus function S_t. An appealing feature of (3.18) is that g disappears because S internalizes the distributional issue. Therefore it follows directly

$$\frac{\partial S_t(b_t)}{\partial b_t} = -1$$

Setting up the Lagrangian of (3.17), let the multiplier of the constraint be μ_t, using the Envelop Theorem on $S_t(b_t)$ and further substitute in expressions for the two interest rates R_h and r, the first order condition of the problem is

$$\eta - R[(1-\eta)\phi_t + 1]\mu_t = 0 \tag{3.19}$$

Rearranging (3.19), we get

$$\mu_t = \frac{\eta}{R[(1-\eta)\phi_t + 1]} \tag{3.20}$$

Therefore, as long as $\eta \in (0,1)$, $\mu_t > 0$. The intuition is quite simple: As long as the worker has a positive bargaining power, firm will always choose to borrow to the upper limit. (3.20) could be written as

$$\mu_t = \left[\frac{1}{(1-\eta)\phi_t + 1}\right]\left(\frac{1}{R_h} - \frac{1-\eta}{R_h}\right)$$

This says that the value of marginally relax the credit limits will benefit firms in two sense. First is that the firm could raise more debt now. However, the actual rise in the debt ceiling is discounted by factor $(1-\eta)\phi_t + 1$. This is because as the debt level increases, the equity value of the firm net of liability is decreasing. Hence there is a feedback effect. Second is that the decrease in the total surplus will improve the bargaining position of the firm by pushing down the wage payment to the worker. Since the worker gets η out of the total surplus, they are forced to bear η of the liability. Mechanically, this works in a similar way as the tax exemption mechanism in Jermann and Quadrini (2012). Again, here this feature relies on the linearity of the preference to mute the channel that the timing of the consumption stream affects the entrepreneur's decision.

3.5 *General Equilibrium*

Now we close our model by characterizing the firms' entry decision. For a filled vacancy, remember the only thing the firm has to do is to train the worker to become productive in the next period, therefore if we let Q_t be the value of a filled vacancy:

$$Q_t = \max_{b_{t+1}} \left\{ \frac{b_{t+1}}{1+r} - H_h + \beta(1-\eta)\mathbb{E}_t S_{t+1}(b_{t+1}) \right\} \tag{3.21}$$
$$s.t.$$
$$b_{t+1} \leq \phi_t(1-\eta)\mathbb{E}_t S_{t+1}(b_{t+1})$$

where we have substituted in (3.15).

Notice that Q_t is just a function of aggregate shocks A_t and ϕ_t, because all firms start with zero liability. Recall that the flow cost of posting a vacancy is κ, free entry condition results in

$$q_t Q_t = \kappa \tag{3.22}$$

Therefore, from (3.22) we could solve for the vacancy filling rate for each combination of the aggregate shock (ϕ_t, A_t). Using (3.3) and (3.4), we could back out the equilibrium labor market tightness θ_t and equilibrium job finding rate p_t. Actually, in this model, the labor market tightness θ_t is the effective "general equilibrium price" which transmits the feedback response from the other end of the market.

4 QUANTITATIVE RESULTS

In this section, we present the quantitative results of our model. We start by describing our calibration strategy, we then report the baseline simulation results for the aggregate economy. In Section 4.3, we discuss the implications of our model if we re-calibrate the model according to different occupations.

4.1 *Calibration*

The model is calibrated at quarterly frequency. A summary of the model parameterizations and the corresponding empirical targets are presented in Table 3.3. Search and matching model is usually calibrated at monthly frequency, however U.S. financial data is only available at a quarterly frequency, this prevents us from adopting the monthly calibration frequency, although we do have our labor market statistics in monthly frequency.[19] Some of our model parameters could be pinned down exogenously and others need to be determined endogenously as we solve the model. We start with those exogenous parameters. All data series unless otherwise specified cover the periods of January 1978 to December 2010.

Predetermined Parameters.—The discount factor $\beta = 0.9906$ is set such that the annual interest rate equals 4%. We obtain the persistence (ρ_A) and standard deviation (σ_A) of the TFP shocks by fitting equation (3.5) to the productivity per worker (NIPA-CPS based) constructed by BLS.[20] More specifically, we first take logarithmic of the series, apply the HP-filter with smoothing parameter 10^5 and then regress the cyclical component on its one quarter lag. This way we estimate $\rho_A = 0.8556$. The unconditional standard deviation of the series is 0.0147, which yields the conditional standard deviation $\sigma_A = 0.0076$. The average productivity is normalized to one. For the credit shocks, the mean credit level (the deterministic part) is calibrated endogenously and will be discussed shortly after. The persistence (ρ_ϕ) and the standard deviation (σ_ϕ) (the stochastic part) is taken from Monacelli, Quadrini, and Trigari (2011). These authors estimated the structural model as a whole using Bayesian estimation. Given the similarity of the structure of our model and the limitation in the data for purpose of standard calibration, we argue that it serves as a reasonable first pass for parameterizations. Thus the persistence ρ_ϕ is set to 0.9650 and the standard deviation σ_ϕ is equal to 0.1430.[21]

[19] Michaillat (2012) uses linear interpolation to impute monthly TFP data from quarterly National Income and Product Account (NIPA) series and Shimer (2010) uses the quarterly statistic moment to infer the monthly counterpart. We feel that such practices bear some arbitrary sense and thus decide not to pursue after them.

[20] BLS series PRS58006163.

[21] We did a couple of robustness checks for this parameterizations choice under the standard calibration practice. The main issue here is that there is no directly comparable counterpart between the search model with credit constraints and the data. Unlike in the case of Jermann and Quadrini (2012) where physical capital can be measured directly, measurement to the value of a particular job is very difficult to come by, if possible at all. While at a first glance, it seems we could use the outstanding debt over net worth to proxy the credit constraint. However, the fact that net worth of the firms is measured in the data according to the market value is problematic. The reason being because of the huge decline in stock market performance which yields a corresponding decline in the net worth of the firms. Under the scenario, even if firms do not borrow any new debt, mathematically it will appear as if the credit standard roars up during the recent financial crisis, a highly counter-intuitive spurious measurement. Therefore we think the net issuance of debt is a more reasonable measurement of our model counterpart in the data, this is also the time series fitted into the model by Monacelli, Quadrini, and Trigari (2011). As of the value of the firm, at least three measurement could be used: the net worth, the business sector GDP and the surplus net of wage bills. All three series are available from NIPA. The estimations with different time series for the matching value yield very similar persistence, their main

Regarding the choice of η, there is no compelling empirical evidence in the literature. Most papers set the number to be 0.5 for convenience [for example Pissarides (2009)], but number as low as 0.117 also seems to gain some support in the literature [Hagedorn and Manovskii (2008)]. Overall it is accepted in the literature that some fluctuation around 0.5 is plausible [Hall and Milgrom (2008)]. We choose the bargaining weight $\eta = 0.35$, a number slightly less than the usual choice of 0.5. This is because our interests in two severe recessions where the drop in either the productivity shocks or the credit shocks limits the set over which the Nash Bargaining problem is well-defined. Our choice of $\eta = 0.35$ is the closest number to 0.5 which grants a well-defined Nash Bargaining problem if we discretize the two shocks using 15 states Tauchen and Hussey (1991) method. We could set η to 0.5 if we limit the span (technically the number of states) of the discretization process, but this will limit the model's ability to account for serious recessions and we are reluctant to give in on this perspective. Another way to circumvent this issue is to solve the model using perturbation method instead of the accurate non-linear solution we adopt here. First-order perturbation method is widely used in solving search and matching model [for example Hagedorn and Manovskii (2008)]. However, as shown recently in Petrosky-Nadeau and Zhang (2013), the perturbation method cannot capture asymmetric response of the model to positive and negative shocks. The non-linearity of the model's response to negative shocks is missing even with second-order perturbation. Since the choice of η will not qualitatively affect our conclusion, and the prevailing choice of 0.5 does not seem to be backed up by strong empirical evidence either, we think our choice of $\eta = 0.35$ is reasonable from a pragmatic perspective. Another parameter for which the value is a bit controversial is the utility while unemployed a. We set $a = 0.71$ following Hall and Milgrom (2008), which is a number now widely accepted in the literature.[22]

To determine the separation rates, we first estimate the job finding rates at the aggregate level following the same procedure in Section 2.1. The resulting average quarterly job finding rates is 52.26%.[23] Using the formula for steady state unemployment rate $u^* = p^*/(p^* + \lambda^*)$ where

discrepancies lie in the resulting standard deviation, which is just a scale effect. If we normalize the standard deviation of the credit shocks such that the standard deviation of the model generated debt-to-GDP ratio (technically this is the implicit estimation target in Monacelli, Quadrini, and Trigari (2011)) matches what is observed in the data, we get very similar numbers as estimated by Monacelli, Quadrini, and Trigari (2011).

[22]In the paper that initiated the Shimer's volatility puzzle [Shimer (2005)], Robert Shimer calibrates $a = 0.462$ to the replacement ratio of unemployment insurance. Hagedorn and Manovskii (2008) uses a much higher value of $a = 0.925$ and argues that this change in calibration strategy addresses the Shimer's volatility puzzle. The economic rationale behind this much larger number is that the flow utility of unemployment does not only come from the unemployment insurance, but also from leisure and home production. However, Costain and Reiter (2008) points out that the implied elasticity of labor supply to unemployment insurance is too high compared to that in the data. Because of this, most literature now uses the estimation by Hall and Milgrom (2008) from the wage rigidity data as a compromise of the two previously used numbers at extremes.

[23]This number is much smaller than the one inferred from the monthly rates using Bernoulli distribution, because at quarterly frequency the sample distribution includes more long-term unemployment people, which has a different labor market characteristic compared to the monthly sample. A simple inference using Bernoulli distribution fails to account for such composition changes.

TABLE 3.3
PARAMETERIZATIONS

Parameter	Variable	Values	Sources
Predetermined Parameters			
Time Preference	β	0.9903	Annual Interest Rate 4%
Productivity Shock Persistency	ρ_A	0.8556	BLS Labor Productivity per job
Productivity Shock Std.dev	σ_A	0.0076	BLS Labor Productivity per job
Credit Shock Persistency	ρ_ϕ	0.9650	Monacelli et al (2011)
Credit Shock Std.dev	σ_ϕ	0.1430	Monacelli et al (2011)
Workers Bargaining Power	η	0.35	See the main text
Unemployment Utility Flow	a	0.71	Hall and Milgrom (2008)
Separation Rate	λ	0.0560	Average Unemployment Rate 6.29%
Training Cost	H	0.67	Heckman et al (1999)
Endogenous Parameters			
Matching Efficiency	l	1.8352	Quarterly Job Finding Rates 52.62%
Mean Credit Level	$\overline{\phi}$	1.9365	Debt to GDP ratio 1.375
Vacancy Posting Cost	κ	1.0924	Average Labor Market Tightness 0.643

Notes: Data Source: See the main text.

u^*, p^* and λ^* are steady state level of unemployment rate, job finding rates and separation rates respectively, by plugging in the average unemployment rate $u^* = 6.29\%$, we could pin down the separation rate $\lambda = 0.0560$. For the training cost H, we follow Heckman, Lalonde, and Smith (1999) and set the monetary cost as two months of wages. This is also the strategy adopted in Kambourov and Manovskii (2009) and Cairo and Cajner (2011).

Endogenous Parameters.—Now we discuss the values of the parameters that cannot be determined outside the model. There are three remaining parameters, namely matching efficiency l, mean credit level $\overline{\phi}$ and vacancy posting cost κ. By plugging in the average quarterly job finding rates 52.62% and average labor market tightness 0.643 [den Haan, Ramey, and Watson (2000)] into the matching function (3.2), solving numerically the resulting non-linear equation, we get $l = 1.8352$. The mean credit shocks level $\overline{\phi}$ is set such that the steady state debt-to-GDP ratio matches the empirical counterpart of 1.375, the latter is calculated from the FFA (debt in business sector) and NIPA (GDP). We then set the vacancy cost κ such that the steady state labor market tightness $\theta = v/u$ equals to 0.643. The resulting numbers are $\overline{\phi} = 1.9365$ and $\kappa = 1.0924$.

With the parameterized model, we solve the model non-linearly using policy function iterations [Coleman (1990)]. As mentioned above, this allows us to keep the non-linearity when the model is hit negatively by either shock and thus delivers more accurate implications for recessions, which is our main objective of the paper. We approximate the TFP shocks and credit shocks by 15 states Markov Chain using Tauchen and Hussey (1991). Further increasing the number of states do not change the results. The algorithm is explained in details in Appendix F.

TABLE 3.4
BENCHMARK SIMULATION RESULTS

Model Specification	u	θ^*	p	A
Data	0.146	0.382	0.144	0.147
Shimer	0.009	0.035	0.010	0.020
$H = 0$	0.0714	0.1261	0.0874	0.0107
	(0.0099)	(0.0196)	(0.0113)	(0.0013)
$H = 0.2$	0.0743	0.1321	0.0913	0.0106
	(0.0144)	(0.0228)	(0.0145)	(0.0013)
$H = 0.67$	0.0813	0.1466	0.1002	0.0106
	(0.0153)	(0.0209)	(0.0177)	(0.0013)
$H = 0.67, Corr = 1$	0.0976	0.1773	0.1233	0.0106
	(0.0176)	(0.0239)	(0.0218)	(0.0013)

Notes: Results from simulating the model under the calibration for aggregate economy. All variables are reported in logs as deviations from an HP trend with smoothing parameter 10^5. Bootstrap standard errors are reported in parentheses.

4.2 *Baseline Simulation Results*

It is well known that textbook search and matching model suffers from the so-called Shimer's volatility puzzle in the sense that TFP shocks along fails to generate the volatility of key labor market variables observed in the data. Our model is a modification of the Pissarides model and therefore it is impractical to expect that we will be immune from this issue. However, since we are examining the business cycle implications of our model, we do not want the business cycle performance of our model to deviate too far away from those in the data. Hence, before we move on to discuss the differential response of different occupations to different shocks, we first simulate our model for the aggregate economy to check the model's performance along this dimension.

In particular, in each simulation, 1,132 "quarterly" observations for all variables are obtained. The burn-in period is set to be 1,000, therefore the first 1,000 observations are discarded. The remaining 132 "quarters" correspond to the 132 empirical counterpart from 1978.Q1 to 2010.Q4. Such simulation is then repeated 20,000 times to wash out simulation randomness. We then calculate the volatility of each variable as log-deviations from an HP trend with smoothing parameter 10^5 for each simulation. The statistics reported in Table 3.4 are then the mean across 20,000 repetitions with the Bootstrap standard deviation listed in parentheses.

The baseline simulation results (Panel 4 in Table 3.4) shows that the model performs reasonably well at the aggregate level. By the construction of the exercise, the means of unemployment rate u, job finding rates p and labor market tightness are matched accurately. Most notably, the inclusion of credit shocks and training costs improves the business cycle performances of the model dramatically. While the original Shimer's model can only explain $0.009/0.146 = 6.16\%$ of the volatility in unemployment rate and $0.01/0.144 = 6.94\%$ of that in the job finding rates, our model is able to account for respectively $0.0813/0.146 = 55.68\%$ in unemployment rate and $0.1002/0.144 = 68.63\%$ in job finding rates.

Recall that we did two modifications on Shimer's model: the credit shocks and the training costs. Simulation results in other panels in Table 3.4 help us to pin down the relative quantitative contribution of these two mechanisms. In particular, in each of the panel, we recalibrate our model according to the procedure explained in the previous section. Therefore, moving from panel 2 to 4 ($H = 0$ to $H = 0.67$), technically we are rebalancing the ratio of training costs against vacancy posting costs in the total hiring costs. When $H = 0$, essentially all hiring costs are from posting vacancies which is the Monacelli, Quadrini, and Trigari (2011) model. Focusing on our variable of interests, job finding rates p, by distinguishing training costs from vacancy posting costs, we are able to push the model 8.89% more closer to the data.

The last row ($H = 0.67$, $Corr = 1$) aims to capture the scenario that financial shocks and TFP shocks usually do not come independently, but rather that a negative productivity shock is often coupled with a corresponding negative realization in the credit shocks. The perfect correlation we assumed here is an extreme case. In this scenario, the financial market and the real economy experiences expansions and recessions at the same time. Therefore what this simulation reflects is the upper bound of the volatility we are able to generate with our current model.

A closer look at the actual simulation series, we found that the reason our model cannot generate the exact volatility observed in the data is actually because our model does not perform very well during periods of expansion. For example, the lowest unemployment rate we were able to get out of our simulations is 5.49%, a little bit higher than the observed 4.21%. However, our model captures extremely well the labor market behavior in periods of recessions. For example, across our simulations, the highest unemployment rate we are able to generate is 13.87% and that of the lowest job finding rates is 34.45%. Since we do not target any of these numbers, this shows that our model, although perhaps not a very good choice to understand the labor market during expansion, but is quite reasonable for understanding recessions.[24] Also by looking at the last column, the volatility of TFP shock, we see that our simulation under performs the actual volatility in the productivity in the actual economy. This comes from the well documented drawback of Tauchen and Hussey (1991) method in approximating AR(1) process with persistence higher than 0.75.[25] Therefore, we argue that it is reasonable to expect that a better approximation on the volatility

[24]This is a common drawback of modeling the financial shocks as credit shocks, see the discussion in Jermann and Quadrini (2012).

[25]If we only wish to match the volatility, in principle we could use the old Tauchen (1986) method. We choose to use Tauchen and Hussey (1991) here because this method has other desirable feature in approximating the conditional expectation, which is important to accurately evaluate the policy functions. See Kopecky and Suen (2010) for a detailed comparison between different computational methods.

of the TFP shocks (possibly credit shocks also) will push the model closer to deliver the desired business cycle performance, which has long puzzled macroeconomists and labor economists.

4.3 *Job Finding Rates by Occupational Groups*

In this section, we examine the implications of our model by occupational groups. To do this, we recalibrate our model twice, targeting the mean job finding rates and productivity differentials for service occupations and the average of manufacturing based occupations respectively. More specifically, we keep most our parameters at their aggregate levels. We only change the hiring costs (κ and H) and the average productivity level ($\overline{A}$) to capture the salient features of the service occupations and manufacturing based occupations. Consistent with our hypothesis, we calibrate our model such that (1) on average service jobs enjoy a higher job finding rates; (2) the productivity of manufacturing based occupations are higher than service occupations. Using subscript s and m to represent the two occupations, we set $H_s = 0.4$ and $H_m = 0.8$ to roughly capture the average training time of around one month (service occupations) and two months (manufacturing based occupations). These numbers are just approximations because of data limitation. However, as we will see shortly after, the model's response to exogenous shocks are mostly driven by the matching surplus and is not affected in a quantitatively significant manner by the choice of these two parameters. We then set $\kappa_s = 1.1545$ and $\kappa_m = 0.8264$ to match the average job finding rates for the two occupational groups. The empirical targets are 58% for service occupations and 45% for manufacturing occupations. We then set the average productivity $\overline{A}_s = 0.8171$ and $\overline{A}_m = 1.1829$ to match the ratio of average wages (1.4427) in manufacturing occupations over service occupations in *American Community Survey 2005* [Autor and Dorn (2013)]. Using the parameterized model, we then conduct our impulse response simulations.

Figure 3.4 reports the results of impulse response. To produce the statistics, under each calibration we simulate our model starting from the deterministic steady state. We then disturb the model twice, one with a negative one standard deviation of productivity shock $-\sigma_A$ and the other case with a negative one standard deviation of credit shock $-\sigma_\phi$. The left panel of Figure 3.4 reports that of model calibrated to the manufacturing occupations and the right panel reports that of the service occupations.

Recall that in our calibration, we only calibrate our model for different occupations in a way such that the model's deterministic steady state matches the corresponding empirical average. We do not force our model to deliver any business cycle predictions. Our model mechanism accounts for the business cycle fluctuations of different occupations remarkably well. More specifically, when the economy is hit by standard TFP shock, the job finding rates for both occupations decrease by approximately 6% from their steady state levels. However, if instead the disturbance originates from the financial sector, service occupations is shocked much stronger comparing to the manufacturing occupations (6% versus 2%). This comes exactly from the Kiyotaki and Moore (1997) credit channel, i.e. service occupations has less matching surplus (thus less collaterizable

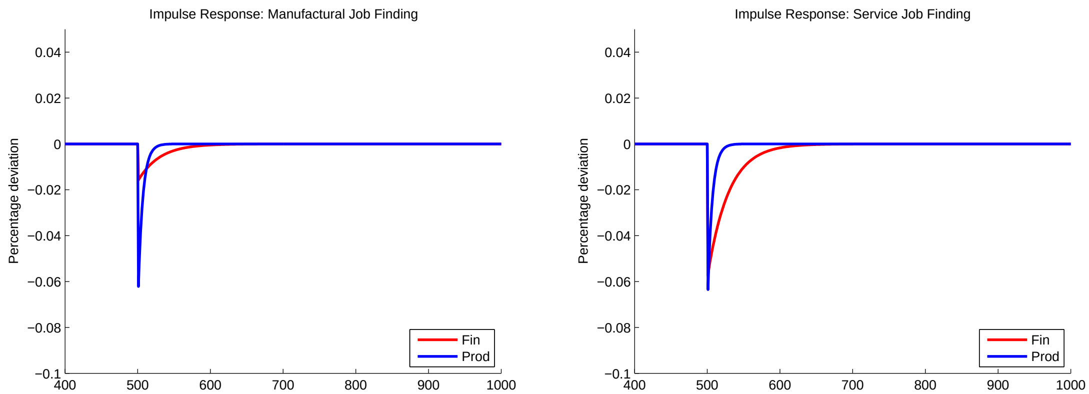

FIGURE 3.4.—IMPULSE RESPONSE OF JOB FINDING RATES

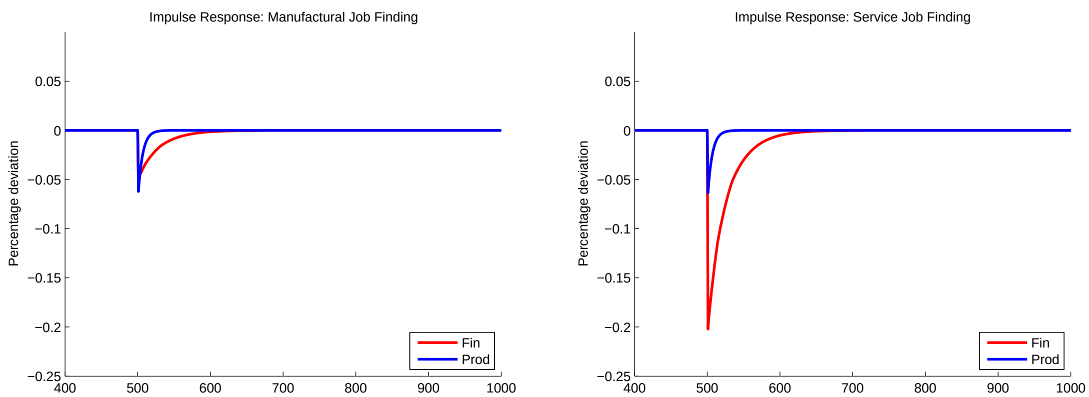

FIGURE 3.5.—IMPULSE RESPONSE OF JOB FINDING RATES, LARGER FINANCIAL SHOCKS

assets) and therefore are more easily affected by shocks to the credit constraints which has first order effect over the financing of working capital. The reason is that recall in our occupational level calibration, the hiring costs are calibrated such that the high productive manufacturing occupations have lower job finding rates in the steady state and in the practice of impulse response, the only perturbation we impose on the economy is a one standard deviation of exogenous shock. Hence any difference must come from the model's response to exogenously imposed shocks.

This property of the model, i.e. different occupations respond similarly to productivity shocks but differently to financial shocks, is robust both qualitatively and quantitatively to the magnitude of the shocks. Figure 3.5 reports the case where the magnitude of the financial shocks is set to 3 standard deviation (TFP shocks remains one standard deviation to help comparing the relative scale of the model's response). In this scenario, we see that the job finding rates of the service occupations response by dropping even further. This quantitatively non-linear response follows from our adoption of non-linear solution to keep the curvature at the left end of the policy functions, which is important for the analysis of recessions. Recall that in Figure 3.3, the current recession is paired with a unprecedent drop in the credit availability, this further lends support to our theory that we observe quantitatively significant drop in the job finding rates in service occupations only in the Great Recession because the deterioration of the credit markets in this recession dwarfs all the postwar economic recessions. This way, we also view our results here as a complement to Hagedorn, Karahan, Manovskii, and Mitman (2013) in the sense we provide another possible explanation for the fact documented in their paper that unemployment insurance policies have particularly strong impact to firms' vacancy creation practices in the Great Recession. The intuition is pretty straight forward. Since the Great Recession is characterized by a serious deterioration of credit standards, the opportunity costs for firms to raise extra fund is larger compared to regular times. Therefore, an increase of wage bill (thereby an increase in the need of fund for working capital) of similar magnitude but happens in the periods of credit crunch is likely to result in larger response from the firms' side. Moreover, the lower the collateral value firms have, the less "buffer-stock assets" they can rely on, and subsequently the more vulnerable they are to such shocks.

5 POLICY IMPLICATIONS

In this section, we discuss quantitatively the policy implications of our model. We start with a brief description on the U.S. employment and training policies that relate most closely to our model mechanisms. Since our macroeconomic model is abstract from the details of particular labor market policies, we believe this will help the readers to grasp intuitively how our results could be interpreted. We then conduct two groups of counterfactual analyses using our model, one corresponds to the WIA Dislocated Worker Program and the other corresponds to the Wagner-Peyser Employment Service.

5.1 *Background*

The U.S. employment and training programs serve two purposes: skill development and job placement. Since our focus in this paper is the macro level labor market performance at the business cycle frequency and those workers become unemployed for cyclical reasons, we therefore will not discuss those programs that aim to integrate those economically disadvantaged into the mainstream economy. These programs typically have a trend and micro feature. Examples of programs fall into this group are the *Job Corps, Reintegration of Ex-Offenders and the Workforce Investment Act Youth Formula Program*. These programs in general are not designed to help fight against cyclical unemployment but aimed at addressing non-cyclical, structural issues. They therefore are more suited to be discussed under traditional cost-benefit analysis or micro level human capital model, using increments in earnings as measurement.[26] Rather, the kinds of programs we have in mind

[26] See for example Heinrich, Mueser, Troske, Jeon, and Kahvecioglu (2009) and Kambourov, Manovskii, and Plesca (2010).

are those that could be used as one of the instruments in the anti-cycle arsenal. Two examples are the *WIA Dislocated Worker Program* and the *Wagner-Peyser Employment Service*. The program descriptions for the WIA is *"The Workforce Investment Act Dislocated Worker Program funds services to support the reemployment of laid-off worker."*, and that of the Wagner-Peyser is *"The Employment Service focuses on providing a variety of employment related services including but not limited to job search assistance, job referral, and placement assistance for job seekers, re-employment services to unemployment insurance claimants, and recruitment services to employers with job openings."*

Following the program description, we therefore mimic in our model the WIA program by reducing the training cost of private employer and the ES program by reducing the vacancy posting cost. Before we move on, we should mention that in the calibration of our model we are actually calibrating our model to the U.S. economy without public training programs because of the small size of public training programs. Our experiments can thus be explained as expansions of the sizes of such programs.

Recall that as is shown in Hagedorn, Karahan, Manovskii, and Mitman (2013), one of the lessons we learned from the current crisis is one of the reason that firms' job creation is discouraged is the unexpected expansion of unemployment insurance. According to programs appropriations summarized in *ETA Workforce System Results*, from 2007 to 2007, in percentage term, the budget attributes to unemployment insurance increases from 33.1% to 36.9% while that for the WIA Dislocated Worker Program and Wagner-Peyser Employment Service decreases respectively from 15.8% to 13.5% (further to 10.8% in FY2011) and from 9.7% to 8.0%. The question we ask is therefore what would happen to workers' job finding rates if we devote more effort on the firms' side instead of on the workers' side.

5.2 *Counterfactual Analysis*

For each of the two occupational groups in section 4.3, we conduct four exercises. We disturb the economy first with negative aggregate productivity shocks of two standard deviation and then with negative aggregate credit shocks of two standard deviation. For each of the shocks, we implement two counterfactual exercises, one with a reduction in the training costs and the other with a reduction in the vacancy posting costs. As is said in the last section, our purpose of these two exercises are to mimic the effect of the expansion of WIA and ES program respectively. The key variable we are focusing on is the changes in the job finding rates in response to different combinations of aggregate shocks and policy instruments. The results are summarized in Table 3.5.

Since all eight (four for each occupation) exercises have very similar structure, we therefore only describe one of them in details in the interests of space. Consider for the service occupation the combination of credit shocks and training costs reduction. Suppose the economy is shocked by

TABLE 3.5
PARAMETERIZATIONS

	WIA Dislocated Worker Program			
	Productivity Shocks		Credit Shocks	
	Service	Manufacturing	Service	Manufacturing
Before	14%	13%	13%	4%
After	8%	10%	6%	1%
	Wagner-Peyser Employment Service			
	Productivity Shocks		Credit Shocks	
	Service	Manufacturing	Service	Manufacturing
Before	14%	13%	13%	4%
After	7%	10%	5%	Absorbed

negative credit shocks, we compare the response of the job finding rates in two different scenarios, one with no policy intervention and the other with a temporary subsidy of 10% of the training costs. This corresponds to column 3 in the upper panel of Table 3.5. By comparing the job finding rates with and without reduction in training costs, we find that the effects of the financial shocks are largely offset by the policy intervention, even we only subsidize in the model for 10% of the training costs. Without policy intervention, job finding rate drops by 13% right after the shock. However, if instead we subsidize for the training expenditure, the job finding rates only go down by 6%. Therefore 10% reduction in firms' training cost reduces the drop in job finding rates by 7 percentage points. The actual amount of subsidy, 10% of the training cost for service occupations, is set to be a yardstick of the size of the intervention in all the other exercises. In terms of dollar terms, this amounts to 10% quarterly wage payment of a worker with hourly wage of \$8, which equals to approximately \$400 per worker. Since the manufacturing jobs usually take longer to train workers, the same amount of subsidy could cover only for 5% of the training costs. The corresponding changes in job finding rates are thus 4% and 1%. Therefore, a 5% subsidy on the training costs remedies the drop in the job finding rates for manufacturing jobs by 3 percentage points under the scenario of credit shocks.

The effect of the WIA-style policy under the scenario of productivity shock is similar. The policy remedies the decrease in the job finding rates for manufacturing jobs also by about 3 percentage points. The effect on service jobs are somewhat marginally smaller, the makeup is now 6 percentage points comparing to 7 in the case of credit shocks.

The reduction in vacancy posting costs (ES-style program) has slightly larger effects compared to their counterparts in the reduction of the training costs. We remind our readers here that we keep the size of the subsidy per job equals to that to the training costs of the service jobs. In the situation of productivity shocks, for the service occupation, the reduction in the drop of the job finding rates is now 7 percentage points as opposed to 6 percentage points in the case of training cost while for the manufacturing occupation, the policy gains is more or less the same. In the situation of credit shocks, the policy gains for both occupations are somewhat larger. Service jobs pick up 8 percentage points in job finding rates as opposed to 7% in the training costs case while manufacturing jobs pick up more than 4% in job finding rates, which is more than offset the initial drop caused by the credit shocks.

Overall, the effect of the subsidy is larger for service jobs, under credit shocks and in the form of subsidy to vacancy posting costs. A couple of points worth mentioning on the actual interpretation of our results. First, it is not surprising that subsidy to the vacancy posting costs has larger effects than for the training costs. Since in our model structure, vacancy posting costs are flow cost that firms are subject to no matter whether they actually hire someone or not. Put differently, it is the cost for opportunity. On the other hand, training costs are paid only when a firm actually hires a new worker, which happens according to a probability depending on the vacancy filling rates (or equally the job finding rates, these are the two sides of the same coin). In other words, although the sizes of the subsidy per job for these two policies are set to be equal, firms only get the subsidy with a certain *probability*. Therefore the *de facto* training costs subsidy is milder. Second, the reason that the effect of the policy is larger for service jobs is because of the same *absolute* amount of subsidy worths more in *percentage term* for these low surplus occupations.[27] Third, the stylized search and matching model we adopt in this paper abstracts from the details of the vacancy posting costs and training costs. In practice, vacancy posting costs are not just the costs of posting advertisements as interpreted literally. They could well include the payments to the current employees who engage in the recruitment process or even for some jobs the expenditure of additional capital equipment that a new position needs. As a result, these costs are usually non-trivial. Likewise, the training costs of a newly hired could represent the payments to the instructors or reflect the productivity gap between a trainee and a mature worker. Hence as a matter of practice, there are also different ways the policies could be implemented. It could be subsidy to the newly hired workers or subsidy to firms' employees that engage in recruitment process. Currently the wage subsidy policies are components to those programs that aimed at improving the employment prospects of people of particular demographic features, for example the WIA Youth Program, what we are proposing is an generalization of such practice to general unemployed people in periods of severe recessions. However, we urge the readers to bear in mind that how in fact these policies are effective will also depend on the particular design of the reform which is beyond the scope of the current paper. For example, as is common in any policies regarding subsidy, moral hazard from the subsidized party needs to be addressed from a microeconomic theory point of view, we leave the discussions of these issues to our microeconomic colleagues in the future. Fourth, the point

[27] An intuitive example would be that if an entrepreneur needs to finance for an $1,000 expenditure, a $200 subsidy covers 20% of the total expenditure. While on the other hand, if the need of external fund is $2,000, a $200 subsidy only covers for 10% of the total expenditure.

of view we analyze the experiments is the effect they impose on job finding rates. If the objective of the policy makers focuses on issues like redistribution, the interpretation of the results from a normative point of view would be different.[28]

In summary, we think that in of severe economic downturn, subsidy for firms' job creation expenditure of hiring and/or training could mitigate the drop in the job finding rates for unemployed workers. Such subsidy works better for service occupations (smaller firms) and in situations of credit shocks as opposed to manufacturing occupations and in situations of productivity shocks. The service occupations particularly need help in periods of credit shocks because they are affected more than manufacturing jobs.

6 Conclusions

In this paper, we documented that low skill service occupations, albeit enjoy higher job finding rates on average, is hit particularly hard comparing to low/middle skill manufacturing based occupations during the Great Recession. Two mechanisms are at work here, hiring costs and credit availability. We offer a unified theory by incorporating Kiyotaki and Moore (1997) model into a standard Pissarides (2009) search and matching model to explain both facts simultaneously. We argue that while productivity shocks affect firms' *willingness* to create jobs, financial shocks operate major by binding firms' *ability* to create jobs. Calibrated to the U.S. labor market data, our model is consistent with the data both qualitatively and quantitatively. Our theory thus deliver interesting policy implications which says subsidies to firms' job creation has larger effect when targeted at service occupations (smaller firms) and when implemented at periods characterized by credit shocks. Our models could be extended along several dimensions. It will be interesting to merge our model into a Merz (1995) business cycle model where capital is explicitly modeled. This enables us to check the implication of our theory not only on job finding rates, but also job separation rates. Regarding the latter, we also found evidences that are not documented previously in the literature. A full fledged business cycle model enables us to carry on discussions about welfare effects of different policies, both in the transition and in the long-run. Also since we have seen that the labor market responds to productivity shocks and credit shocks very differently, it would also be interesting to check the role of financial frictions in other leading labor market models, for example the Lucas and Prescott (1974) island model. We leave these to future works.

[28]To address the redistribution issue, we need either a Lucas and Prescott (1974) island model or an Aiyagari-Huggett model [Huggett (1993) and Aiyagari (1994)] where distribution is endogenous.

APPENDIX FOR CHAPTER 3

C THE 1994 REDESIGN OF CPS

The appendix provides details about the cleaning and construction strategy on Current Population Survey Monthly Basic (CPS, henceforth) in our paper. The raw data could be accessed through National Bureau of Economic Research via `http://www.nber.org/cps`. For the current version of the paper, our data coverage starts from January 1978 and goes all through December 2010. Although the latest available CPS monthly data dates as close as April 2013, we truncate our CPS sample at December 2010 in the main body of the text. The major reason is that the 2010 Census occupational classification was introduced with data for January 2011 as replacement of the Census 2000 classification. As a consequence of the classification change, occupational data beginning with January 2011 are not strictly comparable with earlier years. The *occ1990dd* system we are using does not cover the latest Census classification and we do not want to create an Archilles Heel of spurious change to our empirical analysis. Besides according to the NBER, the current recession ceased at 2009Q3, the truncation would not affect our main conclusion.

In January 1994, CPS introduced a major questionnaire redesign.[29] The way to evaluate the number of short term unemployment workers – a key variable we are using in the duration analysis – is changed since then. This issue is first discussed in Abraham and Shimer (2001), where they proposed a couple of correction methods. Later the general strategy adopted in Shimer (2012a) is widely accepted in the literature, albeit different researchers have slightly different implementations practically (Elsby, Michaels, and Solon (2009), Shimer started circulating his paper in 2005). Interestingly, although Elsby, Michaels, and Solon (2009) challenged Shimer's method, later in 2012 when the paper was published in *Review of Economic Dynamics*, Shimer did not positively respond to the challenge. Therefore which implementation is better still remains an open question. In this paper, we adopt the implementation of Elsby, Michaels, and Solon (2009) because we think the original Shimer's method is too noisy for disaggregated analysis. We strongly encourage the readers to read both papers and make their own judgement on the two methods. However, to the readers relief, the findings in our paper will not be affected.

Since our adjustment is rather standard, we will only sketch the procedure over, for more details please refer to the papers mentioned above and the reference therein. Recall the 4-8-4 structure of CPS samples, there are two time points that a sample household enters the survey, wave 1 and 5. We call these households the *incoming rotation group*. Prior to 1994, all unemployed workers were asked about the length of their most recent unemployment durations, no matter which wave they are in. Our measurement of short term unemployed workers is constructed by head counting the number of unemployed workers who report an unemployment duration of less than or equal to 4 weeks. However, after the 1994 redesign, for workers that are unemployed in consecutive

[29] See Polivka and Miller (1998) for a extensive discussion of the 1994 CPS redesign.

months, CPS ceased of asking the unemployment duration. Instead, the worker's unemployment duration is simply the last reported plus the length of intervening period. As a simple example, suppose a worker reports being unemployed for 3 weeks in wave 2. Prior to 1994, when this worker is interviewed again in wave 3, if his reported labor force status is still *unemployed*, he will be asked again for how long has the most recent unemployment duration lasted. The answer could be any number between 1 and 7. While after 1994, if the worker reports again in wave 3 being unemployed, the question regarding the most recent unemployment duration will be skipped and a number of 7 is assigned automatically. Therefore, theoretically after 1994, among all short term unemploy workers, CPS captures only those who were employed in the previous survey date and switched to unemployed in the next. In practice, CPS made such change because it is documented in the literature that the pre-1994 method is prone to measurement error in reported duration weeks. However, for the purpose of our analysis, this causes another time aggregation bias. In particular, we are missing workers that get a job right after the previous wave of survey is done but lose their job before the next wave of survey is conducted. Empirically, this is reflected by a significant discontinuity of the proportion of short term unemployment among all unemployed workers at January 1994.

However, the survey structure regarding this aspect is not affected by the redesign for the two incoming rotation group. If instead we only look at the two incoming rotation group after 1994, the short term unemployment ratio returns to its pre-1994 level. We checked that this is in fact the case for each of the occupational group. The basic logic behind the correction is to inflate the short term unemployment level after 1994. Different implementation differs in by how much. The original Shimer's paper inflates each month's short term unemployment by the relative ratio between the short term proportion in the incoming rotation group and the full sample for that particular month. Elsby, Michaels, and Solon (2009) argues that the monthly inflating ratio itself is a very noisy series, it could potentially contaminate the accuracy of the estimates. And they actually demonstrated in their paper that it is possible that such noise results in economically significant change in the conclusions under some circumstances. Therefore they propose that instead of doing the adjustment on a monthly basis, a more robust way is to use the average short term ratio across the whole data span after 1994 as the inflating factor.

Since as we demonstrated in the main text of the paper, workers of different occupational groups have very different labor market experiences, it is more reasonable to adjust time series of different occupational groups separately. BLS staff also made similar suggestions when we asked them about seasonal adjusting the series. In particular, the inflating factors we are using for the six occupational groups are respectively: Managers (1.152), Clerics (1.169), Production (1.114), Operators (1.134), Construction (1.145) and Service (1.141). This way we have all the series that is needed in the empirical analysis of section 2.

D Occupational Categorical System

Definitions.—The definition of each occupational group is a key component of our paper, we summarize detailed explanation of the *occ1990dd* system here. The readers are strongly encouraged to read the Data Appendix in David Dorn's PhD thesis and the reference therein.

CPS uses the Census occupational classification which is derived from Standard Occupational Classification (SOC). The Census then aggregates these detailed occupations into a 3-digit (4-digit starting from the Census 2000 Classification) occupational codes in the publicly available data. Each code refers to a specific group of occupations. For example, among college instructors the system has separate codes for "Biological Science", "Chemistry", "Physics", etc with a residual group "Teacher, not elsewhere classified" to record all workers that could not be matched to a more detailed group. The system gets revised every 10 years, mainly for the purpose of reflecting the rises and falls of some particular occupations. For example, in the Census 1970 codes, there is no job title as "Water and Sewage Treatment Plant Operator" while on the contrary, "Food Counter and Fountain Workers" was dropped and enlisted under the residual group "Miscellaneous Food Preparation Workers". As a result, occupational data without modification across different classification systems are not strictly comparable. Across our data span, there are four occupational classifications in effect: the Census 1970 (1978.01 – 1982.12), 1980 (1983.01 – 1991.12), 1990 (1992.01 – 2002.12), 2000 (2003.01 – 2010.12). In fact the primary reason we truncate our analysis at December 2010 is because the Census introduced the 2010 classification codes starting January 2011 and the backward crosswalk table has not yet been issued until the moment the paper is being written. The Census maintains a crosswalk for later classification system to be backward compatible with the Census 1950 system, which is typically referred to as *occ1950*. However, the significant difference between industry and occupational structure in the 1950s and now has led many to cast doubt on the comparability of data based on occ1950. For example, in the occ1950 there are 287 occupations while in 1970 the number increases to 441 with a further expansion to 543 in 2000. Regarding this issue, Meyer and Osborne (2005) carefully constructed a crosswalk with 386 occupations roughly based on Census 1990 system which is later referred to as *occ1990* system. David Dorn then in his PhD thesis modified the occ1990 system to be a balanced panel and named it *occ1990dd* (the original occ1990 system is unbalanced in the sense that some code has no counterpart in some particular years). This modification is not important for our purpose because we are aggregate those unbalanced codes into major occupational groups anyway. We nonetheless adopt the *occ1990dd* because it is now the standard practice adopted in the literature. A detailed list of the occ1990dd occupations can be found in Appendix Table 2 of Dorn (2009).

We use the major occupational groups defined in Census 1990 to aggregate our labor force. There are altogether seven non-institutionalized major categories:

1. Managerial and Professional Specialty Occupations

2. Professional Specialty Occupations
3. Technical, Sales and Administrative Support Occupations
4. Service Occupations
5. Farming, Forestry and Fishing Occupations
6. Precision Production, Craft and Repair Occupations
7. Operators, Fabricators and Laborers

Each major group is also divided into a couple of subdivisions. For the purpose of our analysis, we aggregate group 1 and 2 together and it is shown in the figures in the previous section as the *green* line under the name “Manager”. These jobs cover most of the best paid jobs in the economy and the majority of them have education level that is equal to or higher than a four-year college degree. Notice in this group we also include “policy officer” and “fire-fighters” from the service group because they in general require higher skill than other jobs like janitor or food preparer. Group 3 refers to those white-collar workforce that is on average decently paid and better educated than the labor force as a whole. They appear in Section 1 figures as the *blue* line under the name “Cleric”. Later on we drop these two groups of people as they are unlikely to be the main subject targeted by various publicly sponsored training program. They also perform much better than the other four low-skill occupational groups.

The criterion to aggregate the remaining four subgroups is a little bit different from the Census strategy. For the current moment, our reclassification follows strictly Acemoglu and Autor (2011) and Autor and Dorn (2013). There are four subgroup under group 5: “Mechanics and Repairers”, “Construction Trades”, “Extractive Occupations” and “Precision Production Occupations”. The last one is singled out as “Product” and the *purple* line in previous figures. Group 7 is divided into “Machine Operators, Assemblers and Inspectors” and “Transportation and Material Moving Occupations”. The first one is relabeled as “Operator” and plot as the *yellow* line. The remaining subgroups in Group 6 and 7 are aggregated together with Group 4 to form the “Construction” group with *red* as its color. The rest in the service group is untouched and is the *black* line in the previous section.

To sum up, our reclassified major occupational groups include six categories listed in the order of skill requirement (the same definition used in Autor and Dorn (2013), see their Table 2):

1. Managers, Professional Specialties, Technicians, Financial Managers and Public Safety Officers (Green)
2. Precision Production and Craftsman (Purple)

3. Construction Workers, Mechanics, Natural Resource Extraction, Transportation and Agricultural Related (Red)

4. Machines Operators and Assemblers (Yellow)

5. Clerical Workers, Retail sales (Blue)

6. Low-skill Service Occupations (Black)

*Special Vocational Preparations.—*To evaluate the occupational level training cost, in this paper we turn to the U.S. Department of Labor's *Dictionary of Occupational Titles*, a data source which is not very familiar to macroeconomists, however is getting more attention recently in similar occupational level analysis in labor economics and international trade. DOT and its successor O*NET are proved by a growing literature to be providing quite reliable occupational related information.[30] The first edition of the DOT is published in 1939 and has been revised four times later in 1949, 1965, 1977 and 1991. The purpose of DOT is to "furnish public employment offices ... with information and techniques [to] facilitate proper classification and placement of work seekers". (as quoted in Autor, Levy, and Murnane (2003)) DOT contains information of different attributes along 44 objective and subjective dimensions (for example, training, mathematical requirement, average entry degree level, physical requirement, etc) for more than 12,000 detailed highly detailed occupations. Using the guidelines from *Handbook for Analyzing Jobs*, the Department of Labor field examiners evaluate each of the occupation attributes according to their first-hand observations of workplaces. We use the DOT variable `SVP` to measure the training required for each occupation. Here `SVP` stands for *Special Vocational Training*. The formal definition of SVP from the DOT quotes

> *"SVP is defined as the amount of lapsed time required by a typical worker to learn the techniques, acquire the information, and develop the facility needed for average performance in a specific job-worker situation."*

SVP is a scalar variable which takes *ordinal* value from 1 to 9, their respective meanings are listed below:

1. Short demonstration only

2. Anything beyond short demonstration up to and including 1 month

3. Over 1 month up to and including 3 months

4. Over 3 months up to and including 6 months

[30] See for example, Autor, Levy, and Murnane (2003), Acemoglu and Autor (2011), Autor and Dorn (2013), Autor, Dorn, and Hanson (2013) and Charles, Hurst, and Notowidigdo (2013).

TABLE D6

MEAN AND MEDIAN OF SVP FOR MAJOR OCCUPATIONAL GROUPS

	Manager	Clerics	Product	Construct	Operator	Service
Mean	6.97	3.93	6.35	4.79	3.66	3.92
Median	7.19	3.85	6.85	4.83	3.60	3.46

Data Source: U.S. Department of Labor, Dictionary of Occupation Titles, Revised Fourth Edition. Weighted according to CPS Monthly Basic.

5. Over 6 months up to and including 1 year
6. Over 1 year up to and including 2 years
7. Over 2 years up to and including 4 years
8. Over 4 years up to and including 10 years
9. Over 10 years

DOT data in companion with the *occ1990* categorical system was published by BLS. As is stated earlier this section, our adopted *occ1990dd* system is a slightly modified version of the *occ1990* system. The difference between the two systems are rather minor. *occ1990dd* simply relabels and aggregates several occupations in *occ1990* to create a balanced panel. We fill the information in *occ1990dd* using the original *occ1990* data when the change is simply relabeling and impute the data using average when aggregation is encountered. Since the majority of the occupation codes are the same across the two system, simple average is unlike to cause any significant bias in our imputation.

We then merge the data on SVP with our CPS Monthly Basic and calculate the time series of average and median SVP time for each occupational group using employment size (weighted itself by CPS survey weight) as weight. Despite some minor discontinuity at the year where Census changes the occupational code, both the average and median SVP time is very stable across our data span. In Table 3.2 we therefore report the average level of the average and median SVP time across the whole data span.

In general, the numbers in Table D6 is consistent with our intuition. Service jobs require much shorter training time compares to Production and Construction. The comparison between Operators and Service jobs may seem at odds with our story, as they have very similar SVP time. However, we argue that training time is just one dimension of the total training cost, the cost per hour also makes contribution. According to Autor and Dorn (2013), the average wage across our data span for service jobs is \$8.91, while that for the Operators is \$12.19. Therefore although Service jobs and Operators have similar training time, the actual training cost could differ significantly.

E Data Limitations and Robustness Checks

Our data spans over 30 years and our analysis focus on a rather disaggregate level of labor market, there are some issues readers may concern and some potential limitations with respect to our work. We could relief the readers of some concern, while there are some others we cannot solve due to data limitation. We do not think the main conclusion in this paper will be affected in a significant way, however we think it nonetheless is important to be aware of these limitations. We did various robustness check to the best of data availability and our ability.

Rationale of Duration Analysis?.—In our analysis in Section 2.1, our adopted method is the duration based method. The primary reason is because of limited sample size. While as argued in Fujita and Ramey (2009), the gross-flow analysis using longitudinally linked CPS data is preferred in aggregated level analysis because the estimates are less prone to the noise caused by entrance into unemployment from outside the labor force. This is in general the case with aggregated level analysis or disaggregation based on demographic feature or education attainment, where the response rate is high. However, we do not benefit from this in our analysis. While the 4-8-4 pyramid structure of CPS allows us to longitudinally match up to 75% of the observations, approximately only two-thirds among them have a occupational report. As a result, we lose around half of the sample in the gross-flow calculation. This not only results in biased sample, because failure of longitudinally matching observations does not come randomly, also for estimates of occupational level, the shrinking cell size magnifies the sampling variance and yields very noisy estimates, making it difficult to make strong statement with respect to small or moderate size distinctions between estimators. Besides, there is another issue that is unique to our occupational level analysis. It is very difficult to get reliable estimates with respect to any transition involving the state "Not in Labor Force" (NIL, henceforth). Among connected longitudinal samples who report their status as NIL in consecutive months, on average less than 2% people report their occupation. This is because after 1968 (unfortunately all our samples satisfy this criterion) only a quarter of people who reported not in labor force were asked for their occupations by survey design. There is very little valid information to support meaningful imputation on these people, which consists approximately a quarter of all the successfully linked sample. Any imputation seems just yield the results by assumption. This is also the reason all through our analysis we only focus on observations in the labor force.

Occupational Information.—In a series of papers, Iourii Manovskii and Gueorgui Kambourov have documented and analyzed the macroeconomic effects of the increase in occupational mobility in the U.S. over the last three decades in the 1990s [Kambourov and Manovskii (2008, 2009)]. The readers may worry about our simplifying assumption of treating the labor market of each occupation separately. While the primary purpose of this assumption is to simplify our analysis, it is not likely an issue that will bias our conclusions in a meaningful way. First, compared to the detailed 3-digit level original data, our market separation is on a more aggregated level. Thus although there is a rich movement at the disaggregated level, it is not like that such mobility is in companion with an equally significant movement at the aggregated level. As documented in Kambourov and Manovskii (2008), using PSID (Panel Study of Income Dynamics) the annual average occupational mobility across our data span at 1,2 and 3-digit level is 13%, 15% and 18% respectively. Given this number, the monthly rate is not likely to exceed 2% even at the most disaggregated level, unless the time aggregation of annual rate masks the frequent back and forth switches within a year. To further ease the readers concern, we longitudinally connected our CPS cross sections and found around 3.5% of samples reporting a switch of occupation group in our system. More than half of them reflect regular career promotion of moving from low/middle skill occupations to management positions. Such changes do not involve the experience of unemployment spell, therefore recall equation (3.1) in the main text, it is unlikely that our estimates of job finding rates will be biased too much.

In a recent paper, Kambourov and Manovskii (2013) find that the occupational information contained in CPS is subject to a substantial level of noise caused by coding error and imputation methodology. It is difficult to tell the exact effect that comes with such noises. Although it is hard to imagine that CPS field staff would mistakenly code an economics professor as a machine operator, we would like to be cautious to claim that it is equally unlikely to happen among the low-skill workers, even at a relatively aggregated level. For example, it is not hard to imagine a situation where "Woodworking Machine Operator" (belonging to the group Operators) is coded as "Furniture and Wood Finishers" (belonging to the group Precision Production). The "Hot-deck" imputation procedure introduced to CPS in 1976 is also likely to create systematical noise which could end up with spurious statistical results that are biased on either direction. What makes things worse is the full-scale updates of the imputation procedure in 1989, changes include but not subject to the imputation procedure, weighting procedure, data acceptance program, etc. While CPS provides indicator of whether an observation is imputed in the March Supplements since 1988, such variable is not available in the CPS Monthly Basic, therefore unfortunately there is almost no way for us to draw reasonable inference. Although there is very little we can do about this problem at this moment and our best hope is that these noises would not bias our conclusions in an error-in error-out sense, we nonetheless think it is important for the readers to keep in mind of such issues.

As we stated in the main text, the Census changes three times the occupational code system throughout the analysis periods. Some researchers may concern that our results is contaminated by simply relabeling some certain occupations as others. While we do observe some minor discontinuity at the time when the coding system is altered, quantitatively they are quite mild. A couple of evidences could further mitigate this concern. First, such spurious changes if being significant, we should observe jumps at the switching year (1982, 1992 and 2003), while none of the graphs we presented in Section 1 indicates such jump. Second, both the median and mean of SVP is very stable throughout the whole data span. Since we fix the occupation system to *occ1990dd*, any change in the mean and median comes from changes in the weight assigned to each occupation, which reflects the relative population categorized to each occupation. We think this could at least serve as a partial evidence. Third, careful comparison of the four occupational system reveals that noteworthy changes to the Census occupation system took place between the 1970/1980 and 1990/2000 Censuses. The fact that we consistently observe the dominance of service jobs in job finding rates in all time periods except for the Great Recession alleviates us of the concern that the difference in the response of outflow rates for different occupations is simply because of relabeling of the work force population.

Comparing to the previous issues, a more serious one is caused by the CPS 1994 redesign. Recall that the prevailing strategies in the literature is to inflate the short term unemployment number to correct for the implicit time aggregation bias. The job finding rates calculated will be larger than if we do not adjust for the redesign. The fact that year 1994 is the beginning of a new expansion makes it difficult to distinguish whether the outflow rates of construction workers is singled out because of economic factors not captured in our model or because of our adjustment has asymmetric effects on different occupations. Fortunately, the implication of our model is that under severe credit shock, even the occupations subject to the least training cost is affected seriously comparing to the situation where only productivity shock is in presence. The fact that occupations have visible difference in outflow rates before the crisis now share the same outflow rates during the Great Recession lends support to our hypothesis.

F Computational Algorithm

We discrete the two AR(1) processes using the quadrature methods proposed in Tauchen and Hussey (1991). The key equations to solve our model numerically are (3.18) and (3.20). The core task of solving is model is to get the numerical solution for $S_t(A_t, \phi_t, b_t)$, which does not have a closed form solution.

Equation (3.20) implies that the borrowing constraint is always binding, hence from (3.17) we get

$$b_{t+1} = (1-\eta)\phi_t \mathbb{E}_t S_{t+1}(b_{t+1}) \tag{F1}$$

Substitute (F1) into (3.18), we can eliminate the expectations. It is pretty obvious to show that

$$S_t(b_t) = \nu(A_t, \phi_t) - b_t$$

Therefore the problem reduces to numerically solve the function $\nu(A_t, \phi_t)$. We use policy function iteration to solve $\nu(A_t, \phi_t)$ recursively. More specifically, we guess a functional form for the policy of b_{t+1} as a function of A_t and ϕ_t. Substitute this initial guess into $S_t(A_t, \phi_t, b_{t+1})$, we successfully eliminate the dependence of S_t on b_{t+1}. With this new S_t, we use it as the updated functional form for S_{t+1} and calculate the expectations numerically using Gaussian-Quadrature. This way we get a new S_t. Repeat this process until convergence gives us the functional form for S_t. As is made clear in the main text, with S_t, all other variables of the model could be calculated accordingly.

CHAPTER 4

HOUSING INVESTMENT AND THE HOUSEHOLD LIFE-CYCLE PORTFOLIO CHOICE PUZZLE

1 INTRODUCTION

It is well-known that the standard life-cycle portfolio choice models generate profiles of risky assets over the life-cycle that is in stark contrast with what is observed in the data. One of the earliest example is Cocco, Gomes, and Maenhout (2005). In that paper, a risky asset is introduced into an otherwise standard life-cycle consumption-saving model with incomplete market and uninsured labor income [Deaton (1991), Carroll (1997), Gourinchas and Parker (2002)]. The simulated life-cycle profile of risky assets in the paper is shown in Figure 4.1. On average, the agents start with 100% of their savings in risky assets, and the share gradually declines as the agents get older and accumulate more wealth. On the other hand, as is shown in Figure 4.2, the profiles calculated from the *Survey of Consumer Finances* are hump-shaped, and rarely exceed 50%.[1] This gap between the data and the prediction of standard workhorse models are referred to in the literature as the "life-cycle portfolio choice puzzle" (henceforth, the puzzle).

In this paper, we investigate the role of housing investment in addressing the puzzle. We show that when all three components are included, the quantitative prediction from the standard consumption saving model is improved significantly. The intuition goes as follows. The down payment requirement to buy a house creates saving's motive to the young agents. Permanent shocks to labor income prevent the agents from taking too much risk on the financial market. Stock market participation drives out the type of agents that would like to save only a small amount of money, but with expected future labor income as a buffer chooses to put all the money in risky assets to take advantage of the equity premium—a flip side of the equity premium puzzle [Mehra and Prescott (1985)].

[1] In Figure 4.2, we are plotting the raw data of different cross-sections from the *Survey of Consumer Finances*. As is argued in a famous paper by Ameriks and Zeldes (2004), the actual profile estimated from the data could either be hump-shaped, or monotonically increasing depending on the identification assumption one would like to make. However, regardless of the identification assumptions, the estimated profiles are in sharp contrast with what is predicted by the model, *a lá* the one in Figure 4.1.

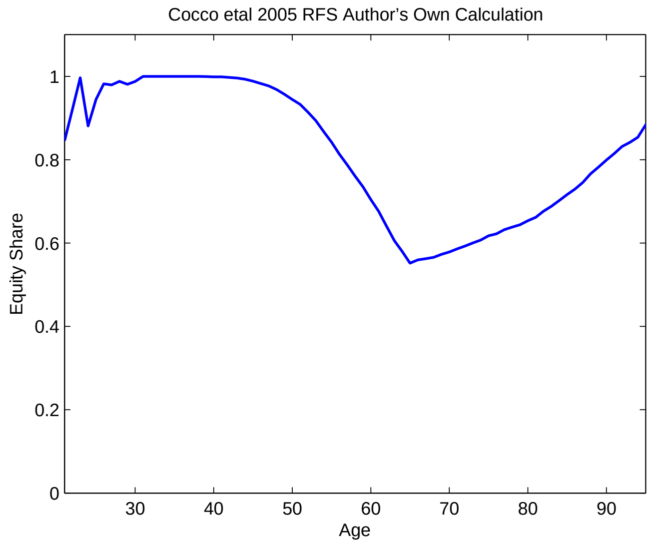

FIGURE 4.1.—LIFE-CYCLE PROFILE OF RISKY ASSETS FROM COCCO, GOMES, AND MAENHOUT (2005)

More specifically, the reason that the puzzle arises when applying the portfolio choice theory [Samuelson (1969), Merton (1969)] to a realistically calibrated life-cycle environment is because the expected labor income dilutes the risk that the agents face in the financial market. As a result, when the total amount of money in the financial market is small relative to the expected future labor income, the agent can afford to take some risk in the financial market in exchange for opportunities to reap the equity premium. The size of the labor income shock that is calibrated from the data is not enough to prevent agents from managing a highly risky portfolio in the financial market. The agents start to withdraw from the risky financial market only when the amount of their financial assets is large relative to labor income. The savings that are created through precautionary and life-cycle motives are not enough quantitatively to lead to such a large pool of financial assets. Housing investment creates an additional saving's motive.

Related Literature.—There is a large literature that attempts to solve the puzzle under the standard Deaton/Carroll framework. As an incomplete list of papers, some of the channels that have been investigated include correlation between labor income and the return of risky assets [Benzoni, Collin-Dufresne, and Goldstein (2007), Lynch and Tan (2011)], the inclusion of habit formation and luxury good [Gomes and Michaelides (2003), Polkovnichenko (2007)], the cash-in-advance and liquidity preference [Aoki, Michaelides, and Nikolov (2014), Campanale, Fugazza, and Gomes (2015)], etc.

Two papers investigating the role of housing assets are closely related to our paper, Cocco (2005) and Yao and Zhang (2005). Both papers modeled the housing investment as a risky assets, and study how the risk associated with housing investment crowds out agent's holding of risky

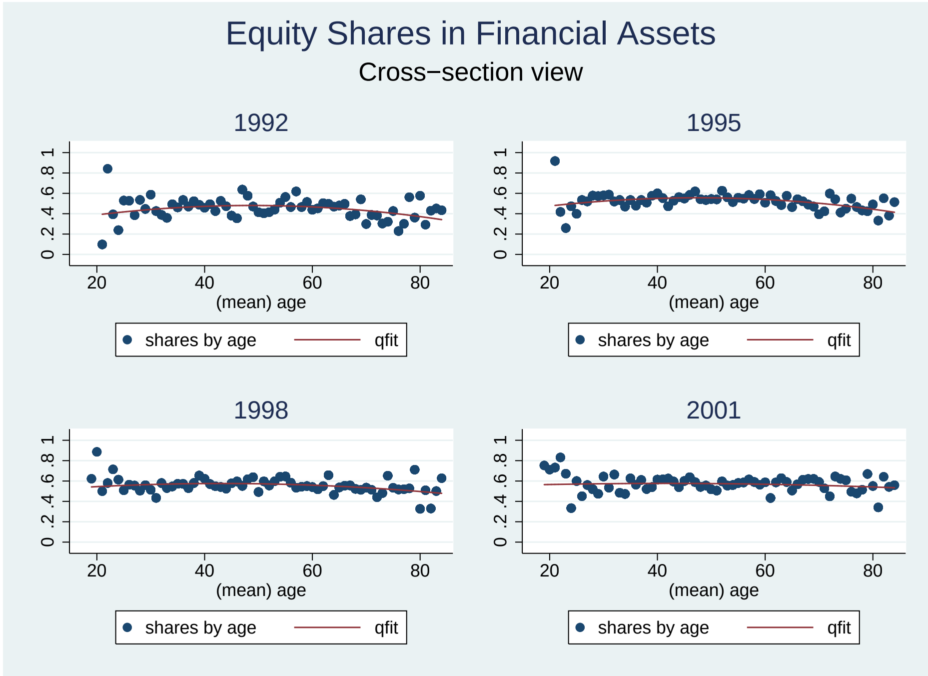

FIGURE 4.2.—DATA SOURCE: SURVEY OF CONSUMER FINANCES

financial assets. On the contrary, our paper focus on a different channel—the saving's motive created by the down payment requirement of buying a house. Therefore, our model differs from Cocco (2005) by allowing agents to rent a room as an option, and differs from Yao and Zhang (2005) by having a more realistic labor income process.

The rest of the paper is organized as follows. Section 2 describes the model. Section 3 explains the choices of parameters, and reports the quantitative results. Section 4 concludes.

2 THE MODEL

We consider a life-cycle consumption-saving model with uninsurable labor income, risk free and risky financial asset, housing investment, and stock market participation costs.

Demographics.—Let t be the age of the agent. The household lives for a maximum of T periods, where for the first T_R periods they get labor income with uncertainty and for the rest of the periods they retire and receive pension. We assume that household maximizes life-time utility:

$$\mathbb{E}_0 \sum_{t=0}^{T} \beta^t \left[\left(\prod_{j=0}^{t} \varphi_j \right) \frac{(C_t^{\sigma} H_t^{1-\sigma})^{1-\gamma}}{1-\gamma} \right], \tag{4.1}$$

where C_t and H_t are non-housing and housing consumption, β represents time preference, ϕ_t

represents the conditional survival probability, σ is the share of non-housing consumption, and γ is risk averse parameter.

Labor Income.—We assume that the labor income process consists of a deterministic trend, a permanent shock, and a transitory shock. More specifically, let Y_{it} be the labor income of agent i at age t, then

$$\log Y_{it} = f(t) + u_{it} + v_{it}, \tag{4.2}$$

where

$$u_{it} = u_{i,t-1} + \varepsilon_{it}. \tag{4.3}$$

This process is widely used in the literature.[2] The deterministic trend captures hump-shape of earnings over the life-cycle, the persistent shock represents promotion or disability that has a lasting effect on one's earnings over an extended period, and the transitory shock represents factors that affect one's earnings only temporarily, for example bonus, temporary illness, etc. We assume that innovations to the permanent shock and to the transitory shock follow respectively $N(0, \sigma_\varepsilon^2)$ and $N(0, \sigma_v^2)$.

We assume that the income of the agents after retirement is a constant fraction of the deterministic plus permanent component in the last working year:

$$\log(Y_{it}) = \log(\lambda) + f(t) + u_t$$

Financial Assets.—There are two financial assets in the economy, a risk-free asset B_t (bond) with certain real rate of return R^f, and a risky asset S_t (stock) with uncertain real rate of return R_t^e. The return of the stock evolves as

$$R_t^e - R^f = \mu + \eta_t \tag{4.4}$$

where μ is the mean of historical equity premium, and η_t is the period t innovation to this excess return. The innovation is assumed to be i.i.d. over time and distributed as $N(0, \sigma_\eta^2)$.

Assuming that the financial market is incomplete in the sense that agent cannot borrow or short-sell financial assets against their future labor income or pension. This means

$$B_t \geq 0$$
$$S_t \geq 0.$$

This can be rationalized by standard moral hazard mechanism.

[2]See for example, Carroll (1997), Gourinchas and Parker (2002) and more recently, Heathcote, Storesletten, and Violante (2014).

Moreover, we assume that participation of stock market requires fixed cost F_p. We model the fixed cost at age t as a constant fraction of the permanent income of that age. We interpret such cost as the opportunity cost of the agent that could be otherwise used to earn labor income:

$$F_p = \lambda_p \cdot F(t)\mathrm{e}^{u_t},$$

where $\lambda_p < 1$ is the ratio.

Housing Market.—The agent can choose to either rent or buy a house. Let $\tilde{H}_t$ be the housing consumption for renters, and H_t be that of the owners. Renters need to pay the per-period rental rate θ^R, while homeowners are subject to a per-period maintenance cost θ^H, with $\theta^R > \theta^H$. To buy a house, the agents can finance up to a fraction π_0 of the total value of their house through mortgage M_t:

$$0 \leq M_t \leq (1 - \pi_0)H_t.$$

Renters can choose to rent rooms of any sizes, while owners can only purchase houses that are larger than a certain threshold. We assume that the minimum size requirement is $e^{u_t}\underline{h}$. The permanent income shock is included for technical reason. In particular, it allows us to normalize the model with respect to u_t to reduce the number of state variables. This is also the reason that the pension and stock market participation cost include the permanent shock e^{u_t}. The trade-off here for the household is that, although the per-period cost of owning a house is less than that of renting a room, the minimum size requirement may leave a young homeowner with too little resource for the consumption of non-housing good, hence decrease the total utility. But because $\theta^H < \theta^R$ is a benefit that a homeowner can enjoy for an extended period of time, a young household will prefer to save as much as possible in the early years to meet as soon as possible to down payment requirement of the minimum house.

We follow Anagnostopoulos, Atesagaoglu, and Cárceles-Poveda (2013) by assuming that the agent can costlessly rebalance the allocation of total wealth among bond, stock and house. We further assume that the interest rate on mortgage is R^f, which is the same as bond. This implies that there is perfect substitutability between mortgage and bond, which leads to

$$M_t = (1 - \pi_0)H_t.$$

As a result, the evolution of personal wealth X_t is characterized by

$$\begin{aligned} X_{t+1} &= R^f B_t + R_t^e S_t + Y_{t+1} + H_t - R^f M_t \\ &= R^f B_t + R_t^e S_t + Y_{t+1} + \left[1 - R^f(1 - \pi_0)\right] H_t \end{aligned}$$

The assumption of costless rebalancing is made in principle to ease the computational burden. Since we are focusing on the saving's motive created by the down payment requirement of purchasing a house, the frictions associated with selling a house is of second order importance to us.

This, however, is important for Cocco (2005) and Yao and Zhang (2005), since they focus on the risk faced by agents when selling a house.

Household Optimization.—With the environment set up as above, the budget constraints for the renters are

$$\begin{aligned} &C_t + B_t + S_t + \theta^R \tilde{H}_t + F_p F(t) \mathrm{e}^{u_t} \mathbb{I}_{\{S_t>0\}} \leq \\ &\qquad R^f B_{t-1} + R^e_t S_{t-1} + Y_t + H_{t-1} - R^f M_{t-1}, \\ &C_t, B_t, S_t, \tilde{H}_t \geq 0, \end{aligned}$$

and those for the owners are

$$\begin{aligned} &C_t + B_t + S_t + H_t + \theta^H H_t + F_p F(t) \mathrm{e}^{u_t} \mathbb{I}_{\{S_t>0\}} \leq \\ &\qquad R^f B_{t-1} + R^e_t S_{t-1} + Y_t + H_{t-1} - R^f M_{t-1} + M_t, \\ &0 \leq M_t \leq (1-\pi_0) H_t, \\ &C_t, B_t, S_t \geq 0, \quad H_t \geq \mathrm{e}^{u_t} h_{min}. \end{aligned}$$

With the budget constraints, households first make two discrete choices: whether to buy a house, and whether to participate in the stock market. The households then choose their non-housing and housing consumption, and the composition of financial assets. Let the lower case letter denote the corresponding variables normalized with respect to the permanent income shock

$$z_t = \frac{Z_t}{\mathrm{e}^{u_t}},$$

the recursive problem of the household can be written as:

$$v(x_t) = \max\left\{v_R(x_t), v_H(x_t)\right\},$$

where v_R is the indirect utility of a renter

$$\begin{aligned} &v_R(x_t) = \max_{c_t, b_t, s_t, \tilde{h}_t} \left\{ \frac{(c_t^\sigma \tilde{h}_t^{1-\sigma})^{1-\gamma}}{1-\gamma} + \beta \varphi_{t+1} \mathbb{E}_t \mathrm{e}^{\varepsilon_{t+1}(1-\gamma)} v(x_{t+1}) \right\} \\ &s.t. \\ &\qquad c_t + b_t + s_t + \theta^R \tilde{h}_t + F_p F(t) \mathbb{I}_{\{s_t>0\}} \leq x_t \\ &\qquad x_{t+1} = y_{t+1} + \mathrm{e}^{-\varepsilon_{t+1}} (R^f b_t + R^e_{t+1} s_t), \end{aligned}$$

and v_H is that of a home owner

$$\begin{aligned} &v_H(x_t) = \max_{c_t, b_t, s_t, h_t} \left\{ \frac{(c_t^\sigma h_t^{1-\sigma})^{1-\gamma}}{1-\gamma} + \beta \varphi_{t+1} \mathbb{E}_t \mathrm{e}^{\varepsilon_{t+1}(1-\gamma)} v(x_{t+1}) \right\} \\ &s.t. \\ &\qquad c_t + b_t + s_t + (\pi_0 + \theta^H) h_t + F_p F(t) \mathbb{I}_{\{s_t>0\}} \leq x_t \\ &\qquad x_{t+1} = y_{t+1} + \mathrm{e}^{-\varepsilon_{t+1}} \left[R^f b_t + R^e_{t+1} s_t + (1 - R^f(1-\pi_0)) h_t \right] \\ &\qquad h_t \geq \underline{h}. \end{aligned}$$

3 Quantitative Results

We solve the model using backward induction. In this section, we first explain our choice of parameters, then we report the simulation results that we bring to the data.

Calibration.—Since the purpose of this study is to investigate under the standard framework, to what extent could the life-cycle portfolio choice puzzle be addressed by introducing the housing investment, we want the parameterizations of our model to stay as close as possible with existing literature. As a result, most of our parameter values are taken directly from the literature. We set agent to enter the economy at age 21, die at age 90, and retire at age 65. The survival probabilities are taken from the *Berkeley Mortality Database*. Discount rate $\beta = 0.96$ and bond return $R^f = 4\%$ are set to be the common values used in the literature. We assume the average equity premium $\mu = 4\%$, and the standard deviation of stock return $\sigma_\eta = 18\%$. The stock market participation cost ratio F_p is set to be the lower-bound of the estimated life-time average 2.5% by Khorunzhina (2013).

Risk aversion is chosen to be $\gamma = 10$, which is the value used by CGM. Notice that although this is larger than the values used by most of the macroeconomics, which is usually 2, it is a common choice in the finance literature. Further, as argued in Chetty and Szeidl (2007), the CRRA with two goods are not directly comparable of that in the one good case. Therefore, we think the choice of $\gamma = 10$ is reasonable here.

We follow Cocco, Gomes, and Maenhout (2005) (henceforth, CGM) by assuming the deterministic part of labor income be approximated by a third-order polynomial

$$f(t) = a + b_1 \cdot t + b_2 \cdot t^2 + b_3 \cdot t^3,$$

and we follow CGM by assigning $a = -2.170, b_1 = 0.1682, b_2 = -0.0323/10, b_3 = 0.0020/100$. The variance of the permanent income shocks $\sigma_\varepsilon^2 = 0.0212$, and that of the transitory shocks $\sigma_v^2 = 0.0440$ are taken from CGM as well, where the authors obtained the estimation from the *Panel Study of Income Dynamics*. The social security replacement ratio is set to be $\lambda = 0.6821$.

Parameters related to housing investment are taken from Li and Yao (2007). More specifically, we choose the down payment requirement $\pi_0 = 20\%$, the per-period rental rate $\theta^R = 6\%$, and that of the maintenance cost $\theta^H = 3\%$. The share of non-housing preference σ is chosen to be 0.2 to match the non-housing consumption share observed in the *Consumption Expenditure Survey*. We calibrate $\underline{h} = 75$ to match the average home ownership rate at 21. A collection of the values of the model parameters are provided in Table 4.1.

Quantitative Results.—The shares of stocks plotted over the net-wealth x_t for various ages are shown in Figure 4.3. The left panel shows that from the original CGM, while the right panel shows that from our model. It is clear that while in the original CGM setup, households maintain a high holding of stocks when they have relatively small quantity of wealth, in our setting this is not the

TABLE 4.1
PARAMETERIZATION

Parameter	Variable	Values	Source
Demographics and Preferences			
Maximum Age	T	90	N/A
Initial Age	t_0	21	N/A
Retirement Age	T_R	65	CGM (2005)
Survival Rate	ϕ_t	—	Berkeley Mortality Database
Discount	β	0.96	CGM (2005)
Risk Aversion	γ	10	CGM (2005)
Labor Income Uncertainty			
Transitory Shock Variance	σ_v^2	0.0440	CGM (2005)
Permanent Innovation Variance	σ_ε^2	0.0212	CGM (2005)
Housing Preference	σ	0.2	LY (2005)
S.S Replace Ratio	λ	0.6821	CGM (2005)
Financial Markets			
Risk-free Rate	R^f	2%	CGM (2005)
Equity Premium	μ	4%	CGM (2005)
Std.dev of Stock Return	σ_η	18.0%	CGM (2005)
Participation Cost	F_p	2.5%	Khorunzhina (2013)
Housing Related Cost			
Minimum House Size	h_{min}	75	Homeownership at Age 21
Down Payment Ratio	π_0	20%	LY (2007)
Maintenance Cost	θ^H	3.0%	LY (2007)
Rental Rate	θ^R	6.0%	LY (2007)

case for agents younger than 50. The intuition is as explained earlier: the housing demand prevents agents from taking too much risk over the financial market.

We then simulate our model using the numerical policy functions. More specifically, we simulate the life-cycle profiles of 10,000 agents, and taking an average over their individual choices. The exercise is run 1,000 times, and we take average over the results. The shares of stocks out of total net-wealth over the life-cycle from our model are shown by the black curves in Figure 4.4. The left panel shows the predicted share of the whole population, while the right panel shows that of the stock market participants. The scatter dots are estimated average share from the 2001 *Survey of Consumer Finances* data, the red curves are fitted profile using third order polynomials. It is clear that the fit of the model is significantly improved compared with previous studies using the Deaton/Carroll model.

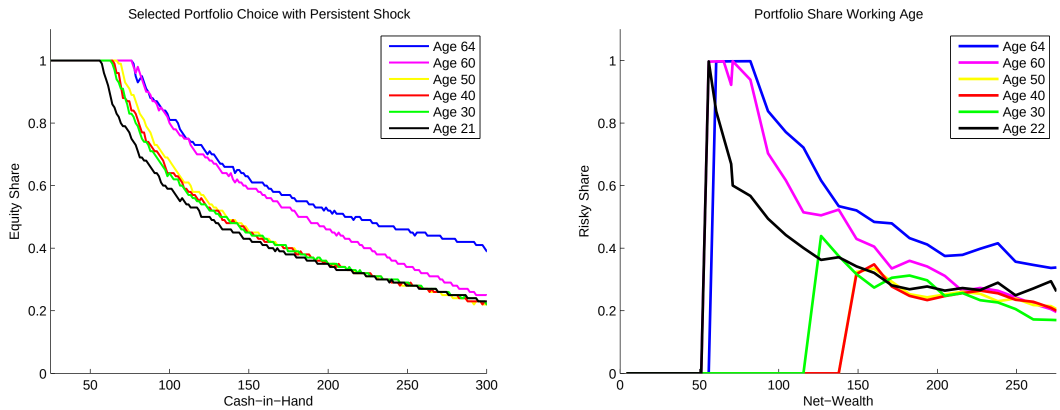

FIGURE 4.3.—POLICY FUNCTIONS OF STOCK HOLDING

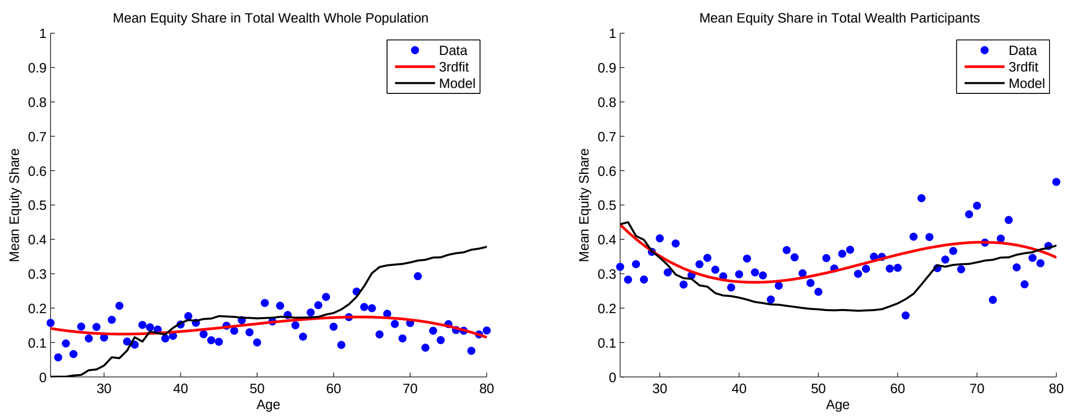

FIGURE 4.4.—PREDICTED PROFILES AMONG NET-WEALTH

4 CONCLUSIONS

In this paper, we investigate to what extend the life-cycle portfolio choice puzzle could be addressed by introducing housing investment into an otherwise standard life-cycle consumption-saving model with uninsured labor income. The puzzle is a flip side of the equity premium puzzle. Under the standard expected utility framework, it could be that either the risk adjusted return to risky assets is too high, or that from the risk free asset is too low. The motivation of our study is that a large fraction of the labor income used to estimated the life-cycle income profile in the data are spent on financing housing consumption in real life [Carroll and Samwick (1997)], however the standard model rules out housing investment by assumption. If we assume that individuals derive utility from risk free housing asset, then the return to risk free assets is underestimated in standard models, which leaves possibility for improvement on the prediction of these models. We show that the saving's motive created by the down payment requirement of home ownership could significantly reduce the gap between the prediction of the model and that observed in the data. Unlike the existing literature, the improvement does not rely on any price risk or illiquidity associated with housing investment, therefore continues to hold even the majority of the individuals in the data do not sell their houses.

The quantitative results in this paper are only preliminary in the sense that the predictions of the model along several dimensions are not consistent with the data. We leave their improvements to future studies.

CHAPTER 5

CONCLUSIONS

This dissertation discusses the effects of market frictions of various forms in shaping the macroeconomic and environmental consequences of both the developing economies and the developed economies. In particular, we show in Chapter 2 that product market frictions lead to both lower output and higher pollution in China; in Chapter 3, we show that frictions in the credit market is important in explaining some novel stylized facts about job finding rates of unemployment workers of different occupations; in Chapter 4, we show that credit market frictions can potentially address the life-cycle portfolio choice puzzle. I believe it is shown that continued research efforts should be devoted to identifying and understanding market frictions which widely exist over the world. We provide here several extensions for future research.

First, an immediate extension to Chapter 2 is to analyze the life-cycle pattern of the pollution treatment technology adoption of firms. This would allow me to understand the upgrade of treatment technology and the effects of environmental policies on the size and age distributions of firms from a dynamic perspective. Second, following recent literature in spatial macroeconomics, I am planning to study the air pollution in China from a spatial perspective by exploiting the firm-level geographic data. It is well-established that firms in larger cities are on average more productive. Theories in economic geography have offered two explanations: firm selection and agglomeration. These two explanations have different implications on the size distribution of firms and hence on pollution. Therefore, it is important to understand how the size distribution of firms change within certain geographic areas and what are the subsequent environmental consequences. Third, several recent studies in the International Trade community have explored the effect of opening to trade on the industrial pollution by the firms [Barrows and Ollivier (2014a,b), Shapiro and Walker (2015)]. It has been shown that unlike the predicted by Melitz (2003) where the most productive firms choose to export and opening to trade drives out the least productive firms, exporting firms in China are typically those lower productive ones [Manova (2013), Manova and Yu (2014)]. Investigation of the environmental consequences of trade in China is thus an important task, given that the Chinese economy is heavily relying on export.

Regarding Chapter 3, a fourth extension is to study the optimal design of labor market policy over the business cycles in an environment featuring training costs and credit market frictions.

Fifth, I find in the data that the job separation rates of service and manufacturing occupations also behave differently over the business cycles. More specifically, while in every post-war recession the job separation rates of manufacturing occupations increase sharply, those of the service occupations only increase mildly. Therefore, investigation of the potential explanations of this fact and further study the job finding rates and separation rates at occupational level in a unified framework could deliver important policy implications.

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