"Second-Class" Workers and China's Productivity Growth

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March 20, 2025

Abstract

This paper studies how the rise of labor agencies affects factor allocation and skill formation in a developing economy. By constructing a novel dataset that covers the near universe of labor agencies in China, I find the spatial expansion of agencies has facilitated inter-regional mobility and reduced labor misallocation among manufacturing firms. However, it is also associated with decreasing hourly wages, widening wage inequality, as well as diminished incentives for educational investment. I develop a Lewisian model of dual economy, where the advanced sector features a hierarchy of tasks that can be outsourced to agencies, to quantify the welfare effects of this particular way of factor reallocation. Agencies introduce surplus labor to auxiliary positions in the advanced sector and thereby promote efficiency gains; but extensive outsourcing may weaken the complementarity between sectoral transition and educational investment, reinforcing the supply of unskilled surplus labor. Therefore while labor agencies may promote productivity growth through a better spatial allocation of labor, they may perpetuate existing inequalities because of greater distortions on human capital accumulation.

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1 Introduction

Reallocating factor inputs to their most productive use has been proven, or at least have the potential, to generate substantial productivity and output gains in many empirical contexts (Hsieh and Klenow (2009)). Yet what type of institutions can facilitate such process, as well as the associated welfare impacts remain an open question. This paper studies an increasingly prevalent labor market institution, i.e., the expansion of labor agencies, and discusses how it lubricates worker reallocation and entails long term welfare consequences through skill formation in a developing economy.

Existing papers generally view that labor outsourcing via agency companies can bring efficiency gains because of better matching and screening of workers, as well as reduced labor hiring and firing costs (Autor (2001), Autor (2003) and Berge et al. (2024)). In the meantime, they have also taught us that agency jobs are mostly "bad" jobs which are often associated with lower wages and social benefits coverage, escalated worker insecurity, as well as little potential for career growth (Kalleberg (2011), Hatton (2011), Case and Deaton (2020), Estefan et al. (2024), Bilal and Lhuillier (2025)). But a natural question follows: if these positions are so undesirable, why don't workers self-select into better opportunities through ex-ante skill acquisition and educational investment? In this paper, I focus on the role of labor agencies in bringing surplus labor to more developed and industrialized areas with higher labor demand, in a developing country setting where worker mobility across space are far from seamless. More importantly, the core determinants of who gets what from such labor reallocation process depends on not only the relative bargaining positions in the tripartite relationship, but the interactions between the extent of outsourcing and ex-ante incentives of educational investment as well. This is particularly pertinent to the context of developing economies where the expansion of labor outsourcing is against the backdrop of sectoral transition of workers and human capital accumulation.[1]

Even though they employ a large faction of the workforce, our knowledge of labor agencies in China, formally known as Labor Dispatch Agencies (LDA) which send workers to fill auxiliary or temporary positions in various workplaces, remains scarce. I construct the first comprehensive dataset that covers the near universe of LDAs in China that registered between 2000 and 2019, and establish a few motivating facts, some of which align with findings from other empirical settings, while others add to our understanding of how the agency sector operates. Consistent with the existing findings, labor agencies in China pay on average lower wages than comparable business service firms. I find that the dispersion of average wage among agencies is substantially higher than that in the manufacturing sector, with the left tail of the dispatched workers identifying themselves as "second-class" workers. Furthermore, the labor income shares in many of the LDAs are below 0.2: this is surprising given the role of agencies as labor market intermediaries, and motivates a closer examination on how these agencies ex-

[1] This also goes back to a classic theme where the boundary of firms determines ex-ante incentives for non-contractible investment decisions (Hart and Moore (1990)).

tract profits when they match workers with firms. Lastly, dispatched workers are less likely to have a college degree, reflecting the limited human capital investments among workers filling the auxiliary positions.

In this paper, I present empirical evidence that the expansion of labor agencies within and across Chinese cities for the past two decades has reduced labor misallocation via facilitating inter-regional worker mobility and led to output gains. At the aggregate level, I find that among the relatively more industrialized and urbanized cities, 1% increase in the total number of LDAs is associated with 0.03% increase in manufacturing employment, as well as 0.01% increase in total industrial employment, and 0.06% increase in industrial GDP during 2000 - 2018. I could not find evidence for similar employment and output gains in less industrialized cities with below median non-agricultural GDP share. This is however consistent with the idea that LDAs facilitate worker reallocation from labor surplus regions with a large agricultural sector to regions with higher labor demand by the industrial sector and higher marginal product of labor. Furthermore, I construct the spatial network of LDAs via ownership linkages where an LDA headquarter in industrialized regions may open up different branches in labor surplus, agricultural regions to facilitate worker reallocation. Drawing on population census in 2005, 2010 and 2015, I find that the expanding spatial network of LDAs significantly increased the total flow of individuals across regions due to work reasons (without changing their initial household *Hukou* registration location). This again aligns with the idea that LDAs facilitate labor reallocation through their spatial network across regions, in a context historically marked by its significant mobility barriers.

In addition to the aggregate effects, the rise of LDAs in Chinese cities has contributed to reduction in dispersion of the marginal revenue product of labor (MRPL) among manufacturing firms, i.e., a core metric for reducing labor misallocation in the macro-development literature (Sraer and Thesmar (2023) and Bau and Matray (2023)). I conduct a classic variance decomposition exercise from the literature on e.g., urban-rural gap (Young (2013)), such that the overall variance of MRPL can be decomposed into a within-city dispersion term and the deviation of city-level mean MRPL from the national mean. The latter term can be further reformulated to involve all pairwise comparisons of cities' MRPL mean. Given this empirical model that distinguishes different components of labor misallocations, I find that the increasing number of LDAs in different cities is associated with reduction of within-city dispersion of MRPL, and the higher number of LDAs in city r which has branches or headquarters in other cities is also associated with lower deviation of city r's mean MRPL from the national mean, although these effects are not precisely estimated. Furthermore, I find stronger evidence that the increasing number of LDA connections through their spatial networks across cities is significantly associated with reduction of pairwise comparison of cities' MRPL mean. In other words, the spatial network of LDAs brings mean MRPL of different cities closer to each other. This again support the notion that the spatial expansion of LDAs reduces interregional misallocation of labor in China.

I also find firm level evidence that the increasing availability of LDAs leads to factor re-

allocation. Due to the endogeneity concerns that the rise of LDAs may be correlated with differential city trends that affect firm level outcomes, I utilize the amendment to Labor Contract Law in 2013 to instrument the availability (and density) of LDAs in different cities. The Labor Contract Law, introduced in 2008, formalized the LDA sector and had therefore led to their rapid entries across the country. The amendment introduced in July 2013 imposed further regulations on LDAs: most importantly, LDAs now need to obtain additional certificates from their local government to operate, and their registered capital need to be no less than 2 million RMB to obtain such certificate. Existing LDAs need to raise their registered capital to meet such requirement; otherwise they were not allowed to function as labor agencies. This allows me to create an exposure measure to the 2013 amendment shock that varies across regions, i.e., defined as the share of LDAs in a city with registered capital below 2 millon RMB in 2012, to instrument the number of LDAs. At the firm level, the 2SLS estimates suggest that for ex-ante high MRPL firms (i.e., above median MRPL across firms within the same 2-digit industry), 1% increase in the number of LDAs in the city is associated with 0.18% reduction of MRPL, as well as 0.18% reduction of TFPR. On the contrary, the ex-ante low MRPL firms have experienced 0.18% increase in MRPL and 0.14% increase in TFPR. I also observe that these ex-ante high MRPL firms increased their overall labor input by 0.04%, but the impact on capital input is limited. Taken together, these results suggest that the expansion of LDAs has led to shrinkage of the MRPL and TFPR dispersions, i.e., reduced labor misallocations at the firm level.

However, the efficiency improvement from labor reallocation via LDA expansion did not translate into wage growth and potentially welfare gains of workers. Based on China Labor Dynamics Survey (CLDS), I find that the increasing availability of LDAs is associated with lower annual wages and higher hours worked among the less educated workers without college degree: 1% increase in LDAs leads to 0.8% reduction of annual wages, and 0.2% increase in monthly working hours; these then translate into 0.87% reduction in hourly wages. On the contrary, college graduates witnessed 5% increase in annual wages but 0.6% increase in working hours at the same time (so overall 0.15% reduction in hourly wages), although these are not precisely estimated. Furthermore, the expansion of LDAs leads to a substantial increase in wage inequality between college graduates and those without a college degree. The large-scale factor reallocation triggered by the institutional change of LDA expansion did not lead to wage growth, contrasting with the evidence from e.g., Bau and Matray (2023) that India's capital market liberalization raised wage bills by 28%. Moreover, the widespread expansion of LDAs also impacted the young who had yet to enter the workforce, which potentially has long run consequences on human capital accumulation. I use the population census to calculate for each city (based on their *Hukou* registration location) the share of 18-24 age group who reported being enrolled in college or have obtained a college degree, as well as who reported working. I find that 1% increase in LDAs is associated with 0.06 percentage points reduction in college share in the 18-24 age group, and 0.02 percentage point increase in the workforce participation. The prevailing presence of LDAs across Chinese cities might have made it "too easy" for the young to join the workforce and weakened the incentives to make long term

investment in human capital.

The empirical analysis then motivate a theoretical framework that quantifies the welfare and distributional effects of the rise of LDAs among firms, workers, and labor market intermediaries. I construct a Lewisian model of dual economy, where the advanced sector firms features a hierarchy of tasks that differ by requirements of firm specific knowledge, and they can outsource auxiliary positions to agency workers. In the model, labor agencies have an increasing returns to scale technology which consists of a fixed cost and a per worker cost when they introduce workers to the advanced sector, and provide general trainings to them. Agencies reallocate labor from labor surplus regions to those with high demand for auxiliary workers, thereby improving production efficiency. Upon making educational investment, backward sector workers can choose to join the modern sector either via labor agencies (which then lead to an auxiliary position) or by themselves (which is more costly but they may become a core worker and climb up the career ladder). Furthermore, agencies may charge additional fees for matching workers with firms, depending on competitiveness of the market for agency workers – this will determine the role of labor agencies in the (functional) distribution of efficiency gains.

The core question I ask is whether these agency intermediaries can provide the right incentives for workers and firms to facilitate upward mobility of the surplus labor from the backward sector in the Lewisian sense, or they perpetuate existing inequalities and generate longer term efficiency **and** welfare loss as extensive outsourcing may discourage educational investment. On the one hand, higher wage gap between the educated and the less educated may encourage the backward sector workers to invest in human capital before they enter the advanced sector. On the other hand, too low initial stock of educated workers in the economy may incentivize firms to not only engage in extensive outsourcing for low-end tasks, but also directly hire the less educated for intermediate tasks. This weakens the complementarity between sectoral transition and educational investment, reinforcing the supply of less educated, surplus labor. Furthermore, the coordination problem of less educated workers to join the agencies or reach the advanced sector by themselves implies that educational investment can be suboptimal in a laissez-faire equilibrium. The theoretical framework therefore highlights a core insight for the expansion of labor agencies in developing economies, where a better spatial reallocation of labor may be associated with greater distortions on human capital accumulation. In the ongoing work, I will use the calibrated framework to explore how counterfactual policies such as limiting the share of dispatched workers in firms' total workforce, varying entry barriers to the agency sector to change the level of competition in the market of agencies, income taxation of different types of workers and redistribution, etc., can achieve both efficiency and equity improvement.

Related Literature This paper is related to the following strands of literature: first, in the macro-development literature on misallocation (which follows the seminal works by Hsieh and Klenow (2009) and Restuccia and Rogerson (2008)), recent papers by, e.g., Sraer and Thesmar (2023) and Bau and Matray (2023), utilize natural experiments to estimate misallocation. But

most of these papers focus on capital market liberalization with less attention on the labor market (except Garicano et al. (2016)). Baqaee and Farhi (2019), Davila and Schaab (2024), and more recently Atkin et al. (2024) and Ghatak and Mookherjee (2024) look at the welfare effects of distortions. I take a different approach by observing a key episode of policy reform in the Chinese labor market, which gives richer policy relevance for understanding the welfare and distributional effects of distortions. Furthermore, this project provides a distinctive empirical example of the LDA expansion, a large-scale policy reform which may promote efficiency gains among manufacturing firms through factor reallocation but may lead to welfare loss at least for some segment of the labor force. Counterfactual exercises of this project will speak to potential policy alternatives in the pre-distribution and redistribution interactions, a core theme which dates to Diamond and Mirrlees (1971).

Secondly, this paper is also related to the ongoing discussion on alternative working arrangements, especially on contract labor and staffing companies (e.g, Autor (2001), Autor (2009), Goldschmidt and Schmieder (2017)), as well as the economic effect of labor regulation (e.g., Besley and Burgess (2004)). Existing theories mostly view agency jobs as transition to permanent positions (Autor (2001)) where labor intermediaries facilitate search and matching for such process (Berge et al. (2024)), or think of outsourcing as reducing labor costs for positions with less firm specific capital (Autor (2003), Bilal and Lhuillier (2025)), an idea which goes back to Becker (1975). I emphasize the role of labor agencies in the development process who bring surplus workers to the modern sector, and highlight the interactions between the extent of outsourcing and human capital accumulation.

Furthermore, among the current empirical papers on agencies, productivity, and welfare, the most related paper is Bilal and Lhuillier (2025) who argue that outsourcing in France leads to a 1.8% increase of aggregate output but 3.1% reduction in earnings and welfare of the low skill service workers. In another related paper, Bertrand et al. (2024) show that the increasing adoption of contract labor reduces the marginal cost of labor faced by large plants because of greater unionization, therefore reduces misallocation and can account for 7.6% of the manufacturing TFP growth in India. Estefan et al. (2024) find that domestic outsourcing of core manufacturing workers leads to lower labor compensation in Mexico, and the recent ban on such outsourcing practices increases labor income share, while reducing capital investment and increasing small firm exits. Felix and Wong (2024) finds that the 1993 outsourcing legalization in Brazil has lead to young workers replacing old workers in the security guards sector. Sociological research on precarious labor relations contributes to the debate on good versus bad jobs (Kalleberg (2011), Hatton (2011)). In this paper, I focus on the geographical expansion of labor agencies and examine the aggregate and distributional impact of the increasing prevalence of a labor market institution, an area where our understanding remains limited. Furthermore, I discuss how labor agencies are able to appropriate profits when they match workers with firms, which crucially depends on the competitiveness of the agency market. This contributes to a better understanding of the profit-making behaviors of labor market intermediaries.

Thirdly, this paper contributes to the earlier theories of economic development with dual

labor market (Lewis (1954)). However, unlike Lewis (1954) or Banerjee and Newman (1998) where the modern sector is characterized by either higher capital intensity or asymmetric information, or Bulow and Summers (1986) where advanced sector wage premium is created to provide incentives, I work out a theory of dual economy where the advanced sector is characterized by a hierarchy of job positions where the boundary of the firm's internal labor market is endogenously determined. Therefore, if a modern sector contains "subsistence" jobs which can then be outsourced, the structure of the job ladder implies differential incentives of ex-ante investment in education and human capital, which in turn affect the earnings of workers from different sectors. Workers from the labor surplus region may never converge to the living standards of highly educated core workers in the advanced region, even though they are working in the same sector. This relates to Case and Deaton (2020)'s argument where labor outsourcing plays an important role in explaining the persistent gap between the less educated and the more educated in the US, because it diminishes the hope of the former to converge to the latter. This paper may also shed light on what kinds of institutions facilitate structural transformation, improve productivity, and at the same time, increase worker welfare.

The rest of this paper is organized as follows: in Section 2, I provide institutional details and data sources, and establish a few motivating facts on the labor dispatch sector in China. In Section 3, I present aggregate level evidence of LDAs on employment, output, and worker mobility. I then discuss my measures of labor misallocation and present the city level and firm level results, which are then followed by results on workers and education investment. In Section 4, I write down a simple static theoretical framework which features endogenous outsourcing and educational investment in a dual economy. I conclude by discusssing next steps of this project.

2 Background, Data, and Motivating Facts

2.1 The Rise of Labor Agencies in China

Labor outsourcing practices, i.e., firms hiring workers through business service agencies, have two origins: in the late 1970s, when foreign companies entered the Chinese market, they were required to hire workers through agency platforms established by the Chinese government (Wang (2019)). Second, following the large scale reform of state-owned enterprises (SOEs) which laid off millions of workers in the late 1990s, labour agencies were set up by the SOEs to facilitate job transition for these laid-off workers (Chen and Chan (2018)). From the early 2000s, as labor costs began to rise, domestic enterprises, private or state-owned, started to adopt dispatched workers and benefited from the more flexible working arrangements. However, such labor outsourcing practices were not legally recognized until the implementation of Labor Contract Law in 2008[2], which formalized the registration of LDAs in China.

[2]Therefore if a dispatched worker made a lawsuit case before 2008 of the company it worked for because of e.g, violation of contracts and lack of financial compensation, such cases might be identified as workers de facto directly working for the company as labor dispatch was not legally recognized by that time. In some ways, the introduction of Labor Contract Law helped to shield companies from such legal claims from their (dispatched)

According to the Labor Contract Law in 2008, registered capital of LDAs should be above 0.5 million RMB, and LDAs should sign labor contract with workers with fixed terms of more than 2 years, and offer monthly wages. Importantly, LDAs are allowed to send their workers "in principle" only to *temporary*, *auxiliary*, or *substitutable* positions. But the vagueness of the boundary of these categories were often exploited by the LDAs, so in practice, the use of dispatched workers were more widespread (Liu (2014))[3]. Firms who need to "borrow" labor from LDAs to fill in these auxiliary positions sign contracts with the LDAs that specify the amount of dispatched labor they use, as well as the total payment conditional on tasks being completed. These labor "borrowers" therefore face lower firing costs as they can simply send back the dispatched workers and request replacements from the LDAs. One prominent feature of labor outsourcing in China is LDAs may send workers to different workplaces across cities (known as "cross-regional dispatch"), especially from the labor surplus region to regions with labor shortage problems. This also gives rise to many legal disputes because of the differences in social benefits and compensation standards across regions. Furthermore, such temporary mobility of workers for work reasons are not restricted by the *Hukou* system.

The rise of LDAs in China brought about numerous cases of labor disputes that reveal firms' abusive use of dispatched labor, such as unequal pay for equal work, overtime work, no career advancement channels, as well as the reluctance of LDAs to pay social insurance for their workers (Wang (2019)). Dispatched workers often regarded themselves as "second-class" or "third-class" workers in the society. LDA regulations therefore faced a clear tradeoff: on the one hand, with the high employment pressure and massive labor migration in the 2000s, LDAs are conducive to reducing unemployment rates (and therefore the related social and political risks) as well as making the production process of enterprises to be more efficient. On the other hand, officials from the Ministry of Human Resources and Social Security (MOHRSS) as well as the All-China Federation of Trade Unions (ACFTU) are concerned with the widespread abuse of dispatched workers. This tradeoff therefore led to disagreements over LDA regulations among officials in different departments of the Chinese government, but got at least partially resolved by the Party leaders in late 2012: amendment of the Labor Contract Law was initiated to protect the rights of dispatched workers, out of the ideological reasons of "maintaining working class's dominant status" in the state as well as the political considerations to reduce industrial disputes and mass incidents (Wang (2019)).

The amendment to Labor Contract Law then took effect on July 1st, 2013, which imposes further regulations on LDAs[4]: most importantly, LDAs need to apply for a labor dispatch

workers (Huang (2017)).

[3]Clarifications on these terms are provided by the subsequent Labor Contract Law Amendment and the No.22 Order of the Ministry of Human Resources and Social Security in China: " *temporary positions* means the positions that exist for not more than six months; *auxiliary positions* means the positions of non-main business that provide services for the positions of main businesses; and *substitutable positions* means the positions that can be held by substitute workers during a certain period of time when the employees of the employers who originally hold such positions are unable to work because they are undergoing full-time study, or on leave or for any other reason."

[4]The Amendment to Labor Contract Law in 2013 is only concerned with LDAs.

certificate granted by the Human Resources Department of the local governments, and the minimum registered capital is raised to 2 million RMB – otherwise the LDAs will not be allowed to operate anymore. The local government will then make a decision in granting the certificates within 20 working days. Besides, if a LDA intends to open up a new branch in a new location, it needs to apply for another certificate from the local government. The amendment also provided more clarity of the boundary of "temporary, auxiliary or substitutable" positions. Furthermore, the MOHRSS imposed another regulation in 2014 that sets up an upper bound of 10% on the share of dispatched labor among total employees for all employers[5]. But according to many case studies, such 10% upper bound has hardly been enforced: companies can write an outsourcing contract (which is still not legally well defined) instead of dispatch contract to avoid the binding upper bound, although workers are sent by LDAs in de facto exactly the same way to firms. In more recent years there had been calls for more stringent regulations on labor dispatch practices, which were rejected due to the economic slowdown.

I plot the time series of monthly new registrations of LDAs in Figure 4: this is based on my LDA dataset which I will describe below. The formalization of LDAs in 2008 has led to accelerating registrations of LDAs across the country, reaching monthly entries of around 1000 LDAs in early 2013. These LDA entrants are predominantly privately owned. But the Law amendment resulted in a sudden drop of LDA registrations, which then climbed up again especially in late 2017 due to e.g., the growing demand of delivery workers from E-commerce platforms in the gig economy. Furthermore, most of the drop in new registrations following the Law amendment are due to local LDAs who do not have headquarter or branches in other cities. Figure 5 illustrates the spatial expansion of LDAs from 2002 to 2018, beginning in relatively developed regions such as Beijing, Shanghai, and Guangdong before spreading to numerous other cities.

2.2 Data

In this paper, I construct the first comprehensive dataset that covers the near universe of LDAs in China that registered between 2000 and 2019. I first obtain the near universe of LDAs from business registration records from National Enterprise Credit Information Publicity System (NECIPE), where I identify each registered enterprise as a LDA if its main business scope contains labor dispatch, and their relevant characteristics of e.g., registered capital are consistent with the legal requirements mentioned above. Then richer data of LDAs such as entry and exit, location, ownership information, modification records of registered capital and business range, number of legal cases such as legal disputes, as well as administrative penalties are manually collected from one of the core business information platforms in China, *aiqicha*. I then construct the spatial network of LDA branches where I identify headquarter of an LDA group as the LDA at the top of the ownership chain where the rests are local branches. In Figure 6

[5]The 10% upper bound originated from a meeting organized by MOHRSS as a comprise between the 5% proposed by ACFTU and the 30% proposed by State-owned Assets Supervision and Administration Commission of the State Council (SASAC) who represented the industrial interests (Wang (2019)).

I present the spatial network of all LDAs aggregated at the city level, where a thicker linkage means that the two cities are connected by a higher number of LDA groups.

I then combine an administrative tax survey dataset of firms, population census, as well as labor survey to study the impacts of LDA expansion. I use the 20% sample of 1% population census in 2005, 2010, and 2015 to construct city level flow of workers (without changing initial *Hukou* registration location), as well as city level averaged education attainment and labor force participation of the 18-24 age group. The administrative tax survey of firms from 2007 to 2016 by the State Taxation Administration contains a repeated cross section of firms, covering various sectors. I construct a subsample panel dataset of manufacturing firms that appear 70% of all years, which is not substantially different from the remaining sample. This also allows me to construct measures of labor misallocation by differentiating non-tax wedges from taxes. I checked the consistency of the tax survey dataset with the more frequently used dataset of Annual Survey of Industrial Enterprises (ASIE) and the correlation of my main variables between the two datasets are around 0.9, suggesting that my firm data is reasonably reliable. I also identify a sample of LDAs in the tax survey dataset which is then used to construct motivating facts on the agency sector, and could be further used to construct proxy measures of total LDA employment in different cities. Besides, I use China Labor Dynamics Survey (CLDS) in 2012, 2014 and 2016 to study how LDAs expansion affect wages and working hours. The China City Statistical Yearbook provides city aggregate measures of industrial employment and GDP, which is used to obtain the aggregate effects estimates.

2.3 Motivating Facts

Drawing on the above mentioned datasets, I am able to construct the following stylized facts: some of them are consistent with existing findings on labor agencies mostly in the developed world, others add to the new understanding of how the labor agency sector operates. These will then motivate my investigation on the welfare impact of LDA expansion.

Fact 1: Agency jobs are paid lower wages than comparable sector.

In Figure 7, I plot the average annual wage (total labor income by total population) provided by the LDAs in the tax survey dataset over 2007 - 2016, which grew from 20k RMB per year in 2007 to 40k RMB per year. This is then contrasted by the growth of annual wage of business service companies excluding LDAs, from 40k RMB to over 80k. Based on the CLDS dataset, Figure 8 shows the (hourly) wage distribution of dispatched workers against the direct hires, where latter has fatter right tail. Taken together, these facts show that agency jobs are generally paid lower wages than comparable sector, which is consistent with the general notion that agency jobs are often classified as "bad" jobs (Kalleberg (2011), Hatton (2011)).

Fact 2: The dispersion of average wage among agencies is substantially higher than that in the manufacturing sector.

Based on the tax survey dataset, Figure 9 presents the distribution of average annual wage of LDAs, contrasted with that of manufacturing firms, as well as the business service companies excluding LDAs. It is interesting to note that the dispersion of the wage distribution of LDAs is much larger than that of manufacturing firms, which potentially reflect the varying skills required by different auxiliary positions. Most notably, the left tail of the LDA wage distribution potentially reflect those LDAs with low skilled, less educated, and "second-class" workers (I will turn to the composition of workers soon). Another observation is that the average wage distribution of the comparable business service firms is a rightward shift of that of the LDAs, consistent with the estimates of average annual wage by year in Figure 7. In Appendix Figure 12, I collect the residuals of average wage for each firms after partially out city and year fixed effects, and plot the residualized wage distribution for the LDAs (again contrasted with manufacturing firms and comparable business service firms). Similar patterns emerge: LDAs' residualized wage distribution has a larger dispersion than that of the manufacturing firms, and the corresponding distribution of comparable business service firms is a slight rightward shift of the LDA's.

Fact 3: Average labor share in total revenue among LDAs is around 0.3.

In the top panel of Figure 10, I use the LDA sample of the tax survey dataset to construct the size distribution of LDAs. LDAs has much fatter tail than the size distribution of manufacturing firms and business service firms, which suggests the agency sector is, unsurprisingly, labor intensive. In the middle panel, I present a binned scatterplot of LDA revenue per worker against labor wage. It shows that 1% increase in revenue per worker is associated with around 0.3% increase in average wage offered by LDAs. I then plot the histogram of labor income share (i.e., total labor income by total main business revenue) of LDAs in the bottom panel, where in many of the LDAs total labor payment to workers only takes up 20% of its total revenue. This is particularly surprising given the role of LDAs as intermediaries in the labor market, whose major revenue source should be labor payment from other firms, and given its labor intensity, such labor payment should then go to the dispatched workers if there is sufficient competition among labor agencies.

Fact 4: Dispatched workers are less likely to have a college degree.

I use the CLDS dataset to explore the characteristics of dispatched workers, although the sample size is fairly small due to missing observations in worker contract information. In Table 1, I decompose dispatched workers versus directly hired workers by their gender, education level, migration status, as well as whether their *Hukou* registration is urban or rural. In the three rounds of CLDS, only 2% of the survey respondents reported themselves as dispatched workers, which is likely to an under-representation of such unique population. Nevertheless, among the surveyed dispatched workers, 57.8% are male, slightly higher than the share of male in direct hires 55.9%. Similarly, migrants (and urban workers) takes up a higher share in dispatched workers than in direct hires, which is consistent with notion that LDIs may send

workers to fill in auxiliary positions in workplaces of different regions. The magnitude is small though, i.e., the share of migrants among dispatched workers is only one percentage point higher than that among direct hires. Perhaps the most substantial difference between direct hires and dispatched workers lies in education level: among dispatched workers, only 13.2% obtained a college or above degree, which is significantly lower than the 21.3% of college graduates among direct hires.

3 Empirical Evidence

In this section, we present empirical evidence for the impact of LDA expansion in China on factor misallocation, wage inequality, and skill formation.

3.1 Aggregate Effects

We begin by examining whether the expansion of LDAs within and across Chinese cities had generated aggregate impacts on sectoral employment, GDP, and worker mobility across cities.

Sectoral Employment and GDP The core hypothesis is that in the Chinese context with substantial barriers of inter-regional worker mobility (which includes, e.g., transportation cost, information barrier or the use of social connection to obtain a job in a new location, etc.), labor agencies are able to facilitate the reallocation of workers from the labor surplus regions to more developed and industrialized regions with higher marginal product of labor and higher labor demand. We therefore expect the expansion of LDAs to have differential impact on cities depending on the degree of industrialization or modernization. We use the city level information from the China City Statistical Yearbook and define $Developed_r = 1$ if city r has above median non-agricultural share of local GDP. The benchmark specification is as follows:

$$y_{rt} = \beta_1 LDA_{rt} + \beta_2 Developed_r \times LDA_{rt} + \gamma_r + \lambda_t + \rho_{rt} + \varepsilon_{rt}, \tag{1}$$

where the outcome variable y_{rt} includes total employment by manufacturing sector, total industrial sector employment, as well as total industrial GDP in city r at time t. γ_r and λ_t are respectively city and time (i.e., year) fixed effects. ρ_{rt} is city specific time trends which account for the potential correlation between unobserved city trends with LDAs expansion and the sectoral outcome variables. LDA_{rt} is the number of LDAs.

The regression results are reported in Table 2. The first two columns says that in more developed areas with above national median non-agricultural GDP share, 1% increase in the number of LDAs is associated with respectively 0.03% and 0.01% increase of employment in manufacturing and overall industrial sectors. By contrast, the employment effects in less developed areas are fairly minimal, although all these results are not precisely estimated. The third column reports that 1% increase in LDAs is associated with 0.04% reduction in industrial GDP in less developed areas, but there is a 0.1% additional gains in more developed cities, which is statistically significant. These results suggest that the expansion of LDAs may generate larger

aggregate impact in developed regions by absorbing surplus labor in the Lewisian way, and the following result on worker mobility may support this as well.

Worker Mobility Across Cities Based on the branch network information in my LDA dataset, I construct $Connection_{rmt}$ as the number of LDA groups that have set up local branches (or headquarters) in city c and m (with $c \neq m$) and therefore may be able to allocate workers between the two cities in year t. I then use the 2005, 2010, and 2015 population census to calculate $flow_{rmt}$, i.e., total flow of individuals who had left their *hukou* registration location r (or m) and stayed in city m (or r) for more than one year. I also calculate such total worker flow due to work reasons, as well as total flows of workers in business service or industrial sector. The following two way fixed effects specification allows me to explore how workers may move across cities along the LDA network:

$$flow_{rmt} = \beta_1 Connection_{rmt} + \mu_{rm} + \lambda_t + \varepsilon_{rmt}, \tag{2}$$

where μ_{rm} is the city pair fixed effects. Table 3 summarizes the results.

According to column 1, 1% increase in the LDA connections linking city r and m is associated with 0.1% increase in total flow of individuals in the population census. Such effects are larger, i.e., 0.17%, if one restricts attention to only flows due to work reasons. Column 3 looks at flow of workers in business service or industrial sector, where one find 0.1% increase due to the 0.8% increase of LDA connections. In Appendix Table 12, I use another measure of the LDA network across cities, i.e., the number of direct linkages such that a LDA headquarter in city r (or m) has an active branch in city m (or r), which yields similar estimates. All these results are precisely estimated, which aligns with the idea that LDAs may send workers to different workplaces in various regions through their spatial branch network.

We now explore how such spatial reallocation of workers through LDA network affects aggregate labor misallocation among manufacturing firms.

3.2 Effects on Labor Misallocation

3.2.1 Decomposing Misallocation

To construct aggregate measures of labor misallocation, I adopt the same notations as Hsieh and Klenow (2009) but consider a simple variation of the framework tailored to differentiate between taxes and non-tax wedges, because our tax survey dataset makes government taxes and subsidies observable. The detailed derivations are in appendix. The core variable to measure distortions is marginal revenue product of capital (after partialling out taxes), which can be used to infer labor market distortion τ_{Lsi}:

$$\hat{MRPL}_{si} = \beta_s \frac{\sigma - 1}{\sigma} \frac{P_{si} Y_{si}}{w L_{si}} \frac{1 - t_{Esi}}{1 + t_{Ssi}} = (1 + \tau_{Lsi}). \tag{3}$$

as well as the marginal revenue productivity:

$$\hat{TFPR}_{si} = \frac{1-t_{Esi}}{(1+t_{Csi})^{\alpha_s}(1+t_{Ssi})^{\beta_s}} P_{si}A_{si} = \frac{\sigma}{\sigma-1}\left(\frac{(1+\tau_{Ksi})R}{\alpha_s}\right)^{\alpha_s}\left(\frac{(1+\tau_{Lsi})w}{\beta_s}\right)^{\beta_s} \tag{4}$$

Decomposition of $\hat{MRPL}$ Dispersion Following Sraer and Thesmar (2023) and Bau and Matray (2023), we focus on the variance of $\log(1+\tau_{sir})$ as a simple metric of aggregate labor misallocation. If we are willing to add more structure to the labor market distortion τ_{Lsi}, we can conduct an interesting variance decomposition exercise, which goes back to e.g., the inequality measurement literature (e.g., Shorrocks (1982)) and studies on urban-rural gap (Young (2013)). This gives us an empirical model to distinguish between different sources of misallocation; more importantly, we will later study how the expansion of LDA within and across cities affect different components of the $\hat{MRPL}$ dispersion. To simplify our notation, let us write $\tau_{sir\equiv}\tau_{Lsi}$ (assuming that firm i doesn't change location r). Specifically, consider that the labor market distortions faced by firm i in region r can be written as

$$\log(1+\tau_{sir}) = \log(1+\tau_{sr}) + \log(1+\tau_s) + \log(1+\nu_{sir}), \tag{5}$$

where the industry specific "regional fixed effect", $\log(1+\tau_{sr})$, captures the local labor market conditions (e.g., the overall shortage of workers in region r because of the mobility barriers), the "industry fixed effect" $\log(1+\tau_s)$ captures the mean labor distortions across industries, and the "residual distortion", $\log(1+\nu_{sir})$, captures the "idiosyncratic" distortions among firms that are orthogonal to $\log(1+\tau_{sr})$.

Then we can decompose the variance of $\log(1+\tau_{sir})$ into within city dispersion, as well as deviation of the city mean distortion from the national mean:

$$\begin{aligned}\text{var}(\log(1+\tau_{sir})) = &\text{var}(\log(1+\tau_s)) \\ &+ \sum_{sr}\rho_{sr}\Bigg[\underbrace{(\log(1+\tau_{sr}) - \log(1+\overline{\tau}_s))^2}_{\text{deviation of city mean from national mean}(\tilde{\Delta}^2_{sr})} + \underbrace{\sigma^2_{sr}}_{\text{within city variance}}\Bigg]\end{aligned} \tag{6}$$

We will then examine how number of LDAs in city r that are connected to other cities may bring down the deviation of city mean MRPL from the national mean $\tilde{\Delta}^2_{sr}$, as well as how local LDAs (that have branches only in only city or don't have branches at all) affect the within city variance σ^2_{sr}.

Another interesting way of variance decomposition that is relevant to our setting is the

following:

$$\begin{aligned}\text{var}\left(\log\left(1+\tau_{sir}\right)\right) &= \text{var}\left(\log\left(1+\tau_{sr}\right)\right) + \text{var}\left(\log\left(1+\tau_{s}\right)\right) + \text{var}\left(\log\left(1+\nu_{sir}\right)\right) \\ &= \underbrace{\frac{1}{2R(R-1)}\sum_{r\neq m}\left[\log\left(1+\tau_{sr}\right)-\log\left(1+\tau_{sm}\right)\right]^2}_{\text{across city variance}(\Delta^2_{srm})} \\ &+ \underbrace{\text{var}\left(\log\left(1+\tau_{s}\right)\right)}_{\text{across sector variance}} + \underbrace{\sum_{sr}\rho_{sr}\sigma^2_{sr}}_{\text{within city variance}},\end{aligned} \tag{7}$$

where $\rho_{sr} = \frac{N_{sr}}{N_s}$ is the share of firms in region r in industry s, σ^2_{sr} is the variance of $\log\left(1+\nu_{sir}\right)$ of all industry s firms in region r, N is the total number of firms and R is the total number of regions. The second equality follows from the fact that $\log\left(1+\tau_{sr}\right)$ is i.i.d. and $\log\left(1+\nu_{sir}\right)$ is i.i.d. for different region r and industry s. Crucially, the across city variance term contains pairwise differences of city level distortions τ_{sr}, which may depend on the availability of LDA linkages, and we will find empirical evidence on this.

Calibration and Calculation Based on my panel dataset of manufacturing firms derived from tax survey 2007-2016, I use income from the main business for $P_{si}Y_{si}$, net value of fixed assets used in production process to capture RK_{si}, and total labor payment to capture wL_{si}[6]. I obtain estimates of α_s and β_s for each two-digit industry s within the manufacturing sector from Shen and Chen (2024), who non-parametrically estimate industry specific production function using the same tax survey dataset for manufacturing firms in China. I present the distribution of $\hat{TFPR}$ (the red curve) in Figure 11, and contrast it with the distribution of TFPR without partially out government taxes and subsidies (the blue curve), where accounting for observable taxes and subsidies reduces the overall dispersion of TFPR by around 1%.

3.2.2 City Level Effects

Based on the above variance decomposition exercises, I explore how the expansion of LDAs as well as their regional linkages affects within city variance and across city MRPL gap. The benchmark specification is as follows:

$$\sigma^2_{rst} = \beta_1 LDA_{rt} + \boldsymbol{X}_{rst} + \varepsilon_{rst}, \tag{8}$$

where σ^2_{rst} is the within city (industry specific) variance of MRPL, and $\boldsymbol{X}_{rst}$ contains city, industry, and year fixed effects, as well as city specific and industry specific time trends. The regression result is in column 1 of Table 4: 1% increase in the total number of LDAs is associated with 0.03 unit reduction of the within city variance term. Then in column 2, I replace LDA_{rt} by the number of local LDAs, i.e., those without branches in other cities and find that the point estimate becomes slightly lower. These local LDAs may work to reallocate workers

[6]The dataset also contains value added information, but the quality is not as good as business income.

across firms or send workers from the rural area to the urban firms within the same city, although these estimates remain statistically insignificant. In column 3 of Table 4, I regress the deviation of city mean MRPL from the national mean $\tilde{\Delta}^2_{sr}$ in equation (6) on the number of LDAs that has established other branches outside city r, to explore if the regionally connected LDAs may bring the city mean $MRPL$ closer to the national mean: 1% increase of such inter-regional LDAs contributes to 0.01 unit reduction in the deviation from national mean, but again the result is not precisely estimated.

The pairwise comparison term Δ^2_{srm} in equation (7) is useful to test if the spatial network of LDAs can contribute to reduction of mean MRPL between given pairs of cities with the following specification:

$$\Delta^2_{srmt} = \beta_1 Connection_{rmt} + \mu_{rm} + \delta_s + \lambda_t + \varepsilon_{srmt}, \tag{9}$$

where δ_s is industry fixed effects, and connection is again measured by the total number of LDA groups that have active branches (or headquarter) in city r and m. I report the regression results in column 2 of Table 5. We now find stronger evidence that 1% increase in the number of linkages between city r and m is associated with 0.009 unit reduction of the squared pairwise comparison of city mean MRPL. I replace $Connection_{rmt}$ by a discrete variable $Connected_{rmt}$ which equals to 1 if and only if $Connection_{rmt} > 0$, and report the results in column 1, which then find point estimates of similar magnitude. In column 3 and 4, I use the alternative measure of direct linkages (between headquarter and local branches), where the existence of such direct linkage ($Linked_{rmt} = 1$) is associated with 0.007 unit reduction of the squared pairwise MRPL difference. Taken together, these results suggest that the expanding LDA networks can contribute to bring city mean MRPL closer to each other when they reach more and more cities.

3.2.3 Firm Level Effects

We now look at the firm level effects on MRPL, TFPR, as well as factor inputs. The core concern for the identification strategy is the potential correlation between differential city trends that affects firm level outcomes and the increasing number of LDAs, which may then bias our OLS estimates. We therefore exploit the 2013 amendment to Labor Contract Law, which requires LDAs to raise their registered capital to be above 2 million RMB, to instrument the number of LDAs across cities over time.

I calculate regional variations in exposure to the policy shock of 2013 amendment, i.e., the increase in minimum registered capital, which affects local availability of LDAs. In order words, I define $ShockExposure_r$ for each city r as the share of LDAs with registered capital below 2 million RMB in 2012, so that with higher $ShockExposure_r$, there will be more LDAs in city r that faces the urgency to increase their registered capital after the 2013 Amendment shock, otherwise they cannot operate labor agency activities anymore. I explore the correlation of such shock exposure measure and city level characteristics, and the regression results are shown in Table 11. As it turns out, I could not find evidence that a city with larger size (i.e., in

terms of GDP, population, and trade volumes) or more institutions providing trainings for the workforce (i.e., universities and vocational schools) is associated with lower or higher of such exposure measure. One reason might be that the 2 million threshold is very close to the median of registered capital distribution prior to 2013, so different cities may have similar density of LDAs with registered capital below 2 million.

For my core results on firm level outcomes which will be shown later, I exploit such regional variations in exposure to the 2013 Amendment shock to instrument the availability of LDAs. As the first stage, I run the following specification:

$$LDA_{rt} = \beta_1 ShockExposure_r \times Post_t + \gamma_r + \lambda_t + \varepsilon_{rt}, \tag{10}$$

where LDA_{rt} is the number of LDAs in city c at year t (while I also weight this by population as well as total area to generate some density measures following Celerier and Matray (2019)). $Post_t = 1$ if and only if time period t is after 2013 Amendment. γ_r and λ_t are respectively city and year fixed effects. I report the OLS estimates in Table 10. According to Column 1, a 10 percentage point increase in the exposure measure is associated with around 3.6% reduction of LDAs following the 2013 Amendment. I find estimates of similar magnitude if one weights the number of LDIs by population size, which are shown in Column 2. These results suggest that $ShockExposure_r \times Post_t$ has quite strong predictive power for the local availability of LDIs, with F-statistics above 10, the threshold for strong instruments (Stock and Yogo (2005)). Column 3 finds that if one weights the number of LDAs by total areas, the estimates can be quite different, and there is a large reduction in F-statistics as well. Lastly, column 4 suggests that the 2013 amendment did not have significant impact on the Herfindahl index of registered capital, a proxy for concentration in the agency market.

Now we are ready for studying the misallocation effects at the firm level. Following Sraer and Thesmar (2023) and Bau and Matray (2023), my core strategy to identify the effect of LDA expansion on factor misallocation is to see how higher number of LDAs generate differential impact for firms with ex-ante high versus low MRPL. Equation (3) suggests that a firm with ex-ante high MRPL are faced with higher ex-ante labor market distortion τ_{sir}. Therefore, if one can observe MRPL reduction (increase) and labor input increase (reduction) for ex-ante high (low) MRPL firms, this will be our evidence of reduction of MRPL dispersion and labor misallocation. My empirical specification is as follows:

$$y_{isrt} = \beta_1 \hat{LDA}_{rt} + \beta_2 HighMRPL_i \times \hat{LDA}_{rt} + \boldsymbol{X_{isrt}} + \varepsilon_{isrt}, \tag{11}$$

where y_{isct} is firm level outcome variables for firm i in industry s and city r at time period t. $\hat{LDA}_{rt}$ is the number of LDAs in city r at time t, which I instrument with $ShockExposure_r \times Post_t$. I classify $HighMRPL_i = 1$ if firm i has above median MRPL among all firms within the same (2-digit) industry during 2007-2009, years before the expansion of LDI truly takes off. $\boldsymbol{X_{isrt}}$ consists of firm and year fixed effects, as well as city and 2-digit industry specific time trend. I include (two-digit) industry$\times$year term to capture any differential trends by two-

digit industries that may bias the estimates. Based on my sample of manufacturing firms over 2010-2016, I report the 2SLS estimates in Table 6.

The first column suggest that 1% increase in the number of LDAs is associated with 0.18% increase of MRPL for ex-ante low MRPL firms, and 0.18% decrease of MRPL for ex-ante high MRPL firms, i.e., evidence for shrinking MRPL dispersion consistent with our city level evidence presented before. The second column and third column imply that following 1% increase in LDAs, ex-ante low MRPL firms reduce their labor input by 0.20%, whereas the ex-ante high MRPL firms increases their labor input by 0.03%, suggesting notable factor reallocation effects. There is no substantial change in capital input, although the ex-ante high MRPL firms witness a 0.06% differential increase compared to the low MRPL counterparts. Lastly, based on the fourth column, there is also sizable reduction of TFPR dispersion, with ex-ante high (low) MRPL firms witness 0.18% reduction (0.14% increase) in their TFPR associated with 1% increase in the number of LDAs. Therefore Table 6 complements the city level evidence on the reduction of MRPL dispersion with firm level evidence on factor input changes and reduction in TFPR dispersion.

3.3 Effects on Wages and Skill Formation

So far I have presented evidence that the expansion of LDAs has led to a more efficient allocation of labor across regions and across firms. Now I use the CLDS datasets in 2012, 2014 and 2016 to explore what happens to workers when there are more LDAs active in the cities, which speaks to the equity aspects of factor reallocation. More specifically, I examine how LDA expansion may generate differential impact on workers with different education levels, since in Table 1 the most substantial difference between dispatched workers and direct hires are their education levels. My regression specification is as follows:

$$g_{jrst} = \beta_1 L\hat{D}A_{rt} + \boldsymbol{M_{jrst}} + \varepsilon_{jrst}, \tag{12}$$

where g_{jrst} is the individual level outcomes (which includes annual wages, monthly hours worked, as well as hourly wages) for individual j in city r, working in industry s at year t. As before, LDA_{rt} is the number of LDAs. $\boldsymbol{M_{jrst}}$ consists of individual and year fixed effects, as well as city and 2-digit industry specific time trend. Furthermore, I run this specification separately for workers with and without a college or above degree, and Table 7 reports the OLS estimates.

Based on the second column, there is substantial differential impact of LDA expansion on annual wages among college graduates and the less educated workers, with the former gaining 0.5% and the latter losing 0.8% of annual wage due to 1% increase in the number of LDAs in the city. Furthermore, following the expansion of LDAs, there are also higher hours worked for both groups, although the estimates are imprecise. Taken together the effects on annual wage and hours worked, I find wage per hour decreases by 0.87% among the less educated workers in the first column, contrasting with 0.15% reduction in hourly wages of college graduates.

Table 8 reports how LDA expansion affects wage inequality between the two groups. I calculate the average hourly wage ratio of college graduates over workers without a college degree, specific to industry s and city r and run the following specification:

$$ratio_{srt} = \beta_1 L\hat{D}A_{rt} + \boldsymbol{X_{srt}} + \varepsilon_{srt}, \tag{13}$$

where again $\boldsymbol{X_{srt}}$ consists of city, industry and year fixed effects, as well as city specific and industry specific time trends. I report the result in column 2 of Table 8, where 1% increase in the total number of LDAs is associated with around 0.05 unit of increase in such "wage premium" of college degree. In column 1, I present a similar regression result but without the wage ratio being specific to industries and again I find strong evidence of increase in wage inequality among workers of different educational backgrounds.

The evidence so far suggests that LDA expansion has led to wage loss and increasing working hours, with the effects being more pronounced among the less educated workers, as well as increase in wage inequality. This is in sharp contrast with the promising efficiency gains among manufacturing firms due to labor reallocation. However, what is perhaps more disturbing is the effect of LDA expansion on the young who had yet to enter the workforce, which we explore using the following specification:

$$y_{rt} = \beta_1 LDA_{rt} + \gamma_r + \lambda_t + \rho_{rt} + \varepsilon_{rt}, \tag{14}$$

where the outcome variables include the city level proportion of respondents in the population census aged 18-24 who reported being enrolled in college or having obtained a college degree, as well as the share of 18-24 respondents who reported working. The results are summarized in Table 9.

I find that 1% increase in the number of LDAs is associated with 0.06 percentage points reduction in the college share in the 18-24 age group, and 0.02 percentage point increase in workforce participation. The leading interpretation of this result is that the increasing number of LDAs makes it easier for individuals especially in the less developed regions to find a job (e.g., in developed areas), which in turn discourage the young to make longer term investment in college education. This in turn has important implications on long run human capital accumulation. The following model formalizes this idea, where the extent of labor outsourcing affects incentives for educational investment and may reinforce the supply of unskilled surplus labor.

4 Theory: Outsourcing and Educational Investment

This section put forward a theoretical framework where the endogenous outsourcing decisions of the firms, and the educational investment / sectoral transition decisions of workers are jointly determined. This allows us to think about how labor outsourcing affects the long term path of development.

The Benchmark Formulation Consider an economy with two regions (sectors) $r \in \{a, b\}$: advanced and backward. The production technology of the backward region is simply $\underline{A}l$ (so the wage rate in the backward region will be $w_b = \underline{A}$). The total population for sector r is L_r, and all workers are ex-ante the same.

Firms in the advanced sector are characterized by a continuum of tasks. Output is given by

$$Y = AK^{\alpha}L^{\beta}, \tag{15}$$

where $\alpha + \beta \leq 1$ and L is an aggregator of labor inputs across tasks $\gamma \in [0, 1]$:

$$L = \left(\int_0^1 \left[\sum_e \theta(\gamma, e, s)\, l(\gamma, e) \right]^{\frac{\sigma-1}{\sigma}} d\gamma \right)^{\frac{\sigma}{\sigma-1}}, \tag{16}$$

where $\theta(\gamma, e, s)$ is the productivity parameter for task γ, which depends on whether the firm provides firm-specific trainings or not, i.e., $s \in \{0, 1\}$, as well as the workers' education level $e \in \{0, 1\}$. The cost of providing the firm-specific training per worker is k. I assume that the firm-specific training is more efficient for tasks that requires more firm-specific information, i.e. $\theta(\gamma, e, 1)$ is increasing in γ, and $\theta(0, e, 1) = \underline{\theta}(e)$. Furthermore, for simplicity, I assume for any $\gamma \in [0, 1]$:

$$\theta(\gamma, e, 0) = 0, \tag{17}$$

so that firm will always provide such trainings to workers. Therefore for notations below, we simply write $\theta(\gamma, e)$ to denote the productivity parameter.

Let us denote the wage rate offered by the advanced sector is $w(e)$. Here we assume that the firm-specific training is not transferable to other workplaces as in Becker (1975) so that workers are hired competitively at wage $w(e)$ without the firm paying differentials to different type of tasks. Since workers of different education levels are substitutable for a given task γ, it is easy to show that the firm will choose educated workers to work on task γ if and only if

$$\frac{\theta(\gamma, 1)}{\theta(\gamma, 0)} \geq \frac{w(1) + k}{w(0) + k}. \tag{18}$$

We assume that $\frac{\theta(\gamma,1)}{\theta(\gamma,0)}$ is increasing in γ, so that there exists a γ^* such that the firm will assign educated workers to positions only with $\gamma \geq \gamma^*$. This says educated workers will work on tasks that require more firm specific expertise, which is consistent with Gibbons and Waldman (1999)'s model of wage growth and promotion dynamics. Denote the optimal labor input for task γ is $\hat{l}(\gamma, e)$.

For all workers directly hired by the firm (and then receive the firm-specific trainings), we assume that there is a probability of δ that it will be promoted as a partner and obtain a share s of firm's profit π. We assume that δ and s are independent of e, i.e., working experiences matter more for becoming a partner. One can micro-found this by assuming a hierarchical job

structure as in Rosen (1982), and setting up Nash bargaining between the firm and its partners in an over-lapping generation model, and π can be determined in the stationary equilibrium. With probability $1-\delta$ the worker will simply retire and obtain 0. Given the wage rate offered by the advanced sector $w(e)$, then the worker will obtain

$$w(e) + \delta s \pi. \tag{19}$$

Before working, agents make the education investment decision $e \in \{0,1\}$, and the cost of education is η which is heterogenous across workers with cumulative density function $F(\eta)$. Furthermore, backward sector workers need to incur an additional fixed cost of ε to move to the advanced sector, and again, ε is another random variable with cumulative density function $G(\varepsilon)$. Let us assume η and ε are independently distributed. This implies that the share of educated workers in all workers originally from the advanced sector is $F(w(1)-w(0))$. For workers originally from the backward sector, they will move to the advanced sector if and only if

$$\max\{w(1)-\eta, w(0)\} + \delta s \pi - \underline{A} \geq \varepsilon. \tag{20}$$

Since in this benchmark model all workers will be directly hired by the firm and offered firm specific trainings, both educated and less educated workers all have a chance to become a partner and obtain $\delta s \pi$. Given they will move to the advanced sector, workers originally from the backward sector will invest in education when $w(1)-\eta > w(0)$. Figure 1 characterize the optimal educational investment and sectoral transition decisions in the (ε, η) space.

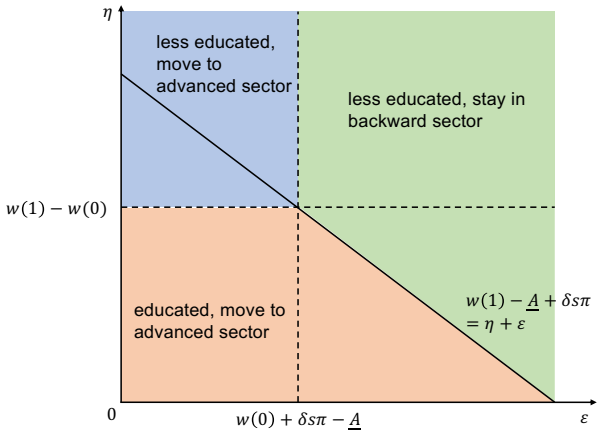


FIGURE 1: EDUCATION INVESTMENT IN THE BENCHMARK MODEL

We now specify the labor market clearing conditions that determine $w(1)$ and $w(0)$. The share of backward sector workers who will invest in education and move to the advanced sector is

$$\omega_{1b} = \int_0^{w(1)-w(0)} G\left(w(1) + \delta s \pi - \underline{A} - \eta\right) dF(\eta), \tag{21}$$

and the share of backward sector workers who do not invest in education but still move to the

advanced sector is

$$\omega_{0b} = G\left(w(0) + \delta s\pi + \underline{A}\right)\left[1 - F\left(w(1) - w(0)\right)\right]. \tag{22}$$

The share of advanced sector workers who invest in education is simply $\omega_{1a} = F\left(w(1) - w(0)\right)$. Then the labor market clearing conditions for $w(1)$ and $w(0)$ are

$$\int_0^{\gamma^*} \hat{l}(\gamma, 0)d\gamma = \left(1 - \omega_{1a}\right) L_a + \omega_{0b} L_b, \tag{23}$$

$$\int_{\gamma^*}^1 \hat{l}(\gamma, 1)d\gamma = \omega_{1a} L_a + \omega_{1b} L_b. \tag{24}$$

It is interesting to note that uneducated workers earn different wages in different sectors because of the mobility cost ε.

Labor Agencies as a "Quick-Fix" Tunnel for Development Now let us introduce labor agencies as a specific technology to transform workers from the backward sector to the advanced one. I argue that the technology of the agencies are efficient in the following two ways: firstly, when they introduce workers in the backward sector to the modern one, they have an increasing returns to scale technology which consists of a fixed cost F and per worker cost ξ. F may entail the cost of obtaining good relationship with the advanced sector firms to secure a fraction of vacancies for agency workers, and ξ may include transportation cost. Secondly, they can provide general trainings to workers $\tilde{\theta}$ such that it is more efficient for tasks that requires less firm-specific knowledge. More specifically,

$$\theta\left(0,0\right) < \theta\left(0,1\right) < \tilde{\theta} < \theta\left(1,0\right) < \theta\left(1,1\right), \tag{25}$$

which says that the labor agencies have a comparative advantage in training workers to fill auxiliary positions, i.e., tasks that require less firm specific knowledge (low γ). We also assume that $\tilde{\theta}$ is independent of e, i.e., education doesn't affect the productivity of agency workers who receive general trainings. Then it follows that the labor agencies will only obtain less educated workers ($e = 0$), which is also generally consistent with the empirical patterns of agency workers in China. Autor (2001) provides a micro-foundation for why agencies are willing to provide such general trainings through informational rents. The per-worker cost for such general trainings is $\tilde{k} < k$. When firm "borrow" workers from the labor agencies, they have to pay a per worker administrative fee of τ.

I assume direct hire workers and agency workers are substitutable within the same task, so that the labor aggregator can now be written as

$$L = \left(\int_0^1 \left[\sum_{t \in \{D,A\}} \sum_e \theta^t\left(\gamma, e\right) l^t(\gamma, e) \right]^{\frac{\sigma-1}{\sigma}} d\gamma \right)^{\frac{\sigma}{\sigma-1}}, \tag{26}$$

where $t \in \{D, A\}$ denotes the type of working arrangement, i.e., direct hires versus agency workers, with $\theta^D(\gamma, e) \equiv \theta(\gamma, e)$ and $\theta^A(\gamma, e) \equiv \tilde{\theta}$. The firm's per worker cost is $w(e) + k$ for direct hires, and $w(0) + \tau$ for agency workers. Then we can determine the advanced sector firm's labor outsourcing decision. First let us define γ^{**} such that

$$\frac{\theta(\gamma^{**}, 1)}{w(1) + k} = \frac{\tilde{\theta}}{w(0) + \tau}, \tag{27}$$

and $\overline{\gamma}$ such that

$$\frac{\theta(\overline{\gamma}, 0)}{w(0) + k} = \frac{\tilde{\theta}}{w(0) + \tau}. \tag{28}$$

Then we can show that if $\gamma^{**} \leq \overline{\gamma}$, the firm will outsource its task with $\gamma < \gamma^{**}$ to agencies and directly hire educated workers to take care of the rest. If instead $\gamma^{**} > \overline{\gamma}$, the firm will outsource tasks with $\gamma < \overline{\gamma}$ to agencies, and directly hire less educated workers for tasks $\gamma \in [\overline{\gamma}, \gamma^*)$ and educated workers for tasks $\gamma \geq \gamma^*$. Firm's production is more efficient now because it get access to a more productive technology of training workers to fill in "auxiliary" tasks (i.e., tasks that requires less firm-specific information) through the labor agencies. This is summarized in Figure 2. Note that $\gamma^{**} \leq \overline{\gamma}$ can be simply rewritten as an upper bound on $w(1)$:

$$w(1) \leq \frac{1}{\tilde{\theta}}(w(0) + \tau)\,\theta(\overline{\gamma}, 1) - k \equiv \overline{w}. \tag{29}$$

Let us also denote the optimal labor input under labor outsourcing for task γ is $\hat{l}^t(\gamma, e)$.

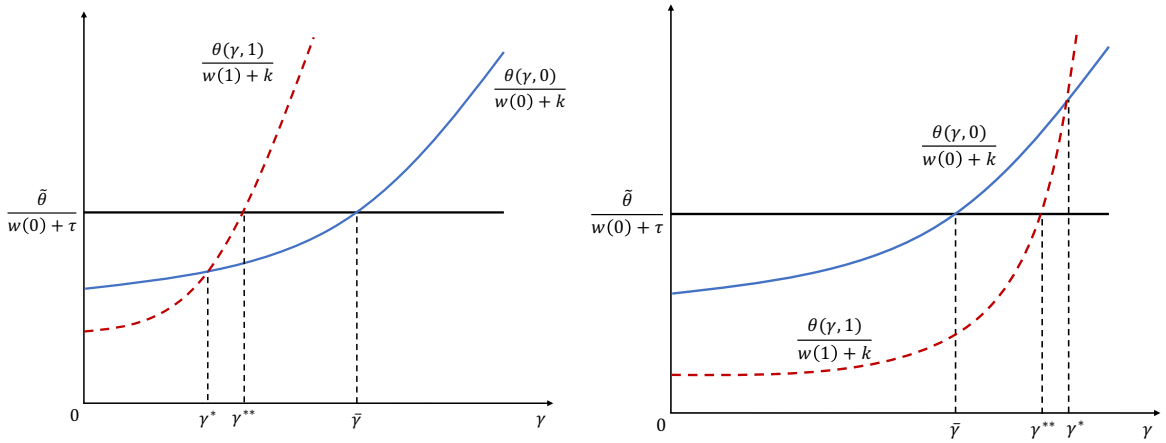


FIGURE 2: OUTSOURCING DECISION: LOW (LEFT) VERSUS HIGH (RIGHT) OUTSOURCING

An important assumption we make in this model is that firms cannot commit to a specific contractual agreement **t** with the worker, so the competitive worker wage at given education level e is independent of **t**. In reality, many firms may simply terminate contracts with their direct hired workers using administrative pressure and ask workers to instead sign contracts with labor dispatch agencies; and sometimes workers are not even entirely clear of the (consequences) of such shift of contractual agreements. Another implication of this assumption is that when $w(1) \leq \overline{w}$ (i.e., outsourcing for $\gamma < \gamma^{**}$), high educated workers know they will

be assigned with a direct hire contract and less educated workers will all sort into agency jobs; as we will see below, such clear sorting of education and outsourcing tasks provides stronger incentives for education investment. When instead $w(1) > \overline{w}$, again high educated workers will be directly hired, but a less educated worker may reach the advanced sector by itself, and would be randomly allocated with a position with contract **t** and receiving corresponding trainings specified above. This reduces incentives for education investment and may reinforce the high outsourcing equilibrium $\overline{\gamma}$.

Let us now analyze how access to agencies affects development outcomes, i.e., workers' incentives to move to the advanced sector and their education investment. There are two development "tunnels" to the advanced sector. One is that you can incur fixed cost ε to reach the advanced sector yourself (i.e. the hard path), and the other one is you attend a labor agency which will facilitate your transition (i.e., without having to incur ε) but you will be surely assigned to an auxiliary task (i.e., the quick-fix path). Therefore when $w(1) \leq \overline{w}$, workers will take the hard path only when they also invest in education. When $w(1) > \overline{w}$, workers may not necessarily invest in education, because it is likely that they are assigned with a direct hire position with career progression to a partner. Now we are ready to characterize the equilibrium of this model. Our first observation is that for less educated workers to accept the agency job offer, we need $w(0) \geq \underline{A}$. Assume L_b is high enough so that perfect competition in the labor market will make sure

$$w(0) = \underline{A}. \tag{30}$$

With the presence of labor agencies, equilibrium wage for the less educated workers is lower than the case without agencies. Now we can discuss the following two types of equilibrium where outsourcing decisions and education investment are jointly determined:

(1) Low Outsourcing Equilibrium When $w(1) \leq \overline{w}$, workers in the backward sector will invest in education and take the hard path to the advanced sector if and only if

$$w(1) + \delta s\pi - \eta - \varepsilon \geq \underline{A}. \tag{31}$$

Otherwise they will join the agency. Importantly, in the low outsourcing equilibrium, education investment and taking the hardcore path become perfect complements. Workers in the advanced sector will invest in education if and only if

$$w(1) + \delta s\pi - \eta \geq \underline{A}. \tag{32}$$

This will give us the supply of educated workers: the share of backward sector workers who invest in education is simply

$$\omega_{1b}^{low} = \int_0^{w(1)-\underline{A}+\delta s\pi} G\left(w(1) + \delta s\pi - \underline{A} - \eta\right) dF(\eta), \tag{33}$$

and the share of advanced sector workers who invest in education is $\omega_{1a}^{low} = F\left(w(1) + \delta s\pi - \underline{A}\right)$. Note that in partial equilibrium, the low outsourcing case also provides the advanced sector workers with higher incentives to invest in education compared to the benchmark case, because of the better sorting of educated workers into core positions with additional gains of $\delta s\pi$. Uneducated workers in the backward sector will be indifferent between staying in region b and moving to region a via agencies. The labor market clearing condition characterizing $w(1)$ is simply to replace ω_{1r} by ω_{1r}^{low} and $\hat{l}(\gamma, 1)$ by $\hat{l}^D(\gamma, 1)$ in equation (24).

(2) High Outsourcing Equilibrium When $w(1) > \overline{w}$, workers in the backward sector obtain $w(1) + \delta s\pi - \eta - \varepsilon$ when invest in education and take the hard path by themselves. If they take the hard path but doesn't invest in education, they obtain $\underline{A} + p\delta s\pi - \varepsilon$, where p is the probability of being allocated with a direct hire position with $\gamma \in [\overline{\gamma}, \gamma^*)$. If they stay in the backward sector or attend the agency, they obtain $\underline{A}$. Workers originally from the advanced sector will invest in education if and only if

$$w(1) + \delta s\pi - \eta \geq \underline{A} + p\delta s\pi \tag{34}$$

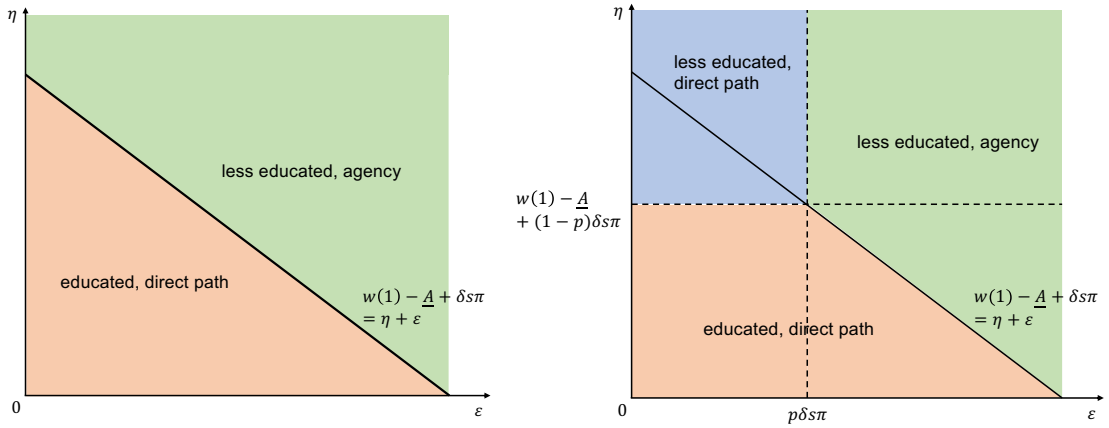


FIGURE 3: EDUCATION INVESTMENT: LOW (LEFT) VERSUS HIGH (RIGHT) OUTSOURCING

The characterization of education investment and choice of development tunnel is summarized in Figure 3 above. The core observation is that in a high outsourcing case, there are less incentives for education investment, which then pushes up wage for educated workers $w(1)$ and reinforces firms' incentives to use agency workers. On the other hand, if there is a high stock of educated workers, and firms may find it easier to fill more positions with educated workers and create less outsourcing positions, which in turn incentivizes backward sector agents to also invest in education. Again the equilibrium wage $w(1)$ will be determined by the labor market clearing condition for educated workers. The share of advanced sector workers who invest in education is $\omega_{1a} = F\left(w(1) + (1-p)\delta s\pi - \underline{A}\right)$. The share of backward sector workers who invest in education is

$$\omega_{1b}^{high} = \int_0^{w(1)+(1-p)\delta s\pi-\underline{A}} G\left(w(1) + \delta s\pi - \underline{A} - \eta\right) dF(\eta), \tag{35}$$

and the share of backward sector workers who do not invest in education but choose the direct path is

$$\omega_{0b}^{high} = G\left(p\delta s\pi\right)\left[1 - F\left(w(1) + (1-p)\delta s\pi - \underline{A}\right)\right] \tag{36}$$

The labor market clearing condition characterizing $w(1)$ is again to replace ω_{1r} by ω_{1r}^{high} and $\hat{l}(\gamma,1)$ by $\hat{l}^D(\gamma,1)$ in equation (24). Furthermore, education investment and taking the direct path to the advanced sector are no longer perfect complements, because individuals may well join the advanced sector themselves without educational investment.

We now discuss how the probability of an uneducated workers being allocated with a direct hire position p is determined. Formally,

$$p = \frac{\int_{\overline{\gamma}}^{\gamma^*} l^D(\gamma,0)d\gamma}{\int_{\overline{\gamma}}^{\gamma^*} l^D(\gamma,0)d\gamma + \int_0^{\overline{\gamma}} l^A\left(\gamma,0\right)d\gamma - L_{bA}}, \tag{37}$$

where the nominator is the total number of core positions created by the firms for uneducated workers, and the denominator is the total demand for uneducated workers except for those who directly join the agency from the backward sector L_{bA}. Let us assume that when backward sector workers are indifferent between joining the agency and staying at the backward sector, they choose the former. Hence $L_{bA} = \left[1 - \omega_{1b}^{high} - \omega_{0b}^{high}\right] L_b$. Here, an interesting coordination problem arises because the more less educated workers in the backward sector attending the agency, the more appealing for the remaining surplus labor to take the direct path. Such positive externality of joining agencies in the backward sector means that in laissez-faire equilibrium, there are too many backward sector workers choosing the direct path without education, and under-employment through agencies compared to the social optimum. Also, higher p implies less incentives to invest in education, as we specify before. This in turn implies under-investment in education. Therefore, the high outsourcing equilibrium creates additional inefficiencies in education investment and the choice of development path.

Let us determine the profits of the labor agency, which can be written as

$$\pi^A = \int_0^{\max\{\gamma^{**},\overline{\gamma}\}} l^A\left(\gamma,0\right)d\gamma\left[\tau - \tilde{k}\right] - \xi L_{bA} - F, \tag{38}$$

Let us assume that imperfect competition in the agencies market leaves each agency earning an equilibrium profit of $\phi \geq 0$, where $\phi = 0$ captures perfect competition. Then the per worker administrative fee that agencies charge is

$$\tau = \tilde{k} + \frac{\phi + F + \xi L_{bA}}{\int_0^{\max\{\gamma^{**},\overline{\gamma}\}} l^A\left(\gamma,0\right)d\gamma}. \tag{39}$$

It is interesting to observe that lower competition in the agency market ϕ raises τ, which may make the low outsourcing-high education case less likely.

Summary So far I have demonstrated that there are potentially two distinct types of equilibrium given access to labor agencies connecting the backward sector to the advanced one. One has lower extensive margin of labor outsourcing (i.e., for tasks $\gamma < \gamma^{**}$), and the wage inequality between educated and uneducated workers is lower, and there are higher incentives to invest in education (at least in partial equilibrium). The other type of equilibrium features higher extensive margin of labor outsourcing (i.e., for tasks $\gamma < \overline{\gamma}$), and higher wage inequality between educated and uneducated workers. In partial equilibrium there are lower incentives to invest in education. These are consistent with the empirical evidence that we have presented before, where higher number of LDAs is associated with higher wage inequality and lower incentives for educational investment. Furthermore there are efficiency loss in this high outsourcing case due to the coordination problem in sectoral transition and under-investment in education. Lastly, what is common to these two types of equilibrium is that uneducated workers will earn the same wage $w(0) = \underline{A}$ in both sectors.

5 Concluding Remarks

This paper studies the expansion of labor agencies in a developing country setting, where the extent of outsourcing interacts with human capital accumulation. Empirical evidence suggests that agencies reallocate workers across regions, leading to productivity and efficiency gains. But a better allocation of labor does not translate into welfare gains: instead, the expansion of LDA networks leads to loss in hourly wage and increase in wage inequality. Furthermore, I find that the prevailing presence of LDAs disincentivizes educational investment among the young. The theoretical framework characterize two types of equilibrium in a dual economy: extensive outsourcing is associated with higher wage inequality and diminished educational investment, and crucially affects the future path of development for the economy in transition, which is consistent with the empirical findings.

In the ongoing work of this project, I am collecting more precise information on LDA entry and exit, categorization, etc., which allows me to probe deeper into the effects of the 2013 amendment, as well as the nature of competition among LDA networks. More importantly, I will introduce the dynamics of human capital accumulation into the framework I have put forward before, and provide quantitative evidence to highlight the tradeoff between efficiency gains from spatial reallocation of labor, and the dynamic (welfare) loss of under-investment in human capital.

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TABLE 1: COMPOSITION OF DISPATCHED WORKERS VERSUS DIRECT HIRES

	Direct Hires	Dispatched Workers
Male	55.9%	57.8%
Female	44.1%	42.2%
Observations	7649	173
College	21.3%	13.2%
Below College	78.7%	86.7%
Observations	7649	173
Migrant	18.1%	19.8%
Non-migrant	81.9%	80.2%
Observations	7637	172
Urban	64.1%	65.7%
Rural	35.9%	34.3%
Observations	7631	172

Notes: This table shows the composition of dispatched workers versus direct hires by gender, college degree, migration status, as well as urban Hukou, using China Labor Dynamics Survey (CLDS) 2012, 2014 and 2016. The survey respondent is classified as a migrant if the place he or she get interviewed is different from the place of his Hukou registration, and has stayed for more than three months.

TABLE 2: AGGREGATE EFFECTS OF LDA EXPANSION 2000 - 2018

	(1) Manufacturing Employment	(2) Industry Total Employment	(3) Industry GDP
LDA	0.0250	-0.00158	-0.0428
	(0.0379)	(0.0316)	(0.0298)
Developed×LDA	0.00657	0.0137	0.104**
	(0.0513)	(0.0443)	(0.0521)
Fixed Effects			
City	Yes	Yes	Yes
Year	Yes	Yes	Yes
City×Year	Yes	Yes	Yes
Observations	5070	4410	3848

Notes: This table reports the OLS estimates of the aggregate effects of LDA expansion on total employment by the industrial sector and industrial sector GDP. The results are obtained based on Chinese city statistical yearbook. All dependent variables as well as LDA are in logarithm. LDA is the total number of LDA in each city. $Developed_r = 1$ if city r has above median non-agricultural share of local GDP. Standard errors reported in parentheses are clustered at city level: $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

TABLE 3: LDA NETWORK AND WORKER MOBILITY ACROSS REGIONS: 2005 - 2015

	(1) Total Flow	(2) Total Flow for Work Reasons	(3) Total Flow for Related Industries
Connections	0.104***	0.167***	0.0840***
	(0.0218)	(0.0240)	(0.0229)
Fixed Effects			
City-City Pair	Yes	Yes	Yes
Year	Yes	Yes	Yes
Observations	31811	31811	31811

Notes: This table reports the OLS estimates of the effect of expansion of LDA network on worker mobility across regions. The results are obtained based on the 1% sample of population census for 2005, 2010 and 2015. All dependent variables as well as LDA connections are in logarithm. Total flow between city r and city m (where $r \neq m$) is calculated as the total headcount for which the respondents reported to have lived in city r (for more than one year) but their hukou registration is in city m, or have lived in city m but their hukou registration is in city r. Total flow for work reasons is measured by such total flow for which the respondents has classified as due to work reasons. Total flow for related industries is measured by such flow of workers working in business service sector or industrial sector. LDA connections are calculated by the total number of LDA groups that have active LDA branches in the two cities. Standard errors reported in parentheses are clustered at city pair level: *$p < 0.10$, **$p < 0.05$, ***$p < 0.01$.

TABLE 4: LDA AND $M\hat{R}PL$ DISPERSION: 2007 - 2016

	(1) σ^2_{sr}	(2) σ^2_{sr}	(3) $\tilde{\Delta}^2_{sr}$
LDA	-0.0339		
	(0.0400)		
Local LDA		-0.0241	
		(0.0390)	
Inter-city LDA			-0.0157
			(0.0148)
Fixed Effects			
City	Yes	Yes	Yes
Industry	Yes	Yes	Yes
Year	Yes	Yes	Yes
City × Year	Yes	Yes	Yes
Industry × Year	Yes	Yes	Yes
Observations	16017	16017	16017

Notes: This table reports the OLS estimates of the effect of LDA expansion on both within city and across city dispersion of $M\hat{R}PL$ among manufacturing firms during 2007-2016. The results are obtained based on the administrative dataset of tax survey of firms. σ^2_{rs} is measured as the within city variance of $M\hat{R}PL$ and $\tilde{\Delta}^2_{rs}$ is the square of deviation of $M\hat{R}PL$ city mean from the national mean. LDA is the total number of LDA in each city, Local LDA is the total number of LDAs in each city that do not have branches in other cities, and Inter-city LDA is the total number of LDAs in each city that have branches in other cities. LDA_r, Local LDA$_r$ and Inter-city LDA$_r$ are in logarithm. Standard errors reported in parentheses are clustered at city level: *$p < 0.10$, **$p < 0.05$, ***$p < 0.01$.

TABLE 5: LDA AND ACROSS CITY $M\hat{R}PL$ DISPERSION: 2007 - 2016

	(1) Δ^2_{srm}	(2) Δ^2_{srm}	(3) Δ^2_{srm}	(4) Δ^2_{srm}
Connected	-0.00908***			
	(0.00162)			
Connections		-0.00945***		
		(0.00180)		
Linked			-0.00679***	
			(0.00231)	
Direct linkages				-0.00571***
				(0.00174)
Fixed Effects				
City-City Pair	Yes	Yes	Yes	Yes
Industry	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes
Observations	667214	667214	667214	667214

Notes: This table reports the OLS estimates of the effect of the expansion of LDA network on across city dispersion of $M\hat{R}PL$ among manufacturing firms during 2007-2016. The results are obtained based on the administrative dataset of tax survey of firms. Δ^2_{rms} is the squared difference of mean $M\hat{R}PL$ of industry s between city r and city m. Connected is a discrete variable which equals to 1 if there exist an LDA group that has active branches in both city r and city m. Connections is the total number of such LDA groups. Linked is a discrete variable which equals to 1 if there exist a headquarter LDA in city r (or m) that has an active branch in city m (or r). Direct linkages is the total number of such headquarter-local branch links between city r and m. Both connection and direct linkage are in logarithm. Standard errors reported in parentheses are clustered at city pair level: $^*p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

TABLE 6: LDA EXPANSION AND FACTOR MISALLOCATION AMONG MANUFACTURING FIRMS: 2010 - 2016

	$M\hat{R}PL$	Labor	Capital	$T\hat{F}PR$
LDA	0.181**	-0.195**	-0.0736	0.142**
	(0.0813)	(0.0956)	(0.0571)	(0.0664)
High $M\hat{R}PL\times$LDA	-0.366***	0.234***	0.0684***	-0.318***
	(0.0165)	(0.0117)	(0.0120)	(0.0153)
Fixed Effects				
Firm	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes
City$\times$Year	Yes	Yes	Yes	Yes
Industry (2-digit)$\times$Year	Yes	Yes	Yes	Yes
Observations	516913	563888	563888	515053

Notes: This table reports the 2SLS estimates of the heterogenous effect of LDA expansion on factor allocation among manufacturing firms during 2011-2016, depending on firms' ex ante MRPL. The 2SLS estimates are obtained through using $ShockExposure_c \times Post_t$ to to instrument the number of LDA for each city. $High\hat{MRPL}_i = 1$ if and only if firm i has ex ante above median $M\hat{R}PL$ among all firms within the same (2-digit) industry. All dependent variables as well as LDA are in logarithm. Labor is measured by total annual labor payment of each firm, capital is measured by the net value of fixed assets used in production process. Standard errors reported in parentheses are clustered at city level: $^*p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

TABLE 7: THE EFFECTS OF LDA EXPANSION ON WAGES AND HOURS WORKED: 2012 - 2016

	Hourly Wages		Annual Wages		Monthly Hours Worked	
	College	Below College	College	Below College	College	Below College
	(1)	(2)	(3)	(4)	(5)	(6)
LDA	-0.151	-0.867**	0.552	-0.804***	0.633	0.229
	(0.877)	(0.360)	(0.484)	(0.283)	(0.859)	(0.294)
Fixed Effects						
Individual	Yes	Yes	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes	Yes	Yes
Industry × Year	Yes	Yes	Yes	Yes	Yes	Yes
City × Year	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1176	4479	1187	4576	1176	4479

Notes: This table reports the OLS estimates of the heterogenous effect of LDA expansion on worker wages, hours worked per month, as well as wage per hour, depending on whether the survey respondent has college or above degree. The results are obtained based on CLDS 2012, 2014 and 2016. All dependent variables as well as LDA are in logarithm. Standard errors reported in parentheses are clustered at city level: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

TABLE 8: LDA EXPANSION AND WAGE INEQUALITY

	(1)	(2)
	Wage Ratio	Wage Ratio
LDA	2.798**	4.790*
	(1.102)	(2.780)
Fixed Effects		
City	Yes	Yes
Year	Yes	Yes
City × Year	Yes	Yes
Industry	No	Yes
Industry × Year	No	Yes
Observations	299	1296

Notes: This table reports the OLS estimates of the effect of LDA expansion on the wage ratio between college graduates and workers without college degree. The results are obtained based on the CLDS dataset. Wage ratio in city r in column 1 is defined as the ratio of average wage of workers with college degree over the average wage of workers without college degree. Wage ratio in column 2 is the industry specific wage gap. LDA is the number of LDAs in logarithm. Standard errors reported in parentheses are clustered at city level: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

TABLE 9: LDA EXPANSION AND EDUCATION INVESTMENT AGED AMONG 18 - 24

	(1) College Share	(2) Workforce Participation
LDA	-0.0607*	0.0196
	(0.0360)	(0.0325)
Fixed Effects		
City	Yes	Yes
Year	Yes	Yes
City × Year	Yes	Yes
Observations	943	942

Notes: This table reports the OLS estimates of the effect of LDA expansion on education investment among the 18-24 age group. The results are obtained based on the 1% sample of population census for 2005, 2010 and 2015. College share for each city is the proportion of respondents aged 18-24 who reported being enrolled in college or having obtained a college degree or higher. Workforce participation for each city is the share of respondents aged 18-24 who reported working. LDA is the number of LDAs in logarithm. Standard errors reported in parentheses are clustered at city pair level: $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}< 0.01$.

TABLE 10: LABOR CONTRACT LAW AMENDMENT AND EXPANSION OF LDA: 2010 - 2016

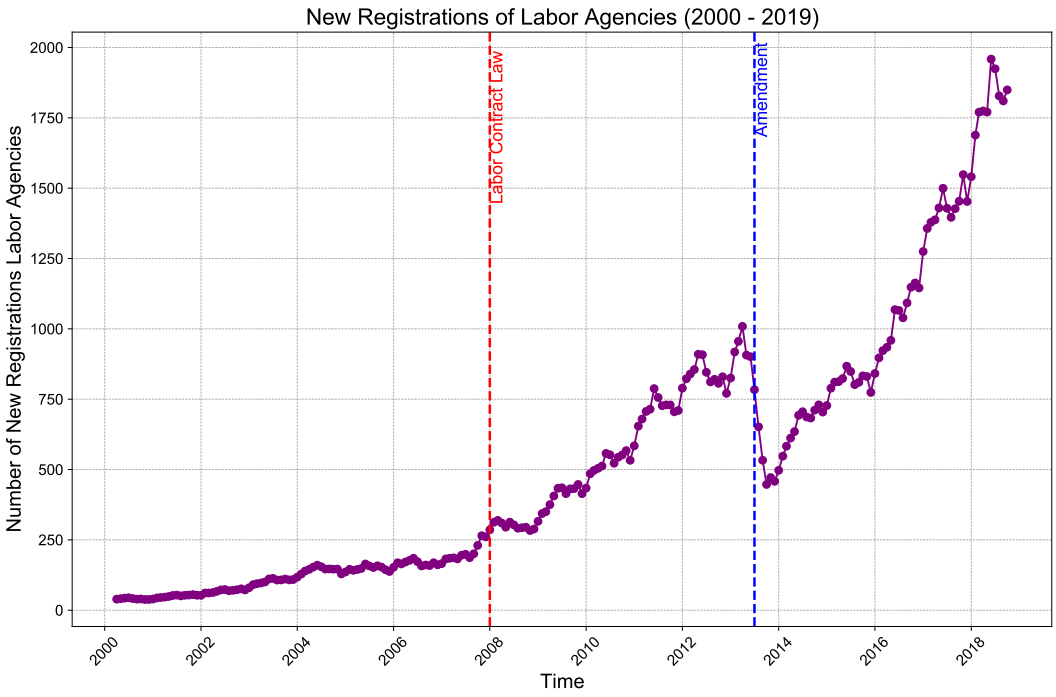
	(1) LDA	(2) LDA per 10k residents	(3) LDA per km^2	(4) Herfindahl Index
Shock Exposure × Post	-0.360***	-0.520***	-1.063**	-0.0318
	(0.101)	(0.0938)	(0.535)	(0.0320)
Fixed Effects				
City	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes
City × Year	Yes	Yes	Yes	Yes
Observations	2127	2012	2013	2127
F statistics	12.60	30.68	3.954	0.988

Notes: This table reports the OLS estimates of the effect of 2013 Labor Contract Law amendment on the expansion of LDA during 2010 - 2016. All dependent variables except the Herfindahl Index are in logarithm. $ShockExposure_c$ is the share of LDA with registered capital below 2 million RMB for each city in 2012. $Post_t = 1$ if and only if time period t is after 2013 Labor Contract Law amendment. Column 1 reports the number of LDAs for each city, whereas Column 2 and 3 present such number respectively weighted by population and area. Herfindahl Index is calculated using the registered capital of active LDAs for each city. Standard errors reported in parentheses are clustered at city level: $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}< 0.01$.

TABLE 11: DETERMINANTS OF SHOCK EXPOSURE OF LABOR CONTRACT LAW AMENDMENT

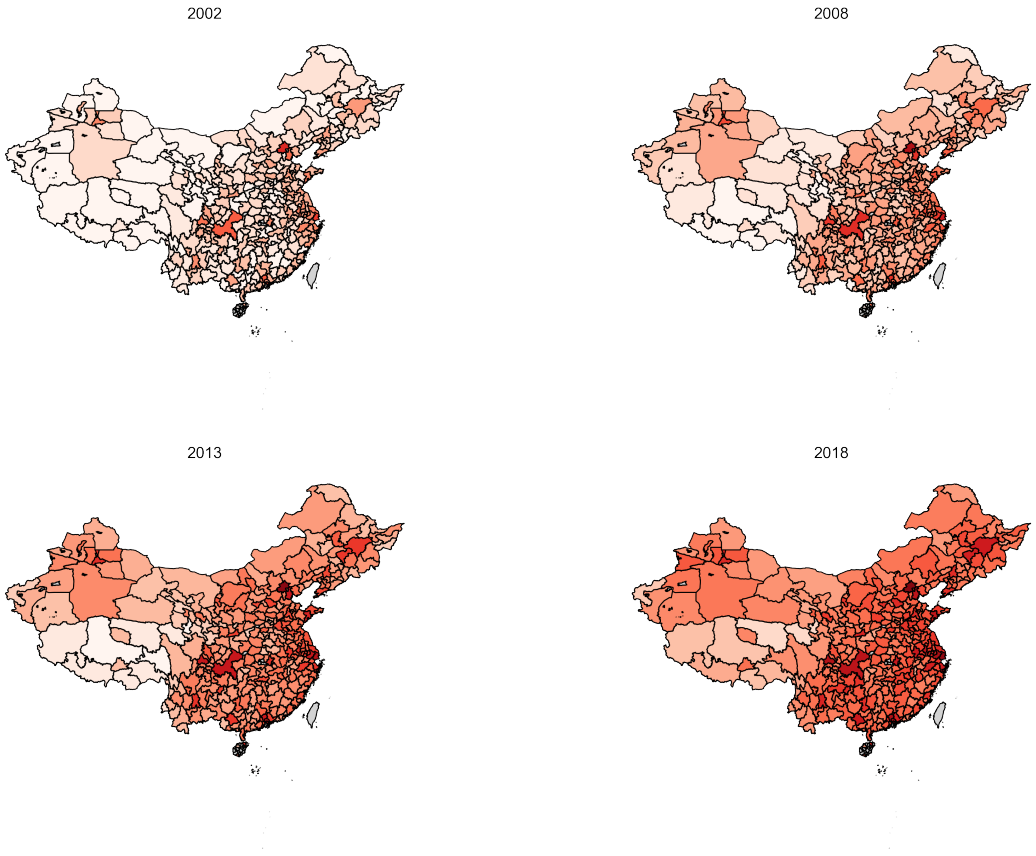
	Shock Exposure								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
GDP	0.00664								-0.00613
	(0.00858)								(0.0263)
Population		0.0226**							-0.0101
		(0.00875)							(0.0225)
Total Area			0.0148						0.0169*
			(0.00902)						(0.0102)
Total Loans				0.00545					-0.0327
				(0.00667)					(0.0236)
Freight Volume via Highway					0.00805				0.00588
					(0.00838)				(0.0118)
Total Employment						0.0172*			0.0416
						(0.00912)			(0.0258)
Number of Universities							0.000259		-0.000545
							(0.00877)		(0.0132)
Number of Vocational Schools							0.0157		0.0124
							(0.0118)		(0.0188)
Commercial Credit Index								0.00253	0.00481
								(0.00226)	(0.00369)
Observations	286	288	288	287	287	287	284	280	276
F Statistics	0.598	6.649	2.675	0.668	0.923	3.536	1.512	1.257	1.126

Notes: This table presents OLS estimates of the relationship between city characteristics in 2012 and shock exposure, which is defined as the share of LDI with registered capital below 2 million RMB for each city in 2012. All the city characteristics (except for Commercial Credit Index) variables are in logarithm. Standard errors reported in parentheses are clustered at city level: $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.



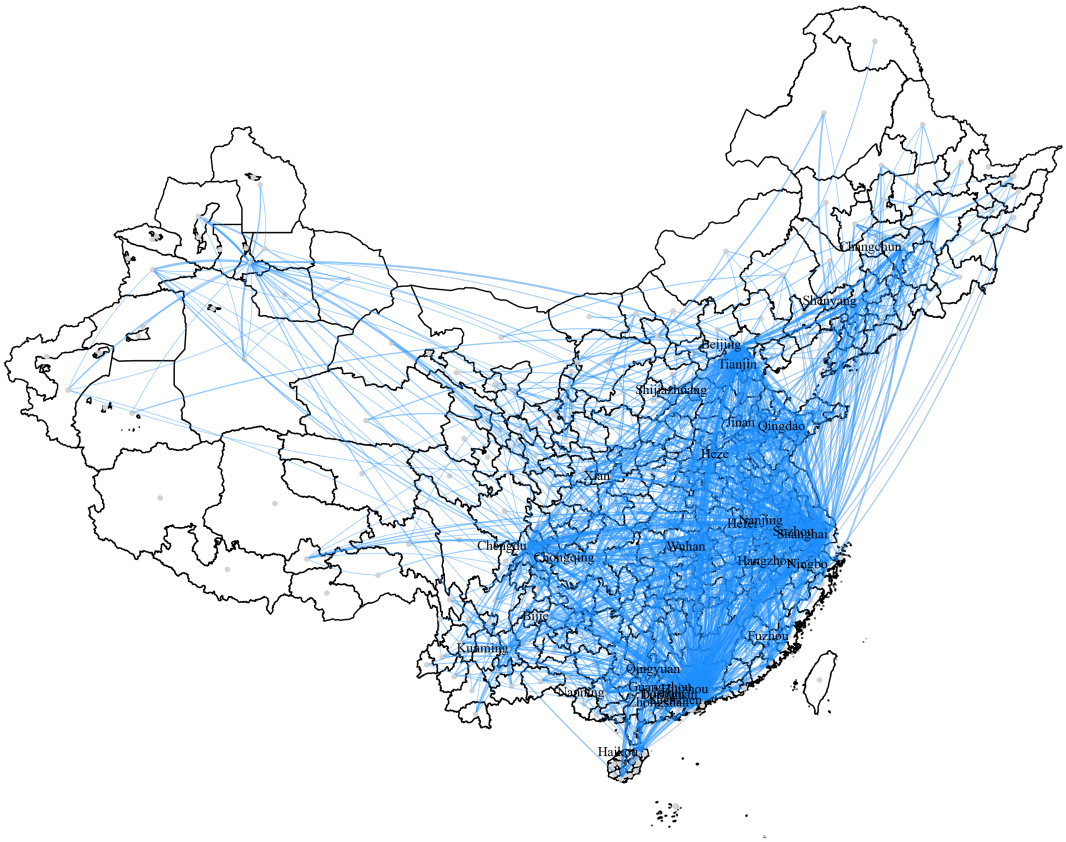
Notes: This figure shows the monthly time series of LDA registrations in China over 2000-2019 (after taking six month moving averages). The red dashed line captures the timing of the introduction of Labor Contract Law in January 2008, and the blue dashed line captures the Amendment to Labor Contract Law in July 2013.

FIGURE 4: LDA REGISTRATIONS: 2000 - 2019



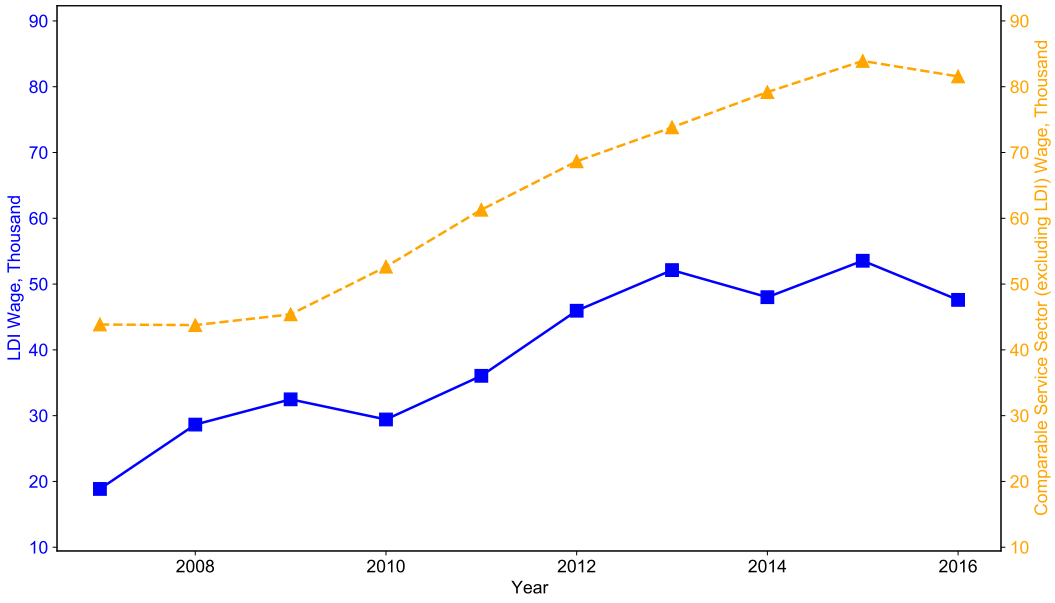
Notes: This figure shows the spatial expansion of LDAs in China over 2002 - 2018, where darker color implies higher number of LDAs.

FIGURE 5: SPATIAL EXPANSION OF LDAS: 2002 - 2018



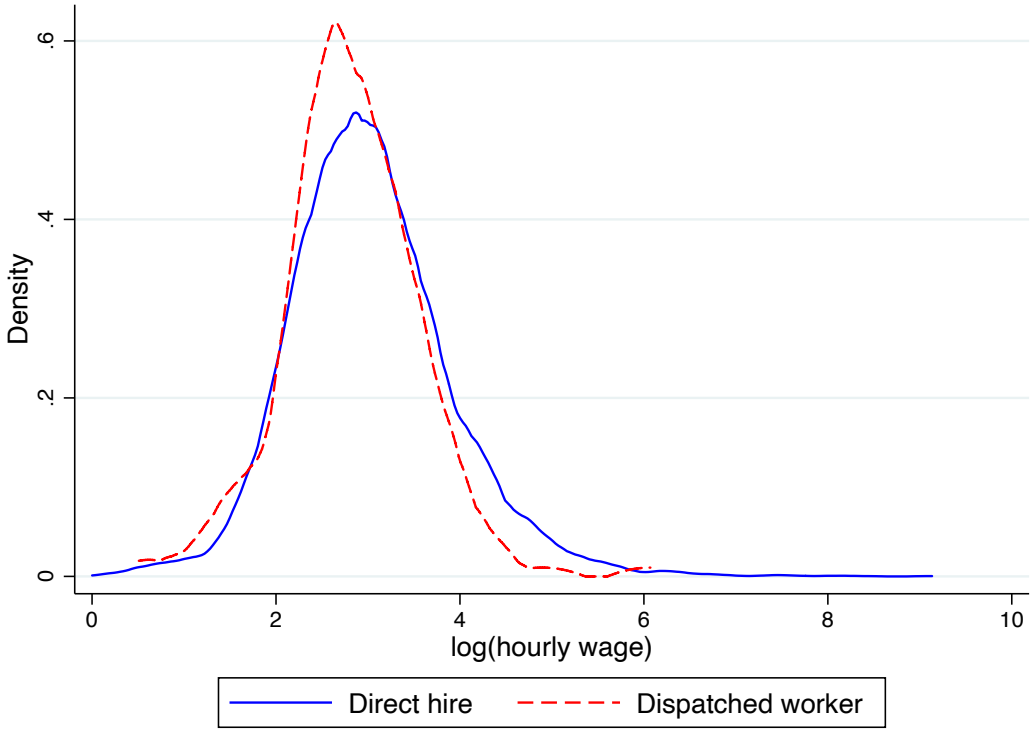
Notes: This figure shows the spatial network of LDAs (defined by ownership structure of headquarters and local branches) aggregated at the city level.

FIGURE 6: SPATIAL NETWORK OF LDAS



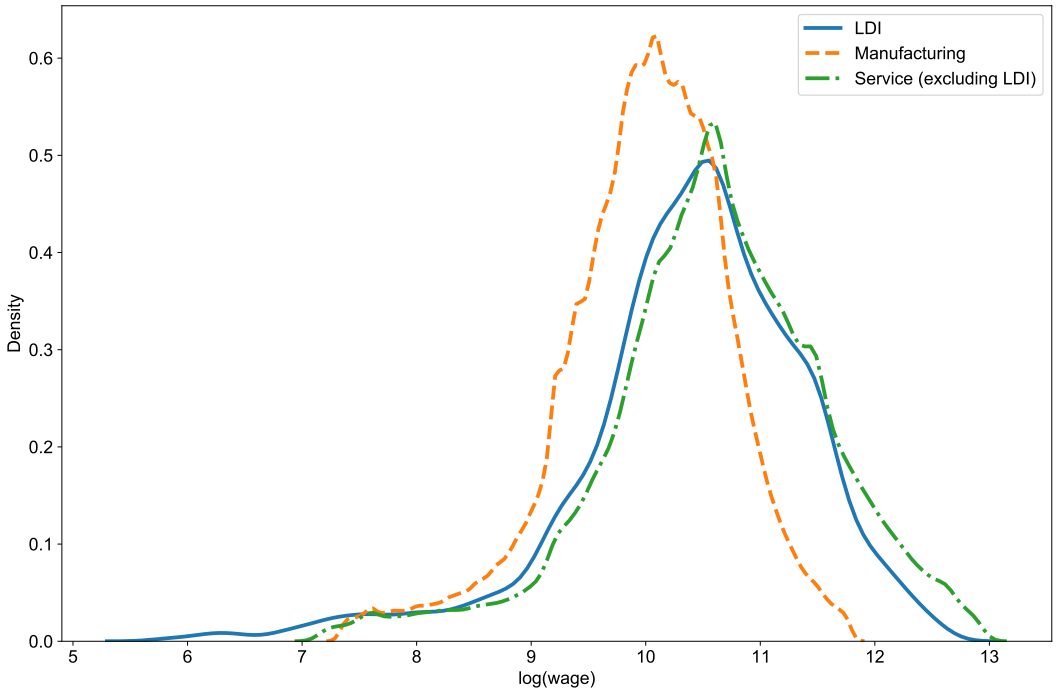
Notes: This figure shows the average annual wage rate (total labor income by total population) of the LDAs in the tax survey dataset (the left axis). The right axis shows the average wage rate of other business service companies registered in the same sectors as LDAs.

FIGURE 7: AVERAGE WAGE 2007-2016: LDAS VERSUS COMPARABLE SERVICE SECTORS



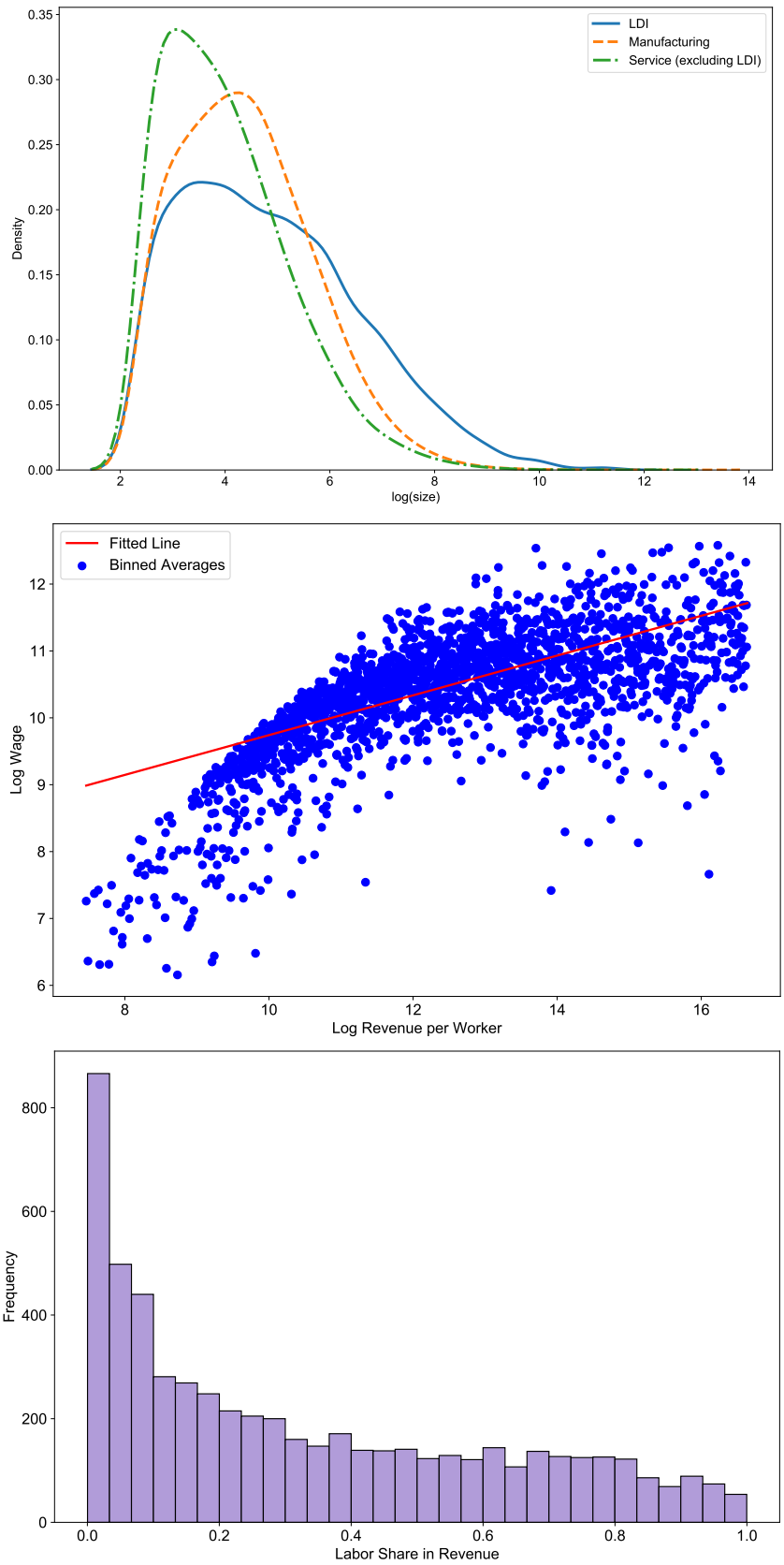
Notes: This figure shows the wage distribution of self reported dispatched workers (blue) as opposed to workers who reported to be directly hired by firms (red).

FIGURE 8: AVERAGE WAGE 2007-2016: LDIS VERSUS COMPARABLE SERVICE SECTORS



Notes: This figure shows the density plot of average annual wage rate (total labor income by total population) of the LDAs in the tax survey dataset (the blue curve). This is contrasted with the distribution of average wage of manufacturing firms (the yellow dashed line), as well as the average wage distribution of business service companies comparable service sectors (excluding LDAs). The annual wage is in logarithm.

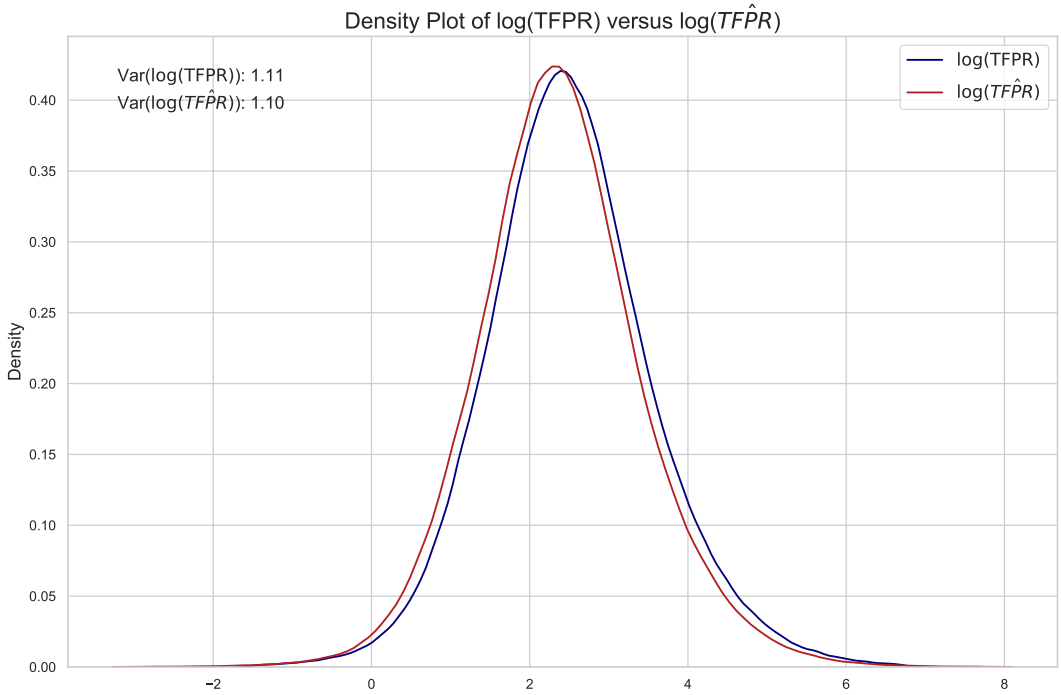
FIGURE 9: DISTRIBUTION OF AVERAGE WAGE AMONG LDAS



Notes: The top panel shows the size distribution of LDAs contrasted with manufacturing firms and business service firms (excluding LDAs). The middle panel shows the binned scatterplot of revenue per worker against average wage among LDAs with the red fitted line, and both axises are in logarithm. The coefficient of the fitted line is 0.27. The bottom panel is the histogram of labor income share (i.e., labor payment by total revenue). LDAs from all panels are from the tax survey dataset.

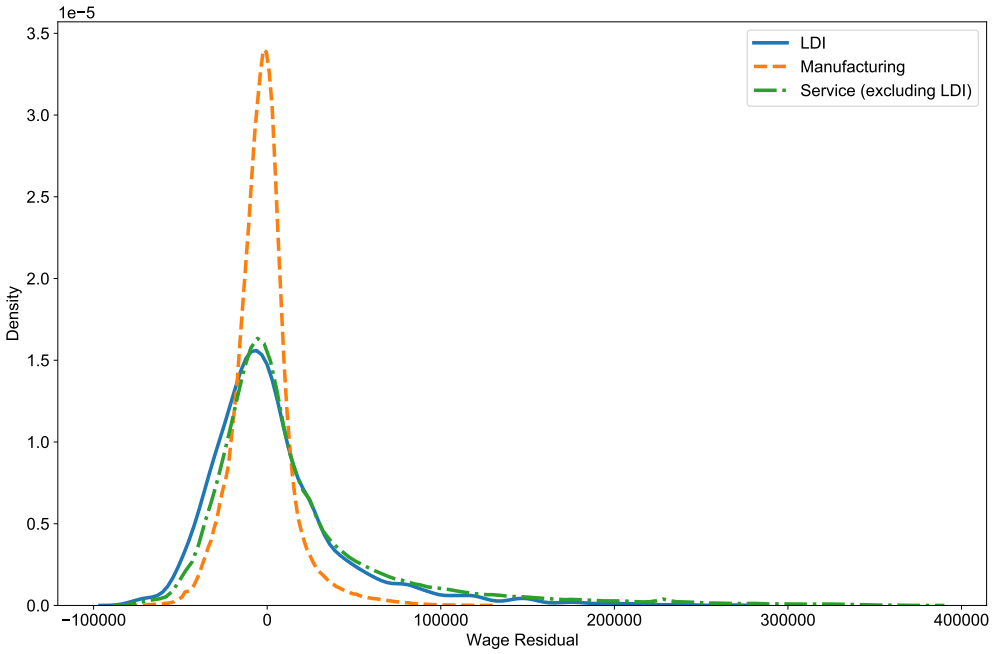
FIGURE 10: LDA SIZE DISTRIBUTION AND LABOR INCOME SHARES

FIGURE 11: DISTRIBUTION OF $\hat{TFPR}$



Notes: This figure shows the density of $\log(\hat{TFPR})$ for all manufacturing firms during 2007-2016 in my panel dataset (the red density curve). This is contrasted with the density plot of $TFPR$ (i.e. the blue dashed curve) without partially out government taxes and subsidies.

A Appendix: Additional Materials



Notes: This figure shows the density plot of residualized annual wage rate (total labor income by total population) of the LDAs in the tax survey dataset (the blue curve), after partially out city and year fixed effects. This is contrasted with the distribution of residualized average wage of manufacturing firms (the yellow dashed line), as well as the residualized average wage distribution of business service companies comparable service sectors (excluding LDAs). The residualized average annual wage is in logarithm.

FIGURE 12: DISTRIBUTION OF AVERAGE WAGE AMONG LDAS

TABLE 12: LDA NETWORK AND WORKER MOBILITY ACROSS REGIONS: 2005 - 2015

	(1) Total Flow	(2) Total Flow for Work Reasons	(3) Total Flow for Related Industries
Direct Linkages	0.134***	0.170***	0.109***
	(0.0223)	(0.0252)	(0.0232)
Fixed Effects			
City-City Pair	Yes	Yes	Yes
Year	Yes	Yes	Yes
Observations	31811	31811	31811

Notes: This table reports the OLS estimates of the effect of expansion of LDA network on worker mobility across regions. The results are obtained based on the 1% sample of population census for 2005, 2010 and 2015. All dependent variables as well as LDA linkages are in logarithm. Total flow between city r and city m (where $r \neq m$) is calculated as the total headcount for which the respondents reported to have lived in city r (for more than one year) but their hukou registration is in city m, or have lived in city m but their hukou registration is in city r. Total flow for work reasons is measured by such total flow for which the respondents has classified as due to work reasons. Total flow for related industries is measured by such flow of workers working in business service sector or industrial sector. Direct linkages are calculated by the total number of linkages where a headquarter LDA in city r (or m) that has an active branch in city m (or r). Standard errors reported in parentheses are clustered at city pair level: *$p < 0.10$, **$p < 0.05$, ***$p < 0.01$.

B Appendix: Derivations of Misallocation Measures

I adopt the same notations as Hsieh and Klenow (2009) but consider a simple variation of the framework tailored to differentiate between taxes and non-tax wedges. The main motivation for such exercises is that interpreting the policy relevances of (reducing) misallocation requires a better knowledge of the sources of distortions, and particularly, the a prior role of the government (e.g., taxes and subsidies): how much of the distortions might have already been corrected by the government policies, and how much of these distortions arise *because of* government intervention. Our tax survey dataset allows us to directly partial out observable taxes from calculation of misallocation.

The production function for Y_{si} of firm i in industry s is Cobb-Douglas:

$$Y_{si} = A_{si} K_{si}^{\alpha_s} L_{si}^{\beta_s}, \tag{40}$$

where we allow for industry specific factor share and decreasing returns to scale $\alpha_s + \beta_s \leq 1$. Profits can be written as

$$\pi_{si} = (1 - t_{Esi}) P_{si} A_{si} K_{si}^{\alpha_s} L_{si}^{\beta_s} - (1 + t_{Csi})(1 + \tau_{Ksi}) R K_{si} - (1 + t_{Ssi})(1 + \tau_{Lsi}) w L_{si}, \tag{41}$$

where there are distortions both at the capital market and labor market τ_{Ksi} and τ_{Lsi}. In addition, the government imposes tax of t_{Esi} on firm revenue which may include excise tax and sales tax for certain products, value added tax (and the relevant exemptions), corporate income tax as studied in Chen et al. (2021), as well as government subsidies. t_{Ssi} captures the social security payments firms need to make for the labor they hire, and t_{Csi} is the taxes on land value, vehicles, as well as property transactions. Note that we can directly observe t_{Esi}, t_{Csi} and t_{Ssi} from the

tax survey data.

From profit maximization, we can obtain the marginal revenue product of capital (after partialing out taxes):

$$M\hat{R}PK_{si} = \alpha_s \frac{\sigma - 1}{\sigma} \frac{P_{si}Y_{si}}{RK_{si}} \frac{1 - t_{Esi}}{1 + t_{Csi}} = (1 + \tau_{Ksi}), \tag{42}$$

whereas the marginal revenue product of labor (after partialing out taxes) is

$$M\hat{R}PL_{si} = \beta_s \frac{\sigma - 1}{\sigma} \frac{P_{si}Y_{si}}{wL_{si}} \frac{1 - t_{Esi}}{1 + t_{Ssi}} = (1 + \tau_{Lsi}). \tag{43}$$

This is how we infer capital and labor market distortions.

We can now define the (after-tax) revenue productivity of firm si as

$$\hat{TFPR}_{si} = \frac{1 - t_{Esi}}{(1 + t_{Csi})^{\alpha_s}(1 + t_{Ssi})^{\beta_s}} P_{si}A_{si} = \frac{\sigma}{\sigma - 1} \left(\frac{(1 + \tau_{Ksi})R}{\alpha_s} \right)^{\alpha_s} \left(\frac{(1 + \tau_{Lsi})w}{\beta_s} \right)^{\beta_s} \tag{44}$$

The physical productivity of firm si can be written as

$$TFPQ_{si} = A_{si} = \frac{Y_{si}}{K_{si}^{\alpha_s} L_{si}^{1-\alpha_s}} = \frac{(P_{si}Y_{si})^{\frac{\sigma}{\sigma-1}}}{K_{si}^{\alpha_s} L_{si}^{1-\alpha_s}} \frac{1}{\left(P_s Y_s^{\frac{1}{\sigma}} \right)^{\frac{\sigma}{\sigma-1}}} \tag{45}$$