DOCUMENT DE TRAVAIL N° 603

THE IMPACT OF CHINESE IMPORT COMPETITION ON THE LOCAL STRUCTURE OF EMPLOYMENT AND WAGES: EVIDENCE FROM FRANCE

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September 2016

BANQUE DE FRANCE
EUROSYSTÈME

DIRECTION GÉNÉRALE DES ÉTUDES ET DES RELATIONS INTERNATIONALES

The Impact of Chinese Import Competition on the Local Structure of Employment and Wages: Evidence from France

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Résumé

La forte croissance des exportations chinoises au cours des deux derniÃ¨res décennies a suscité un vif débat quant à son impact sur l'emploi dans le manufacturier et sur les inégalités salariales. Cet article étudie l'effet de la concurrence des importations chinoises sur la structure des salaires et de l'emploi local en France. Il porte une attention particulière aux effets de débordements au-delà du secteur manufacturier et aux inégalités des salaires. L'emploi local est négativement affecté au sein du secteur manufacturier et au-delà. Les coefficients estimés supposent que chaque emploi détruit dans le secteur manufacturier induit la destruction d'environ 1,5 emplois supplémentaires au niveau local. Ces effets de "multiplicateur local" sont cependant beaucoup plus modestes lorsqu'ils sont exprimés en termes d'heures travaillées ou de revenu du travail. La concurrence chinoise est associée à une polarisation de la structure des emplois dans le secteur manufacturier. La distribution des salaires est négativement affectée de manière uniforme dans le secteur manufacturier alors qu'en dehors de ce secteur l'effet négatif est concentré sur le milieu de la distribution. Si en moyenne les inégalités salariales (mesurées par la ratio du 85ème percentile sur le 15ème percentile) ne sont pas affectées, elles ont augmenté en réaction au choc induit par les importations chinoises dans les zones où le salaire minimum n'est que faiblement contraignant.

JEL-Classification: F16, J23, J31, R11, R23
Mots clés: compétition internationale, bassins d'emploi, distribution des salaires, inégalités salariales

Abstract

The rapid rise of Chinese exports over the past two decades has raised concerns about manufacturing jobs and wage inequality in high-income countries. Spill-overs beyond the manufacturing sector are an important issue given the large size of the non-traded sector in modern economies as well as the imperfect spatial mobility of households. In this paper, I estimate the impact of Chinese import competition onto the structure of employment and wages of local labor markets in France, with an emphasis on spill-overs effects beyond manufacturing and the degree of local wage inequality. Local employment and total labor income in both manufacturing and non-manufacturing are negatively affected by rising exposure to imports. The estimates imply that each local manufacturing job destroyed by Chinese import competition results in the loss of about 1.5 local job outside of manufacturing. These substantial "local multiplier effects" are however much lower when expressed in terms of hours worked or earnings rather than job count. Import competition from China polarized the local structure of employment in the manufacturing sector. The wage distribution is uniformly negatively affected in manufacturing while the non-traded sector experiences wage polarization, i.e. a rise in upper-tail inequality and a decline in bottom-tail inequality. While overall wage inequality is on average not affected, I show that it increased in response to trade shocks in areas where the minimum wage is only weakly binding.

JEL-Classification: F16, J23, J31, R11, R23
Key words: wage distribution, import competition local labor markets, international trade

Non technical summary

The integration of large emerging economies to the world trading system has started to change the conventional wisdom of economists regarding the effect of trade with low-cost countries on manufacturing employment and labor market inequality in developed economies. Among low-wage countries, China stands out as the key player. In one decade (1998 to 2008), China's share of world exports went from 3.3 to 9.5 percent, growing at 15 percent annually in value. Such a sudden rise in import competition might shrink the manufacturing sector. In turn, decline in manufacturing activity, whether or not triggered by trade shocks, is likely to be associated with a host of local spill-over effects onto local labor markets. Given the large size of the non-traded sector in high-income economies, the question of the transmission of trade shocks outside of manufacturing is of outmost importance for the study of the labor market, especially in its spatial dimension.

In this paper, I study the adjustment of local labor markets in France to the massive increase in Chinese import competition. This paper examines how the tremendous increase in Chinese import penetration has affected the local structure of employment and wages, within manufacturing and beyond, in France over the period from 1995 to 2007. It contributes to the literature on the impact of trade shocks on local labor markets in two main ways.

First, I estimate the impact of Chinese trade on different measures of labor market inequality across local labor markets, based on the approach pioneered by Autor et al. (2013). This methodology interacts initial local industrial employment shares with contemporaneous trends in national Chinese import penetration. The resulting variable is an index capturing the exposure of employment areas to the rise of China's manufacturing capacity. I provide causal estimates on the local distributional effects of increased Chinese import competition by estimating wage effects along the hourly wage distribution (whereas existing work focuses on average weekly wage effects). Therefore, I assess whether low-wage jobs are disproportionately more affected than high-wage jobs by China-induced trade shocks and whether local income inequality rises as a consequence of Chinese import competition. It also investigates the possibly job-polarizing (e.g. Goos and Manning, 2007) or skill-biased nature of the employment effect of rising Chinese import competition. The local labor market approach has the crucial advantage of allowing looking at both within and outside manufacturing labor market outcomes.

Second, the paper emphasizes how Chinese import competition spills over outside of manufacturing. In addition, it mobilizes a rich administrative dataset (called "DADS postes") to look at a wider array of labor markets outcomes by sector and occupations - employment but also hours worked, total labor earnings and hourly wage.

I find strong effects of direct competition on the manufacturing sector. A $1000 increase in import exposure per worker causes the manufacturing employment growth to decrease by 6.2 percentage points. Spill-overs onto the non-traded sector are substantial as well. A $1000 increase in the import exposure index is associated with a decline by 3.6 percentage points of local employment growth rate over six years. Considering that the estimated coefficients capture absolute changes and not simply deviations from the aggregate trend, the estimates suggest that, over the period 2001-2007, Chinese imports have led to the destruction of 90,000 and 180,000 jobs in the manufacturing and non-traded sector respectively. These figures imply that about 13 percent of the decline in manufacturing employment can be explained by the rise in Chinese import competition. This figure is smaller than one obtained for the US (Autor et al. 2013) but larger than the values found in most European countries (for example, in Germany (Dauth et al. 2015), or Norway (Balsvik et al. 2015)). An explanation in the German case could be that Germany

has a lower trade deficit with respect to China and also a lower overlap regarding the sectoral composition of its manufacturing sector.

By studying spillovers from the manufacturing sector onto the rest of the local economy, this paper relates to recent works which estimate the elasticity of non-traded to traded employment, also referred to as the "local multiplier effect" of manufacturing jobs (Moretti, 2010). Using China-induced trade shocks as an arguably exogenous source of variation in manufacturing employment, I find this elasticity to be about 0.6 which implies a job-to-job effect of about 1.5. While the estimated local multipliers might seem large, although they are broadly in line with the US literature on the topic (e.g. Dijk, 2014), it is more modest when expressed in terms of hours worked - an arguably more informative statistic than job count regarding the state of the local labor market: the elasticity is 0.29 in terms of hour worked and around 0.26 in terms of overall labor earnings. This finding suggests that empirical work on the magnitude of local multiplier effects should take into account systematic differences in job characteristics across broad sectors of the economy.

Regarding the composition of jobs, I find that in both sectors, job destructions are concentrated in the low and middle skill occupations. The strongest effect occurs in middling jobs in manufacturing, with a clear polarizing effect of import competition on the occupational structure. In contrast, in the non-traded sector, the magnitude of the impact declines monotonically as one considers increasingly skill-intensive occupations.

The final part of the paper investigates how China-induced trade shocks affected the wage distribution in France - looking beyond the average wage. I find dissimilar effects across sectors. Wages are uniformly reduced in the manufacturing sector - which contrasts with findings in the literature based on US (Autor et al., 2013) or German data (Dauth et al., 2014) which find no evidence of wage effect in the manufacturing sector. Accordingly, there is no increase in wage inequality within manufacturing, which is at odds with what one would have predicted based on the polarizing occupational impact of trade shocks. In contrast, in the non-tradable sector, hourly wages are affected only in middle of the distribution. China-induced trade shocks therefore trigger a process of wage polarization within the non-traded sector. The wage polarizing effect of rising Chinese import competition can be rationalized by the strongly binding minimum wage legislation. Using variation in the degree to which the minimum wage binds at the local level and I show that import competition caused an increase in overall inequality in places where the minimum wage is weakly binding.

Holding within-occupation wage distribution constant, job polarization mechanically implies a rise in wage dispersion. The employment shares of middling occupations have been declining in France, but countervailing trends have mitigated the mechanical impact of job polarization on wage inequality, notably a reduction in within occupation wage dispersion as well as a reduction in dispersion of average wages across occupations. While beyond the scope of this paper, understanding the coexistence of a polarizing effect of import competition on the structure of employment and the absence of such effect on the structure of wages in manufacturing appears an interesting venue for future research.

This paper documents substantial employment and earnings impacts on the French labor market of the recent rise of China as a manufacturing power-house. The employment effects are stronger in the manufacturing sector but spillover onto the rest of the local economies, without triggering adjustment in population. The employment effects are unequal across occupations and contributed to polarize the occupational structure within manufacturing. While no average effect on wage dispersion is found, overall wage inequality did rise as a result of trade shocks in areas with only weakly binding minimum wage.

1 Introduction

Rising import competition from low-wage countries and its impact on employment in the manufacturing sector has been a very widely debated issue across the industrialized world. Among low-wage countries, China stands out as the key player. In one decade (1998 to 2008), China's share of world exports went from 3.3 to 9.5 percent, growing at 15 percent annually in value.[1] Figure 1 displays imports and trade balance of France with respect to China and another set of low-wage countries (LWC). China trade's specificity with respect to France, and many high-income countries, stems from the high growth rate of its exports as well as the strong French trade deficit in comparison with other LWCs. Such a sudden rise in import competition might shrink the manufacturing sector. In turn, decline in manufacturing activity, whether or not triggered by trade shocks, is likely to be associated with a host of local spill-over effects onto local labor markets. Given the large size of the non-traded sector in high-income economies, the question of the transmission of trade shocks outside of manufacturing is of outmost importance for the study of the labor market, especially in its spatial dimension.

In this paper, I study the adjustment of local labor markets in France to the massive increase in Chinese import competition. This paper contributes to the literature on the impact of trade shocks on local labor markets in two main ways. First, it applies the methodology developed by Autor *et al.* (2013) with an emphasis on spill-overs outside of manufacturing caused by Chinese imports competition. The rich administrative dataset used allows to look at a wider array of labor markets outcomes by sector and skill-category – employment but also hours worked, total labor earnings. Second, it provide estimates of the impact of Chinese import competition along the local hourly wage distribution inside and outside of the manufacturing sector. It can therefore assess whether low-wage jobs were disproportionately more affected than high-wage jobs and whether local income inequality rose as a consequences of Chinese import competition. Moreover it investigates whether the structure of occupations (classified based on their initial average or median wage rank) was affected by trade shocks. This sheds light on an important aspect of globalization, the rise in North-South trade (deficit), on inequality and the structure of wages and

[1] This figures are based on author's own calculation based on UN Comtrade. Hanson (2012) presents a complete pictures of the role of emerging economies, particularly China, in world trade over the last three decades.

jobs in a high-income country with a highly regulated labor market such as France.[2] I find a strong effect of direct competition on the manufacturing sector. A $1000 increase in import exposure per worker causes the manufacturing employment growth to decrease by 6.2 percentage points. Spill-overs onto the non-traded sector are substantial as well. A $1000 increase in the import exposure index is associated with a decline by 3.6 percentage points of local employment growth rate over six years. Considering that the estimated coefficients capture *absolute changes* and not simply deviations from the aggregate trend, the estimates suggest that, over the period 2001-2007, Chinese imports have led to the destruction of $88,000$ and $190,000$ jobs in the manufacturing and non-traded sector respectively.[3] In both sectors, jobs destruction is concentrated in the low and middle skill occupations. The strongest effect occurs in middling jobs in manufacturing, with a clear polarizing effect of import competition on the occupational structure. In contrast, in the the non-traded sector, the magnitude of the impact declines monotonically as one considers increasingly skill-intensive occupations.

Looking at the impact along the distribution of wages, I find contrasting effects across sectors. Wages are rather uniformly negatively affected in the manufacturing sector. Accordingly, there is no increase in wage inequality within the manufacturing sector, which is somewhat at odds with what one would have predicted based on the polarizing impact of trade shocks on the occupational structure. In contrast, in the non-tradable sector, hourly wages are affected only in middle of the distribution. While no overall impact on the log ratio of the 85 to 15 percentile is found, this absence of impact reflects a decrease in lower-tail inequality (log ratio of the 50 to 15 percentile) and a rise in upper-tail inequality (log ratio of the 85 to 50 percentile). China-induced trade shocks therefore trigger a process of wage polarization within the non-traded sector. The wage polarizing effect of rising Chinese import competition can be rationalized by the strongly binding minimum wage legislation. While, in the absence of cross-sectional source of variation in local minimum wage legislation, it is difficult to explicitly test this, I use variation in the degree to which the minimum wage binds at the local level and show that import competition caused an

[2]See e.g. Avouyi-Dovi *et al.* (2013) for more information on French labor market institutions regarding collective bargaining and the minimum wage in particular. Overall, employee protection legislation (EPL) is high in France, particularly for permanent contract. The labor market is characterized by a strong duality following the promotion of temporary working contracts (see e.g.Bentolila *et al.* (2010).). The minimum wage is strongly binding with a ratio of minimum to median wage equal to 56% in 2000 and 61% in 2007, above the OECD median (source: OECD dataset on minimum relative to average wages of full-time workers).

[3]The assumptions required to formulate aggregate statements are discussed in more details in Section 4.

increase in overall inequality following in places where the minimum wage does not bind.[4]

This paper belongs to a recent but growing literature using local labor markets as unit of observations in order to analyze the impact of exposure to import competition. An earlier strand of this literature investigates the impact of changes in trade policy, mainly tariffs. Given the absence of major changes in tariffs among developed countries, this literature is mainly focused on developing countries (Goldberg and Pavcnik, 2007). Topalova (2010) analyzes the impact of India's trade liberalization during the 1990s on poverty in Indian regions. Kovak (2013) frames his analysis in a classical Ricardo-Viner model of capital specific sector and estimates the impact of trade liberalization in the early 1990s on regional (residual) wages in Brazil. My paper shares a similar empirical approach in that it uses local sectoral specialization interacted with nation-wide sectoral shocks. However I study the impact of Chinese import competition rather than changes in trade policy and allow the wage effects to vary across sectors (traded versus non-traded sector) and along the distribution. Moreover I investigate non-wage outcomes, such as employment and labor income. Also in the Brazilian context, Martincus (2010) analyzes the effect of rising trade openness on the determinants of industrial localization. The seminal contribution by Autor *et al.* (2013) investigates the impact of Chinese competition onto local labor markets in United-States. They interact initial local industrial composition with contemporaneous changes nation-wide sectoral imports to compute an index of exposure to import competition that captures the value of imports-per-worker faced by each local labor markets. In order to isolate the variation in Chinese exports to the US that is driven by supply factors in China, they use Chinese exports to other high-income countries as an instrument for actual Chinese exports to the USA. Here, I follow the same empirical strategy and carry out a more detailed analysis in terms of the local transmission of trade shocks outside of manufacturing. Moreover, given the richness of the administrative dataset used, I can look at effects on hourly rather than weekly wages, thus canceling out variation in labor earnings related to working time. More importantly, I am also able to see how such effects vary along the distribution, for each sector, rather than restricting the analysis to the impact on average wages. This paper is therefore informative not only on distributional effects of trade shocks across areas (some cities lose more than others) but also their within-areas consequences (who within a heavily exposed area is more affected).

Dauth *et al.* (2014) look at the impact of Eastern Europe and China trade on German labor

[4]In this exercise, I focus on the log ratio of the 90th to 15th percentile, in order to obtain a sufficient number of areas where the minimum wage is not binding.

markets. They do not find evidence of strong employment effect of Chinese import competition either inside or outside manufacturing. These findings must be interpreted with the specific context of German-China trade which tends to be much more balanced than the US-China trade. France falls closer to the American case in that it has run a large overall trade deficit and in particular with respect to China ($26 billion in 2007, i.e. 4.5 percent of France's overall trade, see Figure 1). Lasting trade deficits are likely to be associated with stronger labor market effects as workers and resources, in the absence of a binding balanced-trade condition, need not flow from a subset of the traded sector to another to compensate rising imports.

There has been vibrant debate regarding the impact of globalization on inequality, however the difficulty to obtain local measures of wage inequality has impeded the application of the "local labor market approach" to this issue. For instance Harrison *et al.* (2011), in their review of recent theoretical and empirical works on trade and within-country inequality, do not cite any papers looking at the impact of globalization on the distribution of wages using the empirical approach used here. Instead most papers on the topic focus on the impact of globalization on job-polarization, that is the disproportional growth of employment in occupations traditionally located at the bottom and top of the wage distribution (see e.g. Autor and Dorn (2013) and Autor *et al.* (2015)). Alternatively, they examine variation in the non-production workers' wage premium (e.g. Kandilov, 2009). The exhaustive nature of the data and information on hours worked allow to obtain reliable statistics for different quantiles of the hourly wage distribution for each employment area considered. Moreover, examining outcomes at the local labor market level (rather than industry- or firm-level analysis) offers the crucial advantage of studying the impact of trade-shocks beyond the manufacturing sector, which, in high-income economies, accounts for a limited percentage of overall employment. A motivation to resort to an analysis along the wage distribution is based on recent models of international trade which suggests that trade increases inequality in ways that is not captured by the observable skill-premium. For instance, Amiti and Davis (2012) develop a model in which an increase in foreign import competition drives wages up in input-importing and output-exporting firms and reduce wages in firms serving only the domestic market. In case the correlation between firms' share of high-skill employees and importer or exporter-status is not perfect, such an increase in inequality would not be captured by using a measure of skill-premium as dependent variable. Looking at the whole distribution of wages allows to capture such an effect while remaining agnostic about the specific mechanism

driving the change in the wage distribution.

There is a large theoretical literature linking trade and wage inequality. The classic Heckscher-Ohlin framework, considering two factors, high-skill and low-skill, posits that trade should increase the wage gap between skill and non-skill labor in the skill-intensive country. [5] More recent analysis based on less stylized models, featuring for instance labor market frictions (Davidson *et al.*, 1999), firm-heterogeneity and bargaining (Helpman *et al.*, 2010) or fair wage considerations (Egger and Kreickemeier, 2009) lead as well to the conclusion that opening to trade increases wage inequality. It must be noted that a mechanism through which trade increases income inequality in models of international trade with labor market frictions is through an increase in unemployment (e.g. Egger and Kreickemeier (2009); Helpman *et al.* (2010)). However given the nature of the data available, I focus on the price of employed factors, defined here as hourly wage, and do not consider how unemployment risk or difficultly in working full-time is affected by trade in computing the wage distribution. While this can be an important caveat when evaluating the impact on workers welfare,[6] it remains important to see to which extent the structure of wages is affected by import competition and how this spill-overs onto the service sector.

The French case is particularly interesting because unlike other industrialized countries, its wage distribution has become more compact over the past few decades (Verdugo, 2014).[7] It is therefore relevant to see whether this compression occurred despite a possibly inequalizing effect of trade or whether trade per se did not lead to a rise in wage dispersion. Results in the non-traded sector shows that trade shocks led to a decline in bottom tail inequality, a rise in upper tail inequality leaving the overall level of wage inequality stable. I show that the decrease in bottom tail inequality only occurred in places where a sizable share of jobs are covered by the minimum wage and that, on the contrary, the rise in upper tail inequality is constant across regions with different bites of the minimum wage. Overall, these results imply that import competition can lead to increase in total wage inequality but that its effect was on average muted by the bite of the minimum wage, leaving overall wage inequality stable. This exercise provides an illustration of the importance of interactions between shocks and institutions in explaining changes in the

[5] The empirical predictions of the basic HOS model has however been largely discredited by the simultaneous rises in wage inequality in both low-skill and high-skill intensive countries Harrison *et al.* (2011).

[6] For instance, the model featuring costly labor mobility between sectors by Artuc *et al.* (2010), trade liberalization can trigger a decline in the wages of import competing industries and nevertheless lead to a rise in lifetime income due to the possible reallocation of the workforce towards exports-oriented industries.

[7] Regarding the rise of wage inequality in Western Europe, see, for instance, Dustmann *et al.* (2009) for Germany and Goos and Manning (2007) for the United Kingdom.

structure of wages.

The rest of paper is structured as follow. In Section 2, I briefly present the data used in this study. Section 3 presents the empirical strategy adopted to identify and estimate the impact of rising Chinese import competition on a wide array of labor market outcomes. In Section 4, I present and discuss the main results regarding employment inside and beyond manufacturing (Subsection 4.1). This section also presents robustness checks (Subsection 4.2) as well as extensions (Subsection 4.3), notably regarding the effect of import competition on local job polarization. The results focusing on the local wage distribution are presented in Section 5. The conclusion follows.

2 Data

Data for this analysis originates from several sources. Data on employment and wage distribution are drawn from a matched employer-employee dataset, called DADS postes (Déclaration annuelle des données sociales).[8] It contains exhaustive data on non-agricultural salaried job-spells in France. I focus mostly on the competitive sector and do not include workers employed by fully public institutions. Statistics are computed at the "employment zone" level. ("Zone d'emploi" in French.) Employment zones' definition is based on a criterion of self-contained commuting which limits the acuity of issues usually associated with spatial contagion across administratively defined units. There are 348 such units according to their 1990 definition.

I document the sector to which a job is associated by using a 4-digit NACE (rev.1) code reported by the plant (establishment) where the job is located. This NACE code is itself determined based on what the main activity of the plant is (not that of the firm). Based on this information, I can distinguish between employment in manufacturing and in the non-traded sector. More importantly I can construct a very accurate index of exposure to Chinese product competition (see next section). Regarding French and China's trade, I use UN Comtrade data on from 1995 to 2007. The Harmonized System (HS) nomenclature of year 1992 is mapped into 4-digit NACE sector codes using conversion tables available on Eurostat's website RAMON. More details are provided in Appendix A. I restrict the sample to jobs occupied by workers aged between 16 and

[8] Note that this dataset is exhaustive but only follows workers for two years, unlike the Panel DADS which is a 1/24th sample but has a very long panel dimension.

64, with strictly positive earnings and hours worked.[9] I aggregate data at the non-traded versus traded level for each area-year (1995, 2001 and 2007) and take the first difference of the data and obtain a final dataset of 348 areas observed over two 6-year periods.[10]

Summary statistics are presented in Table 1. The average size (measured by non-auxiliary jobs) of an employment zone was 180,000 in 1995, with a median about half the mean, suggesting some skewness. With almost 2 million worker, the Paris employment area is a clear outlier in terms of size. All results presented below are robust to the exclusion of this area. Employment in manufacturing declined during both periods, although much more markedly between 2001 and 2007 than between 1995 and 2001. Hours worked per job are on average much higher in the manufacturing sector than in the non-traded sector (1600 versus 1290 in 1995). Hours worked might thus provide a more comparable and relevant measure than job count when comparing impact of Chinese competition across sectors. The variables ΔIPW and ΔDPW stand for changes in, respectively, imports per worker (IPW) and trade deficit per worker (DPW). The precise definition of these variables is given in section 3. For now, it is sufficient to see that the two variables are very close, owing to the fact that the rise in French-Chinese trade is mainly driven by France's rising purchases of Chinese products. Moreover, it appears that there has been an acceleration in the pace of imports/trade deficit growth between the two periods.

3 Empirical Strategy: Measurement and identification

In this section I describe the empirical strategy adopted to estimate the direct impact of Chinese import competition. To measure the local exposure to Chinese imports, I build on Autor *et al.* (2013) and compute a index of imports exposure, called "Imports-per-Worker". This index interacts initial local industrial composition of the manufacturing sector with contemporaneous nation-wide Chinese imports by sector.

Formally, the index ΔIPW is defined according to the following formula:

[9] I only retain jobs if : (a) earnings are more than 3 times the monthly minimum wage or (b) the length of employment is more than 30 days and more than 120 hours and the ratio hours to days is higher than 1.5. This definition matches the definition of the a "non-annex" job implemented by the French National Statistical Institute and that is used in most statistics about employment in France.

[10] Some data regarding private employment during the 1980s (1982 to 1990) and as well as the share of college graduates are taken from public available census data, for the waves 1982, 1990 and 1999. The Census data for 1990 and 1999 are matched to 1995 and 2001, respectively. We compute pre-trend in employment growth between 1982 and 1990 (matched with period 1995-2001) and 1990-1999 (matched with period 2001-2007).

$$\Delta IPW_{it} = \frac{1}{L_{it}} \sum_{s \in \mathbb{T}} \frac{L_{ist}}{L_{st}} \Delta M_{st} \tag{1}$$

where ΔM_{st} stands for the changes in Chinese exports to France between periods t and $t+1$ for sector s, L_{st} is equal sector s employment in France for at time t. $\mathbb{T}$ refers to the set of sectors in the economy that part of manufacturing (We use $\mathbb{N}$ to refer to the set of non-traded sectors.). L_{it} is total employment in area/period i, t while L_{ist} is employment in area i in sector s at time t.[11]

To estimate the impact of Chinese imports penetration on some local labor market outcomes Y (e.g. employment in manufacturing etc.), I use the following baseline specification:[12]

$$\Delta \log Y_{it} = \Delta IPW_{it}\beta + X'_{it}\delta + \eta_t + \varepsilon_{it} \tag{2}$$

To fix ideas, consider the case where $\Delta \log Y_{it}$ is the growth rate of employment in the manufacturing sector. There are many plausible reasons why in specification (2), ΔIPW might be correlated with the error term ε even after controlling for an extensive set of covariates (discussed more in depth in the next section). Nation-wide sector specific shocks (supply or demand) are partly driving the amount of goods imported in France from abroad. If these shocks affect simultaneously sectoral imports and labor demand, OLS estimates will be biased. To formalize this idea, let us consider the case where the error term ε_{it} can be decomposed between **(i)** a weighted sum of nation-wide sectoral supply and demand shocks (which we denote w_s and x_s respectively) and **(ii)** an error term uncorrelated with any other terms included in the regression. For simplicity we omit the time subscript:

$$\varepsilon_i = a_S \sum_s \lambda_{is} w_s + a_D \sum_s \lambda_{is} x_s + \epsilon_i$$

where the parameter a_S and a_D determines the sign and magnitude of the impact of supply and demand shocks, respectively, on manufacturing employment growth and λ_{is} is an unobserved term representing the "importance" of sector s in location i (a simplification could be to set it

[11] This variable is thus closely related to the widely used Bartik-instrument Bartik (1991) in that it interacts initial sectoral composition and contemporaneous sector-wide trends. Note however, that I use ΔIPW_{it} as a *causal* variable and not as an instrument. In fact, as we will see, there are many outcomes that are affected by ΔIPW_{it} which could raise concerns about the plausibility of the exclusion-restriction when using the Bartik-instrument to instrument, for instance, for changes in local employment or unemployment.

[12] This estimating equation is equivalent of Autor *et al.* (2013). The contribution of the paper lies mainly in exploring different outcomes than those analyzed by them.

equal to $\frac{L_{ist}}{L_{it}}$, i.e. the initial employment share of sector s in location i). Collecting sectoral shocks w_s and x_s respectively in vectors $\mathbf{w}$ and $\mathbf{x}$, noting $\mathbf{m}$ the vector containing the changes in imports to initial employment ratios (with typical element $m_s = \frac{\Delta M_s}{L_s}$) and $\theta_{is} = \frac{L_{ist}}{L_{it}}$ the share of sector s in total employment in location i, and omitting exogenous regressors for simplicity, we can rewrite equation (2) as:

$$\Delta \log Y_i = \beta\theta_i'\mathbf{m} + \lambda_i'(a_S\mathbf{w} + a_D\mathbf{x}) + \epsilon_i \tag{3}$$

This specification is reminiscent of panel model with interactive fixed-effect (Bai) in the sense that the unobserved heterogeneity term λ_i is multidimensional (the length of vector λ_i is here equal to the number of sectors in the economy) and is allowed to interact with shocks that are common through the rest of the cross-sectional units.

Hence OLS estimation of the main specification will be biased due the covariance between ΔIPW_i and $\lambda_i'(a_S\mathbf{w} + a_D\mathbf{x})$ which we can write as:[13]

$$\text{cov}(\theta_i'\mathbf{m}, \lambda_i'(a_S\mathbf{w} + a_D\mathbf{x})) = a_S\theta_i'\text{cov}(\mathbf{m}, \mathbf{w})\lambda_i + a_D\theta_i'\text{cov}(\mathbf{m}, \mathbf{x})\lambda_i$$

If we assume that $s \neq s' \Rightarrow \text{cov}(m_s, w_{s'}) = \text{cov}(x_s, w_{s'}) = 0$ which amounts to ignoring cross-sectors relationships (driven for instance by input-output linkages or substitution in consumption between goods), we get the following expression:

$$\text{cov}(\theta_i'\mathbf{m}, \lambda_i'(a_S\mathbf{w} + a_D\mathbf{x})) = a_S\sum_s \theta_{is}\lambda_{is}\text{cov}(m_s, w_s) + a_D\sum_s \theta_{is}\lambda_{is}\text{cov}(m_s, x_s) \tag{4}$$

We expect the covariance between nationwide unobserved sectoral supply shocks and imports-per-worker ($\text{cov}(m_s, w_s)$) to be negative. When French producers in sector s are subject to a negative supply shock ($w_s < 0$ e.g. mandatory nation-wide reduction in weekly working-time with no reduction in monthly wages), one would expect an increase in purchase in goods s from foreign suppliers, including China and other low-wage countries. That suggests $\text{cov}(m_s, w_s) < 0$. On the other hand, as x_s represents demand shocks, one would expect that $\text{cov}(m_s, x_s) > 0$.

Positive supply and demand shocks are expected under general conditions to increase employment, hence we can assume $a_S > 0$ and $a_D > 0$. According to this framework, the bias introduced

[13] In the derivation of this expression I consider θ_i and λ_i as fixed parameter vectors and $\mathbf{m}$ and $\mathbf{w}$ as random vectors.

by unobserved sectoral shocks could either be positive or negative depending on the relative magnitude of supply and demand shocks and how they affect imports from low-wage country. Because these nation-wide shocks affect each community differently, through to the vector λ_i, including periods fixed-effects does not solve the issue.

We adapt the instrumental variable strategy developed by Autor *et al.* (2013) to the French case. We instrument actual exports from low-wage countries to France by Chinese exports to a set of high-income countries whose economic cycle is weakly related to that France.[14] The formula for the instrument is the following:

$$\Delta IPW_{it}^{o} = \frac{1}{L_{it}} \sum_{s \in \mathbb{T}} \frac{L_{ist}}{L_{st}} \Delta M_{st}^{o} \tag{5}$$

where ΔM_{st}^{o} is Chinese exports to the set of selected other high-income countries. The identifying assumption underpinning the validity of this instrument is that Chinese exports to these countries, i.e. the vector ΔM^{o}, are independent from domestic shocks in France (contained in vectors $\mathbf{w}$ and $\mathbf{x}$ in our example) so that the statistical association between French imports from China and Chinese exports to these high-income countries is only driven by supply-side improvements in China. This assumption seems credible given that China underwent major economic reforms since the 1980s which accelerated over the 1990s, culminating with China's accession to the World Trade Organization in 2001. These reforms were deeply influenced by China's own domestic politics and decided independently from development pertaining specifically to France.[15] The choice of other high-income countries is such that they represent a small percentage of French exports so that the exclusion restriction appears credible.

Figure 2 contain three maps of France regarding IPW and employment growth over the 2001-2007 period. Table 1 shows that decline in manufacturing has taken place over the 2 periods but was much stronger over the second one. Imports and Trade deficit per worker grew faster over the second period as well. Figure 3 displays the first-stage, plotting observations from both periods (after taking out period fixed-effect) as well as a best linear fit and its 95 % confidence interval. The instrument is a strong predictor of the endogenous regressor ΔIPW_{it}. The first-

[14] The list of countries is almost the same as in Dauth *et al.* (2014), except that it excludes the United Kingdom and includes Denmark, South-Korea, Argentina and Chile. The list includes the following countries: Argentina, Australia, Canada, Chile, Denmark, Japan, New Zealand, Norway, Singapore, Sweden, and South Korea. Note that we excluded all countries from continental Europe which are part of the euro zone.

[15] For an extensive account of Chinese reforms, subsequent growth and increasing economic openness see Brandt and Rawski (2008).

stage Kleibergen-Paap F-statistic for the stack specification with no-covariate is 48, clearly above the critical value of 16 suggested by Stock and Yogo (2005) for 2SLS estimates. The corresponding reduced-forms with respect to manufacturing and non-traded employment are plotted in Figure 4.[16] The period we cover stretches from 1995 to 2007. The choice of the beginning date is driven by data availability regarding local sectoral composition, wages and hours worked. The end of the period is marked by the onset of the Great Recession which deeply affected trade flows as well as GDP in ways that is very likely to be correlated across high-income countries, thus making the identifying assumption less credible over the post-2007 period.[17]

4 Results on employment

4.1 Employment and Total Earnings

Manufacturing sector

The first specification measures the impact of IPW on employment and total hours worked in the manufacturing sector. Results are displayed in Table 2. All specifications include the initial value of overall employment in the employment area.[18] Column (1) implies that a $1000 increase in ΔIPW is associated with a 5.8 percentage point decrease in manufacturing employment growth rate. We see in Column (2) that instrumenting ΔIPW by ΔIPW^o yields a higher (in absolute value) coefficient of -8.3. This suggests that, under the maintained hypothesis that the instrument is exogenous, France's increasing imports of Chinese products are for a substantial part explained by French idiosyncratic demand shocks that boost both employment and imports thus causing an upward bias in OLS estimates. This result is similar to what is found for the US case for by Autor *et al.* (2013). In Column (3), we control for the initial share of employment in the manufacturing sector. Under this specification, variation across employment areas comes only from differences in the local specialization within the manufacturing sector and not from differences in terms of share of the manufacturing sector as a whole. It uses the fact that Chinese imports growth has been very uneven across subsets of the manufacturing sector. The inclusion of that term does not

[16] Figures OA1 and OA2 in the online appendix display the first stage and the reduced-form in long-differences.
[17] Figure 1 shows the decline in imports from China occurring in 2008/2009.
[18] This control accounts for the fact there tends to be a negative relationship between city population and its growth rate, as pointed in Card (2007) and Faggio and Overman (2014).

affect substantially the estimate, which is equal to -6.3.[19]

Column (4) and Column (5) test the robustness of the results, relaxing further the identifying assumptions required to interpret the coefficient causally. Column (4) adds a series of additional controls that discards some potential confounding factors. It controls for the initial share of college-educated residents, of women in the employed population foreigners, and production workers in the workforce. Including these controls allows each employment area to have a specific trend proportional to each of these initial shares. The rationale to include production workers is to account for the potential exposure of employment areas to technical change and automatization that could possibly lead to a decline in labor demand by the manufacturing sector independently from globalization (Autor and Dorn, 2013). The share of college graduates accounts for the fact that there has been an increasing gap in employment and unemployment rates between college and non-college educated individuals. The estimate decreases marginally in magnitude from Column (3) to Column (4) with an absolute value of 6.3. Column (5) includes "region"-fixed effects,[20] thus allowing each region to have a specific trend. Again, we do not see a large decline in the estimate which, at a value of 6.2, remains significant at the 1 percent level.

The last point estimate implies that shifting from the 25th to the 75th percentile of the distribution of trade exposure results causes a reduction in 6-year growth rate of 2.62 %.

Another way of gauging the economic significance of the results is to compute an aggregate impact under the assumption that our estimates reflect absolute rather than relative impact. The first-difference approach adopted in this paper identifies the *relative impact* of *changes* in trade exposure. In that sense it identifies how local labor markets exposed to Chinese competition deviate from the aggregate trend. In our setting, making aggregate predictions necessitates additional assumptions such that the coefficient associated with ΔIPW reflect *absolute* changes in outcomes and not simply changes *relative* to the aggregate trend. In fact, aggregate prediction requires period fixed-effects not to be a function of the regressor aggregated across employment

[19]Unlike Autor *et al.* (2013), I do not consider employment over population but growth rate in employment (and other outcomes). This choice is mainly dictated by data availability. The years considered (1995, 2001, 2007) do not correspond to a census year. Hence there is no data on overall working age population. Overall adult (above 18) population, as opposed to working age population (which would typically include the 16 to 65 year olds) can be approximated by the number of registered voters for the presidential elections of 1995, 2001 and 2007. In a set of unreported regressions, I show that adult population proxied by registered voters do not respond to China-induced trade shocks. The same results hold when using the number of fiscal households which, unlike voters, includes foreigners. Results are available upon request. In the absence of reaction of population adjustment, trade shocks' impact on the change of log employment translates roughly one-to-one to the change in the log ratio of employment to adult population.

[20]There are 22 so called "Regions" in metropolitan France.

zones. This assumption is very strong as the surge in Chinese import competition is likely to have affected the aggregate growth rate of employment through other channels than its local impact. This admittedly strong assumption is not necessary in order to obtain consistent estimates of import competition impact on local labor markets but I adopt it in this paragraph in order to, somewhat heuristically, get an order of magnitude of the estimated effect if it was to reflect absolute changes.[21]

I predict import-driven changes in growth rate in manufacturing by using our 2SLS estimates times the observed change in import-per-worker at the local level times the share of variation in imports explained by Chinese supply-side factors. I deduce this share from the R-square of a simple bivariate regression of ΔIPW_{it} on ΔIPW^{o}_{it} (after partialling out all covariates included in Column (5)).[22] This simple computation yields the nation-wide effect of Chinese imports penetration on manufacturing employment. I find a nation-wide effect of -0.31 and -1.77 percentage-points for the first and second periods respectively. This implies that Chinese import competition explains about 13 percent of the decline in the French manufacturing sector employment over the period 2001-2007. In terms of jobs, China-induced trade shocked destroyed $16,000$ jobs over the first period and $88,000$ jobs over the second. This exercise is therefore consistent with the notions that (i) trade with China have become increasingly relevant for industrial employment in developed economies, (ii) other factors, such as technological change, lie behind the rapid decline of industrial employment in France.

Columns (6) and (7) apply the same specification as in Column (5) changing only the dependent variable. Column (6) shows the impact on total hours worked. The estimate is very close to that in Column (5) suggesting no change in average hours worked per job. This is interesting in the light of the widespread notion that import competition has promoted part-time and unconventional forms of employment. Column (7) looks at overall employment earnings (hours worked times hourly wage). The impact is sensibly larger than that on hours worked suggesting a mild decline in the average hourly wage. This result contrasts with those of Autor *et al.* (2013) who

[21] This point is first mentioned by Topalova (2010). See Appendix B for a more formal argument. While this assumption is very strong, it is worth noting that, as mentioned in footnote 19, the fact there is no population adjustment in reaction to local shocks shuts down an important channel through which *relative* effects would be greater than *absolute* ones.

[22] The predicted change for employment zone i at time t is thus equal to: $g_{it} = R^2 \times \beta \times \Delta IPW_{it}$ where R^2 refers to the partial first-stage R-square. The aggregate predicted change is then simply: $\overline{g}_t = R^2 \times \beta \times \overline{\Delta IPW}_t$, where $\overline{x}_t$ means the average of variable x across the cross-section at time t.

find no effect on average weekly wage within manufacturing. Although downward wage rigidity (nominal or real) is a salient feature of the manufacturing sector, it is not incompatible with this finding. Indeed the present results reflect the effect on wage growth in deviation from aggregate trends and could be explained by low wage for the new hires or simply a lower albeit positive wage growth rate. (The local wage impact of China-induced trade shocks will be analyzed in more detailed in Section 5.)

4.1.1 Outside of manufacturing

I now turn to the effect of Chinese import penetration on employment and hours worked in the non-traded sector. The results are displayed in Table 3. The effect is weaker and less precisely estimated. The weaker effect found on the non-traded sector can be rationalized by a reallocation effect: while the decline in demand for non-traded output entails overall job losses in the non-traded sector, employers in this sector benefit nevertheless from a positive local labor supply shocks as a share of workers displaced from the manufacturing sector are likely to be looking for jobs locally (especially given that I find no negative effect on overall population growth). Column (5) shows that a \$1000 increase in ΔIPW is associated with a 3.6 percentage point decrease in non-tradable sector employment growth rate.

Under the same assumptions as in the previous paragraph, I can get an order of magnitude regarding the aggregate impact of Chinese import competition on job displacement in the non-traded sector. Using the formula explained in footnote 22 leads to the conclusion that local growth in non-traded employment was reduced by 0.18% over the first period and 1% over the second. This suggests that $190,000$ jobs in the non-traded sector were destroyed due to spill-overs associated with China-induced trade shocks between 2001 and 2007.[23],

.

The impact of Chinese import competition onto the non-tradable sector is indirect in that it operates through its impact on the manufacturing sector. Based on US data, Moretti (2010) estimates the impact of growth in tradable employment on the growth of the non-tradable sector, which he refers to as a "local multiplier". The author uses a Bartik-shock variable as an instrument

[23]This is much larger number than for manufacturing sector which reflects to a great extent the large size of the non-traded sector with respect to the manufacturing sector. Note also that doing the same computation based on hours worked rather than job count reverses the conclusion regarding the *absolute* size of the effect: more "hours worked" have been destroyed by Chinese import competition in manufacturing than in the non-tradable sector (130 versus 108 millions hours).

for growth in tradable employment and finds a job-to-job impact of 1.57. Dijk (2014) reexamines Moretti's work and after several corrections concludes to a local multiplier effect roughly 33 % lower (1.02 job-to-job effect). The ratio of the estimates from tables 3 and 2 is similar to a "local multiplier effect" in the sense that it defines the elasticity of non-tradable employment to employment in the manufacturing sector. Taking estimates of Column (3) from both tables leads to an elasticity of 0.58, which given an average ratio of non-traded to manufacturing employment of 2.5 suggest a job-to-job effect of 1.46. Overall, these results suggest that shocks to local labor demand induced by trade-shocks trigger spill-overs of roughly the same magnitude as those captured by the Bartik-instrument, which encapsulates sectoral shocks of all sources (Partridge *et al.*, 2016). A set of regressions where I estimate directly local multiplier using either ΔIPW and $Bartik$ as an instrument for growth in non-traded employment. I find statistically indistinguishable estimates. Results are shown in Table 4. This suggests that shocks to local labor demand induced by trade-shocks trigger spill-overs of the same magnitude as those captured

While the estimated local multipliers might seem large, it is much more modest when expressed in terms of hours worked – an arguably more informative statistic than job count regarding the state of the local labor market. We see indeed that the non-traded to traded elasticity obtained by taking the ratio of the two coefficients of Columns (6) in Tables 2 and 3 is 0.29. This is twice smaller than the job-elasticity. This large discrepancy shows that when discussing "local multiplier", conclusions can be very sensitive to the unit of measurement used. Manufacturing to non-tradable spill-over effects when expressed in terms of jobs might tend to overestimate the actual variation in labor demand occurring in the non-traded sector following the local creation/destruction of a job in the local manufacturing sector.

4.2 Robustness Checks

4.2.1 Placebo regressions

In spite of the extensive set of controls, as well as the instrumentation of ΔIPW, there remains the suspicion that results displayed so far could be picking up a secular decline of employment in some local labor markets. I test this possibility by regressing employment growth on lead values of ΔIPW. If future values of ΔIPW predicts current low job growth, it could imply that estimates presented until now are picking up the impact of an omitted factor correlated with rising import

competition (for instance labor-saving technological change). I use data from the French Census for periods 1982-1990 and 1990-1999 an compute overall private employment growth and resort to the administrative data, used in the rest of the analysis, for the 2001-2007. Table 5 displays the results. In columns (1) and (2), employment growth in the private sector (reexpressed in 6 year period equivalent growth rate) for periods 1990-1999 and 2001-2007 is regressed on ΔIPW for periods 1995-2001 and 2001-2007. In columns (5) and (6), employment growth in the private sector (reexpressed in 6 year period equivalent) for periods 1982-1990 and 1990-1999 is regressed on ΔIPW for periods 1995-2001 and 2001-2007. Focusing on the IV regression results, we can see that while ΔIPW is associated with a decline in contemporaneous employment growth (Column 2), it is associated with higher growth rate in lagged employment, suggesting that the negative coefficients estimated above reflect a causal impact of Chinese import competition on job growth rather than a secular decline. On the contrary, employment areas with high lead values of ΔIPW were experiencing above average growth in employment during the 1980s and 1990s which suggests that if anything the present estimates are a lower bound on the true effect. Another approach to rule out spurious effects is to include pre-trends as an explanatory variable (rather than dependent) and assess to which extent the coefficients associated with ΔIPW change. In Column (3) and (4), we see that, reassuringly, the coefficients are not substantially affected suggesting pre-trends are not driving the size of the estimated coefficient. Consistent with the positive coefficient found in Column (6), we find that controlling for pre-trends leads to a stronger estimated impact of Chinese import competitions, suggesting that estimates presented in section 4.1 are if anything a lower-bound for the true effect.

4.2.2 Net trade

Dauth *et al.* (2014) emphasizes that local labor markets can be positively affected by trade. Chinese economic growth is associated with a surge in imports. If some local labor markets are specialized in sectors for which Chinese demand grows particularly fast, Chinese growth could stimulate local labor demand. As shown in the introduction and in Figure 1, French-Chinese trade is particularly unbalanced. In 2007 for instance, French exports to China amounted $14 billion while its imports amounted to $-bn 40, thus leaving a deficit of $-bn 26 equivalent to 4.5 % of French total trade (exports plus imports). In this section, I check whether considering net imports (or trade deficit) as opposed to overall imports lead to substantially different estimates. I

do not test exports and imports separately mainly because I do not dispose of a relevant and valid instrument for French exports to China.[24] Table 6 based on the same specifications as in Table 2 with the only exception that the variable imports per workers has been replaced by a "deficit-per-worker" variable. Coefficients are very close to those in Table 2, although of a somewhat larger magnitude. It is logical as the deficit-per-worker nets out any positive effect associated with rise in exports that would not be captured by the gross imports measure.

These estimates provide some information regarding what would have been the impact in terms of manufacturing employment of balancing trade with respect to China.[25] Given that the average increase in ΔDPW has been \$790 over last period 2001-2007, given a partial R-square of ΔDPW on ΔIPW^o equal to 13%, in the absence of increase in trade deficit, manufacturing employment would have declined about 1 percentage less, representing about 52,000 jobs (based on column 5 coefficient).

4.3 Did trade shocks lead to local job polarization?

This section investigates the impact of import competition on the occupational structure of employment. As is usual with administrative data, there is no information on workers' educational achievements, therefore I use a definition of skill based on occupations. Occupations are consistently defined over the period of interest at the 2-digit level (for 18 occupations). More details on the classification can be found in Appendix B. While the data available does not allow to define occupations with as much precision as in previous works (e.g. Goos and Manning, 2007, use 3-digit occupations), it has some considerable advantages, notably being exhaustive, which allows to consider finer geographical level than with survey data. I first present some descriptive facts about the evolution of this structure.

Describing job polarization

A first method to relate occupation to skill is to rank occupations according to their initial median or average wage. "Job polarization" (Goos and Manning, 2007) is then documented by relating

[24] Imports by China of products made in other high income countries could be a possible instrument. The strength of such instrument is however very low, owing to the fact that Chinese basket of imported goods vary much more across origin-countries so than its export basket (which is quite uniform as attested by the strength of the first-stage).

[25] Balancing trade is equivalent to setting the average deficit per worker (ΔDPW) from its average value to 0.

the growth rate of employment in each occupation to its initial wage rank. A clear limitation of ranking occupation by average or median wage is that it ignores within-occupation wage variation which represents a substantial fraction of overall wage dispersion. Summarizing occupation skill-intensity by a one-dimensional index leads to a substantial loss of information. To deal with this issue, I build on the method developed by Juhn *et al.* (1993). It assumes that each occupation combines labor from every percentile of the wage distribution, in varying proportions. These factor shares are computed for an initial period and held constant. A given percentage change in employment for a given occupation will then be diffused across percentiles proportionally to the employment share of this occupation within each percentile.[26]

Figure 6 plots Equation (6) both in terms of jobs and hours worked.[27] In manufacturing, employment growth is predicted to be negative up to the 80th percentile. Employment at the 10th percentile and median wage are predicted to shrink by 13.5 and 8 % respectively. The slope becomes much steeper above the 80th decile. In the non-traded sector, polarization is shown to occur although for the most part the slope is rather flat. For instance, predicted employment growth is equal to 20 % for the 10th and 75th wage percentile and is the lowest around the median wage at 17 %. The slope is much steeper in the upper part of the distribution: employment is predicted to grow at 22.5 % and 29.5 % at the 80th and 90th percentile respectively. Interestingly, the change in occupational structure would predict a large increase in wage inequality which contrasts with the overall trend of the actual wage distribution whose variance has remained very stable. This suggests that there has certainly been a decline of the between-occupation component of wage dispersion. Section 5 analyzes changes in the actual wage distribution and discusses the

[26]More formally, let us consider an occupation o that, for an initial period, employs L_{op} workers coming from p-wage percentile, such that $L_o = \sum_{p=1}^{100} L_{op}$. Shocks occur at the occupation-level and are denoted $\Delta L_o/L_o$. They affect changes in employment for each percentile denoted as $\Delta L_p/L_p$ according to a weight determined by the fixed employment share of occupation o in percentile p: L_{op}/L_p. We can therefore write down the predicted percentage change in employment for percentile p as:

$$\frac{\Delta L_p}{L_p} = \sum_{o \in \mathbb{O}} \frac{L_{op}}{L_p} \frac{\Delta L_o}{L_o} \tag{6}$$

where $\mathbb{O}$ refers to the set of all occupations. Equation (6) expresses the expected change in employment at wage percentile p as predicted by changes in the occupational structure of employment. Juhn *et al.* (1993) show how this formula can be derived from a model in which (i) each occupation is a distinct sector of the economy, (ii) each sector operates at constant returns to scale and (iii) sectors are subject to factor neutral shocks, i.e. the shocks themselves do not affect the sector-specific factor shares (Juhn *et al.*, 1993, p.432). Note that shocks can be factor neutral within a given occupation while being overall skill-biased, for instance if shocks are relatively larger in low-skill intensive occupations.

[27]We see that while hours worked have not grown as fast as employment over the period, the gap is very stable over wage distribution and we will focus on employment in the reminder of the section. The same conclusions as above broadly hold for both sectors.

contrasts between changes in the job versus wage structures more at length.

Effect of Chinese import competition on job polarization

We now consider the effect of trade on job polarization. Retaining the specification of Column (6) from Table 2 and 3, occupation-sector specific coefficients are estimated (which we denote $\{\hat{\beta}_o\}_{o\in\mathbb{O}}$) and are then reweighed according to the same formula as above (in Equation 6).[28]

Figure 7 plots the results of Equation (7). Interestingly, we see that in manufacturing, the change in occupational structure triggered by import competition has a clear polarizing effect on employment growth which contrasts with the overall trend described above. The effect is of -3% at the 10th percentile, -7 % at the 70th percentile, then vanished and ceases to be significant at the 90th percentile. This pattern is consistent with the process of skill-upgrading caused by Chinese import competition at the firm-level detected by Mion and Zhu (2013). In contrast, the non-traded sector's occupational structure is affected more uniformly.[29]

The pattern of the skill-specific impact of trade shocks would tend to predict a rise in wage inequality, particularly in the manufacturing sector. However there might be countervailing forces - reduction in within-occupation dispersion or decline (increase) in the average wage of initially high (low) wage occupations. Without attempting to decompose overall impact of trade on wages into different component, the next section looks directly at the overall impact of import competition along the local wage distribution.

5 Results on the wage impact along the distribution

There is by now a large body empirical work showing that changes in import exposure has a very heterogenous impact across firms. For instance, Bloom *et al.* (2011) find that the surge in Chinese import competition has a negative employment effect that is considerably smaller for innovative

[28]The formula is the following:

$$\widehat{g}_p = \sum_{o\in\mathbb{O}} \frac{L_{op}}{L_p}\hat{\beta}_o \tag{7}$$

We build standard error for $\widehat{g}_p$ assuming that the estimators for different occupations are independently distributed.

$$\text{Std error}(\widehat{g}_p) = \sqrt{\widehat{Var}(\widehat{g}_p)} = \sqrt{\sum_{o\in\mathbb{O}} \left(\frac{L_{op}}{L_p}\right)^2 \widehat{Var}(\hat{\beta}_o)}$$

The online appendix displays the occupation-specific coefficients simply ranked by average wage (Table OA3).

[29]Occupation specific coefficients as well as a regression table based on a more aggregated definition of occupations are presented in the Online Appendix (see Figure OA3 and Table OA1).

firms. Amiti and Davis (2012) shows that, following a trade liberalization episode in Indonesia, large exporters or importers increased their wages relative to firms serving the domestic market only. Such heterogeneous effects along firm-level characteristics will be associated with increase in wage dispersion in ways that are unlikely to be fully captured by a variable pertaining to individual-level skill, such as college education or type of education. On the other hand such impact will be reflected in the overall distribution of wages. In this section, I estimate the impact of Chinese import competition on each decile of the wage distribution, thus capturing overall changes in wage dispersion while remaining agnostic about which the particular mechanism through which Chinese import competition is affecting inequality.

The upper panel of Table 7 displays the results regarding the manufacturing sector. All deciles except the bottom one are significantly negatively affected by import competition. The estimate is very imprecisely estimated for the 1st decile, resulting in an insignificant coefficient in spite of a very large point estimate. The impact for the median is somewhat lower than the effect on the average wage and imprecisely estimated. The highest estimates are those for the 8th and 9th deciles (although they do not differ significantly from the other coefficients). The distribution of hourly wage in manufacturing is not made less egalitarian by exposure to import competition, instead it's been rather uniformly decreased.[30]

The impact of rising Chinese import competition on the actual local wage distribution within manufacturing contrasts with what one would have predicted based on its impact the occupational structure. While the occupational structure appears to have been strongly polarized, wage dispersion is virtually unaffected. We note that this dual development – job polarization and no increase in wage inequality – holds at the aggregate level. One explanation refers to the large increase in the supply of college educated workers over the period (Verdugo, 2014). This is in a sense the reverse scenario of that developed by Katz and Murphy (1992) which explains the rise in the US college premium over the 1980s by the decline in the growth of the relative supply of college graduates. However this explanation is not particularly compelling in the present case. First, note that my estimates are obtained using cross-sectional variation across local labor markets in import competition. Therefore shocks to the supply of high-skill workers in manufacturing

[30]For instance, moving from the 25th to the 75th percentile in terms of increase in Chinese import competition implies a reduction in wage growth that represents about 8% of the average wage growth at the 20th and 40th percentile and of about 11 % at the 80 and 90th percentile.

would have to be positively correlated to the raise in import competition which does not seem particularly plausible.[31] While beyond the scope of this paper, understanding the coexistence of a polarizing effect import competition on the structure of employment and the absence of such effect on the structure of wage in manufacturing appears an interesting venue for future research.

The lower panel of Table 7 displays results for the non-traded sector. We see that the non-significant effect on average wage hides considerable heterogeneity across deciles. There are clearly negative effects in the middle-part of the distribution, between the 2nd and 7th deciles included. The impact on the median wage is much stronger than that on the average wage. The median wage effect is of the same magnitude as in the manufacturing sector and is more precisely estimated. This shows that trade shocks are diffused to the local non-tradable sector. The bottom decile is not significantly affected, with a point estimated very close to zero. There is also no significant impact on the two top deciles. This is consistent with the finding that employment growth in occupations usually located in the top of the distribution was not affected by trade shocks (See the right panel of Figure 7 and the discussion in Section 4.3). Economically, the impact, while being precisely estimated, appears modest. For instance, moving from the 25th to the 75th percentile in terms of increase in Chinese import competition implies a reduction in wage growth that represents about 4 % of the average wage growth at the 20th percentile, 7 % at the 40h and 50th percentile and 6 % at the 60th percentile.

In Table 8, we report how different measures of wage dispersion/inequality have been affected by China-induced trade shocks. Column (1) displays the estimated effect on changes in the 90-10 log wage differential of the local wage distribution. While the coefficient is positive for manufacturing, it is very imprecisely estimated. It is very close to 0 and insignificant in the non-tradable sector as well. Hence it appears, based on that measure of inequality, that that Chinese import competition, while it had some notable impact on wage and on employment did not move affected local labor markets away from the general trend towards compression of the French wage distribution over the period considered (Verdugo, 2014). We decompose the change of the log 90-10 differential into the sum of the change of the log of the 50-10 ratio (lower-tail inequality) and the change of the log of the 90-50 ratio (upper tail inequality). In the case of manufacturing,

[31] Moreover, controlling for contemporaneous changes in the share of college graduates, an admittedly "bad control" (Angrist and Pischke, 2009), does not affect the results. The reason why the results are barely affected is because the rise in the share of college graduates has been very uniform across local labor markets. For instance the rank correlation between share of college graduates in 1990 and 1999 is 0.96 while the average aggregate share has gone up from 8 to 13%. The results are available upon request.

although point estimates suggest a rise in lower-tail dispersion, none is significantly different from zero. In the non-traded sector however, it appears that the null effect of import competition on the 90th to 10th percentile ratio results from a combination of increase in upper-tail dispersion (Column 2) and compression in the lower-tail of the distribution (Column 3). The binding role of the minimum wage provides a plausible explanation to these findings. I investigate this question further below but first proceed to some robustness checks.

The role of the minimum wage

In this section, I investigate whether the pattern of wage polarization in the non-traded sector, observed in the right-panel of Figure 8 and the absence of increase in overall inequality following trade shocks can be explained by the role of the minimum wage. In this subsection, I use variation the share of workers working at the minimum wage across locations to test whether, following an increase in exposure to Chinese import competition, the "compression" in the bottom tail of the wage distribution occurred only in areas where the minimum wage is binding and whether places where the minimum wage was not binding experienced an increase in overall inequality.[32]

I define overall, lower tail and upper tail wage inequality respectively as the 85-15, the 50-15 and the 85-50 log wage ratio.[33] I introduce an interaction term between ΔIPW and a binary variable equal to 1 if less than 15 % of employees (in manufacturing or the non-tradable sector depending on which sector the dependent variable pertains) in the initial year of the period are paid at the minimum wage. [34] Noting S_{15} the binary variable and Q_{it} a generic statistics regarding the local the wage distribution, the specification we estimate is the following:

$$\Delta \log Q_{it} = \Delta IPW_{it} \cdot \beta_1 + \Delta IPW_{it} \times S_{15,it} \cdot \beta_2 + X'_{it}\delta + \eta_t + \varepsilon_{it} \tag{8}$$

Naturally for all quantiles below the 15th percentile one would expect β_1 to be close to zero, and β_2 to be negative, meaning that wage losses are concentrated in areas/sector where the

[32]The minimum wage is nationally set in France and there is no variation in the legal definition of the minimum wage across employment areas. While there are some legal exemptions to the minimum wage, they account for a small share of the working population, see Kramarz and Philippon (2001).

[33]I do this in order to split the sample somewhat equally, I focus on the 15th percentile. Regarding the non-traded sector wages, roughly 40 % of observations are associated with a 15th percentile in the that is above to the minimum wage. Hence the minimum wage is binding at the 15th percentile for roughly 60 % of observations. At the 10th percentile level, the minimum wage is binding for about 95 % of observations.

[34]This interaction term is then instrumented by the product of ΔIPW^o and the binary variable.

minimum wage is not binding for the 15th percentile.[35]

Table 9 presents results for the non-tradable sector. Columns (1) to (4) repeat baseline results, considering the 15th rather than the 10 percentile. We see in column (1) a small negative effect on the 15th percentile. Column (2) displays a null effect on the 85-15 log ratio. This absence of effect can be unpacked into a positive effect on upper tail inequality (85-50 log ratio, column 3) and a negative effect on lower tail inequality (50-15 log ratio, column 4).

We see in column (5) that areas where the 15th percentile was not covered by the minimum wage experienced a negative impact of import competition, while the others were (unsurprisingly) protected. Column (6) reports results on overall wage inequality. The response of overall wage inequality between places with and without a binding minimum wage is significantly different: inequality grows relatively more in areas where the minimum wage is not binding. Column (7) shows that there is no differences between groups in terms of how upper-tail inequality is affect by Chinese import competition. The coefficient on the interaction term is very close 0 with a p-value of 0.85. Column (8) shows that on the contrary trade shocks compressed the bottom tail of the distribution in areas with binding minimum wage and had virtually no effect in places where the minimum wage does not bind.

The coefficient implies an economically large effect. Over the period the 50-15 log ratio has declined by 1.3 % on average. In cities with a binding minimum wage at the 15th percentile, the average level of exposure to import competition implies a reduction of 0.65 % of this ratio (equivalent to 46 % of the average reduction in this ratio). In employment zones where the minimum wage is not binding, the ratio is only reduced by 0.16 %. The minimum wage appears to imply sizable differences in how the bottom of the wage distribution is affected by trade shocks. This difference is also reflected in overall wage inequality (measured by the 85-15 log ratio) given that there is no offsetting effect on the upper-tail of the distribution.

[35]There are obvious limitations to this exercise, as the initial share of minimum wage employees could be considered endogenous to posterior growth in the 1st decile of the wage distribution. There could be for instance some unobservable characteristics affecting both minimum wage ratios and subsequent wage growth rate. Note however that intuitively, one would expect such unobservables to cause high minimum wage ratio and lower wage growth. On the contrary, our hypothesis states low minimum wage ratios should be associated with lower wage growth when associated with strong exposure rise in Chinese import competition. Consequently, endogeneity of low minimum wage local ratio seems likely to introduce an upward bias in estimates that we expect to be negative.

6 Conclusion

Local employment and total labor income in the manufacturing sector are reduced in employment areas more exposed to Chinese imports. The effect goes beyond manufacturing sector as non-traded employment is also significantly affected. The estimates suggest that the number of jobs displaced is higher in the non-traded than in the traded sector. However this conclusion is reversed when considering hours worked rather than job count, highlighting the usefulness to account for systematic difference in the types of jobs across sectors when assessing the strength of the local spill-overs.

Local employment and total labor income in the manufacturing sector are reduced in employment areas more exposed to Chinese imports. The effect goes beyond manufacturing sector as non-traded employment is also significantly affected. The estimates suggest that the number of jobs displaced is higher in the non-traded than in the traded sector. The strongest employment impact is concentrated on medium and low skill occupations in the the traded and non-traded sector respectively. Contrary to previous works in trade and local labor market literature (Autor *et al.*, 2013; Dauth *et al.*, 2014), wage rates are found to be negatively affected by Chinese import competition.

The job impact of trade is found to be very uneven across skill categories. There is a negative monotonic relationship between skill and the magnitude of the effect of import competition on job growth in the non-traded sector. This relationship is U-shaped within manufacturing, implying that Chinese import competition has polarized the occupational structure of employment in that sector.

Wage rates are found to be negatively affected by Chinese import competition, although the pattern of the effect differs markedly between sectors. The impact is rather uniform in the manufacturing sector and wage inequality does not rise. In contrast with manufacturing, the non-traded sector experienced wage polarization: the median wage declines with respect to both the 15th and the 85th percentile. Finally I show that, while the 85th to 15th wage ratio is not affected on average, it increased as a consequence of China-induced trade shocks in areas where the minimum wage in weakly binding. This result provides a striking example of how labor market institutions mediate the effect of globalization-driven shocks on wage dispersion.

The present study highlights the rising impact of low-wage competition on local labor markets.

The presence of large local multiplier effects associated with large trade-induced displacements combined with evidence that there is little labor mobility in response to shocks in local demand suggest that trade shocks have locally concentrated effects that are likely to be long-lasting. These trends contribute to explain the popularity of place-based policies that generally aim at tempering the local consequences of labor demand shocks. The design and implementation of optimal place-based policies in the presence of strong local labor demand shocks and workers low spatial mobility seem therefore an important area for further research.

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7 Tables

Table 1: Descriptive Statistics

	(1) Period 1995-2001			(2) Period 2001-2007		
	mean	sd	p50	mean	sd	p50
Initial employment in thousands	65.83	101.29	33.63	78.85	118.57	41.53
ΔIPW (in thsds \$, 2001)	0.17	0.12	0.14	1.00	0.65	0.80
ΔDPW (in thsds \$, 2001)	0.15	0.13	0.12	0.79	0.68	0.59
% employment in mfg	28.97	9.44	27.65	24.48	8.72	23.58
% chge in mfg empl.	-1.58	10.13	-0.74	-13.05	9.10	-12.93
% chge in non-tradable sector empl.	25.03	5.23	25.09	7.42	7.69	7.82
Hours worked per job: mfg	1615	69	1619	1496	65	1497
Hours worked per job: non-traded	1299	44	1308	1154	42	1156
Ratio q_{90}/q_{10}, all sectors	2.91	0.52	2.76	2.84	0.56	2.67
Chge Log Ratio : $\Delta \log q_{90}/q_{10}$, all sectors	-2.95	3.18	-3.15	0.74	3.23	0.96
σ log(hrly wages) in mfg	0.45	0.05	0.43	0.45	0.06	0.44
σ log(hrly wages) in tradable sector	0.48	0.06	0.47	0.47	0.06	0.46

Note: See Equation 1 for definition of ΔIPW and ΔDPW. Except for the first line, all averages are computed using 1995 total employment as weights.

Table 2: Direct impact of Chinese import competition on manufacturing

	(1) OLS: Jobs	(2) IV	(3) IV	(4) IV	(5) IV	(6) IV: Hrs	(7) IV: Emp. earnings
	b/se	b/se	b/se	b/se	b/se	b/se	b/se
ΔIPW	-5.876***	-8.349***	-6.262***	-6.313***	-6.224***	-6.084***	-8.636***
	(1.242)	(1.618)	(1.782)	(1.789)	(1.667)	(1.621)	(1.885)
% employment in mfg			-0.151***	-0.205***	-0.097	-0.095	0.040
			(0.059)	(0.069)	(0.067)	(0.072)	(0.076)
% college				-0.653***	-0.368**	-0.405***	-0.442***
				(0.174)	(0.143)	(0.148)	(0.157)
% production workers				-0.362***	-0.181	-0.189*	-0.208
				(0.111)	(0.114)	(0.115)	(0.127)
% women				-1.462**	-1.948***	-2.106***	-2.345***
				(0.650)	(0.506)	(0.596)	(0.687)
% foreigners				-0.465**	-0.496**	-0.498**	-0.543**
				(0.213)	(0.193)	(0.211)	(0.231)
KP stat		48.66	31.09	31.72	32.51	32.51	32.51
Region fixed-effect					√	√	√

Note: $N = 696$. Baseline sample is a balanced panel of 348 employment zones. Outcomes variables are expressed in percentage change over six-year period. All specifications include period fixed effect and log of initial total employment. Robust standard errors are clustered at the employment zone level. *p<.10 ** p<.05, *** p<.01.

Table 3: Impact of Chinese import competition on the nontradable sector

	(1) OLS: Jobs b/se	(2) IV b/se	(3) IV b/se	(4) IV b/se	(5) IV b/se	(6) IV: Hrs b/se	(7) IV: Emp. earnings b/se
ΔIPW	-1.845***	-3.640***	-3.937***	-4.071***	-3.645***	-1.765**	-2.363***
	(0.558)	(0.982)	(1.092)	(1.095)	(0.850)	(0.760)	(0.840)
% employment in mfg			0.022	0.003	0.170***	0.146***	0.177***
			(0.046)	(0.049)	(0.048)	(0.046)	(0.049)
% college				-0.360**	-0.099	-0.187*	-0.351***
				(0.143)	(0.117)	(0.113)	(0.121)
% production workers				-0.140	0.135	0.065	0.036
				(0.085)	(0.091)	(0.085)	(0.092)
% women				-0.731	-0.936**	-1.140**	-1.076**
				(0.448)	(0.472)	(0.453)	(0.503)
% foreigners				0.062	-0.082	-0.154	-0.190
				(0.146)	(0.159)	(0.155)	(0.172)
KP stat		48.66	31.09	31.72	32.51	32.51	32.51
Region fixed-effect					√	√	√

Note: $N = 696$. Baseline sample is a balanced panel of 348 employment zones. Outcomes variables are expressed in percentage change over six-year period. All specifications include period fixed effect and log of initial total employment. Robust standard errors are clustered at the employment zone level. *p<.10 ** p<.05, *** p<.01.

Table 4: Direct estimates of local multipliers

	(1) LM: OLS	(2) RF: ΔIPW^o	(3) FS: ΔIPW^o	(4) IV: ΔIPW^o	(5) RF: Bartik	(6) FS: Bartik	(7) IV: Bartik
$\Delta log(tradable)$	0.232***			0.586***			0.671***
	(0.046)			(0.195)			(0.155)
ΔIPW^o		-1.382***	-2.360***				
		(0.354)	(0.655)				
Bartik					0.508***	0.757***	
					(0.161)	(0.158)	
KP stat				12.99			23.01
Full set of controls	√	√	√	√	√	√	√
Region fixed-effect	√	√	√	√	√	√	√

Note: $N = 696$. Baseline sample is a balanced panel of 348 employment zones. Outcomes variables are expressed in percentage change over six-year period. All specifications include period fixed effect and log of initial total employment. Robust standard errors are clustered at the employment zone level. *p<.10 ** p<.05, *** p<.01.

Table 5: Placebo regression: private employment growth regressed on lead values of import competition

	(1) OLS: Private b/se	(2) IV: Private b/se	(3) OLS: Pre-trend b/se	(4) IV: Pre-trend b/se	(5) OLS: Lagged b/se	(6) IV: Lagged b/se
ΔIPW	-2.495***	-3.755***	-2.383***	-4.512***	-0.785	2.741**
	(0.405)	(0.790)	(0.405)	(0.959)	(0.632)	(1.300)
Pre-trend			0.142***	0.138***		
			(0.038)	(0.037)		
KP stat		32.16		35.52		32.16
All controls	√	√	√	√	√	√
Region fixed-effect	√	√	√	√	√	√

Note: Column (1) and (2) respectively report OLS and IV estimates of specification shown in Equation (2) where the dependent variable is current employment growth rate (in equivalent of 6 years) in the overall private sector. Columns 3 and 4 represent the same specification augmented with pre-trend in private sector growth as control. Columns 5 and 6 respectively report OLS and IV estimates of the same specification where employment growth in the private sector is lagged (1982-1990 for period 1995-2001, 1995-2002 for period 2001-2007). In case, long run unobserved factor driving down manufacturing employment in local labor markets is correlated with future exposure to Chinese import competition, one would expect to find negative coefficients in the Column 5 and 6.

Table 7: Impact along the wage distribution in manufacturing and the non-traded sector

	(1) avwage b/se	(2) 10th b/se	(3) 20th b/se	(4) 30th b/se	(5) 40th b/se	(6) 50th b/se	(7) 60th b/se	(8) 70th b/se	(9) 80th b/se	(10) 90th b/se
Mfg sector										
ΔIPW	-1.607**	-2.838	-1.385*	-1.513**	-1.348*	-1.176	-1.261	-1.470*	-2.238**	-2.250**
	(0.798)	(1.969)	(0.769)	(0.769)	(0.775)	(0.782)	(0.798)	(0.862)	(0.880)	(0.972)
	b/se	b/se	b/se	b/se	b/se	b/se	b/se	b/se	b/se	b/se
Non-traded sector										
ΔIPW	-0.394	0.049	-0.714***	-0.883***	-1.137***	-1.068***	-1.014***	-0.934***	-0.429	0.049
	(0.296)	(0.245)	(0.235)	(0.240)	(0.258)	(0.263)	(0.293)	(0.329)	(0.369)	(0.465)
KP stat	32.51	32.51	32.51	32.51	32.51	32.51	32.51	32.51	32.51	32.51
Full set of controls	√	√	√	√	√	√	√	√	√	√
Region fixed-effect	√	√	√	√	√	√	√	√	√	√

Note: $N = 696$. Baseline sample is a balanced panel of 348 employment zones. Outcomes variables are expressed in percentage change over six-year period. All specifications include period fixed effect and log of initial total employment. Robust standard errors are clustered at the employment zone level. *p<.10 ** p<.05, *** p<.01. Control variables include: initial share of manufacturing jobs, of female employees, of production employees, of foreign-born employees and of college educated employees. Decile are computed based on jobs reporting positive hours worked and wages, weighing by hours worked.

Table 6: Trade deficit per worker: impact on manufacturing employment

	(1) OLS: Jobs b/se	(2) IV b/se	(3) IV b/se	(4) IV b/se	(5) IV b/se	(6) IV: Hrs b/se	(7) IV: Emp. earnings b/se
ΔIPW	-4.731***	-9.981***	-7.656***	-7.661***	-7.596***	-7.425***	-10.540***
	(1.192)	(2.298)	(2.464)	(2.471)	(2.287)	(2.167)	(2.654)
% employment in mfg			-0.141**	-0.183**	-0.077	-0.075	0.068
			(0.062)	(0.075)	(0.073)	(0.078)	(0.085)
% college				-0.643***	-0.327**	-0.364**	-0.384**
				(0.174)	(0.146)	(0.151)	(0.164)
% production workers				-0.395***	-0.170	-0.177	-0.192
				(0.113)	(0.116)	(0.117)	(0.132)
% women				-1.547**	-2.019***	-2.176***	-2.445***
				(0.675)	(0.524)	(0.614)	(0.714)
% foreigners				-0.453**	-0.486**	-0.489**	-0.529**
				(0.227)	(0.212)	(0.229)	(0.255)
KP stat		26.38	16.07	16.60	17.42	17.42	17.42
Region fixed-effect					√	√	√

Note: $N = 696$. Baseline sample is a balanced panel of 348 employment zones. Outcomes variables are expressed in percentage change over six-year period. All specifications include period fixed effect and log of initial total employment. Robust standard errors are clustered at the employment zone level. *p<.10 ** p<.05, *** p<.01.

Table 8: Effect of Chinese import competition on different measures of wage inequality

	(1) $\Delta \log \frac{q_90}{q_10}$ b/se	(2) $\Delta \log \frac{q_90}{q_50}$ b/se	(3) $\Delta \log \frac{q_50}{q_10}$ b/se
Manufacturing			
ΔIPW	0.588	-1.074	1.662
	(1.914)	(0.929)	(1.547)
	(1) b/se	(2) b/se	(3) b/se
Non-traded sector			
ΔIPW	0.000	1.116**	-1.116***
	(0.500)	(0.443)	(0.298)
KP stat	32.51	32.51	32.51
Full set of controls	√	√	√
Region fixed-effect	√	√	√

Note: $N = 696$. Baseline sample is a balanced panel of 348 employment zones. Outcomes variables are expressed in percentage change over six-year period. All specifications include period fixed effect and log of initial total employment. Robust standard errors are clustered at the employment zone level. *p<.10 ** p<.05, *** p<.01. Control variables include: initial share of manufacturing jobs, of female employees, of production employees, of foreign-born employees and of college educated employees. Decile are computed based on jobs reporting positive hours worked and wages, weighing by hours worked.

Table 9: Impact along the wage-distribution depending on the "bite" of the minimum wage

	(1) $\Delta \log q_{15}$	(2) $\Delta \log \frac{q_{85}}{q_{15}}$	(3) $\Delta \log \frac{q_{85}}{q_{50}}$	(4) $\Delta \log \frac{q_{50}}{q_{15}}$	(5) $\Delta \log q_{15}$	(6) $\Delta \log \frac{q_{85}}{q_{15}}$	(7) $\Delta \log \frac{q_{85}}{q_{50}}$	(8) $\Delta \log \frac{q_{50}}{q_{15}}$
ΔIPW	-0.462**	0.323	0.929**	-0.606***	0.291	-0.166	0.856**	-1.022***
	(0.832)	(0.565)	(0.314)	(0.311)	(0.832)	(0.565)	(0.314)	(0.311)
$\Delta IPW \times S$					-1.341***	0.736**	-0.024	0.760***
					(0.237)	(0.359)	(0.343)	(0.199)
$S := I(\text{Share Min Wage} < 15\%)$					0.213	0.327	0.506*	-0.179
					(0.173)	(0.326)	(0.298)	(0.165)
KP stat	32.51	32.51	32.51	32.51	16.79	16.79	16.79	16.79
Full set of controls (see notes)	√	√	√	√	√	√	√	√
Region fixed-effect	√	√	√	√	√	√	√	√

Note: $N = 696$. Baseline sample is a balanced panel of 348 employment zones. Outcomes variables are expressed in percentage change over six-year period. All specifications include period fixed effect and log of initial total employment. Robust standard errors are clustered at the employment zone level. *p<.10 ** p<.05, *** p<.01. The share of minimum wage workers is computed as the share of workers in a given location and sector who hourly wage (*salaire brut horaire*) is comprised between 85 and 105 % of the legal minimum wage. Observations whose wage is reported below 85 % of the minimum wage are dropped. 60 % of employment zones have a share of minimum wage jobs larger than 15 % in the non-traded sector.

8 Figures

Figure 1: Imports and trade balance of France with respect to China and other low-wage countries (list based on Auer *et al.* (2013))

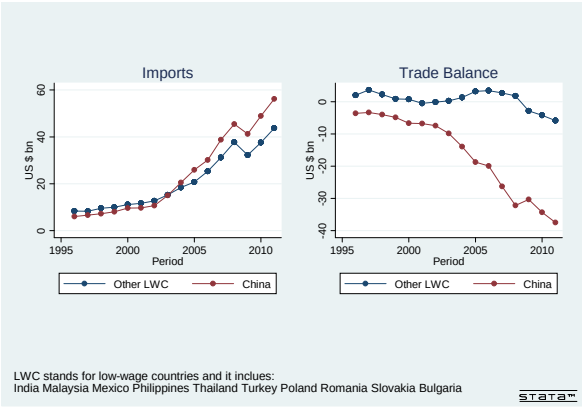
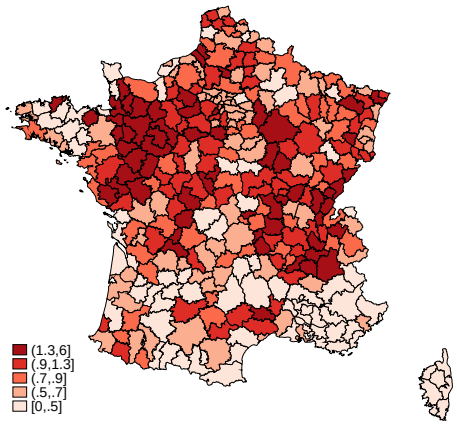
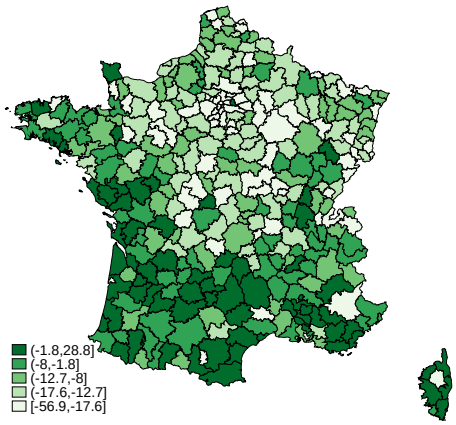


Figure 2: Exposure to Chinese import competition and employment growth (2001-2007)

(a) ΔIPW



(b) Δ ln(tradable)



(c) Δ ln(non-tradable)

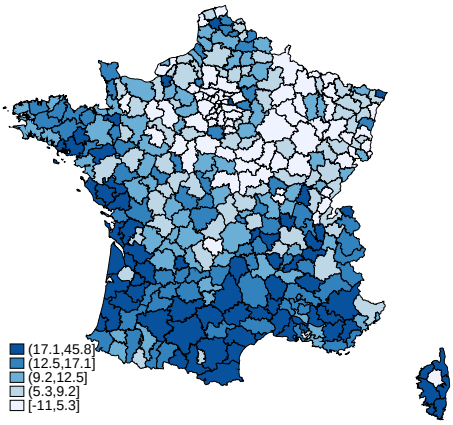
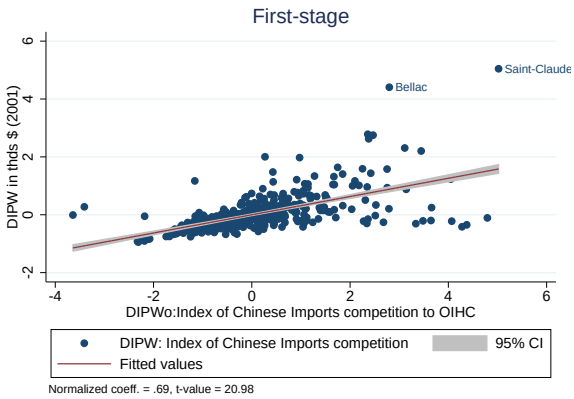
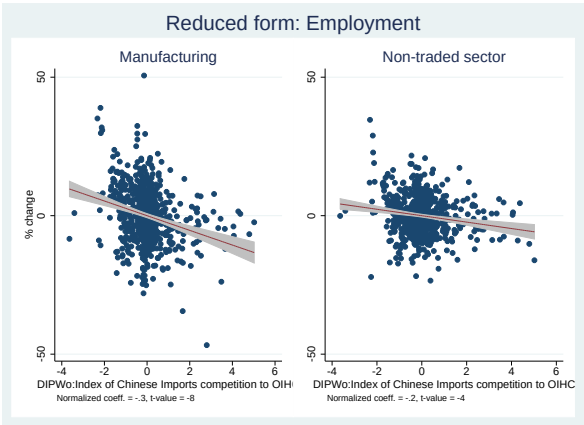


Figure 3: First stage



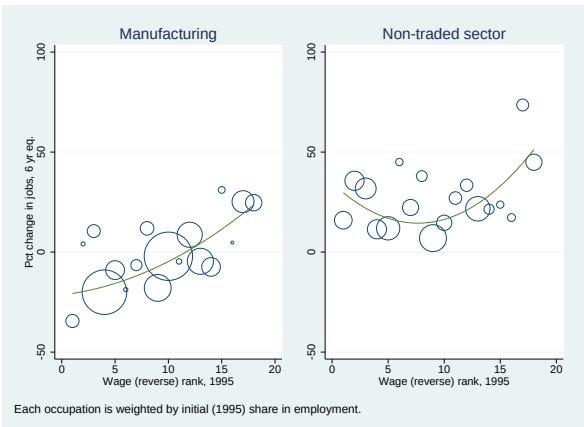
Note: Each dot represents an employment zone for a given period (1995 to 2001, 2001 to 2007). Variables are expressed in deviation from period average. The two outliers in the North/North-West of the graph correspond to two heavily specialized employment areas. The one in the left is specialized in apparel (18% of employment in 2001), the one on the right is specialized in the manufacturing of plastic products (12% of employment). In these two sectors, Chinese exports to France grew at a faster pace than towards others high income countries..

Figure 4: Reduced form



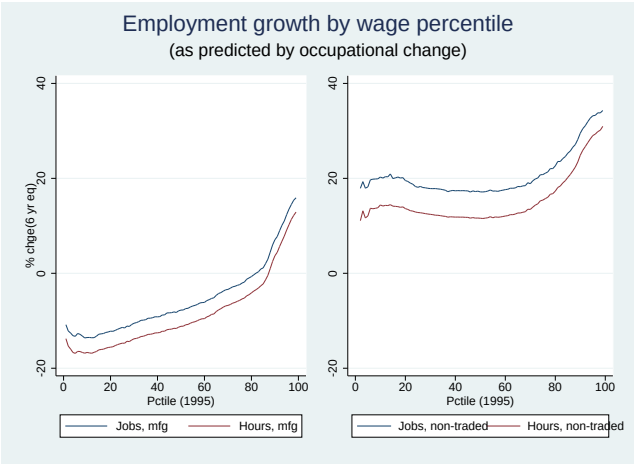
Note: Each dot represents an employment zone for a given period (1995 to 2001, 2001 to 2007). Variables are expressed in deviation from period average.

Figure 5: Employment growth by occupations



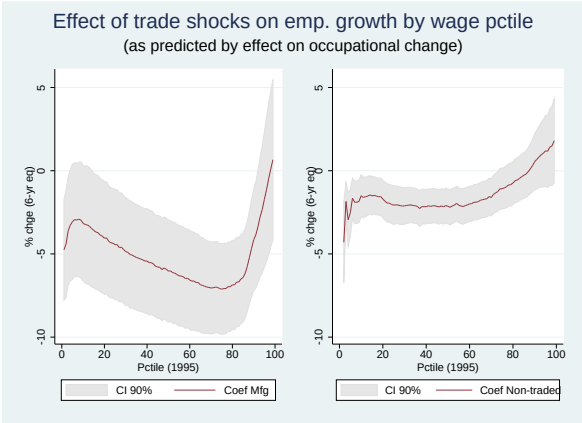
Note: The green line represents a quadratic fit.

Figure 6: Employment growth by wage percentile and occupational change



Note: The main line is obtained by reweighing occupation-sector specific growth rates over the period 1995-2007 (re-expressed in 6 year equivalent growth rates) according to the formula presented in Equation (6).

Figure 7: The impact of Chinese import competition on employment growth by wage percentile (based on occupational change)



Note: Each coefficient plotted comes from the same specification including of controls and region fixed-effects. Control variables include: initial share of manufacturing jobs, of female employees, of production employees, of foreign-born employees and of college educated employees.

Figure 8: The impact of Chinese import competition along the wage distribution

Note: Each coefficient plotted comes from the same specification, including the full set of controls and region fixed-effects. Control variables include: initial share of manufacturing jobs, of female employees, of production employees, of foreign-born employees and of college educated employees.

A Linking trade and employment data

We use data on trade from the website `un.comtrade.org`. The trade data follow the product classification HS 1992 with 6 digit. The data on employment follows the NACE rev 1.1. classification which is equivalent to the 4-digit CPA 2002 classification. To convert HS-1992 6-digit codes into NACE 4-digit codes, we do the following:

1. We use a file available on `un.comtrade.org` to map HS-1992 into HS-2007.

2. We use one file available on `http://ec.europa.eu/eurostat/ramon` to map HS-2007 into CPA 2002. The latter maps n-to-one to the NACE rev 1.1.

3. We obtain a correspondence mapping from HS-1992 into NACE rev. 1.1. All HS-1992 6-digit goods that are not uniquely mapped with a NACE 4-digit sector divided across NACE sectors using weights reflecting each sectors initial "importance" in the economy (the weights are the employment share in 1995). Non-uniquely mapped goods account for about 9 %, 8 % and 6% of French imports from China for years 1995,2001 and 2007 respectively.

Table 10: Total French Imports: Uniquely and Non-Uniquely Mapped ($ millions)

	Total	Uniquely	Non-uniquely	Ratio
1995	5,950	5,385	565	.095
1996	6,833	6,236	597	.0873
1997	7,495	6,874	621	.0828
1998	8,178	7,505	673	.0823
1999	8,943	8,237	706	.079
2000	10,515	9,670	845	.0803
2001	10,450	9,635	815	.078
2002	11,380	10,506	874	.0768
2003	15,850	14,660	1,190	.0751
2004	21,398	19,871	1,527	.0714
2005	26,748	24,737	2,011	.0752
2006	30,968	28,652	2,316	.0748
2007	39,533	37,015	2,518	.0637

Note: A product code HS-1992 is considered "uniquely mapped" if according it is uniquely mapped according to our mapping HS-1992→HS-1996 → NACE built using the conversion tables from RAMON (HS 2007 to CPA) and Comtrade (HS1992 to HS2007). Each observation for product HS1992 that cannot be uniquely mapped to a NACE sector is dropped (either because there is no mapping or the mapping is not unique). Column (4) displays the the trade value non-uniquely matched products as the share of overall imports French imports from China. Trade values are expressed in current dollars.

B Details on the occupation classification

The DADS postes dataset documents occupation at the two-digit level consistently over the period for 18 occupations which accounts for an overwhelming share of overall employment and hours worked (respectively 93.94 and 94.09 % in 1995). I must exclude workers doing an apprenticeship or an internship from the sample as it is not possible to match them consistently to a two digit occupation over the period. Table 11 displays the different occupations, their labels and their initial share of employment.

In the remainder of the appendix, I detail some example of jobs included in the main occupations that are not self-explanatory.[36]

The first category numbered 68 labelled "Unskilled nonspecialized workers" includes such jobs as cleaners and unskilled construction workers.

Category 56 "Personal service workers" includes professions such as hairdressers, waiters or hotel workers.

Category 55 includes different types of more or less specialized basic retail jobs (e.g. floor-level sales person, cashier).

Category 67 "Unskilled industrial workers" includes mainly jobs in the manufacturing sector (production workers in chemistry, textile etc.) and some in non-manufacturing activities, for instance unskilled warehouseman in transport industry or in private postal services.

Category 63 "Skilled nonspecialized workers" includes skilled manual jobs such as plumber, electricians, food related activities (bakers, butchers) and mechanics.

Category 65 "Skilled warehouse and handling workers" includes skilled drivers and warehousemen, for instance those operating heavy equipment (e.g. large trucks).

Category 62 "Skilled industrial workers" includes skilled manual jobs mainly pertaining to manufacturing activities (e.g. welder working with specific types of metals, certain assembly line workers) or construction (e.g. team leader in civil engineering, worker specialized in specific types of concrete).

Category 47 "Technicians" includes many technical professions predominantly employed in manufacturing (e.g. industrial designer) or in construction (e.g. projector, building surveyor).

[36] More details can be found (in French) at the following link: http://www.insee.fr/fr/methodes/default.asp?page=nomenclatures/pcsese/pcsese.htm. While the dataset DADS documents occupation at the 4-digit levels, these detailed definition are not consistent overtime, thus constraining us to work at the 2 digit level.

Table 11: Information on occupations

Code	Label	Rank	Share 1995 (%)	Broad-Skill Category
68	Unskilled nonspecialized workers	18	5.15	Low
56	Personal service workers	17	5.48	Low
55	Retail workers	16	6.91	Low
67	Unskilled industrial workers	15	11.67	Low
63	Skilled nonspecialized workers	14	9.07	Low
53	Security workers	13	0.86	Low
64	Drivers	12	4.24	Low
65	Skilled warehouse and handling workers	11	2.33	Low
54	Administrative workers	10	12.94	Low
62	Skilled Industrial Workers	9	10.83	Low
43	Health and social work intermediate profession	8	2.44	Intermediate
47	Technicians	7	4.26	Intermediate
46	Intermediate administrative workers	6	10.96	Intermediate
48	Foremen	5	2.63	Intermediate
35	Information and entertainment professionals	4	0.92	High
34	Scientific professionals	3	4.73	High
38	Engineers and technical professionals	2	0.95	High
37	Sales executives	1	3.61	High

Category 46 "Intermediate administrative work" includes jobs such as representatives and travelling salesman.

Category 48 "Foremen" includes mainly mid-level managers jobs in manufacturing, in construction and tertiary activities (store manager).

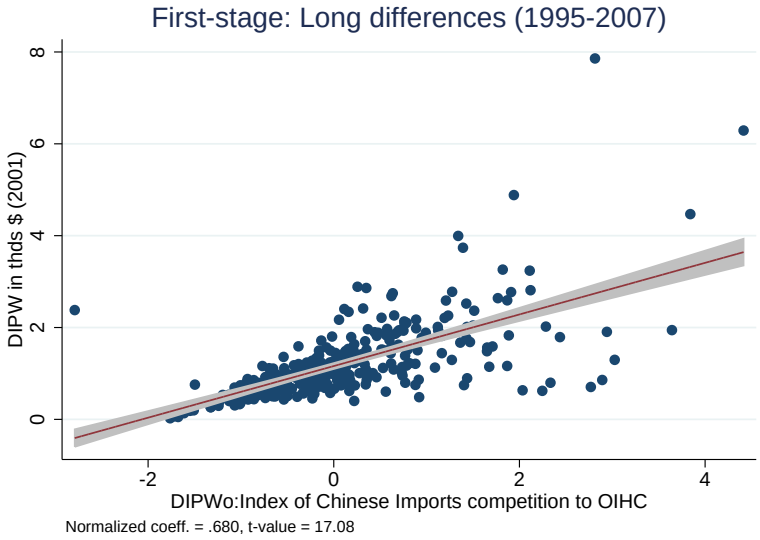
The column broad skill category refers to the categories used in the Table OA1 and is based on a 1-digit classification.

Online Appendix

This online appendix includes additional results and robustness checks.

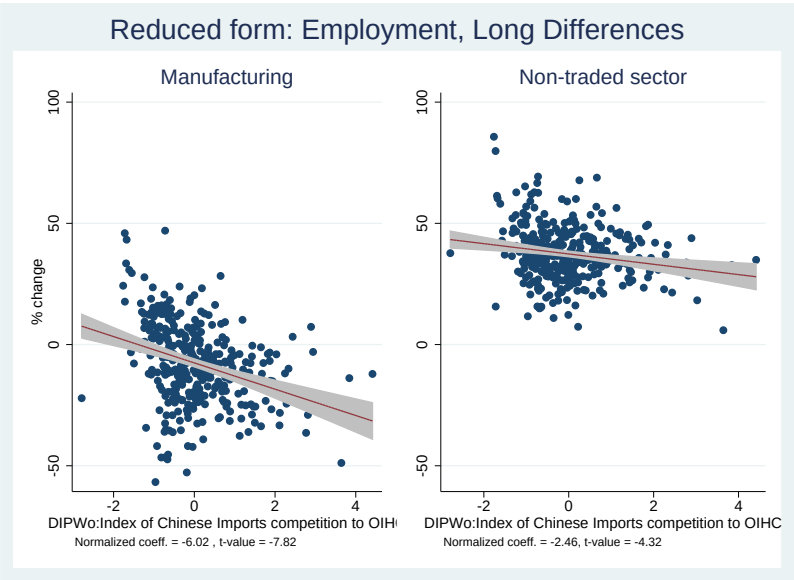
A Additional figures

Figure OA1: First stage: Long-differences



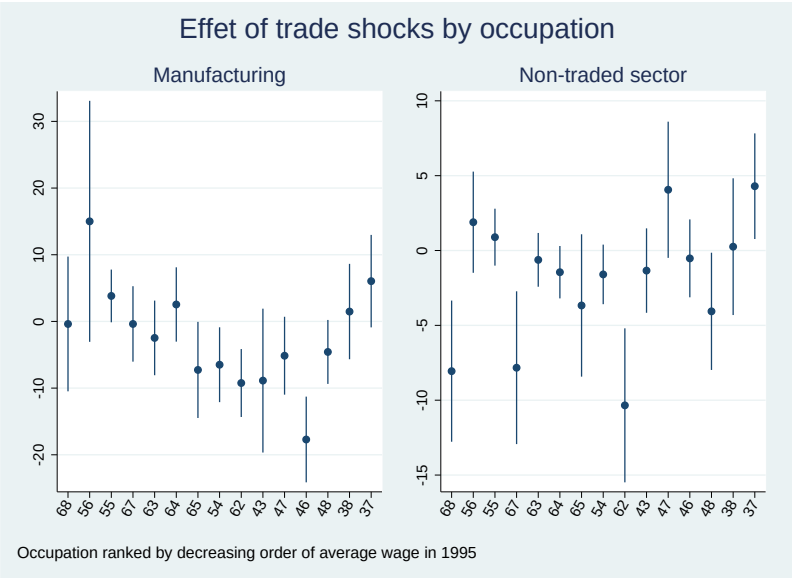
Note: Each dot represents a employment zone over the 12 year period 1995-2007.

Figure OA2: Reduced form: Long-differences



Note: Each dot represents a employment zone over the 12 year period 1995-2007.

Figure OA3: Employment growth by occupations



Note: Labels on the horizontal axis refer to the 2-digit occupations. See Appendix Section B for more details on the occupational classification.

Other tables

Table OA1: Impact on employment by skill category: manufacturing and non-traded sector

	(1) Low Skill b/se	(2) Intermediate Skill b/se	(3) High skill b/se	(4) Low Skill b/se	(5) Intermediate Skill b/se	(6) High skill b/se
Manufacturing						
ΔIPW	-3.638**	-13.024***	-2.631	-3.360**	-13.481***	-2.655
	(1.681)	(3.159)	(3.603)	(1.523)	(3.170)	(3.643)
Non-traded sector						
ΔIPW	-5.909***	-2.980*	5.686**	-4.987***	-1.899	4.950**
	(1.420)	(1.662)	(2.513)	(1.099)	(1.386)	(2.400)
KP stat	32.51	32.51	32.51	32.51	32.51	32.51
Controls (see notes)	√	√	√	√	√	√
Region fixed-effect				√	√	√

Note: $N = 696$. Baseline sample is a balanced panel of 348 employment zones. Outcomes variables are expressed in percentage change over six-year period. All specifications include period fixed effect and log of initial total employment. Robust standard errors are clustered at the employment zone level. *p<.10 ** p<.05, *** p<.01. Control variables include: initial share of manufacturing jobs, of female employees, of production employees, of foreign-born employees and of college educated employees. Skill categories are based on occupation. Clerk and unskilled production workers are considered low skill occupations. Intermediate professions and low-rank managers are considered medium skill occupations, while intellectual professions, senior management are considered high-skill occupations.

B Formulating aggregate predictions on the basis "deviation from cross-sectional average" estimates

Without an assumption regarding period specific intercept (written η_t in Equation 2), finding a negative estimate for β does not allow to distinguish which of the two following statements applies:

1. Trade with China boosts manufacturing employment in France overall but relatively less in place with high exposure to direct Chinese competition.

2. Trade with China reduces manufacturing employment in France overall but relatively more in place with high exposure to direct Chinese competition.

Therefore one cannot make aggregate predictions from micro-estimates without some additional assumption regarding how the period-specific intercept which captures nationwide general equilibrium effects relates to the evolution of Chinese import competition.

The goal of this appendix is to illustrate the the difference between the set of assumptions required to obtain consistent estimate of individual effect and the set of assumptions required to make aggregate predictions. To do so, it focuses on a simple univariate linear data generating process.

Let us consider the following GDP:

$$y_i = \mu + x_i\beta + u_i \tag{9}$$

We assume $E(x_i u_i) = 0$, so that we sidestep issues associated with endogenous regressor. For simplicity and without loss of generality, we also assume that $E(x_i) = 0$. Realization of x_i and u_i are assumed to be i.i.d.

Now, we specify μ as being a function of the (un-weighted) sample mean $\overline{x}_N$.[37]

$$\mu := \mu(\overline{x}_N) = \delta + \overline{x}_N\alpha \tag{10}$$

So while δ and α are fixed parameters, μ is itself a random variable. Note also that $\overline{x}_N\alpha$ introduces a rough notion of spill-overs between units i's. Hence while x_i and u_i are i.i.d, y_i are

[37] The use of a weighted mean does not change the nature of the argument.

not.[38]

In this context, making an "aggregate prediction" is to analyze of the conditional expectation of the cross-sectional average of y_i's conditional on that of x_i's, i.e. $E(\overline{y}_N|\overline{x}_N)$. Under the stated assumption, we have:

$$\frac{\partial E(\overline{y}_N|\overline{x}_N)}{\partial \overline{x}_N} = \alpha + \beta \tag{11}$$

This expression contrasts with the individual effect of x_i on the conditional expected value of y_i.

$$\frac{\partial E(y_i|x_i)}{\partial x_i} = \alpha \times \frac{\partial E(\overline{x}_N|x_i)}{\partial x_i} + \beta = \frac{\alpha}{N} + \beta \tag{12}$$

Throughout the paper, we include period-fixed effect, which in the context of the DGP above, is akin to using an OLS estimator in deviation from the cross-sectional average.

$$\hat{\beta}_{OLS} = \frac{\sum_{i=1}^{N}(y_i - \overline{y}_N)(x_i - \overline{x}_N)}{\sum_{i=1}^{N}(x_i - \overline{x}_N)^2} \tag{13}$$

Substituting Equations 9 and 10, we obtain:

$$\hat{\beta}_{OLS} = \beta\frac{\sum_{i=1}^{N}(x_i - \overline{x}_N)(x_i - \overline{x}_N)}{\sum_{i=1}^{N}(x_i - \overline{x}_N)^2} + \frac{\sum_{i=1}^{N}(u_i - \overline{u}_N)(x_i - \overline{x}_N)}{\sum_{i=1}^{N}(x_i - \overline{x}_N)^2} = \beta + \frac{\sum_{i=1}^{N}(u_i - \overline{u}_N)(x_i - \overline{x}_N)}{\sum_{i=1}^{N}(x_i - \overline{x}_N)^2} \tag{14}$$

Clearly under the assumption $E(x_i u_i)$, we have plim $\hat{\beta}_{OLS} = \beta$.

It suggests that in the case where the common intercept is a function of the mean of the regressor, using cross-sectional variation in deviation from the aggregate trend only allows to obtain an approximation of $\frac{\partial E(y_i|x_i)}{\partial x_i}$. However, as N grows to infinity,[39] we have: $\frac{\partial E(y_i|x_i)}{\partial x_i} \longrightarrow \beta = \text{plim } \hat{\beta}_{OLS}$. Hence assuming $\alpha = 0$ is not required to retrieve consistent estimates of $\frac{\partial E(y_i|x_i)}{\partial x_i}$.

However, $\frac{\partial E(\overline{y}_N|\overline{x}_N)}{\partial \overline{x}_N}$ does not become arbitrarily close to β as N grows large. Moreover, α cannot be identified using an estimator based on deviations from the cross-sectional average. As

[38] It is a special case of a spatial lagged in x model where the weighing matrix contains only $1/N$ as entries. It is straightforward to extend the argument to more general weighing matrix, allowing for instance $\overline{x}_N\alpha$ to be a weighted rather than a simple average, as long as the weights are not i-specific, therefore ensuring that aggregate effects can be properly "taken out" by demeaning.

[39] I focus on asymptotic results because in the paper, estimation is carried out using instrumental variable estimator which has desirable properties asymptotically but not in finite samples. Moreover, given the large number of observations (348 by cross-section) it seems reasonable to consider the case where $\alpha/N \approx 0$.

a result, when making aggregate predictions, it becomes necessary to make an assumption on the sign and magnitude of α. I assume $\alpha = 0$ throughout the paper, which appears to lead to conservative predictions as one would expect negative spill-overs across local labor markets, particularly given the absence of reallocation of population across local labor markets (which would be an important channel for positive spill-overs, see footnote 19).