# Trade and Inequality: Evidence from Worker-Level Adjustment in France*

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**Abstract**

We use nationally-representative matched employer-employee panel data to investigate the effect of Chinese import competition on French workers between 2001 and 2006. We document a negative impact of Chinese import competition on earnings for workers in the bottom third of the earnings distribution. The effect of Chinese competition is negligible on workers with higher earnings. In addition, we exploit the richness of the dataset to document novel margins of adjustment. First, we show that the decline in earnings in the bottom third is accounted by a reduction in hours worked, while wages per hour are not significantly affected by Chinese competition. Workers in the bottom third experience reductions in the number of hours per working contract and more churning across employers. Second, we show that low-earners are relatively more likely to change occupations in response to a trade shock and to switch to relatively lower-paying occupations.Low-earners are also relatively more likely to stay in the same industry. Finally, we also document that Chinese competition increases the probability of changing the place of residence, which mostly occurs for workers who also change the industry they work in.

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# 1 Introduction

One of the most important changes in international trade in the last twenty-five years has been the increasing role of China in the world economy. The French economy, as the vast majority of developed economies, has experienced a spectacular increase in imports from China.[1] For example, the value of Chinese imports increased by 461,2% between 2000 and 2013. By contrast, in the US, the growth was 383,4% over the same period.

This paper studies how French workers adjust to the increase of import competition from China. We exploit a rich matched employer-employee panel data set to analyze different margins of worker adjustment. Our starting analysis and identification strategy follows the work of Autor et al. (2014) for the United States. We use China's growth in exports to France between 2001 and 2006 at the industry level as an exogenous trade shock (after being properly instrumented) and document their impact on worker earnings.[2] The richness of our dataset allows us to analyze the effect of import competition along several dimensions that go beyond what is possible in the U.S. with social security records as done by Autor et al. (2014). We analyze the effect of Chinese competition on wages, hours worked, number of jobs, number of employers and the probability of changing occupation, industry and place of residence.

We first document the effect of Chinese competition on worker earnings. We find that the effect of Chinese competition is heterogenous across the income distribution. Only workers in the bottom third of the distribution are significantly affected by Chinese competition. Quantitatively, the average manufacturing worker in the bottom tercile experienced a reduction in cumulative earnings over the 2001-2006 period of 3.5% of her 2001 earnings. This effect varies substantially depending on the exposure of the industry in which workers are employed in 2001. We find that a worker in the bottom third of the earnings distribution who is initially employed at a highly exposed industry (90th percentile) looses 10% more of her 2001-earnings than a worker initially employed in a low-exposure industry (10th percentile). These results are in contrast with the findings of Autor et al. (2014) for the U.S., who find a significant effect on the average worker.

Then, we analyze how different adjustment margins contribute to the decline in earnings. In particular, we start by decomposing earnings as average wage per hour times total hours worked. We estimate the effect of Chinese competition on these two margins. We show that the decline in earnings is driven by reductions on the number of hours worked, while average wages remain unaffected by Chinese competition. We find that the average effect of Chinese exposure on a worker in the bottom tercile is to reduce hours worked over the 2001-2006 period by 3.3% of the total hours worked in 2001. This amounts to a reduction of around

[1] Figure 1 reports the evolution of Chinese imports in France.

[2] The 2001-2006 is the period of faster rise in Chinese exports. China joined the WTO in December 2001. We finish in 2006 because we want to exclude the effects of the Great Recession, which started on August 2007. Our results are robust to a wider time window.

67 hours. If we compare a worker initially employed in an industry at the 90th percentile of Chinese exposure relative to a worker employed in an industry the 10th percentile, our estimates imply a decline in hours worked over the 2001-2006 period that represent 8.7% of the hours worked in 2001. This amounts to 176 hours less hours worked for the more exposed worker.[3]

To further understand why low-earning workers experienced a larger fall in the number of hours worked, we decompose hours worked in average hours worked per employer times the number of employers over the 2001-2006 period. We show that workers initially exposed to Chinese competition have lower average hours worked per employer, and this effect is especially large for workers in the bottom third of the wage distribution. The number of employers of workers initially exposed to Chinese competition has also increased and more so for workers in the bottom third of the earnings distribution. These results imply an increase in job churning across low-earners. To the extent that job turnover is costly and that employers may invest less in human capital of workers with short employment spells, this is an additional margin that may make low-earners worse-off than high-earners.

The second major dimension of adjustment that we analyze is worker mobility We start investigating the effect of import competition on worker mobility across occupations and industries. Our first piece of evidence focuses on changes in occupations. We find that low-earner workers are more likely to change occupation in response to trade competition than high-earners (38% more on average). Moreover, when switching occupations, low-earners are much more likely to downgrade to lower-earning occupations (relative to their initial occupation) than high-earners. Then, we analyze the effect of import competition on changing industries. We document that high-earners tend to avoid downgrading their occupations by switching industries: high-earners are much more likely (29%) to change industries as a response to Chinese competition than low-earners. Lastly, we also analyze how changes in occupations interplay with the industry in which a worker is employed. We show that low-earners are 35% more likely than high-earners to change occupation but stay in the same industry. In contrast, high-earners are 20% more likely to stay in the same occupation but change industry. These results paint a picture consistent with the view of low-earners being "stuck" in industries and churning across jobs and occupations in the same industry, while high-earners being able to switch more easily across industries without changing occupation (and presumably being able to keep their occupation-specific human capital).

Finally, we exploit the regional information in our dataset to analyze the effect of import competition on geographical mobility. We find a positive effect of Chinese competition on the probability of changing place of residence. However, our main finding is that changing

[3]If we decompose the effect on hours worked between the extensive margin (exiting hour sample) and the intensive margin (working less hours), we find that both these effects are present. Most of the variation appears to be driven by changes in the intensive margin.

the place of residence is a by-product of changing industry. That is, while trade increases the probability to change employment zone (EZ) and industry, it does not change the probability to change EZ and stay in the same industry. An implication of this result is that the spatial distribution of industries may shape the effect of a trade shock on workers. Namely, the more diversified is the industry composition of a region, the less workers need to change EZ to work in another industry.

*Related literature.* This paper relates to several strands of the literature that studies the labor market impacts of international trade. First it relates to the relatively large and emerging literature that uses longitudinal administrative datasets to analyse the worker-level effects of trade, such as Menezes-Filho and Muendler (2007), Autor et al. (2014), Dauth et al. (2014, 2016, 2017), Keller and Utar (2016) and Dix-Carneiro and Kovak (2017). The present paper adds to this literature by looking at the differential effect of trade between across the earning distribution a broad set of outcomes.

A recent and fast-growing class of papers has been focusing on the regional effects of trade. It includes Topalova (2007), Autor et al. (2013), Kovak (2013), Balsvik et al. (2015), Hakobyan and McLaren (2016), Malgouyres (2016) and Dix-Carneiro and Kovak (2016). Studies of this kind focus on the dynamics of regions while, in this paper, we are interested in the dynamics of workers.

## 2 Empirical Strategy

Our empirical strategy follows Autor et al. (2014) to identify the effect of trade competition on worker outcomes. This approach exploits the variation across industries in the evolution of exposure to Chinese imports. Our measure of Chinese Exposure in industry $j$ is

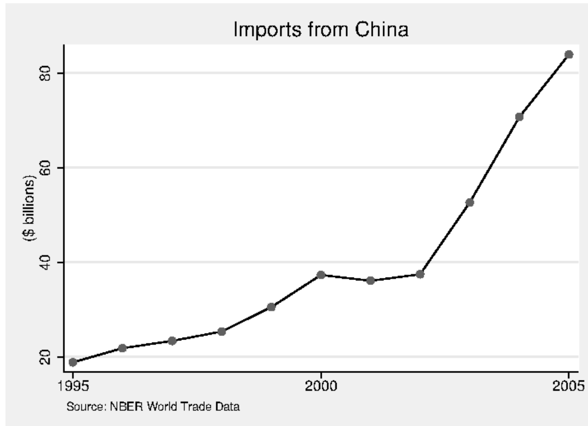
$$CX_j = \frac{\Delta M^{FC}_{j,2006-2001}}{Y_{j,2001} + M_{j,2001} - E_{j,2001}},$$

where $\Delta M^{FC}_{j2001-06}$ is the change in French imports from China between 2001 and 2006 and $Y_{j,2001}+M_{j,2001}-E_{j,2001}$ is initial absorption (measured as industry sales, $Y_{j,2001}$, plus industry imports, $M_{j,2001}$, minus industry exports, $E_{j,2001}$).

The years we study comprise one of the period of major growth of Chinese exports to France. The year when our measure starts, 2001, coincides with China joining the World Trade Organization. Figure 1 documents the evolution of French imports from China. It is clear that, after joining the WTO in December of 2001, the growth rate of Chinese exports increased substantially. We choose our ending date to be 2006 to avoid potential confounding effects of the Great Recession.[4]

[4] In the Online Appendix we show that our results are robust to extending the sample.

Figure 1: Evolution of French Imports from China




To identify the causal effect of Chinese competition, we need to instrument our measure of Chinese exposure. We follow Autor et al. (2014) and instrument $CX_j$ with

$$CXO_j = \frac{\Delta M^{OC}_{j,2006-2001}}{Y_{j,1998} + M_{j,1998} - E_{j,1998}}, \tag{1}$$

where $M^{OC}_{j,2006-2001}$ is the change in imports from China in industry $j$ by a group of high-income countries other than France (which we discuss below). There are two differences between the instrument and our measure of Chinese exposure. First, in the numerator there is the change in imports from a group of high-income countries other than France. Second, the numerator is a lag of initial absorption. Since the exclusion restriction requires that the industry where the worker is employed in 2001 to be independent of Chinese trade, we use lag measures (year 1998) of industry outcomes because workers and/or firms may have anticipated the rise in Chinese imports and changed their behavior accordingly.

We instrument changes in French imports with imports from other countries because we want to capture changes driven by Chinese imports shocks that are orthogonal to changes in French demand. Thus, by using changes in imports from similar countries, we capture the common component of Chinese competition driven by the improvements in Chinese exporting capabilities (for example, lower trade barriers due to China joining the WTO and/or lower production costs). To select these high-income countries, we follow Dauth et al. (2014), who applied the same identification approach to Germany. This group is formed by countries with an income level similar to France and outside the European Monetary Union. In particular, the group of countries consists of Australia, Canada, Japan, Norway, New Zealand, Sweden, Singapore, and the United Kingdom.[5]

[5]In the Online Appendix we show that our results are robust to using the same control group as in Autor et al. (2014).

# 3 Data

## 3.1 Measure of Industry Exposure

To compute our measure of industry exposure, we use disaggregated import-export data from Comtrade. To make our results comparable to Autor et al. (2014), we convert the data from the HS classification to the SIC classification. This allows us to define industries and industry controls as in Autor et al. (2014). [6]

To illustrate the extent of the heterogeneity of the shock across industries, Figure 2 plots the distribution of our measure of Chinese exposure across industries.

We want to emphasize two things. First, there is a lot of heterogeneity across industry groups. The group with the highest value of average exposure is textile with 15.95. In contrast, the average exposure of paper is null. This ranking of Chinese competition is very similar to the ranking in the U.S. in Autor et al. (2014). This is what we would expect given that the increase in Chinese imports was mainly driven by the change in supply of goods (either due to lower production costs in China or a reduction in trade costs). Second, we can see that there is a lot of variation within each industry group. This implies that to understand the effect of Chinese competition on labor outcomes we need to have disaggregated data.

Finally, notice that there is not a clear correlation between exposure and the share of production workers in 2001. This lack of correlation could suggest that Chinese competition did not have a significant effect for the average worker in France. However, the large dispersion on exposure suggests that some French workers may be more hit than others. This relationship was different in the U.S.. Autor et al. (2014) find a positive correlation between exposure and share of manufacturing workers.

## 3.2 Employment data

Our main source of information on workers is the matched employer-employee panel DADS (in French Déclaration Annuelle de Données Sociales) collected by the French National Institute for Statistics (INSEE).

The panel DADS contains earning histories for all individuals born in even-numbered years in October, which corresponds to slightly more than 4% of French population working in private sector. We can follow these individuals over time as they are attributed a unique identifier. An individual exits the sample if and only if her labor supply for one year was zero for a given year of if she switches to a sector non-covered by the DADS (e.g. moving abroad, moving into unemployment or self-employment, or dropping out of the labor force). Our data spans the period 1994-2010. However, as discussed above, we focus on 2001-2006 in our baseline regressions and show in Online Appendix that the results are robust to expanding

[6] We use the same cross-walk used in Autor et al. (2013).

the sample. We follow Autor et al. (2014) and restrict our sample to private-sector attached workers.

The DADS are collected from compulsory fiscal declarations made annually by all employers for every single worker. Reported wages are used to compute income taxes. Misreporting is severely punished with fines, which guarantee the high quality of the data.

In addition to wages, the data contains information on other variables of interest. For example, number of hours worked, place of work and place of residence (both at the municipality level), industry, type of contract and occupation. Occupations are defined through the PCS classification (The Classification of Professions and Socio-professional Categories). At the 2-digit level, the classification has 22 positions listed in appendix table 8. As suggested by their labels and their average wage differences, occupations vary in their skill content. It is therefore likely that occupations are differently affected by Chinese competition.

An important advantage our dataset is that we have information on the number of hours worked. This information will allow us to better understand the effect of Chinese competition on the extensive margin. As emphasized in Autor et al. (2014), they only have data on the number of years with positive income, which may underestimate the effect of trade on the extensive margin.

Table I contains summary statistics for the main outcomes. Column 1 reports the statistics for the main sample of attached workers, while Column 2 focusses on workers employed in the manufacturing sector. Note that the average attached worker (column 1) had cumulative earnings over 2001 to 2006 of 5.26 times her initial incomes, had a decline of 11.5 percentage points in hours worked and an increase in hourly wage of 9.59 percentage points.

# 4 The Effect of Chinese Competition on Earnings

## 4.1 The Impact of Trade Exposure on Worker Earnings

We start analyzing the effect of Chinese competition on the cumulative earnings of the average worker over the 2001-2006 period. We estimate the linear model

$$\Delta y_{ij} = \alpha + \beta CX_j + \gamma_i X_i + \gamma_j X_j + \varepsilon_{ijt}, \tag{2}$$

where $\Delta y_{ij}$ denotes cumulative earnings between 2006-2001 normalized by 2001 earnings for worker $i$ working in industry $j$ in 2001, $CX_j$ is Chinese exposure in France, $X_i$ are worker control variables and $X_j$ are industry control variables. In addition, we include a dummy for being a woman, dummies for tenure, firm size and labor market experience, industry fixed effects (3-digit), birth-year fixed effects and control for pre-trends for the 1999-2001 period.[7]

[7]The dummy bins for experience are 0-3 years, 4-5 years, 6-8 years, 9-11 years, 12+ years. The dummy bins for tenure are 0-1 year, 2-5 years, 6-10 years, 11+ years. The dummy bins for firm size are 1-99 employees,

We report regressions using two measures of cumulative earnings. The first measure is cumulative earnings over 2001 to 2006 normalized by initial earnings. This measure imputes zero earnings when a worker drops out of the labor force. As such, this measure captures both the extensive and intensive margins of adjustment. That is dropping from being a wage earner or having changes in earnings (without them dropping to zero). Since we are also interested in the outcomes of workers conditional on remaining on the labor force, our second measure normalizes cumulative earnings also by the number of years worked in the 2001-2006 period. This latter measure inform us of changes in the intensive margin of earnings.

Columns (1) and (2) of Table 1 reports the OLS estimates of running (2) for the two outcome measures. We find a coefficient of -.39, significant at 10%, in column (1). This implies that the average decline in earnings implied by the OLS is around 1.2% of the 2001 earnings. The second measure of the change in earnings is also negative albeit insignificant.

To correct for the endogeneity of Chinese exposure, we use the instrument for Chinese exposure of industry $j$, $CX_j$ explained in Section 2, equation (1). The effect of trade on cumulative earnings by running 2SLS on equation (2) is reported in columns (3) and (4). Note that this is the same regression as in Autor et al. (2014). The coefficient of exposure is negative but only significant at 10 percent. This result implies that we find only very mild support for the hypothesis that the average worker in a more exposed industry did experience a significantly different evolution on earnings than a worker in a less exposed industry. The estimated coefficinet of $-.55$ in column (3) implies that the effect for the average industry (which has exposure of 3%) is $-.55 \times 3\% = -1.7\%$ of the 2001 earnings. Comparing an industry at the 90th percentile of exposure to one in the 10th, the difference in earnings is $-.55 \times 7.9\% = -4.4\%$. The corresponding number for the 75th to 10th split is $-.55 \times 2\% = -1.1\%$. This result is in contrast to the findings of Autor et al. (2014) for the U.S. labor market, who find a larger ($-14\%$ difference) and significant negative coefficient.

#### 4.1.1 Trade and Earnings Inequality

The estimated coefficient on the average worker may hide heterogeneous effects of Chinese import competition across different types of workers. For example, low-earning workers may negatively affected, while high-earners may be unaffected, resulting on a mildly negative average effect. In order to investigate the effects of Chinese competition on earnings inequality, we interact trade exposure with the earnings tercile of the worker in her cohort. In other words, our baseline regression augments the previous regression with the interaction between industry exposure and workers' earnings tercile,

$$\Delta y_{ij} = \alpha + \beta CX_j + \delta CX_j T_i^{2001} + \gamma T_i^{2001} + \gamma_i X_i + \gamma_j X_j + \varepsilon_{ijt}, \quad (3)$$

100-999 employees and 1000+. These controls are chosen to mimic the set of controls as in Autor et al. (2014).

where $T_i^{2001}$ is the tercile of worker $i$ in the earnings distribution in 2001 (normalized by the second tercile). The main coefficient of interest is $\delta$. If $\delta$ is different from zero, it means that the effect of Chinese competition depends on the initial position of the worker on the earnings distribution.

Columns (5) and (6) in Table 1 report the coefficients of running this regression with our two measures of cumulative earnings. For ease of exposition, we do not report the coefficient on the earnings tercile dummies but it is included in both regressions. We normalize the tercile of the worker with the second tercile, so that the coefficient $\beta$ can be readily interpreted as the effect of trade exposure for the worker in the second tercile of the earnings distribution in 2001. Note that the interpretation of this coefficient is different from columns (1) to (4). The fact that that the coefficient of exposure is more significant for columns (3) than (1), implies that the effect of exposure of the median worker (in the second tercile) is different than the average worker. That is, whereas the average worker is slightly affected by Chinese competition, cumulative earnings of the median worker are significantly lower. This finding underscores the need of analyzing the trade affect across the income distribution.

Our coefficient of interest, the interaction term, is positive and statistically significant in both columns. These coefficients imply that the effect of trade on cumulative earnings is heterogenous on the earnings of the workers. That is, for the same level of Chinese import penetration, low-earnings workers are more affected than high-earnings workers. It means that trade with China induced an increase in earnings inequality in France. Autor et al. (2014) find a similar result when splitting the sample in terciles according to the position of the worker in the earnings distribution with respect to her cohort.

Quantitatively, the effects for the average worker in the bottom tercile are as follows. For a worker employed in the average French industry Chinese competition implies a decline $(-1.63) \cdot 3\% = -4.9\%$ of her 2001 earnings. Comparing an average worker of the bottom earnings tercile employed to a highly exposed sector (90th percentile) to a shielded sector (10th percentile) we find a difference in the effect of $(-1.63) \cdot (7.9\% - 0\%) = -12.9\%$ of 2001 earnings.

From this analysis we conclude that Chinese competition had a large effect on earnings inequality. Workers in the top of the earnings distribution were barely hit (modest positive effect) by Chinese competition. In contrast, low-earnings workers experienced a large reduction in earnings.

These findings are confirmed by running a more flexible estimation in which we interact directly the earnings tercile with industry exposure,

$$\Delta y_{ij} = \alpha + \sum_i \beta_{T_i^{2001}} CX_j \times T_i^{2001} + \gamma_i X_i + \gamma_j X_j + \varepsilon_{ijt}. \tag{4}$$

The results of this estimation are reported in columns (1) and (2) of Table 2 The effects implied

Table 1: Effect of Chinese Competition on Worker Earnings

| | OLS | | 2SLS | | | |
|---|---|---|---|---|---|---|
| | $\frac{\text{Cum. Earn.}}{\text{Earn. 01}}$ | $\frac{\text{Cum. Earn.}/\text{Earn. 01}}{\text{Years}}$ | $\frac{\text{Cum. Earn.}}{\text{Earn. 01}}$ | $\frac{\text{Cum. Earn.}/\text{Earn. 01}}{\text{Years}}$ | $\frac{\text{Cum. Earn.}}{\text{Earn. 01}}$ | $\frac{\text{Cum. Earn.}/\text{Earn. 01}}{\text{Years}}$ |
| | (1) | (2) | (3) | (4) | (5) | (6) |
| Exposure | -0.386* | -2.607 | -.550* | -5.469* | -1.454*** | -17.11*** |
| | (.219) | (1.698) | (.312) | (3.138) | (.530) | (5.850) |
| Exposure × Normalized Tercile | | | | | .454** | 5.776*** |
| | | | | | (.180) | (1.963) |
| 10-Industry FE | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Birth-Year FE | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Other Controls | ✓ | ✓ | ✓ | ✓ | | |
| Observations | 348,812 | 348,812 | 348,812 | 348,812 | 348,812 | 348,812 |

Terciles are normalized so that the second tercile is zero (thus, the first tercile is $-1$ and the third, 1). This implies that the coefficient on exposure for regressions (5) and (6) is the effect on the second tercile. Std. dev. clustered at 3-digit industry level. Significance at corresponding p-values denoted by *** 1%, ** 5%, * 10%.

from this regression paint a similar picture. The average effect of Chinese exposure for a worker in the bottom tercile is $-1.18 \cdot 3\% = -3.5\%$ of 2001 earnings. Comparing an average worker of the bottom earnings tercile employed to a highly exposed sector (90th percentile) to a shielded sector (10th percentile) we find a difference in the effect of $-1.18 \cdot (7.9\% - 0\%) = -9.3\%$ of the 2001 earnings.

#### 4.1.2 Decomposing the Effect on Earnings: Wage and Hours Adjustment

We next empirically investigate the role played by two different margins of adjustment of earnings: hours worked and hourly wages. We decompose cummulative earnings over 2001

Table 2: Non-parametric Effects on Earnings

| | $\frac{\text{Cum. Earn. 01-06}}{\text{Earn. 01}}$ |
|---|---|
| Ind. Exposure × Bottom Tercile | $-1.1^{***}$ |
| Ind. Exposure × Middle Tercile | $-.16$ |
| Ind. Exposure | $-.08$ |
| 10-Industry FE | ✓ |
| Birth-Year FE | ✓ |
| Other Controls | ✓ |
| Observations | 348,812 |

and 2006 as

$$\frac{\text{Cum. Earnings 2001-06}}{\text{Earnings 2001}} = \frac{\text{Average wage 2001-06}}{\text{Wage 2001}} \cdot \frac{\text{Number hours 2001-06}}{\text{Number hours 2001}}$$

and analyze the effect of Chinese competition on each of these two components separately. That is, we run the same baseline specification, (3) using as outcome variables *(i)* the normalized average hourly wage over the period 2001-06 and *(ii)* the normalized number of hours over the same period.

The results of these regressions are reported in columns 1 and 2 of Table 3. Column 1 analyzes the effect of Chinese competition on the average wage during 2001 to 2006 (normalized by the initial wage). The coefficient of the interaction term is not statistically different from zero. This implies that the effect of Chinese competition on average wages paid was the same for high- and low-earnings workers. However, the negative coefficient on exposure implies that the average wage of median worker exposed to Chinese competition was lower.

Given that the effect on wages is homogenous across the earnings distribution, the differential adjustment must be at the extensive margin (number of hours). Column 2 confirms this reasoning by reporting the coefficient of running the regression on the number of cumulative hours. The coefficient on the interaction term is positive and statistically significant. Thus, the low-earning workers exposed to Chinese competition worked relatively less hours than high-earnings workers. Moreover, the coefficient on exposure implies that the median worker employed in industries more exposed to Chinese competition worked significantly less hours throughout this period than high-earnings workers.

As a robustness check to the different margins of adjustments reported above, we perform a similar decomposition of the growth of annual earnings by comparing earnings and hours in 2006 and 2001, rather than using the cumulative values for the 2001-2006 period. In this case, we are restricting the sample to workers that were employed in these two years. Thus, this second measure proxies for changes on outcomes for stayers. Note that if we define annual earnings as

$$\text{Annual Earnings}_t = \text{Hourly wage}_t \times \text{ Number hours}_t,$$

it follows that the change in annual earnings between 2006 and 2001 can be written as,

$$\Delta \text{ Annual Earnings} = \Delta \text{ Hourly wage} + \Delta\text{Number hours},$$

where $\Delta\text{Annual } X = \ \ln(X_{2006}) - \ln(X_{2001})$.

Columns 3 to 5 of Table 3 report the heterogeneous effect of trade competition for each of the three variables, respectively. Column 3 reports the heterogeneous effect on annual earnings. The coefficient on the interaction term is positive and statistically significant. This evidence is consistent with columns 3 and 4 of Table 1. Low-earnings worker exposed to

Chinese competition suffer a large loss in earnings, whereas high-earnings workers are barely (positively) hit.

Column 4 of Table 3 reports the effect of trade competition on the change of hourly wages. Note that the coefficient on the interaction term is not statistically different from zero. This coefficient implies that the change of hourly wages does not depend on the earnings of the worker. This evidence is consistent with Column 1 of Table 3.

Finally, column 5 of Table 3 analyzes the effect of Chinese competition on the number of hours. The interaction term is positive and statistically significant. It means that low-earnings workers in industries exposed to Chinese competition worked less hours than high-earnings workers. In other words, the reason why Chinese competition increases earnings inequality is that high-earnings workers were able to work more hours than low-earnings workers. This finding, which is consistent with the coefficient on Column 2, is one of the contributions of this paper. Since we have data on hours worked, we can uncover this margin of adjustment, which would be hidden if we only had data on the number of years worked. Actually, we note that Chinese competition does not have any effect on the number of years worked.

We repeat this analysis using a non-parameteric identification. Table 4 reports the same dependent variables as Table 3 where we interact income terciles directly with Chinese exposure in a manner analogous to (4). Note that in this table we are not restricting the effect of Chinese competition to be linear across the income distribution but we let this effect to be different for each tercile. Note that in this case the omitted tercile is the third tercile. Thus, the coefficient of exposure is the effect of the Chinese competition for the richest workers.

The first thing to notice from column (3) is that, indeed, the ranking on the effect of Chinese competition on earnings is robust. Low-earning workers are more hurt by Chinese competition than high-earning workers. In addition, notice that the only statistically significant coefficient is the interaction with the first tercile. It implies that low-earning workers are the most affected workers. In other words, the negative effect of Chinese competition is concentrated among low-earning workers. We obtain the same qualitative results if we consider cumulative earnings as in Table 1.

From the rest of the columns in Table 4 we want to emphasize that, consistent with Table 3, the main margin of adjustment is the extensive margin (columns 2 and 5). Low-earners exposed by Chinese competition worked less hours. The evidence on wages is more mixed. From column (1) it seems that middle-earning workers experienced a reduction in wages. However, for the sample of workers which were working in both 2001 and 2006 we do not find this effect. One explanation for the fact that the adjustment of low-earners workers were on number of hours is that the wage of these workers is close to the minimum wage. We plan on analyzing this hypothesis in future versions of the draft.

In terms of magnitudes of the effects for the average worker in the bottom tercile, we find that the reduction in hours for a worker employed in the average industry represents

Table 3: Decomposition of Effect on Earnings

| | $\frac{\text{ave. wage}}{\text{wage}_{01}}$ (1) | $\frac{\text{Cum. Hrs.}}{\text{Hours}_{01}}$ (2) | $100\times \ln\left(\frac{\text{Earn.}_{06}}{\text{Earn.}_{01}}\right)$ (3) | $100\times \ln\left(\frac{\text{Wage}_{06}}{\text{Wage}_{01}}\right)$ (4) | $100\times \ln\left(\frac{\text{Hours}_{06}}{\text{Hours}_{01}}\right)$ (5) |
|---|---|---|---|---|---|
| Exposure | -.0811** | -110.5** | -48.58** | -10.89 | -38.07** |
| | (.036) | (46.18) | (19.32) | (7.806) | (15.19) |
| Exposure × Tercile | .0224 | 44.62** | 15.93** | .431 | 15.62** |
| | (.1688) | (20.22) | (6.500) | (3.533) | (5.469) |
| 10-Industry FE | ✓ | ✓ | ✓ | ✓ | ✓ |
| Birth-Year FE | ✓ | ✓ | ✓ | ✓ | ✓ |
| Other Controls | ✓ | ✓ | ✓ | ✓ | ✓ |
| Observations | 348,812 | 348,812 | 272,382 | 272,382 | 272,382 |

2SLS regressions. Std. dev. clustered at the worker level. Significance at corresponding p-value denoted by *** 1%, ** 5%, * 10%. Columns 1 and 4 use the hourly average wage in the corresponding year. Columns 3, 4 and 5 report coefficients multiplied by 100 so that the variable of interest can be interpreted as a growth rate.

$-1.1 \cdot 3\% = -3.3\%$ of hours worked in 2001. This corresponds to 67 hours. Comparing workers employed in industries in the 90th percentile of exposure relative to the 10th percentile, we find that those in the 90th percentile reduce hours by a $-1.1 \cdot 7.9\% = 8.7\%$ more. This represents around 176 hours.

To sum up, in this section we have decomposed the effect of Chinese competition on earnings inequality. The main result is that the negative effects of Chinese competition on earnings are focused on low-earners. After decomposing the effect on earnings between average wage and hours worked, we find that the reason for this differential effect is that low-earners adjusted more the number of hours worked than other workers.

## 4.2 Decline in hours worked and the change in the nature of jobs

A robust finding so far is that low-earnings workers have experienced a relatively higher decline in total hours worked. We next explore whether the adjustment in hours worked happens either at the intensive or extensive margin. That is, do workers keep their jobs and work less hours in the same job or they are fired and need to change jobs more often? Our results on cumulative hours are silent on this decomposition. Given that we only have data for employed workers, we can indirectly shed light on this question by analyzing whether there has been a change in the average job duration and the number of employers a worker has over the 2001-2006 period.

Table 4: Decomposition of Effect on Earnings: Non-parametric Estimates

| | $\frac{\text{ave. wage}}{\text{wage}_{01}}$ (1) | $\frac{\text{Cum. Hrs.}}{\text{Hours}_{01}}$ (2) | $100\times \ln\left(\frac{\text{Earn.}_{06}}{\text{Earn.}_{01}}\right)$ (3) | $100\times \ln\left(\frac{\text{Wage}_{06}}{\text{Wage}_{01}}\right)$ (4) | $100\times \ln\left(\frac{\text{Hours}_{06}}{\text{Hours}_{01}}\right)$ (5) |
|---|---|---|---|---|---|
| Exposure | .002 | 1.747 | -3.264 | -6.491 | 3.362 |
| | (.0260) | (34.82) | (8.121) | (5.905) | (6.597) |
| Exposure × Bottom Tercile | -.0488 | -85.97** | -31.57** | -1.793 | -30.06*** |
| | (.0344) | (40.71) | (12.83) | (7.112) | (10.70) |
| Exposure × Middle Tercile | -.0767** | 22.30 | -9.387 | -10.61 | .577 |
| | (.0315) | (61.79) | (7.279) | (7.585) | (8.125) |
| 10-Industry FE | ✓ | ✓ | ✓ | ✓ | ✓ |
| Birth-Year FE | ✓ | ✓ | ✓ | ✓ | ✓ |
| Other Controls | ✓ | ✓ | ✓ | ✓ | ✓ |

2SLS regressions. Std. dev. clustered at the worker level. Significance at corresponding p-value denoted by *** 1%, ** 5%, * 10%. Columns 1 and 4 use the hourly average wage in the corresponding year. Columns 3, 4 and 5 report coefficients multiplied by 100 so that the variable of interest can be interpreted as a growth rate.

Guided by the following decomposition on total hours worked,

$$\frac{\text{Total Hours Worked } 06-01}{\text{Total Hours } 01} = \frac{\text{Average Hours Worked per Employer } 06-01}{\text{Average hours worked per employer } 01} \times \frac{\text{Cum. Number of Employers } 01-06}{\text{Number of Employers } 01}, \tag{5}$$

we proceed by estimating (7) using as dependent variable normalized hours worked per employer and normalized number of employers. We define a worker to be be with the same employer if they are employed by the same establishment.[8]

Table 5 reports the results of this decomposition exercise, (5). Columns (1) shows that the average number of hours worked per job of the median worker go down relative to 2001 by around 7%. The coefficient of 2% in the interaction term with decile individual earnings shows that this reduction is specially concentrated among low-earning workers. In fact, the negative effect doubles to 15% for the earners in the first decile, while it is inexistent for workers in the tenth decile. Column (2) shows that these unequal results on the earnings distribution are robust to controlling for the firm size decile of the initial establishment. The negative coefficient on the interaction with establishment decile provides mild evidence (significant at 10%) that workers employed initially in larger establishments experience a larger decline in hours worked per employer. Overall, these results suggest that low-earnings workers tended

[8]The results are robust to defining if they are in the same firm.

Table 5: Job turn-over and Average Hours Worked per Job

| | $\frac{\text{Average Hours Worked per employer06−01}}{\text{Average hours worked per employer 01}}$ | | $\frac{\text{Number of employers (estab) 06-01 01−06}}{\text{Number of employers (estab) 01}}$ | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| Exposure | -.071** | -.083* | .499** | .442* |
| | (.028) | (.048) | (.247) | (.237) |
| Exp.×Ind.Decile | .020** | .031*** | -.085** | -.082** |
| | (.010) | (.008) | (.039) | (.031) |
| Exp.×Est.Decile | – | -.010* | – | .015 |
| | | (.011) | | (.053) |
| 10-Industry FE | ✓ | ✓ | ✓ | ✓ |
| Birth-Year FE | ✓ | ✓ | ✓ | ✓ |
| Est. & Ind. Deciles | ✓ | ✓ | ✓ | ✓ |
| Other Controls | ✓ | ✓ | ✓ | ✓ |
| Observations | 328,658 | 328,658 | 328,658 | 328,658 |

2SLS regressions, st.dev. in parenthesis. Clustering done at worker level.

to reduce the average hours worked per job in the 2001-2006 period.

Columns (3) and (4) analyze the effect of Chinese competition on the number of employers over the period. We find that workers more exposed to Chinese competition tend to switch employers more often. Moreover, this effect is heterogenous across the earnings distribution. Indeed, low-earnings workers change more of employer than high-earnings workers. Lastly, the coefficient on the interaction with firm size decile is not statistically significant. Thus, the effect of Chinese competition on the number of employers does not seem to depend on the initial size of the firm.

To sum up, we have shown that workers more exposed to Chinese competition have experience a larger reduction on the number of hours work with an employer and more churning across employers. Moreover, these effects are exacerbated for low-earningsworkers.

### 4.3 The role of initial firm characteristics

We have documented that the effect of the Chinese trade shock is heterogenous across the earnings distribution. To better understand this result, we want to investigate to which extent our results may be driven the type of firms that employ workers being different across the earnings distribution.[9] To explore the effect of firm characteristics on worker outcomes, we

[9] There are different theoretical reasons for this to be the case. For example, it could be due to sorting of workers across firms. It could be that high-earning workers are employed in different firms than low-earning workers. Alternatively, observationally equivalent workers may have different outcomes depending on the type of firm they were employed in 2001. For example, if small firms tend to produce lower quality goods (e.g., Fally and Faber, 2016) they could be more exposed to Chinese competition than larger firms.

Table 6: Effect on Earnings with Establishment Size Controls

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| | $\frac{\text{Earn. 06}-\text{01}}{\text{Earn. 01}}$ | $\frac{\frac{\text{Earn. 06}-\text{01}}{\text{Earn. 06}}}{\text{Years Worked}}$ | $\frac{\text{Average Wage}}{\text{Wage 01}}$ | $\frac{\text{Hours 06}-\text{01}}{\text{Hours 01}}$ |
| Exposure | -.674** | -.078* | -.017 | -.50* |
| | (.336) | (.041) | (.019) | (.26) |
| Exp.×Ind.Decile | .162*** | .024*** | .008 | .157** |
| | (.056) | (.008) | (.005) | (.070) |
| Exp.×Est.Decile | -0.128 | -.0198** | -.024*** | .016 |
| | (.095) | (.009) | (.009) | (.088) |
| 10-Industry FE | ✓ | ✓ | ✓ | ✓ |
| Birth-Year FE | ✓ | ✓ | ✓ | ✓ |
| Est. & Ind. Deciles | ✓ | ✓ | ✓ | ✓ |
| Other Controls | ✓ | ✓ | ✓ | ✓ |
| Observations | 328,658 | 328,658 | 328,658 | 328,658 |

2SLS regressions, st. dev. in parenthesis. Clustering done at worker level The ommited category is the 5th declie for individuals and firms.

add to our baseline regression the interaction between Chinese exposure and the establishment size decile of the establishment employing the worker in 2001.[10]

$$\begin{aligned}\Delta y_{ij} \quad = \quad & \alpha + \beta CX_{fj} + \delta CX_{fj} D_i^{2001} + CX_{fj} \times \text{Estab. Size Decile}_{i,2001} + \\ & \gamma_i^{Size} \text{Estab. Size Decile}_{i,2001} + \gamma^D D_i^{2001} + \gamma_i^{x_i} X_i + \gamma_j^{x_j} X_j + \varepsilon_{ijt}, \qquad (6)\end{aligned}$$

We measure firm size by the number of employees in a given establishment in 2001. The definition of establishment decile is based on the 2001 establishment distribution.

We report the coefficients of this regression in Table 6. First, we see in column (1) that our baseline result is robust to the inclusion of the interaction with establishment size. The effect of trade on cumulative earnings is heterogenous across the earnings distribution. The magnitude of the effect is similar to the coefficient in our baseline regression (.162 and .181, respecitvely). We also see that the non-interacted effect of exposure is negative and significant. We have omitted the fifth deciles of earnings and establishment deciles. Therefore, this coefficient implies that trade reduces the cumulative earnings of worker employed in 2001 in a firm with median size and with median earnings. Finally, note that the coefficient on the interaction with establishment is negative but not significant. Thus, it seems that the size of the initial firm is not relevant for the evolution of earnings.

Column (2) reports the effect of trade on cumulative earnings normalized by years worked.

[10] Our motivation for using establishment size comes from the tradition of models à la Hopenhayn-Melitz, in which establishments differ by their productivity and firm size captures these differences in productivity.

In this case, the coefficient on the interaction with firm size decile is negative and significant. It implies that a worker employed in 2001 in a larger firm experiences a larger fall in cumulative earnings (normalized by years worked) than their peers working in smaller firms. This suggests that a worker that starts in a large firm tends to experience a decline in the average wage in the future.[11]

To explore this hypothesis, Columns (3) and (4) decompose total earnings in average wage per hour and total hours worked. We see in column (3) that, indeed, workers that started 2001 in a large establishment have tended to experience a reduction in their average wage relative to workers employed in smaller establishments. Moreover, consistent with Table 3, there is no evidence that the change in the average wage is heterogenous across the earnings distribution. Conversely, in column (4), we see that low-earning workers have tended to decrease hours worked more than high-earnings workers, while there is no differential effect across establishment sizes. Indeed, the adjustment on hours worked across the earnings distribution is consistent with the results in Table 3.[12]

# 5 The Effect of Chinese Competition on Earnings on Mobility

## 5.1 Mobility: Employment zone, occupation and industry

In this subsection, we investigate non-pecuniary margins of adjustment of workers to the trade shock. We focus on workers' decision to change their place of residence (measured at the Employment Zone, EZ), occupation and/or industry. This exercise allows us to shed light on additional margins in which high- and low-earners may cope differently with the trade shock. Even though we do not have direct measures, there may be pecuniary and non-pecuniary costs associated to changing occupation, industry or place of residence, which may exacerbate trade effects on welfare inequality.

We proceed by estimating a separate model for each of the three adjustment decisions. All models are multinomial logits with three possible outcomes: "stay", "change" and "exit".

[11] Since our outcome variable is normalized by the years a worker is employed, this suggest that relative to column (1) we have a more precise measure of the decline in yearly earnings.

[12] Another possible proxy for establishment productivity is the average wage paid to workers. We investigate whether our results are robust to this alternative measure of establishment productivity. We estimate specification (7) replacing establishment size by average establishment wage,

$$\begin{aligned} \Delta y_{ij} \quad &= \quad \alpha + \beta CX_{fj} + \delta CX_{fj} D_i^{2001} + CX_{fj} \times \text{Estab. Wage Decile}_{i,2001} + \\ &\quad\quad \gamma_i^{Wage} \text{Estab. Wage Decile}_{i,2001} + \gamma^D D_i^{2001} + \gamma_i^{x_i} X_i + \gamma_j^{x_j} X_j + \varepsilon_{ijt}. \end{aligned} \tag{7}$$

Results are consistent with our baseline results. We also find a negative interaction significant at 10% between establishment average wage and Chinese exposure, while before we obtained a negative coefficient but only significant at 20%.

“stay” is set as the reference outcome so that the general expression of the three models is:

$$\ln \frac{Pr(d_{ij} = k)}{Pr(d_{ij} = \text{“}stay\text{''})} = \alpha(k) + \beta(k)CX_j + \delta(k)CX_jD_i^{2001} + \gamma(k)_iX_i + \gamma(k)_jX_j,\ k = \{\text{“}move'', \text{“}exit''\}, \tag{8}$$

with $CX_j$ Chinese exposure in France. $X_i$ and $X_j$ are respectively the same worker and industry control variables as in above specifications. $d_{ij}$ is the decision of worker $i$ working in industry $j$ in 2001. $d_i$ has three modalities: “stay”, “move” and “exit”. The exact definition of outcomes “stay” and “move” is model specific. For instance, when it comes to studying the decision to change industries, “stay” and “change” refer to “working in the same 3-digits industry in 2001 and in 2006” and “working in a different 3-digits industry in 2001 and 2006”, respectively. The definitions adjust accordingly when we analyze employment zone transitions and occupation transitions. Coefficients should be interpreted as the effect of explanatory variables on the probability of an outcome relative to the probability to stay. For instance, for k=“move”, a one unit increase in $X_i$ generates a $100 * \gamma(move)_i$ percents change in a worker’s probability to move relative to her probability to stay.

Table 10 reports the coefficients obtained by running the three multinomial logit models. The first thing to notice is that the exposure variable in the “exit” equation is significant and positive in all models (columns (3), (6) and (9)). This means that trade competition increases median worker’s probability to exit the sample. This is consistent with trade decreasing labor demand and thus driving workers out of employment. To get a sense of the magnitude of this effect, we report the average marginal effect of exposure by decile of the earning distribution. According to column (3), at the median, a one standard deviation change in trade exposure causes a 0.36 percentage point increase in the probability to exit the sample.

Moreover, note that the coefficient on exposure is positive and statistically significant in the decision of moving occupations (columns 2) and industries (column 8). It implies that the probability of changing occupation or industry increases with Chinese competition. Quantitatively, a one standard deviation change in exposure increases median worker’s probability to change occupation and the probability to change industry by respectively 0.53 and 0.76 percentage points, respectively. The coefficient on the probability to change EZ is positive but only significant at 10 percent. We want to emphasize that these findings are consistent with the Hecksher-Ohlin trade model. Workers hit by the trade shock are able to reallocate to other industries/occupations.

Next, we turn to the results regarding the differential adjustments of low-income and high-income workers. The coefficient on the interaction between Chinese exposure and income decile is only negative and statistically significant on the decision to change occupation (table 10, panel A, column 2). Thus, high-income workers are less likely to change occupations than low-income workers. In order to get a sense of the magnitude of this difference, we report in panel B the average marginal effect of exposure on the probability to change occupations at different deciles.

For workers in the first decile, a one standard deviation exposure change increases the probability to change occupations by 1.39 percentage points while for workers in the 10 decile, the same shock decreases the probability by .68 percentage points. Panel B also reveals that high-income workers tend to be more likely to change industries than low-income workers (to the exception of decile 2 in column 8, the AME is increasing and goes from being insignificant to significant). At the 1st decile, a one sd increase in exposure .34 percentage points. For the 10th decile, the number is 1.32 percentage points. These results suggest that high-income workers are more able to change industry without changing occupation that low-income workers. To the extent that changing occupation is related to a worse employer-employee match (positive sorting of skill and occupation), it may explain why trade increases income inequality.

### 5.2 The interdependence of Mobility Decisions

Why do workers tend to change employment zone and occupation in response to an industry specific shock? Are these changes just side effects of the fact that workers move across industries, and that these industries happen to differ in terms of spatial and occupational composition? Or do we also observe workers changing, say, occupation in response to the shock, while staying in the same industry? In order to answer these questions, we estimate two additional multinomial logits respectively looking at the joint decision to change EZ and industry on the one hand and at the joint decision to change occupations and industry on the other hand. The general expression of these two models is:

$$\begin{aligned}\ln \frac{Pr(d_{ij}=k)}{Pr(d_{ij}=\text{``}stay, stay'')} =& \alpha(k)+\beta(k)CX_j+\delta(k)CX_jD_i^{2001}+\gamma(k)_iX_i+\gamma(k)_jX_j,\\ &\text{with } k=\{\text{``}stay, move'', \text{``}move, stay'', \text{``}move, move'', \text{``}exit''\}, \qquad (9)\end{aligned}$$

Since the models look jointly at two dimensions of adjustment, the decision variable $d_{ij}$ may now take on 5 outcomes: the worker may keep the same situation between 2001 and 2006 ("stay, stay"), may change along exactly one of the two dimensions ("stay, move" or "move, stay"), may move along both dimensions ("move, move") or may exit the sample. We set "stay, stay" as the reference outcome.

Results suggest that the effect of Chinese competition on the decision to change EZ depends on the decision to change industries. This becomes appearant in panel B of table 11: while trade increases the probability to change EZ and industry (column 4), it does not change the probability to change EZ and stay in the same industry (column 2). Changing EZ is therefore a by-product of changing industry. An implication of this result is that the spatial distribution of industries may shape the effect of a trade shock on workers. Namely, the more diversified the industry composition of a region, the less workers need to change regions to work in another industry and, thus, shelter from the trade shock.

When it comes to occupations, the patterns of interdependence depend on workers earnings. For low-income workers, trade increase the probability to change occupation without changing industry while it decreases the probability to change industry without changing occupation. The opposite is true for high-income workers: the probability to only change occupation decreases and the probability to change only industry increases. The fact that low-income workers mainly adjust through occupations suggest that (i) the trade shock is concentrated on low skill occupations (hence forcing low-income workers unable to change industries out of their occupation) and (ii) low-income workers are less mobile across industries than high-income workers (or low skill occupations are less substitutable across industries).

### 5.3 Occupation Changes: Upgrading or Downgrading?

In previous section, we have found evidence that workers tend to respond to trade competition by changing occupations. We now look at a following question: how do workers new occupation compares to their initial one? Is it more skill-intensive? less skill-intensive? Does it depend on the initial income of the worker? In order to answer these questions, we rank 2-digit occupations according to their median wage in 2001. We then run a multinomial logit estimating the effect of trade on a worker's probability to either move up or down the "occupational ladder" between 2001 and 2006 or to simply keep the same occupation.

Average marginal effects of trade are reported in table 12. When it comes to the probability to stay in the same occupation, results are consistent with above findings: A one standard deviation change in trade exposure change the likelihood to change occupation by +1.9 percentage points at the first decile and -0.9 percentage points at the tenth decile.

Poor workers response seems to be evenly distributed between upward mobility and downward mobility. By contrast, most of the reduced mobility of rich workers comes from a lower probability to move up the occupational ladder. Part of these results may be mechanical in the sense that, by construction, poor workers are at the bottom of the ladder and thus are more likely to move up, conditionally on moving. Now, the fact remain that Chinese competition, by pushing poor workers out of their occupations, tend to concentrate the labor force in the upper part of the occupational ladder.

## 6 Conclusion

In this paper, we have analyzed the effect of Chinese competition on French workers between 2001 and 2006. This is a period of important growth in Chinese imports, after China joined the WTO in 2001. We have documented that the adjustments of French workers to trade competition has been heterogenous across the income distribution. In terms of earnings, we have found that only workers in the bottom tercile of the income distribution are negatively affected by Chinese competition. Workers with higher income are not significantly affected.

Making use of the detailed information in the matched employer-employee dataset, we document that most of the adjustment in earnings occurs through hours worked and not through average hourly wages. Low-earners work relatively less than high-earners due to the trade shock. Moreover, we show that their turnover, in terms of employers, is much higher.

Finally, we have also documented non-pecuniary adjustments along three dimensions. We have analyzed how the trade shock affects the probability of workers changing their place of residence, occupation and industry (including ceasing to be employed). Our results show that the trade shock increases the likelihood that workers cease to be employed, change occupation and industry. We find that high-earners are less likely to change occupations. Lastly, we also show that changes in the place of residence go hand-in-hand with changes in industry.

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# A Tables and Figures

Figure 2: Industry Trade Exposure and Share of Production Workers

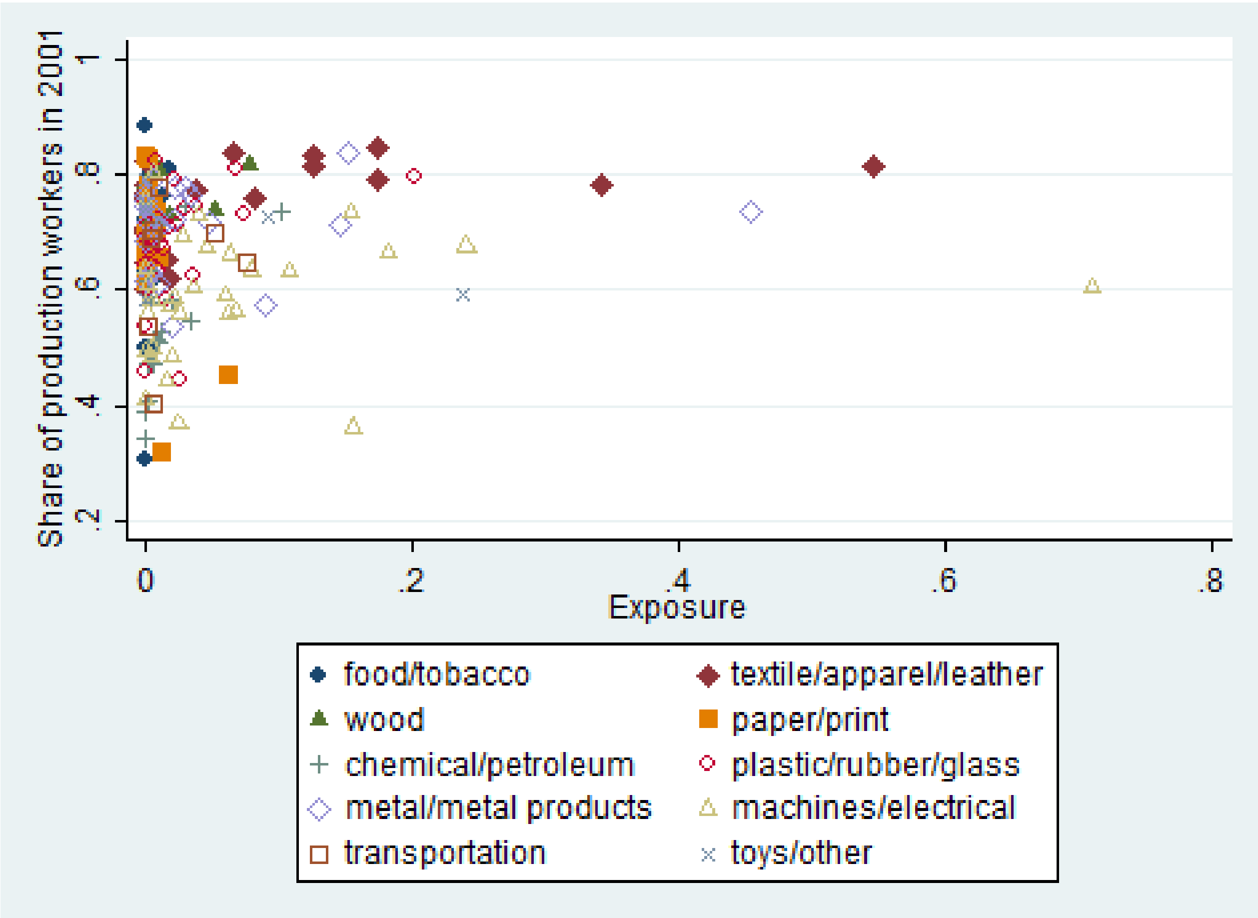

Table 7: Summary Statistics

| | All workers |
|---|---|
| Panel A: trade exposure, 2001-2006 | |
| $\Delta$imports from China to France/ France consumption 2001 | 8.37 |
| | (46.0) |
| P90, P10 interval | [8.30,0] |
| P75, P25 interval | [0,0] |
| | |
| Panel B: main outcome variables, 2001-2006 | |
| total earnings 2001-2006/ earnings 2006 | 5.26 |
| | (1.74) |
| 100* total hours 2001-2006/ hours 2001 | 513.9 |
| | (185.2) |
| 100*log difference annual wage,2001-2006 | -1.973 |
| | (48.61) |
| 100*log. difference annual hours,2001-2006 | -11.50 |
| | (45.99) |
| 100*log. difference hourly wage, 2001-2006 | 9.59 |
| | (23.75) |
| 100*total earnings norm. by earnings and years | 101.0 |
| | (17.18) |
| normalized number of hours per employer (est.) | .95 |
| | (.25) |
| normalized number of employers | 1.50 |
| | (.79) |
| Panel C: worker characteristics in 2001 | |
| Female | .40 |
| Tenure 0-1 year | .10 |
| Tenure 2-5 years | .24 |
| Tenure 6-10 years | .31 |
| Firm size 1-99 | .39 |
| Firm size 100-999 | .28 |
| Firms size >1000 | .32 |
| | |
| Sample Size | 328,658 |

Table 8: List of occupations

| PCS code | description of occupation |
|---|---|
| 21 | Small business owners and workers |
| 22 | Shopkeepers |
| 23 | Heads of businesses |
| 34 | Scientific and educational professionals |
| 35 | Creative professionals |
| 37 | Top managers and professionals |
| 38 | Technical managers and engineers |
| 42 | Teachers |
| 43 | Mid-level health professionals |
| 46 | Mid-level managers & professionals |
| 47 | Technicians |
| 48 | Supervisors and foremen |
| 53 | Security workers |
| 54 | Office workers |
| 55 | Retail workers |
| 56 | Personal service workers |
| 62 | Skilled industrial workers |
| 63 | Skilled manual laborers |
| 64 | Drivers |
| 65 | Skilled transport and wholesale workers |
| 67 | Unskilled industrial workers |
| 68 | Unskilled manual laborers |

Table 9: Firm Wage Deciles as Controls

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| | $\frac{\text{Earn. 06-01}}{\text{Earn. 01}}$ | $\frac{\frac{\text{Earn. 06-01}}{\text{Earn. 06}}}{\text{Years Worked}}$ | $\frac{\text{Average Wage}}{\text{Wage 01}}$ | $\frac{\text{Hours 06-01}}{\text{Hours 01}}$ |
| Exposure | -.575* | -.071* | -.023 | -.38 |
| | (.346) | (.042) | (.020) | (.31) |
| Exp.×Ind.Decile | .297*** | .040*** | .013** | .277** |
| | (.057) | (.008) | (.005) | (.060) |
| Exp.×Firm Wage Decile | -0.168* | -.021** | -.015* | .010 |
| | .090 | (.009) | (.009) | (.083) |
| 10-Industry FE | ✓ | ✓ | ✓ | ✓ |
| Birth-Year FE | ✓ | ✓ | ✓ | ✓ |
| Est. & Ind. Deciles | ✓ | ✓ | ✓ | ✓ |
| Other Controls | ✓ | ✓ | ✓ | ✓ |
| Observations | 328,658 | 328,658 | 328,658 | 328,658 |

2SLS regressions, st. dev. in parenthesis. Clustering done at worker level Source: 2709 IVreg indiv and firm wage deciles attached earnings and hours The ommited category is the 5th percentile for individuals and 10th decile for firms?

Table 10: Testr Mobility: Occupation_CZ_ Industry

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) |
|---|---|---|---|---|---|---|---|---|---|
| | **Occupation (2-digit)** | | | **Employment Zone** | | | **Industry (3-digit)** | | |
| | stay | move | exit | stay | move | exit | stay | move | exit |
| **Panel A: Coefficients** | | | | | | | | | |
| Exposure | | 0.832*** | 0.777*** | | 0.651* | 0.505* | | 1.609*** | 0.888** |
| | | (0.252) | (0.286) | | (0.345) | (0.258) | | (0.599) | (0.415) |
| Exposure × | | | | | | | | | |
| Ind. Percentile/100 | | -0.293*** | -0.0832 | | -0.027 | 0.040 | | 0.218* | 0.115 |
| | | (0.062) | (0.055) | | (0.074) | (0.047) | | (0.128) | (0.082) |
| **Panel B: Average Marginal Effects** | | | | | | | | | |
| Decile 1 | -0.375*** | 0.302*** | 0.073 | -0.092 | 0.047* | 0.046 | -0.122 | 0.073 | 0.049 |
| Decile 2 | -0.045 | -0.039 | 0.084** | -0.130* | 0.049 | 0.081* | -0.364** | 0.237*** | 0.127** |
| Decile 3 | -0.286*** | 0.211*** | 0.075* | -0.106* | 0.049* | 0.057 | -0.191* | 0.118* | 0.073 |
| Decile 4 | -0.240*** | 0.164*** | 0.076** | -0.112** | 0.050* | 0.062* | -0.226** | 0.141** | 0.0846* |
| Decile 5 | -0.192*** | 0.115*** | 0.077** | -0.117** | 0.050* | 0.067* | -0.260** | 0.165*** | 0.096* |
| Decile 6 | -0.144*** | 0.065** | 0.079** | -0.122** | 0.050* | 0.072* | -0.295** | 0.188*** | 0.107** |
| Decile 7 | -0.095* | 0.014 | 0.082** | -0.127** | 0.050 | 0.077** | -0.330** | 0.212*** | 0.117** |
| Decile 8 | -0.045 | -0.039 | 0.084** | -0.130* | 0.049 | 0.081* | -0.364** | 0.237*** | 0.127** |
| Decile 9 | 0.006 | -0.093** | 0.087* | -0.134* | 0.048 | 0.086* | -0.399** | 0.261*** | 0.137** |
| Decile 10 | 0.059 | -0.148*** | 0.090* | -0.136 | 0.048 | 0.090* | -0.433** | 0.286** | 0.147** |
| 10-Industry FE | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Birth-Year FE | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Other Controls | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Observations | 378,492 | 378,492 | 378,492 | 378,492 | 378,492 | 378,492 | 378,492 | ✓ | ✓ |

2SLS regressions, t-statistics in parenthesis. Clustering done at worker level.

Table 11: EZ/occupation mobility: a by-product of industry mobility?

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | |
|---|---|---|---|---|---|---|---|---|---|---|
| | Employment Zone, Industry | | | | | Occupation, Industry | | | | |
| | stay, stay | move,stay | stay,move | move,move | exit | stay, stay | move,stay | stay,move | move,move | exit |
| **Panel A: Coefficients** | | | | | | | | | | |
| Exposure | | 0.441 | 1.759*** | 1.463*** | 0.957*** | | 0.535** | 1.362** | 1.838*** | 1.064** |
| | | (0.676) | (0.670) | (0.596) | (0.456) | | (0.232) | (0.632) | (0.643) | (0.419) |
| Exposure × | | | | | | | | | | |
| Ind. Percentile/100 | | -0.071 | 0.199 | 0.202* | 0.091 | | -0.219*** | 0.396** | -0.003 | 0.047 |
| | | (0.133) | (0.144) | (0.122) | (0.087) | | (0.081) | (0.156) | (0.117) | (0.090) |
| **Panel B: AME** | | | | | | | | | | |
| Decile 1 | -0.164 | 0.015 | 0.068 | 0.014 | 0.067 | -0.260** | 0.120** | -0.041 | 0.119** | 0.062 |
| Decile 2 | -0.317** | -0.037 | 0.152** | 0.079*** | 0.123** | -0.223** | -0.136** | 0.130*** | 0.098** | 0.131** |
| Decile 3 | -0.213* | 0.008 | 0.094** | 0.028 | 0.0839* | -0.252*** | 0.060 | -0.003 | 0.113** | 0.082* |
| Decile 4 | -0.237** | 0.002 | 0.107** | 0.036** | 0.092* | -0.248*** | 0.027 | 0.019 | 0.110** | 0.093* |
| Decile 5 | -0.259** | -0.005 | 0.119*** | 0.046** | 0.100** | -0.242*** | -0.010 | 0.043 | 0.107*** | 0.102** |
| Decile 6 | -0.280** | -0.014 | 0.131*** | 0.056*** | 0.108** | -0.237*** | -0.05 | 0.070** | 0.104*** | 0.112** |
| Decile 7 | -0.300** | -0.025 | 0.142** | 0.067*** | 0.116** | -0.230** | -0.091* | 0.098** | 0.101** | 0.122** |
| Decile 8 | -0.317** | -0.037 | 0.152** | 0.079*** | 0.123** | -0.223** | -0.136*** | 0.130*** | 0.0981** | 0.131** |
| Decile 9 | -0.333** | -0.052 | 0.163** | 0.092*** | 0.131** | -0.216* | -0.183** | 0.165*** | 0.095** | 0.140** |
| Decile 10 | -0.347* | -0.07 | 0.172** | 0.106*** | 0.138* | -0.208 | -0.234*** | 0.202*** | 0.092** | 0.148** |
| 10-Industry FE | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Birth-Year FE | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Other Controls | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Observations | 378,492 | 378,492 | 378,492 | 378,492 | 378,492 | 378,492 | 378,492 | | | |

2SLS regressions, t-statistics in parenthesis. Clustering done at worker level.

Table 12: Occupational mobility: downgrading or upgrading?

| | (1) down | (2) status quo | (3) up |
|---|---|---|---|
| Decile 1 | 0.195** | -0.415*** | 0.220*** |
| Decile 2 | 0.005 | 0.045 | -0.050 |
| Decile 3 | 0.135* | -0.293*** | 0.158*** |
| Decile 4 | 0.106* | -0.229*** | 0.123*** |
| Decile 5 | 0.079 | -0.163*** | 0.084*** |
| Decile 6 | 0.053 | -0.096** | 0.043* |
| Decile 7 | 0.028 | -0.026 | -0.002 |
| Decile 8 | 0.005 | 0.045 | -0.050 |
| Decile 9 | -0.017 | 0.118** | -0.101** |
| Decile 10 | -0.037 | 0.192*** | -0.155*** |
| 10-Industry FE | ✓ | ✓ | ✓ |
| Birth-Year FE | ✓ | ✓ | ✓ |
| Other Controls | ✓ | ✓ | ✓ |
| Observations | 266,172 | 266,172 | 266,172 |

Average marginal effects obtained from an IV multinomial logit with three outcomes: being in the same occupation in 2001 and 2006 ("status quo"), being in a lower median wage occupation in 2006 ("down") and being in a high median wage occupation in 2006 ("up"). The estimation is run over the sample of workers present in the data both in 2001 and 2006. Clustering done at worker level. $***p < 0.001$, $**p < 0.05$, $*p < 0.1$.