The Effect of Import Competition across Occupations

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Abstract

We empirically examine the effect of import competition on worker earnings across occupations. To guide our analysis, we develop a stylized factor-proportions model that emphasizes industries using occupations in different intensities. We derive an occupational exposure index that summarizes the overall exposure of a given occupation to rising import competition. Using nationally-representative matched employer-employee French panel data from 1993 through 2015, we obtain evidence consistent with the predictions of the model. We find that workers initially employed in occupations highly exposed to Chinese competition –as measured by our occupational exposure index– experience larger declines in earnings. We also document that workers tend to move out of hard-hit industries, but they tend to remain in their broad initial occupation. Our estimates imply that the overall effect of import competition on workers' earnings can be roughly equally attributed to variation across workers' initial industry and occupation.

Keywords: Occupations, Inequality, Import Competition.
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1 Introduction

A flourishing empirical literature in international economics spearheaded by Autor et al. (2013, 2016) has documented that the incidence of import competition from low-wage economies on workers in advanced economies is larger than previously thought. A central finding of this literature is that an increase in import competition negatively affects the earnings of workers in that industry. This mechanism has been documented, for example, by Autor et al. (2014) for the United States and Dauth et al. (2014) for Germany in the context of the rise of Chinese competition.[1] A parallel literature has emphasized that the effect on the "average" worker in an industry masks substantial heterogeneity across workers within the industry. Recent contributions by Ebenstein et al. (2014) and Traiberman (2019) among others have documented that a substantial part of the variation in worker earnings adjustment to trade shocks appears to be accounted by variation across occupations within industries, rather than differential exposure to trade across industries.[2]

The goal of this paper is to investigate the role of occupations in the adjustment of worker earnings due to rising import competition from low-wage countries. In particular, using French matched employer-employee panel data, we document that rising Chinese competition has had substantial heterogeneous effects on earnings adjustment across occupations. We establish this heterogeneity in the adjustment across occupations both in reduced form and using an occupational exposure index derived from a factor-proportions theoretical framework. Moreover, we show that the magnitude of the effect of Chinese competition operating through the initial occupation of a worker is of roughly the same magnitude as that operating through workers' initial industry of employment. The richness of our data allows us to also *(i)* document slow dynamics of adjustment over a nineteen year span, *(ii)* separately report the adjustment of wages and hours worked and *(iii)* show how one pervasive feature of European labor market regulation, collective agreements, has interacted with the heterogeneous adjustment across occupations.

We use matched employer-employee panel data from French Social Security records spanning 1993 through 2015, supplemented with exhaustive firm-level balance-sheet information. This long panel allows us to trace out the effects of trade, which we find to build up over time and have a significant effect on worker's adjustment.[3] In our baseline exercises, we use a fairly coarse aggregation of occupations in seven groups provided by the French statistical agency (INSEE): skilled production workers, unskilled production workers, administrative staff, technical staff, other mid-level occupations, engineers, and executives. This grouping is based on the description of the jobs, their hierarchical position in the firm, and their required level of education. Thus, this list of occupations encapsulates job characteristics beyond years of education, e.g., managers and engineers or administrative and technical staff require the same years of education. We choose this level of aggregation as our baseline to capture substantial heterogeneity across

[1] Dauth et al. (2014) also analyse the effect of the rise of import competition from Eastern European countries.

[2] See the discussion in the related literature for further references.

[3] This finding is consistent with previous studies studying the dynamic adjustment to trade shocks, e.g., (Autor et al., 2014), (Dix-Carneiro and Kovak, 2019) and Kovak (2013a).

jobs performed by workers while still making it manageable to interpret.[4]

Following an already large and growing literature, we use the "China shock" as the exogenous increase in import competition. Our identification strategy closely follows Autor et al. (2014). The goal is to isolate the supply-shock component of the rise of Chinese exports in France that is orthogonal to other drivers of the rise of Chinese competition. As in Autor et al., we do so by instrumenting industry Chinese competition in France with the rise in Chinese exports in other advanced economies outside the European Monetary Union (as in Dauth et al., 2014). Using this identification strategy and leveraging the rich set of worker and firm controls in our data, we compare "observationally equivalent" workers initially employed in the same occupation, but different industries. The underlying identifying assumption is that, absent industry-specific "China shocks," these workers would have experienced comparable earning trajectories.[5]

As a first step in studying trade adjustment of French workers, we document the effect of the rise in Chinese exports in a reduced-form setting. We begin by showing that, on average, French workers experienced earning losses between 1997 and 2015 comparable to U.S. workers over the same period. We then show that these losses were substantially heterogeneous across occupations. For example and perhaps surprisingly, we find that "engineers", a skilled occupational category, experience the largest decline in earnings, followed by workers in industrial and manual occupations that require a certification. Conversely, administrative staff (which includes accountants and secretaries) does not experience a decline in earnings, while technical staff (which includes designers of electronic material and site managers), experienced a statistically significant, but less severe decline in earnings. These examples suggest that occupations more attached to manufacturing industries have borne the bulk of the adjustment from rising Chinese competition. They also suggest that the effect of trade on earnings is non-monotonic in education (or some other proxy of skill). Thus, education is not a sufficient statistic for studying the effect of trade on earnings. Other dimensions, such as workers' possibility of performing an occupation across different industries, may play an important role.

To illustrate the role of occupations and formally test it, we develop a theoretical framework. We consider a small open economy with J industries and I occupations, where each occupations is used with different intensity across industries. This model can be interpreted as a factor proportions model with occupations being factors of production (or a specific factor model in the limiting case in which a given occupation is only used in one industry). We thus emphasize the role of occupation specificity by assuming that workers can switch industries after a trade shock, but they are fixed in their occupations.[6] We construct

[4]We also show that our results go through when we consider a finer classification of occupations (two-digits). Moreover, since our theoretical framework emphasizes mobility across industries but not occupations, we believe that this assumption is better captured by relatively broad occupations.

[5]Lack of detailed occupational data has prevented the analysis of the effect of the "China shock" across workers in different occupations for the United States. Autor et al. (2014) note that our exercise cannot be performed using U.S. Social Security data, because it does not have information on workers' occupations.

[6]We think this is a reasonable assumption for the short- and medium-run response given that *(i)* we focus on attached workers with full-time jobs before the shock and *(ii)* we consider broad occupational categories. Indeed, this assumption appears to be supported by our data since we find no significant mobility across occupations.

a summary statistic, that we call OCcupational eXposure index (OCX), that encapsulates the effect of the China shock across occupations. The model predicts that there exists a negative correlation between the occupational exposure index OCX and the change in worker's earnings. This index is constructed as a weighted average over industry exposure to Chinese competition, where the weights for each occupation are given by the occupation's industry factor intensity.[7] Intuitively, if occupation A is only used in an industry hit by Chinese competition, while occupation B is evenly used in all industries, OCX_A is larger than OCX_B. Thus, the decline in earnings of workers in occupation A, due to import competition, will be larger than for workers in occupation B.

Figure 1 shows suggestive evidence consistent with this empirical prediction. Indeed, there is a strong, negative partial correlation between the increase in exposure to Chinese competition of each occupation, measured by the occupational exposure index OCX, and workers' change in relative earnings over the 1997-2015 period.[8] We show that this correlation persists (and becomes slightly larger) after instrumenting the occupation exposure index with an index constructed using lagged occupation factor intensities (from 1994) and Chinese exposure in other advanced economies (as in our reduced-form exercise). We find that the decline in relative earnings is the highest in occupations that were used intensively in highly-exposed industries and, thus, have a high occupation exposure index. The estimated magnitude of the effect across occupations is substantial. Moving from the occupation with the lowest occupation exposure index (which corresponds to middle-skill occupations such as retail workers) to the highest (which corresponds to skilled production workers such as metal welders and turners) implies losing almost two yearly (1997) total earnings over the 1997-2015 period.

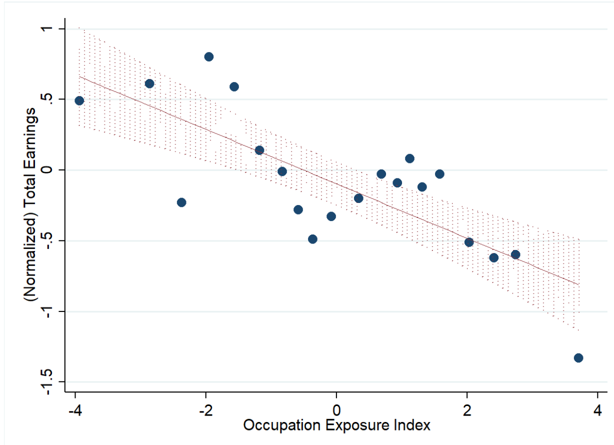
Importantly, we find that our occupational exposure index predicts the loss of earnings even when we control for workers' direct industry exposure to Chinese competition. This means that even within an unexposed industry, a worker employed in an exposed occupation will suffer larger earning losses than workers employed in unexposed occupations. Quantitatively, we find that the predictive power of occupational and industry exposure are comparable. A one standard deviation increase in occupational exposure leads to losing 71% of 1997 earnings over the 1997-2015 period. By contrast, a one standard deviation increase in industrial exposure leads to losing 82% of 1997 earnings over the same time period. These results highlight the importance of the general equilibrium effects of trade across industries and within occupations. Therefore, this finding suggests that policies aiming at redistributing the gains from trade should also target workers from exposed occupations in addition to workers from exposed industries.

The variation in workers' earnings predicted by the differential exposure of occupations to the China shock is robust to controlling for the differential exposure to computerization and robotization across occupations, as measured by the occupational routine task index developed in Autor and Dorn (2013). Our re-

[7] As we further discuss in Section 2, our preferred measure of relative earnings is computed as the average yearly worker earnings between 1997 and 2015 relative to their average 1997 earnings.

[8] The pairwise correlation is -0.77 and statistically significant. We exploit the rich information in our data to partial out worker, initial firm, industry, and region characteristics (as we discuss further below).

Figure 1: Occupational Exposure Index and Change in Earnings



Notes: Figure depicts the means of equal-sized bins containing 1/20th of the data. The Occupational Exposure Index corresponds to the index derived in the theory Section 2, and it is computed as a weighted-average of the industry exposure to Chinese competition. The weight (occupation-intensity) is the wage bill of the occupation. (Normalized) Total Earnings is the sum of worker's annual earnings between 1997 and 2015 divided by initial earnings. Both measures have been partialled out using the baseline set of worker, firm, industry and location controls described in Section 4.

sults also hold after controlling for a rich set of firm-level controls (suggesting that within-industry worker reallocation emphasized in Burstein and Vogel (2017) is not the driver of our results),[9] using different levels of aggregation for occupations, alternative definitions of factor intensity and when accounting for the effect of increased trade with Eastern Europe during the same time period.

We leverage the richness of our data and provide evidence on margins of adjustment other than total earnings. First, we decompose the effect of trade on total earnings between hours and wages and we show that even though trade adjustment operated through both margins, the effect on hours is larger. Second, we show that workers initially employed in industries that are highly exposed to Chinese competition move to other industries—and away from manufacturing, which has the highest exposure. Moreover, despite changing industry, we find that workers stay in their initial occupation: there is no effect of Chinese exposure on the probability of workers changing occupation. This result is consistent with our view of workers' broad occupations as factors of production.

Finally, we provide suggestive evidence on the role of labor market regulation in shaping trade adjustment differentially across industries. We find that labor regulation exacerbated the negative effect of Chinese competition on cumulative earnings. Moreover, we document that the negative effect of regulation is concentrated among skilled production workers and technical staff, whereas it is neutral for the rest of occupations. That is, it seems that labor regulation exacerbated the losses of workers in low-wage occupations.

[9]We control for firm size dummies, firm average and standard deviation of log-wages, firm capital and investment rate (in addition to worker-level, industry level and commuting zone controls).

Detailed Overview of the Paper Section 2 presents our theoretical framework. Our goal is to establish a connection between the effect of rising Chinese competition and its differential effect across occupations. We present a factor-proportions theory in which different industries use occupations in different intensities. We then introduce the rise of Chinese competition as a negative price shock, as first proposed in Autor et al. (2013). Our contribution is to show that there exists a simple summary statistic, the occupational exposure index OCX, that encapsulates the effect of the rise in Chinese competition on worker earnings.

Section 3 presents our empirical strategy and data sources. Our identification strategy of the trade shock builds on the previous work that has used the China shock at the industry level, starting with Autor et al. (2014). France, like the vast majority of developed economies, has experienced a spectacular increase in imports from China—faster, if anything, than the U.S.[10] We use China's differential industrial growth in exports to France between 1997 and 2015 as a trade shock. We instrument the rise in Chinese exposure in France to isolate the supply shock coming from China using the rise in Chinese exports in other advanced economies outside the European Monetary Union.[11] We then infer the effect of Chinese competition on worker adjustment by comparing observationally equivalent workers exposed to different levels of Chinese competition.

Our worker-level panel data comes from the matched employer-employee dataset DADS. These data comprise Social Security records of around 4% of the French population working in the private sector. We supplement this dataset with additional firm-level data (from the DADS Fichier Postes and the BRN/FICUS). Taken together, these data provide detailed information on working histories and employer characteristics. In our baseline exercises, we use a fairly coarse aggregation of occupations in seven groups provided by the French statistical agency (INSEE): skilled production workers, unskilled production workers, administrative staff, technical staff, other mid-level occupations, engineers, and executives. This grouping is based on the description of the jobs, their hierarchical position in the firm, and their required level of education. These seven occupations differ substantially in their exposure to Chinese competition. For example, production workers and engineers work in industries that are, on average, three times more exposed than administrative staff.

Section 4 presents our main results. We focus on workers that were attached to the labor market over the 1994-1996 period.[12] This allows us to examine workers that, absent the trade shock, would not have any problem participating in the labor market. The dependent variable that we use throughout our analysis is motivated by our theory. It corresponds to cumulative 1997-2015 worker earnings normalized by initial (1997) worker earnings. As a first step towards documenting heterogeneity in trade adjustment by

[10] The value of Chinese imports increased by 461,2% between 2000 and 2015 in France. In comparison, in the United States, the growth was 383,4% over the same period.

[11] This IV strategy has been used extensively in previous work, see among others, Autor et al. (2014, 2016); Dauth et al. (2014, 2016, 2017).

[12] Workers are defined as attached if they earn at least the monetary equivalent of 1500 hours/year at the legal minimum wage, over 3 consecutive years prior to 1997. Building on the literature studying displaced workers and mass layoffs (e.g., Jacobson et al., 1993), our goal is to zoom in the effect of the trade shock by looking at workers with stable labor income prior to the shock.

occupation, Section 4.1 performs a reduced-form analysis. We estimate a log-linear specification where future worker earnings normalized by initial worker earnings are regressed on our industry-level measure of Chinese competition in the worker's initial (1997) industry. In this regression, we control for (1) a rich array of worker, initial firm and industry characteristics, and commuting zone fixed effects, (2) the initial trade exposure of the industry (separately controlling for Chinese and non-Chinese competition). The 2SLS coefficient on Chinese competition informs us of the effect of the China shock on relative earnings. Pooling all occupations together, we find that, for the average manufacturing worker, an increase of one standard deviation in Chinese exposure amounts to losing 82.5% of the 1997 average worker earnings over the 1997-2015 period.[13]

We then estimate our reduced-form regression separately by occupation, and find that the pooled reduced-form regression masks substantial heterogeneity across occupations. Workers employed in 1997 as production workers, technical staff, engineers or executives experience a significant fall in (normalized) cumulative earnings over the 1997-2015 period. In contrast, Chinese exposure has a smaller negative insignificant effect at conventional levels among unskilled production workers, administrative staff or other mid-level occupations. Quantitatively, a one standard deviation increase in Chinese competition implies a decline in cumulative earnings for engineers (the most affected occupation) by 332% of their initial yearly earnings. By contrast, we cannot reject a zero effect for administrative and other middle-skill occupations. These results lend support to our interpretation that the effect of trade depends on the usage of the occupation in hard-hit industries. A priori, it would seem that administrative staff may dampen the effect of the trade shock by changing industry–taking advantage of the fact that a broad spectrum of sectors make use of this occupation. On the contrary, engineers who are highly specialized in a specific industry exposed to Chinese competition would have a harder time finding a similar job elsewhere. We also document that the effect of the trade shock builds over time. It takes between 5 and 10 years to generate a significant drop in earnings across occupations. This delayed effect echoes similar findings for the U.S. (Autor et al., 2014) and Brazil (Dix-Carneiro and Kovak, 2019).

After having documented substantial heterogeneity in trade adjustment across occupations, we empirically test whether our interpretation is borne out by the data. As we have discussed, the prediction of the model requires checking whether the effect of the occupation exposure index on future (1997-2015) relative to initial (1997) worker earnings is negative. The occupation exposure index derived from our theory is a weighted-average of the industry exposure, where the weight is the share of the wage bill of the occupation in the industry. As we have shown in Figure 1, the correlation between the two is indeed negative. Workers initially employed in occupations that are more intensively used in hard-hit industries experience the largest declines.

We find that this negative relationship persists and becomes somewhat stronger when we instrument

[13] This effect is around three-quarters of magnitude to that of the U.S. reported in Autor et al. (2014). It is not possible to compare the results across occupations since these are not reported in the U.S. Social Security records.

the occupation exposure measure to account for potential alternative drivers of the rise in Chinese competition in France. We instrument the occupation index with an occupation index constructed using industry-exposure to Chinese competition from other advanced economies outside the European Monetary Union and lagged (1994) factor-intensity as weights (to account for potential anticipation effects). Quantitatively, comparing the effect on the average worker initially employed in the occupation with the lowest exposure index (which corresponds to middle-skill occupations such as retail workers) to the highest (which corresponds to skilled production workers such as metal turners) implies a difference in earnings of 188% of the 1997 worker total earnings over the 1997-2015 period. As we have discussed, we include in our regression a direct control of industry exposure to Chinese competition for the industry in which each worker was initially employed. This implies that the occupational exposure effect that we document happens *in addition* to the effect of direct industry exposure.

We show in Section 4.3 that our results are robust to controlling for the differential effect of computerization and robotization across occupations. In particular, our results change little when we control for the routine task index of each occupation, which proxies for how easily machines can replace workers in a given occupation (Autor and Dorn, 2013). We also show that our results hold after augmenting our baseline firm-level controls (for size, average and variance of log-wages) with firm capital and investment. This suggests that within-industry reallocation due to firm heterogeneity and capital-skill complementarity, which also have been proposed as drivers of the US skill premium (Burstein and Vogel, 2017; Parro, 2013), are not driving our results. We also show that our results remain (and become stronger) after accounting for the effect of the expansion of the European Union towards Eastern Europe. However, we find that the effect of this expansion toward the East was substantially more modest for France than for Germany (Dauth et al., 2014).

Section 5 exploits the richness of our data to explore different margins of adjustment. We first analyze whether the adjustment operates more on the extensive or on the intensive margin. To this end, we decompose the effect on relative earnings through changes in relative hours worked versus relative wages. We find evidence that both margins are operative. However, quantitatively, the extensive margin accounts for the larger part of the variation. In Section 5.2, we document the effect of the trade shock on mobility across industries and occupation. First, we show that workers initially employed in hard-hit industries tend to leave that industry *regardless* of their initial occupation. We also show that they tend to move towards sectors outside manufacturing, which have lower Chinese exposure (or none). Perhaps more surprisingly, we also document that, despite changing jobs and leaving their initial industry, workers do not tend to change their initial occupations. We find no effect of Chinese competition on the probability that workers change occupation. This facilitates the interpretation of occupations as factors of production.

A final contribution of this paper is to shed light on how trade adjustment interacts with labor regulation. The discontent with globalization in most developed countries has coincided with the large increase in Chinese competition. Arguably, one of the most critical policy questions is how labor institutions should be designed to mitigate the effects of international trade. In Section 6, we construct a measure of pre-shock labor regulation at the industry level (based on collective agreements) to provide suggestive evidence on this interaction and how it varies across occupations. We find that labor regulation exacerbated the negative effect of Chinese competition on cumulative earnings. We document that the negative effect of regulation is concentrated among skilled production workers and technical staff, whereas it is neutral for the rest of occupations. That is, it seems that labor regulation exacerbated the losses of workers in low-wage occupations.

Related literature This paper relates to several strands of the trade literature. We emphasize the importance of the initial occupation to understand the trade adjustment. This finding is consistent with previous studies, among others, Ebenstein et al. (2014), Bernard et al. (2006), Utar (2018), and Traiberman (2019). Our paper is most closely related to Ebenstein et al., who use CPS data for the 1984-2002 period to document that adjustment to globalization operates mostly through occupational exposure rather than industry exposure. Relative to them we use an instrumental strategy to obtain the effect of import competition on worker adjustment. Also, we provide a theoretical foundation for using an occupational exposure index.[14]

This work follows the tradition of studying trade and labor inequality through the lens of a factor-proportions model. However, we depart from most of the previous literature by *not* focusing on the skill premium. Instead, we consider a more disaggregated set of factors (occupations). A related literature has directly documented the importance of factor specificity on trade adjustment. This list includes, among others, Topalova (2010) and Kovak (2013b). Both studies examine the effect of trade liberalization on wages in developing countries using a specific factors model. Our approach is similar. The most important difference is that we examine the effect of trade across different occupational groups. Our paper is also related to the relatively large and emerging literature that uses longitudinal administrative datasets to analyze 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 (2019). The main departure is to examine the effect across occupations, which is largely absent from this literature.

Finally, our identification strategy builds on the "China industry Shock" introduced in Autor et al. (2014) and subsequently used in Dauth et al. (2014), among others.[15] The main difference with this literature is that we analyze the differential effect of the "China Shock" across occupations and relate this heteroge-

[14] Traiberman (2019) estimates a dynamic structural model for the Danish labor market and documents substantial frictions to occupational mobility that account for the majority of the dispersion in workers earnings. Our results are consistent with the findings in Kambourov and Manovskii (2008, 2009a,b) who document that occupational tenure plays a central role in determining worker's wages (as opposed to tenure in an industry or employer). This finding is consistent with human capital being occupation specific, which implies that switching occupations can have a much greater impact on worker wages than switching industries. See also Topel (1991), Neal (1995), Parent (2000), and Poletaev and Robinson (2008) for earlier studies consistent with the importance of occupation-specific human capital. Many macro-labor models also use this assumption to account for life-cycle earnings profiles (see Kong et al., 2018 and the references therein).

[15] Pierce and Schott (2016) provide an alternative instrument for China shock for the U.S. and show that it accounts for the decline in the U.S. manufacturing employment. Dauth et al. (2016) follow worker histories of German workers and study the rise of China and the fall of the Iron Curtain. They find skill-upgrading within exporting sectors, while the effects are more muted for importing sectors.

neous effect to occupation exposure to Chinese competition, as motivated by our theoretical framework. In addition, we investigate other margins of adjustment (wages, hours, etc.), which help us to understand these effects and are consistent with our factor proportion narrative.[16]

2 Theoretical Framework

The goal of this section is to demonstrate how industry trade shocks can generate differential effects across occupations when industries use occupations in different intensities. Our starting point are the results presented in Autor et al. (2013) and Autor et al. (2014). They argue that the "China shock" should be interpreted as a supply shock from the point of view of the receiving country, and that it can be rationalized as a relative decline in the equilibrium price of the sectors affected by the China shock. Our theoretical framework takes this price shock as given and shows how these price shocks translate into a differential effect in earnings across occupations. We also derive from our model a measure of occupational exposure to trade shocks that we use in our empirical analysis.

Given our interest on the differential effect of trade shocks across occupations, we present a model that builds on the factor proportion theory of trade with an arbitrary number of industries and factors, as in Ethier (1984). A key simplifying assumption of the theory presented here is to think of occupations as factors of production, rather than modeling the underlying factors that each occupation embeds. That is, we think of different industries using engineers, accountants, etc., in different intensities (allowing for a positive elasticity of substitution between them), while we abstract from explicitly modelling the underlying factors that each occupation brings to production. As a result, in the model that we present, each worker is fixed in their initial occupation. That is, workers are allowed to change industries they work in, but not their occupations. In our view, provided that the definition of occupation is not too narrow, this is a reasonable assumption for thinking about short- and medium-run adjustment to a trade shock, since each occupation embeds a set of skills that is hard to replicate with workers from other occupations (e.g., workers initially qualified to be accountants are unlikely to be hired as nurses or engineers after the trade shock). Moreover, from a practical stand point, this assumption allows us to have a substantial amount of heterogeneity in factors of production (by using occupations) relative to the standard two-by-two interpretation of factor proportion theory as high- and low-skill workers (e.g., Leamer, 1996).[17]

We consider a small open economy with $j = 1, \cdots, J$ perfectly-competitive industries. Each industry produces a homogeneous good according to a production function that combines occupations o_{ij}, $i =$

[16] A recent and fast-growing stream of the literature has focused on the regional effects of trade. It includes, among others, Topalova (2007), Autor et al. (2013), Kovak (2013b), Balsvik et al. (2015), Hakobyan and McLaren (2016), Malgouyres (2016), and Dix-Carneiro and Kovak (2017). These studies focus on the effects of trade across different regional labor markets. In this paper, we study the impact of trade at the worker level while controlling for regional differences.

[17] See also Traiberman (2019).

$1, \cdots, I$, as

$$Y_j = A_j \prod_{i=1}^{I} o_{ij}^{\alpha_{ij}}, \tag{1}$$

Let p_j denote the price of the good produced in industry j. Assuming that factor markets are perfectly competitive, we have that the elasticity of the equilibrium price to each wage is constant

$$\frac{\partial \ln p_j}{\partial \ln w_i} = \alpha_{ij}. \tag{2}$$

We can express the relationship between prices, factor intensities, and wages in a compact form using matrix algebra. Let $\boldsymbol{P} \equiv (\ln p_1, \cdots, \ln p_J)'$, $\boldsymbol{W} \equiv (\ln w_1, \cdots, \ln w_I)'$, and $\boldsymbol{A} = [\alpha_{ij}]_{i=1,\ldots,I, j=1,\ldots,J}$ be the $I \times J$ matrix whose i-th row and j-th column correspond to α_{ij}. We have that

$$\boldsymbol{P} = \boldsymbol{A}'\boldsymbol{W}. \tag{3}$$

Consider now two equilibria, denoted by superscripts 0 and 1, with good prices $\boldsymbol{P}^1$ and $\boldsymbol{P}^0$, and factor prices $\boldsymbol{W}^1$ and $\boldsymbol{W}^0$ in which there is positive production in all sectors. It follows that

$$(\boldsymbol{P}^1 - \boldsymbol{P}^0)'\boldsymbol{A}'(\boldsymbol{W}^1 - \boldsymbol{W}^0) = (\boldsymbol{P}^1 - \boldsymbol{P}^0)'(\boldsymbol{P}^1 - \boldsymbol{P}^0) > 0. \tag{4}$$

Equation (4) states that, for *any* two equilibria, the previous relationship has to hold. The interpretation of this equation can be done along the lines of Ethier (1984): On average, high values of $(\ln w_i^1 - \ln w_i^0)$ are associated with high values of α_{ij} and $\ln p_j^1 - \ln p_j^0$.

As pointed out by Deardorff (1993), we can recast this result in terms of a correlation. It suffices to normalize the product of prices in equilibrium k so that $\prod_{j=1}^{J} p_j^k = 1$ for $k = 0, 1$. Under this normalization, the variance of log-prices, $\boldsymbol{P}$, is directly given by (4). Since each row of $\boldsymbol{A}$ adds to one, it follows that the sum across all the I entries of the column vector $\boldsymbol{A}\boldsymbol{P}^k$ is also zero. Combining these observations with Equation (4), we find that

$$\text{Cov}\left(\boldsymbol{A} \cdot \Delta\boldsymbol{P}, \Delta\boldsymbol{W}\right) > 0, \tag{5}$$

where Δ is the difference operator, $\Delta\boldsymbol{P} = \boldsymbol{P}^1 - \boldsymbol{P}^0$. Note that each entry $i = 1, \cdots, I$ of $\boldsymbol{A} \cdot \Delta\boldsymbol{P}$ is a factor-intensity weighted average of the log-price changes, $\sum_{j=1}^{J} \alpha_{ij} \Delta \ln p_j$. The positive correlation in Equation (5) implies that, on average, occupations used intensively in sectors experiencing substantial declines in prices should also experience declines in earnings. Moreover, note that this result holds for an arbitrary number of goods and factors. To the reader familiar with factor proportion models this is indeed a statement of the Stolper-Samuelson theorem for an arbitrary number of goods and factors in terms of elasticities (rather than the more commonly used levels).

Despite its simplicity, this is a novel result to the best of our knowledge. The key difference with Ethier (1984) formulation of the Stolper-Samuelson theorem is that, in his formulation, the equivalent term to $\boldsymbol{A}$ in

Equation (5) depends on equilibrium prices evaluated at an intermediate equilibrium point between 0 and 1. These equilibrium prices are thus unobserved and not pinned down by the theory.[18] Moreover, since Ethier states the result in changes and not elasticities, even using a Cobb-Douglas production function would not eliminate the dependence of $\boldsymbol{A}$ on prices. As a consequence, his result remained mainly as an elegant theoretical derivation. The proposed empirical attempts to test Ethier's result so far either considered an infinitesimal change in prices (e.g., Deardorff, 1993) or Leontieff production functions to eliminate the dependence of the cost function on equilibrium input prices (Bernhofen et al., 2014). In contrast, our formulation in terms of elasticities holds for any two equilibria and allows for a positive elasticity of substitution across factors of production (albeit it constrains this elasticity to be one, since we are assuming Cobb-Douglas production functions).[19]

To build a connection with our empirical exercise, we assume that in equilibrium 1 there is a rise in Chinese competition that is heterogeneous across domestic industries. Following Autor et al. (2013), we conceptualize the China shock CX as the world price vector changing from $\boldsymbol{P}^0$ to $\boldsymbol{P}^1 = \boldsymbol{P}^0 - \beta \boldsymbol{CX}$, with $\beta > 0$. That is, there is a negative relationship between Chinese exposure CX and the change in prices, $\Delta \boldsymbol{P} = -\beta \cdot \boldsymbol{CX}$. Given this assumption, Equation (5) becomes $\mathrm{Cov}(\boldsymbol{A} \cdot \boldsymbol{CX}, \Delta \boldsymbol{W}) < 0$. This implies that occupations more intensively used in more exposed industries experience, on average, a larger decline in earnings.

More concretely, we can write each entry i of $\boldsymbol{A} \cdot \boldsymbol{CX}$ as an occupation-specific exposure index. The index is computed by weighting industry-specific exposure to Chinese competition by how intensively each industry uses occupation i measured by α_{ij}

$$OCX_i \equiv \sum_{j=1}^{J} \alpha_{ij} CX_j. \tag{6}$$

Using this notation, Equation (7) can be equivalently stated as

$$\mathrm{Cov}(\boldsymbol{OCX}, \Delta \boldsymbol{W}) < 0. \tag{7}$$

Equation (7) is the core result of our theoretical framework since it provides a theoretical foundation for using an occupational exposure index and a clear testable implication on worker adjustment at the occupational level. Before summarizing this prediction below, we note that our formulation of the OCX is similar to the reduced-form occupational exposure index used in Ebenstein et al. (2014) to assess the impact of offshoring on US workers.

[18] This is the case because Ethier's proof uses the intermediate value theorem.

[19] It is possible to go beyond the Cobb-Douglas production functions we have assumed so far and generalize the result to neoclassical production functions with arbitrary patterns of substitution across production factors and bias of technology. The key insight for this derivation is that under constant returns to scale and perfect competition, firms' optimality conditions imply that we can locally approximate the cost function with a Cobb-Douglas cost function with varying factor shares—which we observe in our data. Details are available upon request.

Empirical Prediction *The decline in relative earnings $\Delta\boldsymbol{W}$ is, on average, larger in occupations that are more intensively used in industries more exposed to Chinese competition. Formally, as stated in Equation (7), this implies that there is a negative correlation between changes in worker earnings and their occupation exposure to Chinese competition.*

The intuition for this result follows from the logic of a standard factor-proportion theory model. After an increase in Chinese competition, the change in the rewards to a given occupation depends on how specific this occupation is to the industries most exposed to Chinese competition. If an occupation is mainly used in industries highly exposed to Chinese competition, workers performing this occupation will experience a large decline in earnings because output and, consequently, labor demand will fall the most for these industries. Similarly, if an occupation is mainly used in industries with zero (or very low) exposure to Chinese competition, the earnings of workers performing this occupation will not be affected.

Bringing the Theoretical Framework to the data One appealing property of our empirical prediction is that it is stated in terms of the sign of a covariance. This immediately suggests testing for this result using standard OLS techniques with the occupation exposure index OCX_i derived from our theory (Equation 6) as independent variable. In particular, in our empirical specification, we consider a regression in which the dependent variable is the change in workers' earnings between two equilibria,[20] and the independent variable is the occupational exposure index OCX of the initial occupation of a worker n. The estimated OLS coefficient of this regression corresponds to $\hat{\beta} = \mathrm{Cov}(\boldsymbol{OCX}, \Delta\boldsymbol{W})/\mathrm{Var}(\boldsymbol{OCX})$. This covariance term corresponds to the covariance defined in Equation (7) with wages averaged at the occupation cell. Since the variance is always positive, the sign of $\hat{\beta}$ coincides with the covariance term. Thus, a negative sign of $\hat{\beta}$ is consistent with the theoretical prediction of our framework, while a positive coefficient would reject it.

In the standard neoclassical factor-proportion theory, it is assumed that labor is homogeneous and that wages are equalized within and across industries for any occupation. In practice, however, workers are heterogeneous in their earnings capacity for reasons not included in the model. In our empirical specification, we will include a rich set of controls that absorb some of these observable differences across workers (age, experience, gender, tenure, location, industry, and firm characteristics). After these differences are partialed out, our empirical covariance measure will infer the average changes at the averaged i or ij cell. Indeed, the regression result of changes in workers' earnings on the occupational exposure index after partialing-out this set of rich controls corresponds to Figure 1 in the Introduction, where we have documented a negative correlation between the ratio of relative earnings and the occupation exposure (see Section 4 for a full description of the controls). Finally, a central concern in implementing our regression approach is that there may be unobserved factors driving both the occupational exposure index and earnings (despite including a rich set of controls). For this reason we will follow an instrumental variable

[20] Our theory abstracts from labor supply, since workers supply one unit of labor inelastically. Thus, through the lens of our theory, looking at worker earnings or wages is equivalent. Of course, in practice, labor supply is elastic. We also analyze the effect on relative wages in the empirical section and document similar results.

approach that we will discuss at length in Section 3.2.

Construction of Empirical Counterparts to Variables in our Theory Before concluding the section, we discuss the construction of two key variables for our empirical analysis: our outcome variable, the change in worker earnings', and our measure of occupation intensity. We begin discussing the construction of our outcome variable. A literal interpretation of our model would suggest using a measure of workers' total labor earnings in the final year of our data (2015) relative to their earnings in the initial year (1997). This is not our preferred specification for two reasons. In our theoretical framework, there are only two time periods and there is no entry and exit of workers in the labor market. However, in practice, the China trade shock may put workers with positive earnings in 1997 in different earnings trajectories over the 19-year period that we consider. Some of them may exit the labor force, generating periods of zero earnings, or reduce the number of hours they work. Given these considerations, we instead interpret the final equilibrium point of our model as a the accumulated worker earning trajectories. We thus construct our measure of worker changes in earnings as

$$\frac{\sum_{t=1997}^{2015} E_{n,t}}{E_{n,1997}}, \tag{8}$$

where the numerator is the total earnings of a worker over the 1997-2015 period and the denominator, earnings in 1997. The advantage of this formulation is that the dependent variable can be readily interpreted as multiples of initial worker earnings. Moreover, it coincides with the outcome variable that has been extensively studied in assessing the effect of the China shock, e.g., Autor et al. (2013) and Autor et al. (2014). This makes our baseline results easier to compare with these studies.[21]

Next, we discuss the construction of the measure of occupation intensity at the industry level. The first-order condition of the firm problem in industry j implies that

$$\alpha_{ij} = \frac{w_i o_{ij}}{p_j Y_j}, \tag{9}$$

where the numerator is total labor payments to occupation i in sector j, and the denominator is the value of production. Our preferred measure is based on the share of total payments to occupation i in industry j relative to total labor payments, which is implied by our theoretical framework. However, our baseline model assumes that labor payments coincide with the value of total sectoral output. This implicitly assumes that there are no intermediates or other factors of production. To account for these additional factors, as a robustness check, we also compute occupation intensity measures as the occupation labor payments relative to (1) the value of total sectoral output (measured as value of total shipments) and (2)

[21] This expression corresponds to a first-order Taylor approximation to the exact expression we would obtain from our theoretical framework, which would be $\ln\left(\sum_{t=1997}^{2} 015 E_t / E_{1997}\right)$ around the average accumulated earnings $\bar{E} = \sum_{t=1997}^{2015} E_t$ being equal to initial earnings. Taking a Taylor approximation around 1, we obtain $\ln\left(\frac{\overline{E_n}}{E_{n,1997}}\right) = \frac{\overline{E_n}}{E_{n,1997}} - 1 + o\left(\frac{\overline{E_n}}{E_{n,1997}} - 1\right)$..

sectoral value added.[22]

3 Identification and Data

We document the heterogeneous effect of trade across occupations leveraging on the spectacular growth of Chinese exports to France over 1997-2015. In this section, we first argue that this is a good empirical setting for the task at hand and discuss our identification assumptions. We then present the data sources used to conduct our empirical exercise. We put special emphasis on the discussion of our worker-level data and the construction of the occupation variables that enter into our regression analysis.

3.1 Identification

In our analysis, we use the industry-specific variation in the rise of Chinese exports to France between 1997 and 2015 to document heterogeneous impacts across occupations and test the empirical prediction of our model. During this period, Chinese exports to high-income countries (including France) increased steeply. Much of this effect comes from internal Chinese policy reforms and technology upgrading (Autor et al., 2016). Another important factor is the accession of China to the WTO in December of 2001, which triggered a surge in Chinese exports and FDI towards China (Erten and Leight, 2017).

The rise in Chinese exports to France has substantially differed across industries (see Table 1 below). To exploit this variation, we use industry-level measures of Chinese competition as our measure of industry-specific shock. We follow the empirical strategy developed in Autor et al. (2014), and proxy industry exposure by the evolution of the import penetration rate of goods imported from China. More concretely, we define our measure of industry j's Chinese eXposure, CX_j, as

$$CX_j = \frac{\Delta M^{FC}_{j,2015-1997}}{Y_{j,1997} + M_{j,1997} - E_{j,1997}}. \tag{10}$$

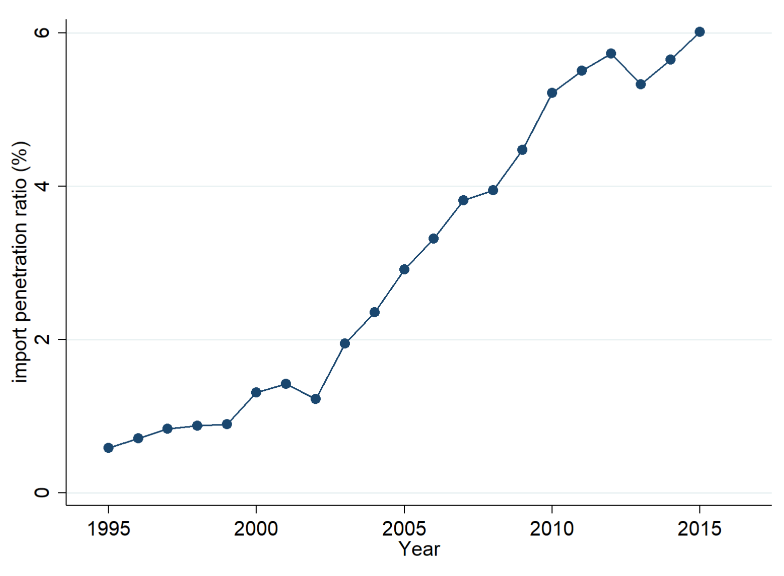
The numerator corresponds to the change in French imports from China in industry j over the period 1997-2015, denoted, $\Delta M^{FC}_{j,2015-1997}$. The denominator is total domestic market absorption in France of these goods at the beginning of the period. This is measured by industry sales, $Y_{j,1997}$, plus industry imports, $M_{j,1997}$, minus industry exports, $E_{j,1997}$. Normalizing by domestic absorption is meant to capture whether the change in Chinese imports in a given industry was large or small relative to its initial total size.

Figure 2 depicts the evolution of Chinese exposure defined in Equation (10) for the overall French economy starting in 1994. Chinese exposure increased more than six-fold throughout the period. The picture also shows an acceleration around 2001, which corresponds to China's accession to the WTO.[23]

[22]Both shipments and value added are model-consistent measures that can be derived from the first-order conditions of the producer, depending on whether the production function is interpreted in terms of gross output or value added.

[23]The import penetration ratio of Chinese goods in France increases annually by 0.14 p.p. from 1995 to 2001, prior to China's accession to the WTO. This pace jumps to an annual rate of 0.44 p.p. after that date, a pace that is 2.8 times as fast. Even though this

Figure 2: Import penetration of Chinese Imports in France



The choice of our starting and final dates are constrained by data availability (see the discussion in Section 3.2).

An important feature of our empirical exercise is that it leverages the substantial amount of heterogeneity in Chinese exposure across narrowly defined industries. This allows us to credibly compare observationally equivalent workers that work in different narrowly defined industries within the same broad sector of the economy. For this reason, we conduct our analysis at the four-digit industry level (which corresponds to 577 industries), and always add broad sector fixed effects in our analysis. The downside of this approach is that France does not produce sectoral price indices at this level of disaggregation, which would allow us to proxy for the importance of the trade shock at industry level (as suggested by our theory). For this reason, our preferred specification is to capture shocks to foreign export supply directly using the Chinese exposure rather than prices (as Autor et al., 2014). This can be thought of as a reduced-form representation of the export shock.[24]

However significant the Chinese import shock might be, all worker adjustment outcomes that we study may also reflect other domestic shocks affecting demand for French industries' goods. In order to isolate the exogenous, foreign-supply-driven component of the import shock, we use the instrumental variable approach proposed by Autor et al. (2014) and instrument the measure of French Chinese exposure (10) with an analogous measure of industry-level change in import penetration from a set of comparable high-

acceleration was less dramatic than in the US (Autor et al. (2014) report a four-fold increase for the annual pace), the steeper trend in France after 2001 goes on practically unaffected by the Great Recession, and resumes swiftly after a mild downturn in 2012. The United States experiences a qualitatively similar pattern.

[24]In Section 3.2 we show that there is a negative relationship between Chinese exposure and the change in industry prices at a roughly 2-digit level of aggregation over 2000-2015.

income countries,

$$CX_j^A = \frac{\Delta M^A_{j,2007-1997}}{Y_{j,1994} + M_{j,1994} - E_{j,1994}}, \tag{11}$$

where $M^A_{j,2007-1997}$ is the change in imports from China in industry j abroad for a group of high-income countries excluding France. This group is formed by countries with an income level similar to France and outside the European Monetary Union.[25] We also note that we use a three-year lag on the denominator to minimize anticipation concerns. We assign our instrumental industry exposure variable CX_j^A to workers based on their lagged industry of affiliation, so as to minimize the potential downward bias arising from workers' sorting into industries in expectation of rising competition from China.

This instrumental-variable strategy relies on the pervasive nature of the "China shock" across high-income countries. China's increased comparative advantage in manufacturing industries should affect industries similarly across high-income countries. As in Autor et al. (2014), industries in France and in the group of other high-income countries experienced very similar trends in import penetration of Chinese goods, vindicating the identification strategy for our purposes: an OLS regression between the two measures of industry exposure, CX and CX^A, adjusted for the size difference between France and the group of countries, results in a coefficient equal to 1.19, with a t-statistic equal to 23.8 and a R^2 equal to 0.72.[26]

3.2 Measurement of Industry Exposure

To compute our measure of industry exposure, we use trade flows from Comtrade on product-level imports, in the 6-digit HS (Harmonized System) classification, which we map into NACE, the European classification of economic activities, that is present in our longitudinal matched employer-employee dataset (see below).[27] In order to measure market absorption at the NACE 4-digit level, we need a measure of industry-level shipments. For this purpose, we aggregate firm-level sales from the BRN/FARE,[28] a comprehensive confidential corporate tax data source, at the NACE 4-digit level.

Table 1 reports the list of the most and least exposed industries. As one would expect, the most exposed industries are to be found in the apparel industry, in the manufacturing of consumer goods such as games and toys, imitation jewellery, luggage, as well as in the manufacturing of electrical goods. On the other hand, industries like manufacture of bread, production of mineral water or operation of diaries and cheese making are not exposed to Chinese competition.

Our theoretical framework operated under the assumption, borrowed from Autor et al. (2013, 2016), that Chinese exposure imposes downward pressure on sectoral prices, i.e., $\Delta \boldsymbol{P} = -\beta \boldsymbol{CX}$. We can directly

[25]We select the same nine countries as in Dauth et al. (2014), who applied the same identification approach to Germany: Australia, Canada, Japan, Norway, New Zealand, Sweden, Singapore, the United States and the United Kingdom.

[26]This correlation is stronger than in Autor et al. (2014), where these respective values are: 0.85, 9.20, and 0.34.

[27]To do so, we use the European Classification of Products by Activity (CPA) as an intermediary: the HS6 classification maps into the CPA, whose 4 first digits correspond to the NACE.

[28]BRN/FARE stands for "Bénéfices Réels Normaux/Fichier Approché des Résultats d'Ésane" in French. Both datasets compile corporate tax reports on French firms' balance sheets. BRN covers the period 1993-2007 while FARE covers 2008-2015. They are exhaustive for firms above a size or turnover threshold.

Table 1: Top and Bottom Ten Manufacturing Industries in terms of Chinese Exposure

(a) Most Exposed Industries

NACE	Industry description:	CX_j (%)
3650	Manufacture of games and toys	87.1
3661	Manufacture of imitation jewellery	77.2
1821	Manufacture of workwear	67.1
1920	Manufacture of luggage, handbags and the like	60.1
2624	Manufacture of other technical ceramic product	52.2
2941	Manufacture of portable hand held power tools	49.2
2875	Manufacture of other electrical products n.e.c.	48.5
1824	Manufacture of other wearing apparel and accessories	44.1
3230	Manufacture of television and radio receivers ...	41.8
3001	Manufacture of office machinery	41.8

(b) Least Exposed Industries

NACE	industry description:	CX_j (%)
2224	Pre-press activities	0.0
1551	Operation of dairies and cheese making	0.0
2662	Manufacture of plaster products for construction	0.0
1552	Manufacture of ice cream	0.0
1581	Manufacture of bread	0.0
1561	Manufacture of grain mill productss	0.0
2663	Manufacture of ready-mixed concrete	0.0
2320	Manufacture of refined petroleum products	0.0
2830	Manufacture of steam generators	0.0
1598	Production of mineral water and soft drinks	0.0

test this assumption using our data. The only caveat is that French sectoral price indices exist at a much more aggregated level than the 4-digit industry for which we have our trade flows data and that we use in our analysis. While we cannot test this assumption at the 4-digit industry level (577 industries in our matched dataset), we document a negative correlation between changes in log-prices and Chinese exposure at a more aggregate level (52 industries) for the 2000-2015 period.[29] Table A.2 in Appendix A shows that the coefficient of running an ordinary least squares regression of the change of French sectoral log-prices on Chinese exposure (defined as in Equation 10) is negative and statistically significant. Moreover, this finding is robust to instrumenting Chinese exposure with our instrument based on Chinese exposure in other advanced economies (Equation 11).

3.3 Worker-Level Data

Our data on French workers' employment histories comes from the matched employer-employee DADS (Déclarations Annuelles de Données Sociales) panel. These data are an extract from the DADS Fichier Postes, which we also use to construct firm-level controls. The DADS Fichier Postes is an exhaustive administrative dataset that contains the Social Security records of all salaried employees in any private and semi-public firm.[30] From this exhaustive set of employed workers, the DADS Panel tracks over time those workers who were born in October in even years, which amounts to an overall coverage of slightly more than 4% of the French population working in the private sector.[31] Since we are interested in labor-market adjustments that operate through market forces, we exclude workers initially employed in semi-public firms from our sample.

The DADS Panel contains detailed information on the characteristics of a match between a worker and an employer. In a given year, an observation corresponds to a worker's employment spell at a given firm

[29]This corresponds to the A88 classification by INSEE. There is no data at this or finer level of disaggregation for an earlier period.

[30]These data are maintained by the French National Statistical Institute (INSEE). They are compiled from the mandatory filings by employers to the Social Security. The DADS excludes the self-employed, central government entities ("Fonction Public d'État"), domestic services, and individuals affiliated to the French Social Security System working for employers that are located abroad.

[31]The DADS Fichier Postes, and the DADS Panel in particular, have been used in other economic studies dating back to Abowd et al. (1999) and Postel-Vinay and Robin (2002). Note that only the DADS Panel dataset allows for a longitudinal study of workers' employment history, by assigning each sampled worker a fictitious ID, while the exhaustive source does not, for confidentiality purposes.

within that year, specifying its duration, start and end date, total gross and net wages,[32] hours worked, and the 2-digit occupation.[33] Workers' individual characteristics include age, sex, place of residence, date of entry in the labor market, and seniority at the current employer. Information on employers contains their 4-digit industry, their geographical location at the municipality level, as well as their unique identifier. The data therefore allows us to closely track an individual worker across all their employment spells over the period of interest, 1997-2015. In particular, we observe the worker's transitions across establishments, industries, geographical locations,[34] and 2-digit occupations. We construct worker-level outcome variables measuring total earnings, hours worked, wage per hour, and worker commuting zone. Note that this allows us to decompose workers' total wage earnings over 1997-2015 into an intensive margin, the hourly wage rate, and an extensive margin, total hours worked.

To study the effects of the rise in Chinese exports on French workers, we focus our analysis on workers attached to the labor market prior to this trade shock. The rationale for focusing on these workers is to capture the effect of the trade shock on workers that were "settled" in their jobs and would otherwise have no problem participating in the labor market.[35] We define attached workers as those who, in each of the four consecutive years from 1994 to 1997, received a wage income higher than the equivalent to 1500 annual hours paid at the national minimum wage. Note that the focus on attached workers makes our outcome variables as comparable as possible across observationally identical workers, as their situation prior to the shock is more likely to reflect a stationary state, rather than a transient one.

In our sample, we count 163,207 attached workers, who were born between 1942 and 1976. When we match this dataset with firm level-data BRN/FICUS to compute the measures of factor intensity (9) that use value of shipments or value-added as denominators, the sample drops to 154,669. We use the former sample to estimate the effect of Chinese exposure across occupations, since we do not need this industry information. We use the latter sample to test the empirical prediction of our model, since we need to use the factor intensity measures. For ease of exposition, Table A.1 in the appendix reports the summary statistics only for the latter one. The summary statistics of both samples are almost identical.

3.4 Occupational Groups

To document the heterogeneous effect across occupations of the rise of Chinese exports, we use the information on the occupation of the employee in 1997 reported in the DADS Panel. Occupations are reported according to the PCS-ESE classification (Professions et Catégories Socioprofessionnelles - des Em-

[32] The wage variable in the data aggregates all types of transfers from an employer to a worker that are specified on the employment contract.

[33] Even though the 4-digit occupation is reported by employers, the information at the 2-digit occupation level is more reliable as it is processed statistically by the INSEE (see below for more details). Caliendo et al. (2015) and Harrigan et al. (2021) also use this classification.

[34] The geographical unit is the commuting zone (*Zone d'emploi*). Over the period of study, mainland France is decomposed into 348 commuting zones.

[35] This focus is in line with the prior trade literature, e.g., Autor et al. (2014) which in turn builds on the displaced workers and mass-layoffs literature (e.g., Jacobson et al., 1993) to motivate the focus on attached workers.

plois Salariés des Employeurs privés et publics), which is the reference classification of occupations used by the French public administration.[36]

To classify occupations in our baseline exercises, we use a fairly coarse aggregation in seven groups that comprise subsets of 2-digit level (CS2) occupations. We take these groupings from the "socio-professional groups" created by the French National Statistical Agency (INSEE). These broad groups are defined based on the description of the jobs, their hierarchical position in the firm, and their required level of education. The advantage of this relatively coarse classification is that it goes beyond the 1-digit classification of occupations and, as we show below, it captures substantial heterogeneity in occupational exposure that is muted at the 1-digit level of aggregation, while it still maintains the total number of occupations in a number that is easier to interpret and digest. The occupational groups that we consider are defined as follows:

1. *Unskilled production workers* (PCS=67 and 68): this category comprises unqualified industrial and manual workers (i.e., without needed certification work in a given occupation). Examples of these occupations include: construction workers, cleaners, unqualified assembly and production line workers.

2. *Skilled production workers* (PCS=62, 63 and 65): this category comprises qualified industrial and manual workers operating in occupations that require certification. Examples of these occupations include: chauffeurs, bulldozer drivers, metal turners, mechanical fitters.

3. *Administrative staff* (PCS=46 and 54): this category comprises mid-level managers, professionals and office workers. Examples of these occupations include: accountants, sales representatives, secretaries, administrative occupations.

4. *Technical staff* (PCS=47 and 48): this category comprises technicians and supervisors. Examples of these occupations include: designers of electronic material, quality control technicians, site managers

5. *Other mid-level occupations* (PCS=42, 43, 55 and 56): this category comprises teachers, mid-level health professionals, retail workers, and personal service workers.

6. *Engineers* (PCS=38): this category comprises technical managers and engineers. Occupations in this category also include architects, and manufacturing directors.

7. *Executives* (PCS=37): this category comprises top managers and professionals. Examples of these occupations include: auditors, lawyers, chiefs of staff, commercial and sales directors.

Table 2 reports summary statistics by occupations in our sample. We also report 1-digit broad aggregates of the occupations. Occupational groups within the 1-digit Managers category have an average

[36] We use the 1982 and 2003 versions of the PCS-ESE classification.

Table 2: Summary Statistics by Occupation

		% of 1997 occupation in				
PCS Code	Description	Sample	Exposed	No-Manuf.	Chn. Exp.(%)	Hrly. Wage(€)
3	**Managers**	14.1	12.4	16.2	2.0	20.9
37	Executives	7.4	5.0	9.3	1.7	21.3
38	Engineers	4.8	7.2	4.0	3.4	20.2
34-35	Other Eng.	1.9	0.2	2.9	0.1	21.4
4-5	**Mid-Level**	45.8	31.3	54.7	1.4	10.4
46-54	Admin. Staff	22.5	14.0	28.0	1.4	10.2
45-48	Tech. Staff	11.7	16.6	9.4	2.8	11.6
42-43-55-56	Other Mid.	11.6	0.7	17.3	0.2	9.4
6	**Production**	40.1	56.3	29.1	3.5	8.2
62-63-64-65	Skilled	30.3	37.1	24.2	2.6	8.6
67-68	Unskilled	9.8	19.2	4.8	6.1	7.3

Notes: Sample, Exposed and No-Manuf. correspond to the share of each occupation in the sample, highly exposed industries (above the 75th percentile of Chinese exposure) and outside from the manufacturing sector. Chn. Exp. is the average of Chinese Exposure for each occupation. Hrly. Wage is the average hourly wage of each occupation in 1997.

hourly wage (in 1997) of 20.9€, which is above the rest of the groups. Even though there is not much difference in hourly wages within the group, we can observe substantial differences in exposure to Chinese competition. The average engineer works in an industry with twice as much exposure to Chinese competition than the average executive. The second broad 1-digit group corresponds to Mid-Level Occupations (CS1-4 and CS1-5) and it is the largest in size. The hourly wage (in 1997) was substantially lower than that of managers, 10.4€ on average. There is substantial heterogeneity in exposure to Chinese competition within the group. The average exposure among technical staff is twice the exposure among administrative staff (2.8% vs 1.4%), whereas the other occupations are hardly exposed to Chinese competition (0.2%). Finally, the last broad 1-digit occupational group corresponds to Production workers. The hourly wage of production workers is the lowest (8.2€) and the average exposure to Chinese competition is the largest (3.5%). Within production workers, the skilled ones have relatively higher wages but a larger share of them work in highly exposed industries.[37]

Taken together, the evidence presented in Table 2 paints a picture consistent with a substantial heterogeneity in exposure to Chinese competition across occupations. Given this finding, it is perhaps natural to expect that the effect of Chinese competition will be heterogeneous across occupations. This is the empirical question we aim to analyze in the next section.

[37] Finally, we note that we do not report the coefficients for occupation 34-35 (other managers) when we break down our analysis by occupation because it is a very small (1.9%) and heterogeneous group. Similarly, we have excluded from our sample workers that were initially employed in occupations with PCS code starting with 2 (Business Heads and CEOs) because they represent a very small share of sample (2.2%) that is an extremely heterogeneous (it includes craftsmen, small business owners, and CEOs). We do, however, include both groups of workers when we estimate pooled regressions that do not do not distinguish by occupation. Also, as we have discussed, we focus on workers employed in private firms. In practice, this implies that we exclude from our sample occupations operating in the public/non-profit sector. These categories correspond to: managerial public servants(33), clergymen (44), intermediate-level public servants (45), public service employees (52) and policemen, military, and security workers (53).

3.5 Industry-Occupation Specificity and Index of Occupational Exposure

Before turning to our regression analysis, we discuss the empirical counterparts of our measure of industry specificity of an occupation (9), α_{ij}, and the occupation exposure index (6), OCX_i. As discussed in Section 2, our preferred measure of specificity of occupation i in industry j, α_{ij}, is the ratio between the wage bill of occupation i in industry j and the total wage bill of industry j in 1997. Table A.3 in the appendix reports summary statistics of α_{ij} by occupation. We find that there is substantial variation across occupations in terms of average specificity and its dispersion.[38]

Specificity by itself does not need to be correlated to changes in earnings. As our results in the theoretical framework demonstrate, it is the inner product between factor specificity and industry exposure that should be correlated with the change in earnings across occupations. Intuitively, the occupations that should experience larger adjustments in earnings are those that are on average more exposed to the trade shock because these occupations tend to be demanded by industries that are on average more exposed to the trade shock. We use Equation (6) from Section 2 to construct our measure of occupation exposure to Chinese competition. As we have discussed, this measure is a weighted average of our measure of Chinese exposure at the industry level CX_j using industry-occupation intensities α_{ij} as weights,

$$OCX_i = \sum_{j=1}^{J} \alpha_{ij} CX_j. \tag{12}$$

Table 3 reports the value of OCX_i for each of our occupations. According to this measure, Engineers and Skilled production workers are the most exposed occupations to Chinese competition. Conversely, other middle-skill occupations appear to have the lowest exposure. It is interesting to note that exposure differs across occupations that appear to require similar levels of education (e.g., executives vs. engineers, administrative staff vs. other middle-skill occupations). This suggests that our occupational index captures variation that goes beyond the traditional notion of skill as years of education that is usually emphasized in factor proportion theory. Table A.3 and A.4 in the online appendix report the occupation exposure indexes when using alternative measures of occupation-intensity based in gross output and value added. As it can be readily observed by comparing these tables, the ranking of OCX_i is consistent throughout. Even though the occupation index in Table 3 is our preferred measure, we show that our empirical results are robust to using these other two measures of factor intensity to construct the occupation exposure index.

Finally, to construct an instrument of the occupation exposure index, we proceed by taking the measures of Chinese exposure in other countries CX_j^A discussed in Equation (11), and computing the weighted

[38] As a robustness check, we also present the results when we use two alternative measures of α. Tables A.1 and A.2 in the online appendix report summary statistics for α_{ij} when using the wage bill over shipments and over the value added of the sector, respectively.

Table 3: Occupation Exposure Index

	OCX_i	OCX_i^A
Executives	1.48	21.84
Engineers	5.22	28.84
Administrative Staff	2.80	38.00
Technician Staff	2.49	37.15
Other Middle-skill Occ.	0.18	1.98
Skilled Production Workers	7.16	72.46
Unskilled Production Workers	3.53	48.57

Notes: Measures constructed according to Equations (12) and (13).

sum using industry-occupation intensities in 1994 as weights,

$$OCX_i^A = \sum_{j=1}^{J} \alpha_{ij}^{1994} CX_j^A. \tag{13}$$

We use the measure of industry-occupation factor intensity in 1994 to account for potential anticipation effects in an analogous way as we have accounted for them in constructing CX_j^A.[39]

4 Effect of Trade Across Occupations

This section reports the main results of the paper. First, we present reduced-form evidence on the negative effect of Chinese competition and its heterogeneity across occupations. We then use the occupational exposure index derived in Section 2 to show that occupations that are, on average, used more intensively in highly-exposed sectors experience a larger drop in earnings relative to their 1997 level. This heterogeneous adjustment in earnings across occupations is consistent with the empirical prediction derived from our factor proportion theoretical framework.

4.1 A Reduced-Form Look at Heterogeneous Effects Across Occupations

As a first step of our empirical investigation, we run the following worker-level regression

$$E_n = \gamma_0 + \beta \cdot \text{Chinese Exposure}_{j(n)} + \gamma_1 \cdot \text{Controls}_n + \varepsilon_n, \tag{14}$$

where worker n was employed in occupation *i(n)* in 1997, was working in industry *j(n)* in 1997, and $E_n = \left(\sum_{t=1997}^{t=2015} E_n^t\right) / E_n^{1997}$ denotes cumulative earnings between 1997 and 2015 normalized by the earnings in 1997 for worker n.[40] This measure imputes zero earnings at time t if a worker does not have any earnings in that year (e.g., they drop out of the labor force). Thus, this measure captures both the extensive and

[39] The correlation between OCX_i and OCX_i^A is around 0.8.

[40] If a worker is employed in more than one industry or occupation during 1997, we select the one in which the worker has been employed for a longer period.

intensive margins of adjustment. We decompose these margins (hours worked and wages) in the next section.

All our regressions include the same set of $\text{Controls}_{ij(n)}$ to absorb differences at the worker, industry, and geographical level. As worker controls, we include a dummy for being a woman, birth-year fixed effects, dummy bins for labor market experience, tenure at the initial (1997) firm, and initial (1997) firm size.[41] To control for worker earnings histories, we include the log hourly wage, the log of yearly hours worked and the log of total yearly earnings averaged over 1993 to 1997, the log change in hourly wage, hours worked and total earnings between years 1993 and 1997, the log wage at the initial (1997) firm, and the interaction of all the previous variables with worker age. To control for firm heterogeneity, we also control for the average and variance of log wages paid at the firm in which worker i was employed in 1997.[42] In Section 4.3, we show that our results are robust to controlling also for firm capital and investment.

To control for industry trends and heterogeneity, for each four-digit sector j, we include as controls the total wage bill, average wage and hours worked in 1997, and the change in these variables between 1994 and 1997. We also include ten broad sector fixed effects.[43] We also add as two separate controls the level of initial (1997) Chinese and non-Chinese import penetration. Finally, to account for geographical heterogeneity, we include workers' initial (1997) commuting zone fixed effects.[44]

Through the lens of our model, worker-level controls and regional fixed effects absorb observable worker differences in their effective supply of human capital because of differences in gender, experience, etc. Including these controls allows us to obtain an effective return per occupation. Firm-level controls, industry controls, and regional fixed effects control for within 4-digit industry differences such as firm-level price adjustments to Chinese competition.

Figure 3 reports the 2SLS coefficients of the effect of Chinese exposure on the cumulative earnings, β in Equation (14), for the pooled regression and for a regression that we estimate separately by occupations, according to the initial worker occupation in 1997.[45] The first column in the figure reports the estimated effect on the pooled regression across occupations. Thus, it corresponds to the effect on the average worker in our sample. The coefficient on Chinese Exposure is negative and statistically significant, implying a decline in earnings for the average worker. As a result, this first regression estimate documents a negative effect on the average worker coming from the differential industry exposure to the China shock. Quantitatively, our estimated coefficient means that a one standard deviation increase in Chinese exposure reduces cumulative earnings of a manufacturing worker by $5.07 \cdot 16.29\% = 82.5\%$ of the initial earnings. Alter-

[41] 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, 100-999 employees and 1000+.

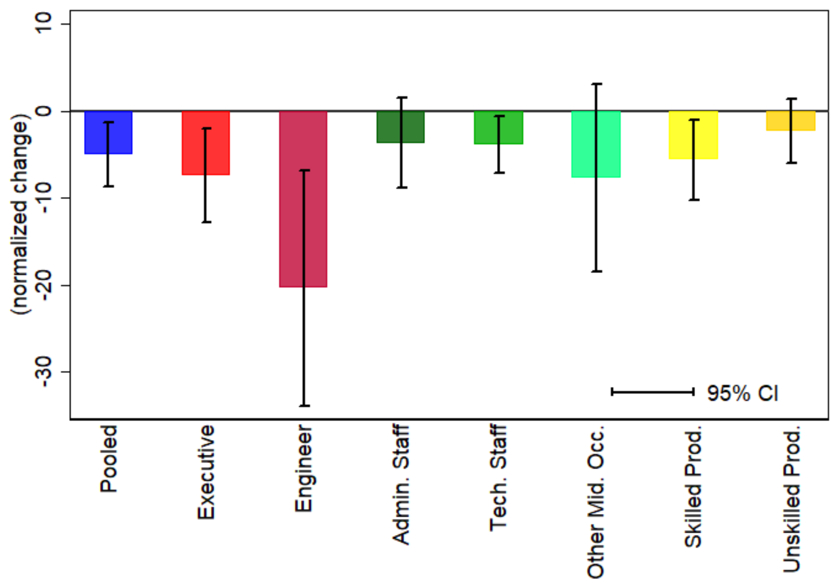
[42] If a worker is employed in more than one firm, we use the firm that employed the worker for a longer time in 1997. Note that we construct the firm-level controls using the DADS-postes, which contains information on *all* workers in the firm.

[43] These correspond broadly to 2-digit industry fixed effects. Analogous to Autor et al. (2014), these groups are: food/tobacco, wood/furniture, chemical/petroleum, metal/metal products, transportation, textile/apparel/leather, paper/print, plastic/rubber/glass, machines/electrical, and toys/other.

[44] We use the commuting zone (zone d'emploi) of the place of residence of the worker. Using the employment zone of the establishment where the worker works yields very similar results (since they are highly correlated).

[45] The corresponding tables for these regressions can be found in the Appendix.

Figure 3: Cumulative Effect on Earnings Across Occupations



Notes: Each bar corresponds to the coefficient of "Chinese exposure" for a separate 2SLS regression. The dependant variable is cumulative (normalized earnings) of each occupational group between 1997 and 2015. Standard errors are clustered at the industry level. The lines correspond to the 95% confidence interval. See Appendix for the coefficients of each regression.

natively, moving from an industry in the 10th to the 90th percentile of the Chinese exposure distribution results in a reduction in cumulative earnings of 82.5 percent of initial income (since a one standard deviation in exposure corresponds almost exactly to the 90-10 gap). This calculation can be used to benchmark the effect of Chinese competition relative to the US, as this pooled specification is very similar to the main specification in Autor et al. (2014). Our estimated average effect for France is around three-quarters of the effect reported by Autor et al. (2014) for the US.[46] This suggests that the effect of Chinese competition in France is of a similar order of magnitude to the US, albeit somewhat smaller.

If the adjustment were different across occupations, the average effect that we have documented would be masking substantial heterogeneity across occupations. The logic of the factor-proportions model that we presented is precisely that the adjustment in earnings should be heterogeneous across occupations, with the occupations more intensively used in highly-exposed industries experiencing larger falls in normalized earnings. The second to seventh columns in Figure 3 report the 2SLS coefficient on Chinese exposure, β in Equation (14), when we estimate separately the effect of Chinese exposure for each of our occupational groups. Note that with this empirical strategy, we allow the coefficient of each control variable appearing in Equation (14) to be different across occupations. The picture that emerges from the estimated effects across occupations is that the effect of Chinese exposure on cumulative earnings varies substantially across occupations.

[46] According to their estimates, a one standard deviation increase in Chinese exposure would translate, 18 years after the shock, into a fall in cumulative earnings of 114 percent.

We find that the effect is negative and significant for executives, engineers, technical staff and skilled production workers. In contrast, we find a negative but insignificant effect for administrative staff, other middle-level occupations, and unskilled production workers. These results suggest a pattern consistent with our proposed factor-proportions framework. Using the average Chinese exposure by occupation reported in Table 2, we see that the effect is significant in the occupations that have the highest values of Chinese exposure and have a higher fraction of workers employed in highly exposed sectors. Workers in occupations related to engineering, technical staff or skilled production are highly concentrated in manufacturing sectors that are highly exposed. This implies that, after the Chinese shock, workers in these occupations appear to have less transferable skills to the less affected industries relative to, for example, administrative staff or unskilled production workers. As a result, they experience the largest decline in earnings.

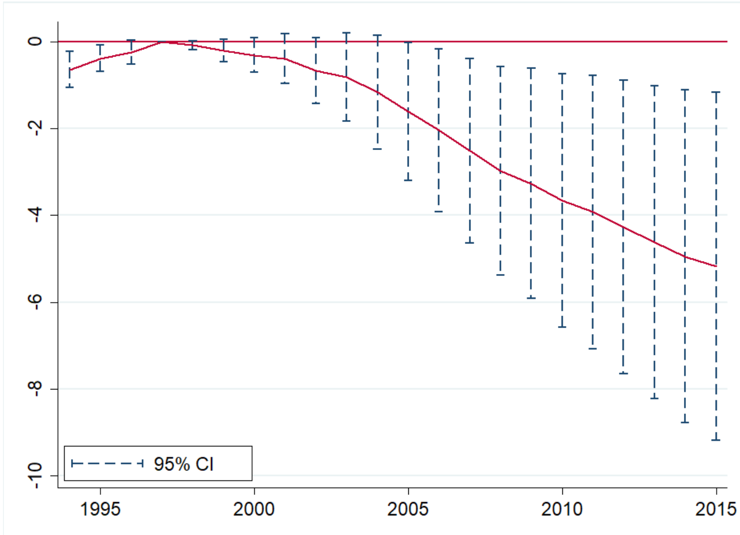
In terms of magnitude of the effect, we find that engineers are the most affected. The coefficient on (normalized) earnings is negative and statistically significant, -20.31. Executives and technical staff also experience a significant fall in (normalized) earnings but to a smaller extent (the coefficients are .-7.45 and -3.90, respectively). Quantitatively, the coefficient implies that for workers initially employed as engineers, a one standard deviation increase in Chinese exposure translates into a reduction of 332 percent ($= 20.38 \cdot 16.29$) of their initial earnings. This is in contrast to unskilled workers, administrative staff or other mid-level occupations, for which we cannot reject the hypothesis that they do not experience any significant reduction in earnings (even though we find negative but relatively small point estimates).

In sum, this exercise has shown that there is substantial heterogeneity in the effect of Chinese competition across broad occupations. For example, French engineers experience an effect that it is four times larger than for the average French worker, while we cannot reject an effect equal to zero for administrative staff. We conjecture that this heterogeneity is also present in other countries, like the US. Unfortunately, the US Social Security data does not include occupational data, making it hard to test this hypothesis.

Dynamic Effect on Earnings Before further investigating the relationship between the effect on relative earnings and occupational exposure, we document the dynamic response of trade adjustment. We show that, consistent with previous studies for other countries, trade adjustment also builds up slowly over time in France. This finding underscores the importance of having long panels to capture trade adjustment. As we discussed in the Introduction, the slow adjustment that we document is in line with the interpretation of Factor Proportions Theory as one of "long-run" outcomes suggested by Neary (1978). Specifically, we plot the estimated coefficient β in Equation (14) when we construct our normalized variable, E_{ij}, up to period T for $T \in [1994, 2015]$. Thus, the coefficient reported for year 2015 corresponds to our previous results.

Figure 4 and 5 plot the cumulative effect of Chinese exposure over our sample period for the pooled regression and the different occupational groups, respectively. The general pattern that emerges is similar

Figure 4: Dynamic Effect on Earnings for the Average Worker



Notes: Solid red line corresponds to the coefficient of "Chinese Exposure" on a rolling 2SLS regression between year x and 1997 for each occupational group. The dependent variable is normalized cumulative earnings up to x. Standard errors are clustered at industry level. Dark region correspond to the 95% confidence interval.

in all panels. We do not observe any clear trend before the China shock (1997). However, after the shock, the coefficient becomes negative and follows a negative trend throughout. Within this general picture, there are some particularities across occupations. First, the negative slope is the largest for engineers, who experienced a significant decline in (normalized) earnings since 2002. Second, unskilled production workers have an almost zero trend for the whole period. Third, skilled production workers, technical staff, and executives have a similar trend and the coefficient does not become negative until the late 2000s.[47]

4.2 Occupational Exposure and Earnings

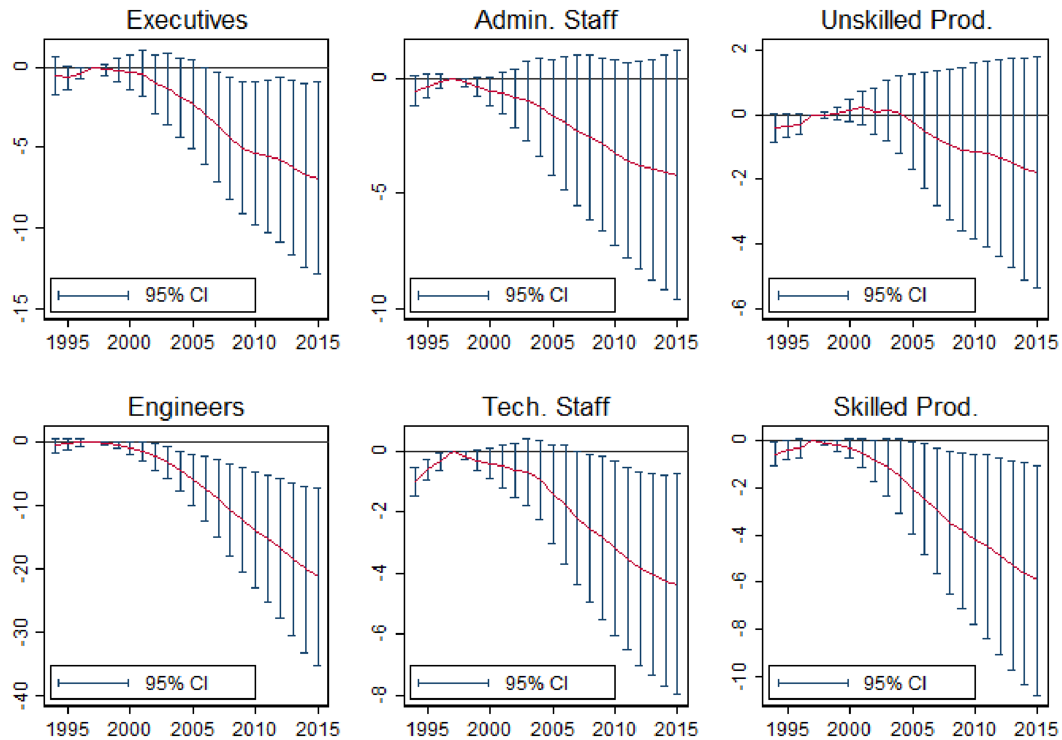
In the previous section, we showed that the effect of the China shock differed across occupations. We also pointed out that occupations more intensively used in exposed industries (as measured by employment shares) seemed to be the ones experiencing the largest declines in relative earnings. Next, we use the model-implied measure of occupational exposure specificity that we introduced in Section 2, $OCX_i = \sum_j \alpha_{ij} CX_j$, in our regression setting. In particular, we estimate

$$E_n = \gamma_0 + \beta \cdot OCX_{i(n)} + \gamma_1 \cdot CX_{j(n)} + \gamma_2 \cdot \alpha_{ij(n)} + \gamma_3 \cdot \text{Controls}_n + \varepsilon_n, \tag{15}$$

where we augment our baseline set of controls with the initial (1997) worker's occupation specificity measure $\alpha_{ij(n)}$ and initial sectoral Chinese exposure (i.e., the term $CX_{j(n)}$) to control for potential direct effects that these variables could be capturing separately, e.g., differential adjustment costs to change industry

[47]It is interesting to notice the somewhat delayed effect of the China shock in France compared to the U.S. (Autor et al., 2014). The reason for this delayed response is outside the scope of the paper and we leave it for future research.

Figure 5: Dynamic Effect on Earnings Across Occupations



Notes: Solid red line corresponds to the coefficient of "Chinese Exposure" on a rolling 2SLS regression between year x and 1997 for each occupational group. The dependent variable is normalized cumulative earnings up to x. Standard errors are clustered at industry level. Dark region correspond to the 95% confidence interval.

depending on the workers' occupation for $\alpha_{ij(n)}$ or the direct effect of workers' initial industry exposure to Chinese competition for $CX_{j(n)}$. The empirical prediction, derived in our theoretical section, is that $\beta < 0$. That is, the decline in earnings should be larger for workers employed in occupations more specific to the industries with higher Chinese exposure.

Table 4 reports the estimated β and γ_1 coefficients from regression (15). We report both the OLS and the 2SLS regression using our instrument for occupational exposure constructed from lagged 1994 occupation factor intensity and Chinese exposure in other countries (Equation 13).[48] Panel A reports the coefficients of our preferred measure of occupation exposure, based on occupation intensity measured as shares of the wage bill of the occupation in the industry. We find a negative and significant effect in all columns, supporting the theoretical prediction of our theoretical framework. Columns (1) and (2) correspond to the OLS and IV of the normalized earnings measures, respectively. We find a negative coefficient that is

[48]We cluster standard errors at the occupation and industry level (two-way clustering). The results are also significant at 1% if we instead compute one-way clustered standard errors at the occupational or industry level. Given that we have only seven occupations in our baseline it is not clear that the asymptotic "sandwich" formula for standard error is a good approximation. For this reason, we also report the p-value of a two-way wild bootstrap clustering procedure, which also yields significant results. In particular, we report the two-tail p-values computed using wild bootstrap-t techniques as in Cameron et al. (2008) with a 6-point distribution and 1000 bootstrap iterations.

slightly larger (in absolute terms) for the IV regression. The attenuation in the OLS coefficient suggests that there is some mild negative demand shock co-existing with the supply shock that we identify.

In terms of magnitude, moving from the occupation with the lowest occupation exposure index (other middle-skill occupations) to the highest (skilled production workers) implies losing almost two years of 1997 total earnings ($-0.27 \cdot (7.16 - 0.18) = -1.88$) over the 1997-2015 period. Alternatively, increasing occupational exposure by one standard deviation in our worker sample implies a loss of $-0.27 \cdot 2.64 = -71.2\%$ of 1997 total earnings. Since we are including workers' initial industry as a control in our regression, this finding implies an additional effect of worker occupational exposure to the China shock of a similar magnitude to the effect of an increase of one standard deviation on the industry exposure of the worker. This effect can also be computed from the coefficient on initial industry exposure to Chinese competition also reported in Table 4. A one standard deviation increase in industry exposure leads to a 91.9 percent decline of 1997 total earnings.[49] In other words, the regression results imply that beyond the effect coming from the exposure of the workers' industry to the China shock, there is an additional effect of comparable magnitude that comes from the initial occupation of the worker. Through the lens of our theoretical framework, this effect operates through general equilibrium across industries and it captures the average exposure to the China shock across industries of a given occupation.

Panels B and C in Table 4 report the coefficients of the occupation exposure index when we use two alternative measures of occupation exposure index, so that the production function explicitly accounts for capital, intermediates and other factors of production.[50] Panel B defines occupation-intensity as the ratio of the wage bill of the occupation over shipments in the industry (Table A.3). In Panel C, we compute employment shares using value-added instead of shipments (Table A.4). In all specifications, the coefficient of the occupation exposure index is negative and significant. Quantitatively, the effects are similar.[51]

In sum, the negative β coefficient in Equation (15) documented in this section confirms the empirical prediction of our theoretical model. Given a negative industry shock, occupations more specific to that industry experience larger declines in earnings. The intuition is that if there is a shock to an industry and a worker is employed in an occupation that is very specific to that industry, this worker will be tied to that industry and will experience a large decline in earnings. In contrast, if the occupation is not very specific to the industry that experiences the shock, the worker can switch industry and soften the shock. In Section 5.2, we provide evidence on mobility across industries consistent with this argument. Also, it is important to stress that we obtain this result having the industry trade shocks as controls, thus, the occupational effects that we uncover appear to be an additional important margin of adjustment to the China shock.

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[49] The estimated coefficient on Chinese exposure $CX_{j(n)}$ in this regression (i.e., including occupational exposure, Equation 15) is marginally larger relative to the pooled regression coefficient that we use to obtain the effect of industry exposure on the average worker, Equation (14), with values -5.08 and -5.66, respectively. From the pooled regression, we remind the reader that we find that the magnitude of an increase of one standard deviation in industry exposure implies an -82.5% decline of 1997 earnings.

[50] In this case, we can add an additional "catch-all" factor of production whose factor share is the complement to the labor share, $1 - \sum_i \alpha_{ij}$, and whose "earnings" are determined by the difference between labor payments and total factor payments.

[51] According to the estimates in Panel B, moving from other middle-skilled occupation to skilled production workers implies losing almost 1.96 years of (1997) earnings ($-0.80 \cdot (2.52 - 0.07) = -1.96$) over the 1997-2015 period. In Panel C, the loss is 1.93. Therefore, the magnitude of the earnings loss is robust to the different specifications.

Table 4: Occupation Exposure Index and Cumulative Earnings

Dep. Var. is Cumulative Normalized Earnings, $\frac{\sum_{t=1997}^{2015} \text{Earnings}_t}{\text{Earnings } 1997}$	(1) OLS	(2) IV
Panel A: α_{ij} constructed with Wage bill		
Occ. Exposure Index OCX_i	-0.21	-0.27
Standard dev. (two-way clust.)	(0.05)***	(0.07)***
p-value from wild bootstrap	[0.00]***	[0.05]**
Chinese Exposure CX_j	-3.51	-5.66
Standard dev. (two-way clust.)	(1.16)**	(1.79)***
p-value from wild bootstrap	[0.00]***	[0.05]**
Panel B: α_{ij} constructed with Gross Output		
Occ. Exposure Index OCX_i	-0.61	-0.80
Standard dev. (two-way clust.)	(0.15)***	(0.21)***
p-value from wild bootstrap	[0.00]***	[0.02]**
Chinese Exposure CX_j	-3.44	-5.50
Standard dev. (two-way clust.)	(1.17)**	(1.80)***
p-value from wild bootstrap	[0.00]***	[0.07]*
Panel C: α_{ij} constructed with Value Added		
Occ. Exposure Index OCX_i	-0.26	-0.33
Standard dev. (two-way clust.)	(0.06)***	(0.09)***
p-value from wild bootstrap	[0.00]***	[0.02]**
Chinese Exposure CX_j	-3.43	-5.48
Standard dev. (two-way clust.)	(1.16)***	(1.80)***
p-value from wild bootstrap	[0.00]***	[0.07]*
Controls	Y	Y
Observations	154,669	154,669

Notes: Cluster robust sandwich standard error are in parentheses (two-way clustering at industry and occupation level). In squared brackets, two-tail p-values computed using wild bootstrap-t techniques as in Cameron et al. (2008) with a 6-point distribution and 1000 bootstrap iterations. ***, **, * denotes significance at 1%, 5%, and 10%, respectively. All regressions include the same controls, as described in the main text. The coefficients of occupation specificity, α_{ij}, which are not statistically different from zero, are not reported for ease of exposition.

4.3 Robustness Checks and Extensions

Before investigating workers' adjustment mechanisms, we discuss, in this section, several robustness checks to our empirical finding of a negative effect of occupational exposure on worker earnings.

Computerization One potential concern with our analysis is that the expansion of trade with China coincided with the widespread decline in communication costs and computerization. Autor and Dorn (2013) show that, in the United States, automatization of routine tasks contributed to the recent increase in wage polarization and low-skill services growth. To quantify the effect of computerization, Autor and Dorn (2013) created a Routine Task Intensity (RTI) index based on the tasks performed by each occupation.[52] Autor and Dorn argue that occupations with a high routine task intensity index are more likely to be automated because tasks in these occupations follow tight and standardized procedures. Using Autor and Dorn's RTI index, we assign a routine task intensity to each of our occupational groups.[53] As expected (and in line with Autor and Dorn), the most routine-intensive occupation is administrative staff and the least routine-intensive occupations are engineers and executives. This suggests that the occupations most affected by the China shock are different from the ones being affected by computerization.[54] Panel A of Table A.5 reports the estimated coefficients of our baseline regression when we add RTI as a control for computerization. We find that the occupation exposure index remains negative and statistically significant. Quantitatively, both the OLS and IV coefficients are very similar to our baseline specification.[55]

Firm Heterogeneity in Capital and Investment The literature on trade and inequality is rich and vibrant. In addition to the factor-proportions theory, other mechanisms have been proposed to explain how trade affects wage inequality in the US and other advanced economies. In an influential paper, Burstein and Vogel (2017) argued that within industry reallocation towards skill-intensive firms is an important driver of the rise of the skill premium. They argue that skill-intensive firms tend to be more productive. Thus, since a reduction in trade costs allows more productive firms to grow, it also increases the demand for skill and the skill premium. In our baseline exercise, we control for workers' initial (1997) firm size, and the firm average and variance of log wages—which already control for a substantial degree of firm heterogeneity. We show here that our results are robust to also controlling for firm capital and investment (averaged from 1994 through 1997). Since more productive firms are not only more skill-intensive but also more capital-intensive, firm capital is an additional control for firm productivity. We also include pre-shock investment to (partially) account for capital intensity going forward. We note that these additional controls also absorb (at the firm-level) the mechanism proposed by Parro (2013) of capital-skill complementarity at the sectoral level to account for the rise in the skill premium. Panel B in Table A.5 shows that the estimated coefficient on the occupational exposure index changes little when adding firm capital and investment as controls.

Trade Shock from Eastern European Countries The increase in trade with China coincided with the expansion of the European Union towards the East. In May 2004, a group of 10 countries, including the Czech Republic, Hungary and Poland, became new members of the European Union. Dauth et al. (2014)

[52]In particular, from the Dictionary of Occupational Titles they obtain scores for routine, abstract and manual pre-computerization. The routine task index is defined as ln(routine)−ln(manual)− ln(abstract). See Autor and Dorn (2013) for more details.

[53] To match the occupation classification in Autor and Dorn (2013), Occ1990-DD, with our occupations, we use the title description. In particular, we use the following correspondence: Executives (4-22), Engineers (44-59), Administrative Staff (303-389), Techinical Staff (203-235), Other Middle Skilled Occupations (243-283), Skilled Production Workers (503-699) and Unskilled Production Workers (703-889).

[54]This view is consistent with Basco and Mestieri (2013) that argue that the IT revolution enabled the offshoring of routine tasks, which tend to be associated to middle-skill occupations.

[55]In addition, the coefficient on the RTI is negative, but not statistically different from zero. This suggests that our baseline worker and firm controls already absorbed part of the variation embedded in the RTI.

argue that, for Germany, the effect of trade with Eastern Europe was more important than trade with China. German imports from the Czech republic, Hungary and Poland combined accounted for 12 percent of total German imports in 2015, which was more than China (10 percent). This pattern is very different for France. In 2015, Chinese imports were more than twice as large as imports from Eastern European Countries (8.8 vs 3.9 percent).[56] To the extent that France's increase in imports from Eastern European countries and China are from similar industries, our theoretical framework implies that we should find similar results when including import growth from Eastern Europe.

To explore this hypothesis, we replicate for France the exercise performed by Dauth et al. (2014) for Germany. We follow their identification strategy and selection of countries, which amounts to extending our baseline Chinese Exposure measure by including other low-wage countries, especially Eastern European countries.[57] Panel C in Table A.5 reports the coefficient on the occupation exposure index when using the increase in import penetration from low wage countries in our baseline regression (15), rather than just China. As in our baseline exercise, the coefficient is negative and statistically significant both for the OLS and IV specification.[58] Quantitatively, the IV coefficient implies that one standard deviation increase in the occupational exposure index implies a reduction in cumulative earnings of 86% of 1997 earnings. In our baseline specification, which included only China, the same exercise yields a reduction of 71.2%.[59]

Finer Employment Classification and Additional Robustness Checks Table A.6 in the online appendix replicates the exercise from the previous section when we use a 2-digit occupations classification rather than our baseline occupational groups. This is the finer level of disaggregation that we have that it is consistent over the entire time period we consider. In this case, we still find a negative, significant effect of occupational exposure.[60] Panels A and B in Table A.6 also show that we obtain similar results if we only include our baseline controls (i.e., do not include the initial occupational specificity and industry exposure of the worker as controls) and when we only include industry exposure (i.e., do not include the initial occupational specificity).

5 Additional Results on Adjustment: Hours, Wages and Mobility

This section presents additional reduced-form results on the effects of Chinese competition on the adjustment of French workers. First, we decompose the effect on earnings between hourly wages and hours. Then, we investigate the effect of Chinese competition on the mobility of French workers across industries

[56]In comparison, the weight of Eastern European countries in US imports is almost negligible (less than one percent).

[57]These countries are Bulgaria, Czech Republic, Hungary, Poland, Romania, Slovakia, Slovenia, Belarus, Estonia, Latvia, Lithuania, Moldova, Ukraine, Azerbaijan, Georgia, Kazakhstan, Kyrgyzstan, Tajikistan,Turkmenistan, and Uzbekistan. We note that this list includes countries outside the European Union and countries that became members in 2007 like Bulgaria and Romania. The construction of the import penetration and instrumental variable are done in an analogous manner as for China. See Dauth et al. (2014) for further details.

[58]The two-way clustered standard errors imply significance at 1%, while the wild bootstrapped p-value is significant at 7%.

[59]The standard deviation of the occupation exposure index to low wage countries is 17.22, while it was 2.48 in the baseline.

[60]The two-way clustered standard errors have a p-value of less than 5%, while the wild bootstrapped has p-value of 7%.

and occupations.

5.1 Decomposing the Effect on Earnings: Adjustment in Hours and Wages

This section investigates through which margins the decline in earnings takes place. We decompose the overall change in cumulative earnings in changes in hours worked and hourly wages

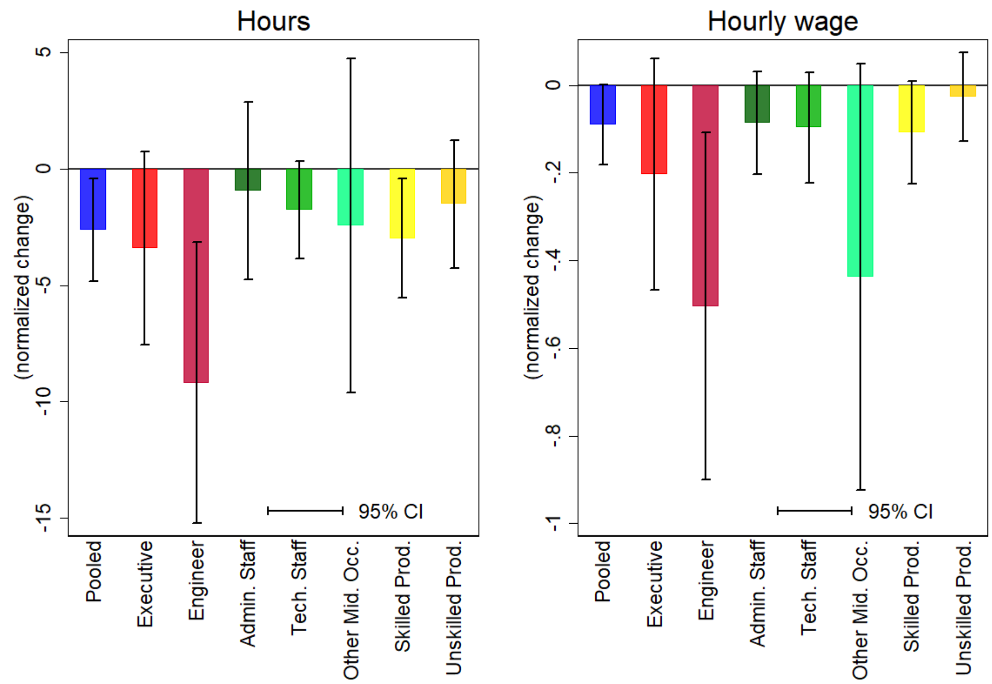
$$\frac{\text{Cum. Earnings 2015-1997}}{\text{Earnings 1997}} = \frac{\text{Average wage 2015-1997}}{\text{Wage 1997}} \cdot \frac{\text{Number hours 2015-1997}}{\text{Number hours 1997}}$$

and analyze the effect of Chinese competition on each of these two components separately. For these exercises, we run the same reduced-form specification as for earnings, Equation (14), but we use as outcome variables *(i)* the normalized average hourly wage over the period 1997-2015 and *(ii)* the normalized number of hours over the same period instead normalized earnings.

Extensive Margin: Hours The left-hand side of Figure 6 reports the coefficients of the effect of Chinese exposure on hours. For the average worker, the coefficient is negative and significant at 5%. Quantitatively, a one standard deviation increase in Chinese Exposure translates into a reduction on (normalized) cumulative of hours of 42 percent of 1997 total number of hours. Once again, these coefficients hide substantial heterogeneity across occupations. When we run the regression separately for each occupation, we observe that this negative effect on hours is driven only by engineers and skilled production workers, whose respective coefficients are -9.19 and -2.99, respectively. Quantitatively, for engineers starting in an industry with one standard deviation more in Chinese exposure translates into a fall in (normalized) cumulative hours of 149.62 percent of 1997 total number of hours. Other than for these two occupations, none of the coefficients is statistically different from zero.

Intensive Margin: Wages The right-hand side of Figure 6 reports the coefficients for the effect of Chinese exposure on normalized average hourly wages. For the average worker, the coefficient is negative but it is not statistically significant (at the conventional 95 percent confidence interval). However, this non-effect is misleading because there is one occupational group that experiences a large drop in wages: engineers. The coefficient of exposure for engineers is -0.504. Quantitatively, it implies that, being in an industry that experiences a one standard deviation increase in Chinese competition in 1997, reduced engineers' average wage by 8.14 percent.Therefore, engineers experienced a fall in both hours and wages. For the other groups, even though the coefficients are negative, they are not statistically different from zero. For skilled workers, the coefficient is smaller and only significant at 10 percent. A possible explanation why skilled production workers did not experience a significant fall in wages is that their wages were closer to the minimum wage and, thus, it was more rigid. We documented in Table 2 that the average hourly wage of engineers was 20.2 euros per hour, compared with 8.6 for skilled production workers.

Figure 6: Decomposing Effect on Earnings



Notes: Each bar corresponds to the coefficient of "Chinese exposure" for a separate 2SLS regression. Hours is 100* (number of hours of each occupational group between 1997 and 2015) normalized by hours in 1997. Hourly wages is the (normalized) average wage per hour between 1997 and 2015. Standard errors are clustered at the industry level. The lines correspond to the 95% confidence interval. See Appendix for the coefficients of each regression.

Dynamic Effect on Hours and Wages Figures A.2 and A.4 in the online appendix report the dynamic cumulative effects for hours and average hourly wages, respectively. For the average worker, there exists a negative trend in hours starting with the trade shock, and the coefficient becomes statistically significant around 2008. For wages, we do not observe any trend and the coefficient is not statistically different from zero in any year. This is the general pattern for the occupational groups but there are significant exceptions, as shown in Figures A.3 and A.5. Engineers experience a declining trend in both hours and wages right after the trade shock. For hours, the coefficient becomes significant in 2003 and for wages in 2008. For occupations with seemingly more specific skills (technical staff, skilled production workers, and executives), the pattern is similar to that for engineers but the negative slope of the trend is smaller. This difference in the trends implies that, for these occupations, the effect of Chinese competition on hours became significantly negative later and it did not become negative for hourly wages. Finally, we want to mention that, perhaps surprisingly, there is not a trend in either hours or wages for unskilled production workers.

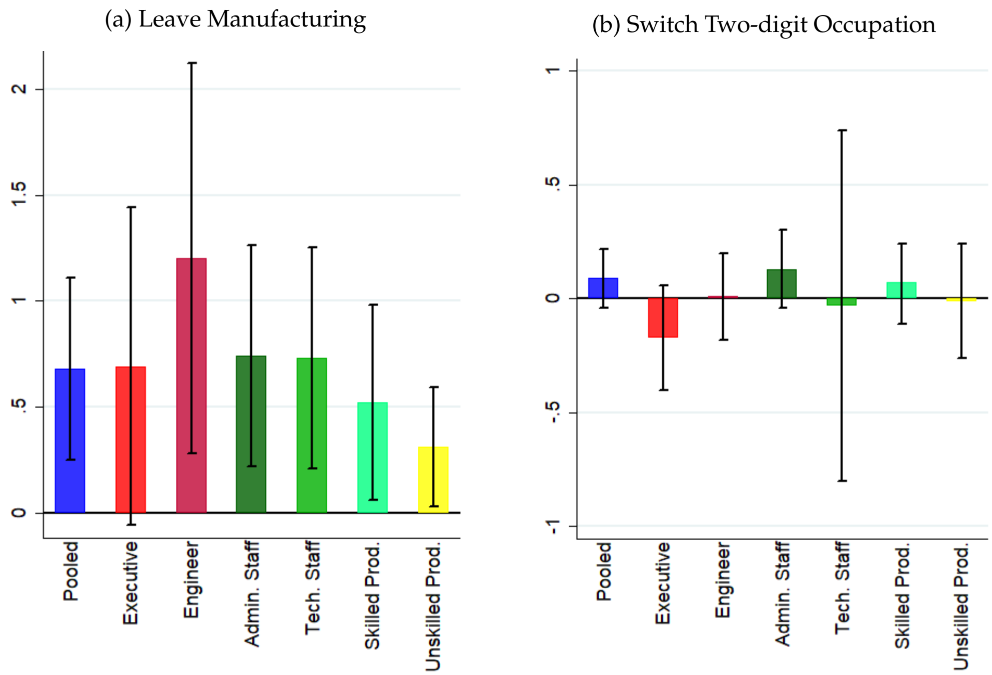
5.2 Mobility Across Occupations and Industries

We now turn our analysis to investigate the effect of Chinese competition on mobility across occupations and industries. The goal is to better understand the effects on earnings we have documented so far, and shed light on additional dimensions of workers' adjustment. Moreover, we can assess the plausibility of the assumption that we have made in our theoretical framework of workers being fixed in an occupation and only changing industries. Consistent with this assumption (albeit less stark of a result), we document that workers are more likely to change industry than occupation following the trade shock.

Mobility Across Industries To investigate workers' mobility, we run the same reduced-form specification as in Equation (14), changing the dependent variable on the left-hand side to the number of different industries j in which workers were employed between 1997 and 2015. First, we define an industry change using the industry variation in our baseline exercise, i.e., four-digit industry definitions. In this case, we find a significant positive effect on the pooled regression across occupations. The coefficient is insignificant for engineers and mildly significant (90 percent) for executives. However, it is positive and significant for the rest of the occupational groups (see figure A.1 in the online appendix). One potential concern with this result when comparing it to mobility across occupations is that we have a much finer definition of industries than occupations. We address this concern here by also estimating our mobility equation when we aggregate industries as much as possible and only distinguish between manufacturing and non-manufacturing. Figure 7a reports the results of again running specification (14), but with the dependent variable being a dummy equal to one if the worker is still active but not employed in the manufacturing sector in 2015. We notice that the effect for the average worker is once again positive and statistically significant. The coefficient varies across occupations but it is positive and statistically significant for all occupations (it is only mildly significant for executives with p-value of 10%). This evidence is consistent with the view that workers initially working in industries hard-hit by the Chinese shock switched industries and tended to move outside the manufacturing sector *regardless* of their initial occupation.

Mobility Across Occupations Figure 7b shows that, in contrast to mobility across industries, there is no effect of Chinese competition on the probability of workers changing their initial occupation. This panel reports the result of using specification (14), but having as dependent variable a dummy equal to one if the occupation of a worker in the last period in which they appear in the sample is different from their initial occupation. Here, we define occupation as a 2-digit occupation. Notice that this classification allows for changes within our broad 7-group occupational classification. Thus, it is more demanding than using only variation at our baseline 7-group because we count as an occupational switch any change in a 2-digit occupation. For example, a worker that stays in our administrative staff occupation category throughout the sample but who is initially employed as a secretary (which has occupational code 46) and then switches to being an accountant (which has occupational code 54) would be counted as a switcher. As

Figure 7: Mobility Across Industries and Occupations



Notes: Each bar corresponds to the coefficient on Chinese exposure for a separate 2SLS regression. in panel a, the dependant variable is a dummy equal to one if the worker leaves manufacturing by 2015. In panel b, the dependent variable is a dummy equal to one if the worker switches between 2-digit occupations and zero otherwise. Standard errors are clustered at the industry level. The lines correspond to the 95% confidence interval. See Appendix for the coefficients of each regression.

the figure shows, the estimated coefficient of the effect of Chinese competition on occupational mobility is not different from zero for either the average worker (pooled regression) or for any of the occupational groups. To be sure, let us emphasize that doing the very same exercise with only our baseline seven occupations to measure switchers yields even starker results of lack of mobility across occupations.

To conclude, the evidence presented in the section paints a picture consistent with the view that workers hit by the Chinese shock tended to switch the industry they worked in (and leave manufacturing), but they tended to remain in their initial occupation. Thus, these results lend support to the simplifying assumptions made in the theoretical framework of thinking about occupations as factors of production that are mobile across industries, as capturing important features of the data (in an admittedly stylized way).

6 Labor Market Institutions and Trade Adjustment

In this final section, we investigate how the rising import competition from China interacts with the French labor market. One of the most salient features of the French labor market compared to, for example, the United States is the role of collective agreements. Collective agreements are the most prevalent rent-sharing mechanism and play a key role in wage determination (Venn, 2009). We investigate whether collective agreements can shape the effects of a trade shock by analyzing the evolution of cumulative earnings of

Figure 8: Interaction Effect of Regulation and Chinese Exposure

Notes: Each bar corresponds to the coefficient of the interaction between "Chinese exposure" and "Industry Regulation" for a separate 2SLS regression. Earnings are cumulative normalized earnings between 19997 and 2015. Hours is 100*(total hours)/initial hours. Hourly wages is normalized average wages per hour. Standard errors are clustered at the industry level. The lines correspond to the 95% confidence interval. See Appendix for the coefficients of each regression.

employees across industries with different degrees of collective bargaining. To the best of our knowledge, this interaction has not been examined before.

Our measure of market regulation is based on the number of collective agreements before the China shock. We obtain these data from Avouyi-Dovi et al. (2013), who have digitized the universe of collective agreements in France from 1992 onwards.[61] These authors also note that the most important topic in the vast majority of collective agreements is wage setting. In our data, around 71% of workers are covered by collective agreements (a very similar number to the one reported by Avouyi-Dovi et al., 2013). We follow Avouyi-Dovi et al., 2013 and Carluccio et al. (2015) and proxy the intensity of regulation in the industry by the number of collective agreements in a given period.[62] In particular, we define an industry as regulated if the number of collective agreements in that industry is above the median number of agreements from 1992 to 1997. We then re-estimate our baseline regressions introducing the interaction of industry exposure to Chinese imports with this regulation dummy variable (and also include the regulation dummy as a control).

[61] They have used it to estimate the effect of collective agreements in France in Avouyi-Dovi et al. (2013) and Carluccio et al. (2015).
[62] Labor law in France is such that if no agreement is reached, firms are allowed to set their own contracting conditions, see Avouyi-Dovi et al., 2013.

Cumulative Earnings Panel A of Figure 8 reports the 2SLS regression results of our reduced-form regression (14), when we introduce the interaction between industry exposure and regulation as explanatory variable. The dependent variable is normalized cumulative earnings between 1997 and 2015. We only report the coefficient of the interaction term (but also include as regressors separately the terms appearing in the interaction). A negative coefficient implies that the negative effect of trade in cumulative earnings is exacerbated with regulation. The coefficient of the interaction term for the average worker is negative and statistically significant. Once again, this average effect masks substantial heterogeneity. Indeed, the negative coefficients are only statistically significant for technical staff (-6.66) and skilled workers (-6.77). Therefore, from this figure we can conclude that labor regulation did not help workers to cope better with the trade shock and it penalized low-paid workers like skilled production workers relatively more.

Decomposing Change in Earnings Panel B and C of Figure 8 report the coefficients of decomposing the effect of regulation on earnings between hours and hourly wages, respectively. Since collective agreements are mainly concerned with wages, one would expect that regulation has a larger incidence in wages than hours. On the other hand, one could also argue that since collective agreements represent a constraint on wages, they give incentives to employers to use hours to adjust to the trade shock. From the coefficients in both panels, the two interpretations seem right. For the average worker, we observe that the coefficient of the interaction term is negative and statistically significant for both hours and hourly wages. When we run the regression for each occupation, a similar picture emerges. For wages, the coefficient is negative and significant only for technical staff and skilled workers. The coefficient is much larger (in absolute terms) for technical stuff (-0.27 vs -0.17). An explanation for this difference may be that the wage of skilled workers is closer to the minimum wages and, thus, there is less margin of adjustment. For hours, once again, the negative coefficient is only significant for technical staff and skilled workers. In this case, the two coefficients are more similar (-1.01 vs -0.81) than for wages. These coefficients on hours reinforce the interpretation that one of the reasons why the effect on wages is substantially larger for technical staff is that wages are lower for skilled production workers.

To sum up, we document that regulation shapes the effects of Chinese competition. Workers in less regulated industries were able to better cope with the trade shock. Moreover, we document that the effect of regulation also depends on the occupation of the worker. Low-wage occupations like skilled production workers and technical staff are more negatively impacted from being in a regulated industry than higher wage engineers, whose earning profile does not depend on the level of regulation of the industry.

7 Conclusions

Rising import competition from low-wage countries is of increasing concern for policy makers in advanced economies. In this paper, we have documented an additional margin of adjustment of workers to rising competition from Chinese exports. We show that workers' initial occupation plays a substantial role in accounting for their overall earnings adjustment. The effect of workers' initial occupation is similar in magnitude to the effect of workers' industry exposure. A one-standard deviation increase in occupational exposure implies a 71.2 percent decline of initial (1997) worker earnings over the 1997-2015 period (the corresponding figure for industry exposure is 82.5 percent). Workers in the most exposed occupation (engineers) lost almost two years of 1997 total earnings relative to the least exposed occupations over the 1997-2015 period.

We also show that our finding of heterogeneous earnings' adjustment across occupations can be rationalized through the lens of a factor-proportions model in which occupations are treated as factors of production. This assumption of occupations as factors of production is meant to capture the notion that the knowledge and capabilities of workers in one occupation may be hard to transfer to other occupations. Moreover, it allows us to provide a sharp characterization of worker earnings' adjustment in terms of their occupational exposure index. Perhaps surprisingly, we show that attached workers tend not to change their occupation after the rise in Chinese competition, lending support to the assumption of workers being fixed in their occupation. The policy implications of our findings suggest that only focusing on the effect of trade competition on skilled and unskilled workers may be misleading. For example, we find that workers initially employed as engineers are the most hard-hit by Chinese competition. Thus, the occupational content of import competition should also be taken into account when considering the design of alleviating policies for affected workers.

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A Additional Tables and Figures

Table A.1: Summary Statistics

	Mean	Std. Dev.	Nb. Obs.
Panel A: Trade exposure, 1997-2015			
Δ Imports from China to France/Initial absorption	0.88%	8.51%	154,669
Δ Imp. from China to France/Init. absorp. - Manufacturing	2.63%	16.29%	59,764
Panel B: Main outcome variables, 1997-2015			
100* Cumulative earnings 1997-2015/Earnings 1997	1580.1	1136.3	154,669
100* Total hours worked 1997-2015/Hours worked 1997	1093.2	741.5	154,669
100* Average hourly wage 1997-2015/Hourly wage 1997	141.0	28.5	154,669
Panel C: Worker characteristics in 1997			
Female	.36	.13	154,669
Employed in manufacturing	.35	.12	154,669
Tenure 0-1 year	.09	.01	154,669
Tenure 2-5 years	.25	.06	154,669
Tenure 6-10 years	.23	.05	154,669
Firm size 1-99	.29	.08	154,669
Firm size 100-999	.33	.11	154,669
Firms size >1000	.39	.15	154,669

Table A.2: Log Change in Price, 2000-2015

	OLS	IV	OLS	IV
Chinese Exposure	-0.490***	-5.959***	-0.490*	-5.959*
	(0.001)	(0.006)	(0.259)	(3.070)
Observations	52	52	52	52

Notes: Robust Standard errors shown in parenthesis, without clustering in columns 1 and 2 and clustered at the industry level in columns 3 and 4. * and *** denote significance at 10% and 1% level, respectively. All regressions include an intercept. Industries are weighted by the number of workers in each industry in year 2000. Industry classification corresponds to INSEE's A88.

Table A.3: Factor Specificity by Occupation α_{ij}

	Mean	Std. Dev.	p25	p75
Executives	0.25	0.15	0.11	0.41
Engineers	0.19	0.15	0.08	0.25
Administrative Staff	0.32	0.18	0.16	0.49
Technician Staff	0.22	0.15	0.12	0.27
Other Middle-skill Occ.	0.46	0.19	0.36	0.61
Skilled Production Workers	0.39	0.17	0.29	0.49
Unskilled Production Workers	0.17	0.12	0.08	0.25

Notes: Factor specificity computed as the wage bill of occupation i in industry j divided by total wage bill in that industry, both in 1997.

Table A.4: Effect of Chinese Exposure on Earnings Across Occupations

	(1) Pooled	(2) Executive	(3) Engineer	(4) Ad.Staff	(5) Tech.Staff	(6) Other	(7) Skilled	(8) Unskilled
Panel A: Earnings								
Chinese Exposure	-5.075***	-7.453***	-20.38***	-3.699	-3.899**	-7.740	-5.652**	-2.302
	(1,878)	(2.739)	(6.924)	(2.644)	(1.664)	(5.487)	(2.362)	(1.892)
No. Observations	163,207	12,193	7,492	37,715	19,678	19,764	47,606	15,336
Panel B: Hours								
Chinese Exposure	-2.609**	-3.409	-9.185***	-0.942	-1.759	-2.442	-2.990**	-1.517
	(1.126)	(2.115)	(3.083)	(1.936)	(1.070)	(3.664)	(1.305)	(1.393)
No. Observations	163,207	12,193	7,492	37,714	19,677	19,764	47,608	15,337
Panel C: Wages								
Chinese Exposure	-0.0901*	-0.203	-0.504**	-0.0863	-0.0966	-0.437*	-0.108*	-0.0265
	(0.0469)	(0.135)	(0.202)	(0.0597)	(0.0643)	(0.248)	(0.0596)	(0.0516)
No. Observations	163,207	12,193	7,492	37,714	19,677	19,764	47,608	15,337

Notes: Earnings are (normalized) cumulative earnings between 1997 and 2015. Hours are 100*(sum of number of hours between 1997 and 2015)/hours in 1997. Wages are (normalized) average wages between 1997 and 2015. Standard errors are clustered on start-of-period 3-digit industry. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A.5: Occupation Exposure Index and Earnings: Robustness

Dep. Variable: Cumulative norm. earnings, $\frac{\sum_{t=1997}^{2015} \text{Earnings}_t}{\text{Earnings } 1997}$	(1) OLS	(2) IV
Panel A: Computerization		
Occ. Exposure Index OCX_i	-0.15	-0.19
std. dev.	(0.03)***	(0.05)***
p-value from wild bootstrap SE	[0.00]***	[0.04]**
Occ. Routine Index	-0.003	-0.020
std. dev.	(0.10)	(0.06)
p-value from wild bootstrap SE	[0.88]	[0.88]
Panel B: Firm Capital and Investment		
Occ. Exposure Index OCX_i	-0.18	-0.25
std. dev.	(0.03)***	(0.05)***
p-value from wild bootstrap SE	[0.00]***	[0.02]**
Panel C: Low Wage Countries		
Occ. Exposure Index $OLWX_i$	-0.02	-0.05
std. dev.	(0.01)*	(0.02)***
p-value from wild bootstrap SE	[0.00]***	[0.07]*
Controls	Y	Y

Notes: The dependant variable is (normalized) cumulative earnings between 1997 and 2015. In Panel A, Occupation Routine Index is taken from Autor and Dorn (2013). We map their occupation classification (Occ1990 DD) to our occupational groups using the definition in their Appendix (see also footnote 53). In Panel B we include average firm capital and investment. In Panel C, Low Wage Countries Occupation Exposure Index, $OLWX_i$, is computed analogously to China Exposure (see description in main text). This measure includes the increase of imports from China and Eastern Europe, as defined in Dauth et al. (2014). Cluster robust sandwich standard error are in parentheses (two-way clustering at the industry and occupation level), and in squared brackets we show two-tail p-values computed using wild bootstrap-t techniques as in Cameron et al. (2008) with a 6-point distribution and 1000 bootstrap iterations. ***, **, * denotes significance at 1%, 5%, and 10%, respectively.