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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 model that emphasizes industries using occupations in different intensities. We show that an occupational exposure index summarizes the overall exposure of an occupation to industry-level trade shocks. Proxying these industry-level trade shocks with rising Chinese competition and 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. The magnitude of our estimates implies that the effect of rising Chinese competition on workers' earnings due to differences in workers' occupations is of comparable magnitude to the effect of workers' sector of employment. This finding suggests that accounting for the distributional effects of trade across occupations is quantitatively important.

Keywords: Occupations; Inequality; Import Competition

JEL classification: F11, F14, F16

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NON-TECHNICAL SUMMARY

How does global competition reshape labor markets, not just across industries, but within the occupations that define them? This study investigates the distributional effects of rising import competition from low-wage economies, particularly China, on workers in various occupations within the French labor market. By focusing on the period from 1997 to 2015, it sheds light on how exposure to trade shocks impacts earnings and job trajectories differently across occupations.

Using an innovative occupational exposure index, which measures the degree to which occupations are utilized in industries exposed to international trade shocks, the study reveals significant heterogeneity in how different professions are affected by trade shocks. Workers employed in occupations more intensively used in industries exposed to Chinese competition, such as production workers—both skilled and unskilled—experience significantly greater declines in earnings compared to those in less exposed roles, such as administrative or mid-level service occupations. For instance, while unskilled production workers may see annual earnings reductions of up to 20% of their initial (1997) earnings, administrative roles often face declines of less than 5%, and engineers show even smaller impacts, reflecting the varied exposure levels across these groups.

The study categorizes occupations into broad groups based on hierarchical roles and skill requirements, determined by the level of education, job responsibilities, and hierarchical position within firms. These include unskilled and skilled production workers, administrative staff, technical staff, engineers, and executives. Each group's exposure to trade shocks is evaluated using an occupational exposure index that combines industry-specific trade shock data with the intensity of occupational usage in those industries. This approach allows for a nuanced understanding of how specific occupational traits influence vulnerability to global competition.

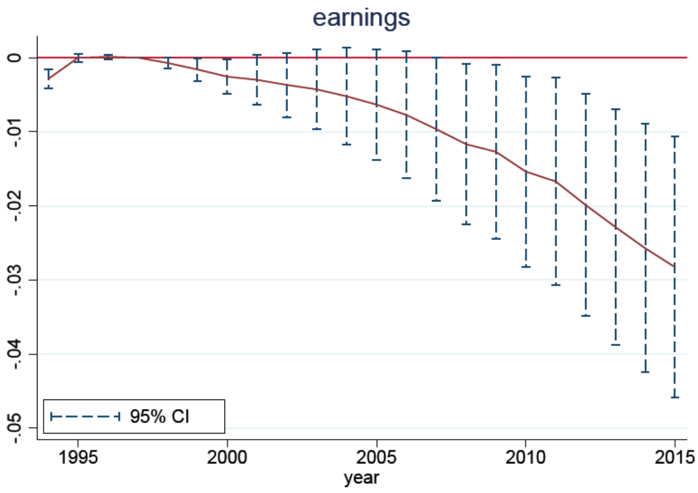
To guide its empirical analysis, the paper develops a theoretical model treating occupations as factors of production, with different roles and intensities across industries. By leveraging matched employer-employee panel data from French social security records, it captures the dynamic nature of trade adjustment, documenting both immediate and long-term effects. The results show that while workers in highly exposed occupations face pronounced income declines, they tend to remain in their original occupations rather than transitioning to entirely new roles, underscoring the rigidity of occupational mobility in the face of global competition.

A key methodological innovation of the paper is its use of an instrumental variable approach to isolate the effects of Chinese import penetration from other concurrent economic changes, such as automation or shifts in domestic demand. This robust identification strategy ensures that the observed impacts are causally linked to the "China shock" rather than unrelated factors.

The findings carry important policy implications. They suggest that interventions aimed at mitigating the adverse effects of globalization should consider the specific vulnerabilities of occupations within industries, rather than focusing solely on sector-wide adjustments. Supporting skill development and mobility within highly exposed occupations may help workers adapt to the rapidly evolving global economy. Additionally, policies addressing the broader labor market impacts of trade, such as wage insurance or targeted retraining programs, could help alleviate the distributional challenges posed by rising global competition.

This study contributes to the growing literature on the heterogeneous impacts of trade, offering new insights into how occupations shape the adjustment process and highlighting the nuanced ways globalization influences labor markets.

Figure 1. Cumulative Impact of the China Shock on Occupational Earnings



Note: This figure shows the cumulative impact of occupational exposure to Chinese import competition on worker earnings from 1997 to 2015. Exposure combines industry trade shocks with occupational intensity, measured by changes in China's import penetration. Higher exposure leads to greater earnings losses, with heavily exposed occupations losing up to 20% of 1997 earnings annually. Graph Interpretation: At year =2010 on the graph, a 1% increase in exposure corresponds to a cumulative earnings reduction of 1.8% (computed from 1997 to 2010) relative to 1997 earnings.

L'impact de la concurrence des importations selon les professions

RÉSUMÉ

Cette étude examine empiriquement l'impact de la concurrence des importations sur les revenus des travailleurs à travers les différentes professions. Pour guider notre analyse, nous développons un modèle stylisé qui met en avant les industries utilisant des professions avec des intensités différentes. Nous montrons qu'un indice d'exposition professionnelle résume l'exposition globale d'une profession aux chocs du commerce international au niveau industriel. En utilisant comme indicateur de ces chocs l'augmentation de la concurrence chinoise, et en exploitant des données de panel représentatives de l'ensemble du marché du travail français de 1993 à 2015, nous obtenons des résultats cohérents avec les prédictions du modèle. Nous trouvons que les travailleurs initialement employés dans des professions fortement exposées à la concurrence chinoise, mesurées par notre indice d'exposition professionnelle, connaissent des baisses plus importantes de leurs revenus. L'ampleur de nos estimations implique que l'impact de l'augmentation de la concurrence chinoise sur les revenus des travailleurs, en fonction des professions, est comparable à l'impact du secteur d'emploi des travailleurs. Cette constatation suggère qu'il est quantitativement important de prendre en compte les effets distributifs du commerce à travers les professions.

Mots-clés : professions ; inégalités ; concurrence des importations

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 an important 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 earnings adjustment using a theoretically-motivated occupational exposure index. The richness of our data allows us to also document slow dynamics of adjustment, and separately estimate the adjustment of wages and hours worked.

We implement our empirical analysis on 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] We use a fairly broad 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.,

[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 (2013).

managers and engineers or administrative and technical staff require the same years of education.

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 workers initially employed in the same industry, but in different occupations. The underlying identifying assumption is that absent occupation-specific "China shocks," these workers would have experienced comparable earning trajectories.[4]

In the theoretical framework guiding our empirical exercise, we consider a small open economy with J industries and I occupations, where each occupation is used with different intensities across industries. This model can be interpreted as the standard factor proportion model, with occupations being factors of production. That is, we assume that workers can switch industries, but they are fixed in their initial occupation.[5] 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 a weighted sum over industry exposure to trade shocks, where the weights are the occupation's industry factor intensities. In our application, we proxy for the trade shocks with the measure of Chinese exposure proposed by Autor et al. (2014).[6] 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. To be sure, our model is stylized. For instance, we do not model the mobility decision of workers across industries nor the number of hours worked. As such, the model serves as a theoretical motivation (instead of

[4] The 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.

[5] 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. This assumption is supported by our data since we find no significant mobility across occupations.

[6] 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 1997 earnings.

microfoundation) for our empirical analysis.[7]

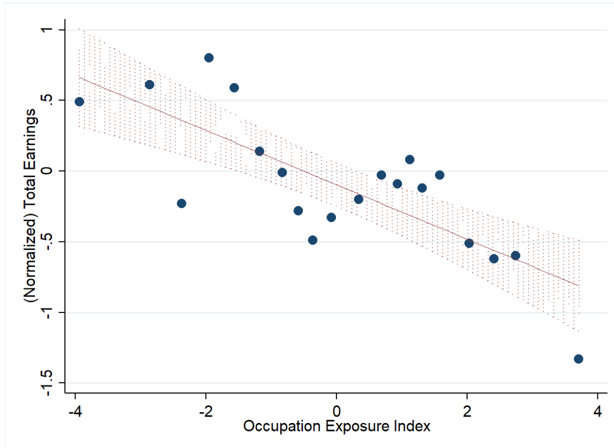
Figure 1 shows suggestive evidence consistent with our empirical prediction. Indeed, there is a strong, negative partial correlation between the increase in exposure to Chinese competition of each occupation, measured by the occupational exposure index OCX, and workers' change in relative earnings over the 1997-2015 period.[8] We show that this correlation persists (and becomes slightly larger) after controlling for a rich set of worker and firm characteristics, and instrumenting the occupation exposure index with an index constructed using lagged occupation factor intensities (from 1994) and Chinese exposure in other advanced economies. The estimated magnitude of the effect across occupations, within industries, is substantial. Over the 1997-2015 period, a one standard deviation increase in occupational exposure across manufacturing industries represents an annual loss of 4.7% of initial (1997) total earnings. This effect is quantitatively similar to the effect on workers' earnings of their (initial) industry exposure. Our estimates for France of this latter effect imply that a one standard deviation increase in industry exposure translates into an annual loss of 3.9% of initial (1997) earnings. Thus, our results illustrate that standard measures of industry exposure mask substantial heterogeneity in the effect of trade across occupations.

Our baseline specification includes both industry and regional fixed effects. The inclusion of both sets of fixed effects is important because it addresses two potential confounding biases. First, a substantial strand of the literature has emphasized that workers initially employed in an industry more exposed to rising Chinese competition experience a larger decline in earnings (see, for example, Autor et al., 2014). By including industry fixed effects, we absorb these effects and compare workers in the same industry with different occupational exposure. Second, another important strand of the literature, starting with Autor et al. (2013), emphasizes that regions more exposed to Chinese competition experience a larger decline in employment. By including region fixed effects, we also absorb these regional effects. Lastly, we use the implementation of Borusyak et al. (2022) of the inference method proposed by Adao et al. (2019). In all our regressions we compute shift-share robust standard errors following their procedure and we also control for the sum of manufacturing shares in our empirical specifications.

[7]We also show that, under more stringent assumptions, it is possible to derive a closed-form relationship between an occupational index and changes in workers' earnings. In particular, we generalize the specific factors model in Kovak (2013) to multiple occupations and show that our findings also go through in this case: workers in more exposed occupations experience larger earnings losses. In this case, however, the interpretation of the occupational exposure index is not as straightforward since the model-implied loadings of the occupational index on industry exposure shocks are a non-linear combination of cost shares and employment shares.

[8]The pairwise correlation is -0.77 and statistically significant.

Figure 1: Occupational Exposure Index and Change in Earnings



Note: The figure reports results based on our final sample of French workers, as described in Section 3. The Occupation Exposure Index of a worker employed in occupation i is equal to $OCX_i = \sum_{j=1}^{J} \alpha_{ij} CX_j$, with α_{ij} being the share of occupation i in the production costs of industry j and CX_j the industry exposure to Chinese import competition (see Section 3 for further details). (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. We bin workers in 20 quantiles of residualized OCX. The figure depicts the mean residualized Total Earnings by quantile.

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 automation across occupations, as measured by the occupational routine task index developed in Autor and Dorn (2013). Our results also hold when (i) we control 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]; (ii) when we consider different definitions of factor intensity and (iii) when we control for the effect of increased trade with Eastern Europe during the same time period. We also provide empirical evidence consistent with a negative effect of occupational exposure to the "China shock" using an occupational exposure index derived from the specific-factors theory.[10]

Finally, we leverage the richness of our data to provide evidence on margins of adjustment other than total earnings. First, we decompose the effect of trade on total earnings between hours and wages. We show that even though trade adjustment operated through both margins, the

[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).

[10]We perform the analogous instrumental variable approach to our baseline exercise and include the same set of fixed effects and controls. Consistent with the prediction of the model, we document a negative effect of occupational exposure, OCX^{SF}, on worker earnings.

effect on hours worked is quantitatively 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 to Chinese competition. Moreover, despite changing industries, we find that workers stay in their initial broad occupation: there is no effect of Chinese exposure on the probability of workers changing occupations. This last finding lends support to our assumption of considering workers' broad occupations as factors of production.

Related literature This paper relates to several strands of the literature. We emphasize the importance of workers' initial occupation to understand how their earnings adjust to trade shocks. This finding is consistent broadly 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 study the impact of offshoring on US workers. They document that adjustment to globalization operates mostly through occupational exposure rather than industry exposure. There are two main differences of this paper relative to them. First, on the empirical front, our data allows us to consider worker fixed-effects (by taking first differences) and we use an instrumental strategy to obtain the effect of import competition on worker adjustment. Second, we provide a theoretical foundation for using an occupational exposure index in the regression analysis—thus lending theoretical support to papers such as Ebenstein et al. (2014) that have already used occupational exposure indices to assess the effect of trade shocks.[11,12]

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 (2013). Both studies examine the effect of trade liberalization on wages in developing countries using a specific fac-

[11] The weights on industry trade shocks used to construct our model-implied occupational exposure indices are, however, different from the industry employment shares proposed in Ebenstein et al. (2014).

[12] 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).

tors model. Our approach is similar. The most important difference is that we examine the effect of trade across different occupational groups.[13] 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.[14] The main difference with this literature is that we analyze the differential effect of the "China Shock" across occupations and relate this heterogeneous 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.[15]

2 Theoretical Framework

The goal of this section is to illustrate how industry trade shocks can generate differential effects across occupations when industries use occupations with different intensities. Our starting point is 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 it translates into a differential effect in earnings across occupations. We relegate all derivations to Appendix C.

The central result of our theoretical framework is that the effect of trade shocks across occupations is summarized by an occupational exposure index—which we use in our empirical analysis.

[13] The derivation of a closed form equation for the particular case when we introduce specific factors is a generalization of Kovak (2013) to more than one occupation.

[14] 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.

[15] 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 (2013), Balsvik et al. (2015), Hakobyan and McLaren (2016), Malgouyres (2017), Curuk and Vannoorenberghe (2017), Galle et al. (2017), 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.

This result holds for an arbitrary number of industries and occupations and it is stated as a correlation result. We show that for a broad class of factor-proportions models, earnings should decline relatively more in occupations that are, on average, more exposed to negative industry trade shocks—which in our empirical analysis we proxy using the China shock.[16]

The key assumption of the theory is to treat 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 while allowing for a positive elasticity of substitution between them. In other words, workers are fixed in their initial occupation. They are allowed to change industries but not their occupation. In our view, provided that the definition of occupation is *not too narrow*, this is a reasonable assumption for examining workers' 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.

Model Setup We consider a small open economy with $j = 1, \cdots, J$ industries. Each industry j has a representative firm that produces a homogeneous good according to a production function that combines workers employed in occupations o_{ij}, $i = 1, \cdots, I$, according to a Cobb-Douglas production function with factor shares $\alpha_{ij} \in [0, 1]$. Labor belonging to each occupation is fixed and inelastically supplied, but can freely move across industries. Firms take wages in each occupation and good prices as given, and price at their marginal cost of production. We denote by w and p the (column) vectors of the equilibrium wages paid to workers of each occupation and industry prices, respectively. Combining the insights from Ethier (1984) and Deardorff (1993), we obtain the following result.

Lemma 1 *For any two trade equilibria in our economy for which there is positive production in all industries, the following inequality holds*

$$Covariance\left(\hat{w}, A \cdot \hat{p}\right) > 0, \tag{1}$$

where $\hat{w}$ and $\hat{p}$ denote the difference of equilibrium log-wages and log-prices in the two trade equilibria,[17]

[16] In the appendix, we show that for the particular case of the specific-factors model, it is possible to derive a structural relationship between changes in occupations earnings' and industry trade shocks, which is again mediated through an occupational exposure index.

[17] Denoting the initial and final equilibria by superscripts 1 and 2 respectively, $\hat{w} \equiv \log w^2 - \log w^1$, etc.

and $A = [\alpha_{ij}]_{i=1,...,I,j=1,...,J}$ is the $I \times J$ matrix whose i-th row and j-th column corresponds to α_{ij}.

Equation (1) implies that occupations more intensively used in sectors experiencing larger declines in prices should experience higher reductions in earnings. Note that each entry $i = 1, \cdots, I$ of the second term of the covariance, $A \cdot \hat{p}$, is an occupation-specific sum of the log-price changes, weighted by i's occupation factor-intensity across industries,

$$\sum_{j=1}^{J} \alpha_{ij} \hat{p}_j. \tag{2}$$

As we discuss below, the construction of our baseline occupation exposure index builds on this result.

The derivation of the covariance result, Equation (1), only relies on firm's cost-minimization and taking equilibrium prices as given. Thus, it does not make any assumption on how wages are determined. For this reason, it encompasses models in which labor markets are perfectly competitive, where firms can either have constant returns to scale (e.g., the Heckscher-Ohlin model), or decreasing returns to scale on mobile factors (e.g., the specific-factors model), and models in which wages may be determined through other mechanisms, e.g., union bargaining.[18] However, note that there are models that violate these assumptions. For these latter models our result does not necessarily apply, e.g., if firms have monopsony power.

Bringing Lemma 1 to the Data To build a connection with our empirical exercise, we implement the difference between two trade equilibria in Lemma 1 as pre- and post-China shock. That is, we start from an initial trade equilibrium pre-China shock, and then allow for a rise in Chinese competition that is heterogeneous across industries to obtain the final equilibrium. Ideally, we would like to have data on sectoral price changes so that we can use Equation (2) directly. Unfortunately, disaggregated price series spanning our time frame do not exist in France. Instead, following the argument laid out in Autor et al. (2013) of the China shock being a supply shock, we use the industry "China shock" measure proposed in Autor et al. (2014) as a proxy for the change in the sectoral price vector of goods faced in France, $\hat{p}$.

[18]This generality comes at the expense of stating a result in terms of a covariance. To obtain a tighter, structural relationship between changes in output prices and workers' earnings, we need to make further assumptions. In the appendix, we show that it is possible to obtain a structural relationship between $\hat{w}$ and $\hat{p}$ by specializing the model to the specific-factors model. In the context of regional shocks, Kovak (2013) and Adao et al. (2020) derive structural relationships between exposition indices and earnings.

Assumption 1 *There is a negative relationship between industry Chinese eXposure CX and the change in log-prices between the pre- and post-China shock equilibria. That is,* $\hat{p} = -\gamma \cdot CX$*, for some* $\gamma > 0$ *and where CX denotes the column vector of industry-specific exposure to the "China shock" proposed by Autor et al. (2014).*

Even though we cannot test this assumption, since we lack detailed price series data, Table A.4 in the Appendix reports the coefficient of regressing the log-change in more aggregated price series (two-digit) on the Chinese exposure measure of Autor et al. (2014). Consistent with our assumption, the coefficient is negative and statistically significant.

Combining Assumption 1 with Equation (1), we find that Lemma 1 can now be stated in terms of a covariance between workers' earnings and an Occupation-specific Chinese eXposure index, which we denote as OCX. More specifically, if we focus on occupation i, Equation (2) becomes the exposure of occupation i to the "China shock,"

$$OCX_i \equiv \sum_{j=1}^{J} \alpha_{ij} CX_j. \tag{3}$$

Using this notation, the covariance result from Equation (1) can be equivalently stated like

$$\text{Covariance}(\hat{w}, OCX) < 0. \tag{4}$$

This result implies that occupations more intensively used in industries more exposed to the "China shock" experience, on average, a larger decline in earnings. Equation (4) is the foundation of our empirical exercises. We empirically test Equation (4) by running a linear regression in which the dependent variable is the change in workers' earnings between the two equilibria,[19] and the independent variable is the occupation exposure index in Equation (3).[20]

If the China shock was the only shock on industry prices and there were no shocks to labor productivity, we could test Equation (4) in the data through a simple OLS regression of $\hat{w}$ on OCX. However, in our empirical analysis, besides the China shock (and an extensive set of controls), industry prices can change due to unobserved shocks. We address this issue by proposing an

[19] 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.

[20] Absent endogeneity concerns, the estimated OLS coefficient of this regression is $\hat{\gamma} = \text{Cov}(OCX, \hat{w})/\text{Var}(OCX)$. This covariance term corresponds to the covariance defined in Equation (4) with wages averaged at the occupation cell. Since the variance is always positive, the sign of $\hat{\gamma}$ coincides with the covariance term. Thus, a negative sign of $\hat{\gamma}$ is consistent with the theoretical prediction of our framework, while a positive coefficient would reject it.

instrumental variable approach that we discuss below.[21]

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.

[21] For instance, consider the case in which there are shocks to industry prices other than the China shock,

$$\hat{p} = -\gamma CX + u, \tag{5}$$

with $-\gamma < 0$ being the causal impact of CX on $\hat{p}$ and u some unobservable shock on industry prices. How does the presence of u affect the test of the model? Let us re-write wages in a linear regression form:

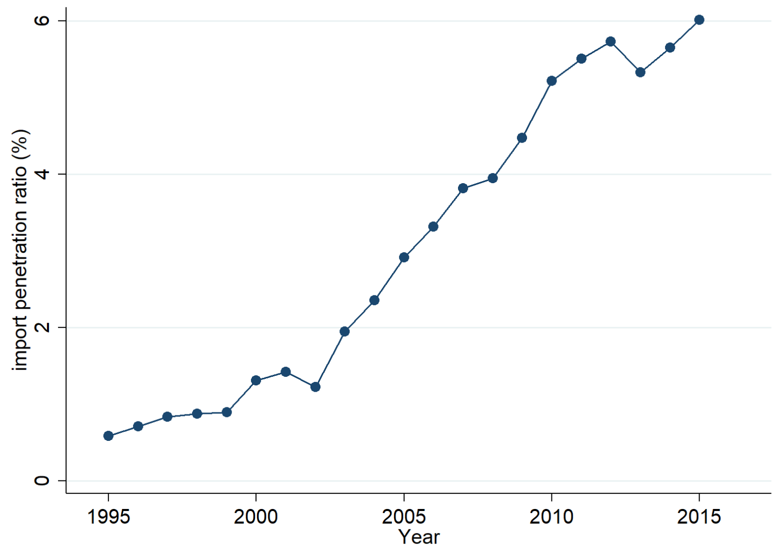
$$\hat{w} = \beta A \cdot \hat{p} + e, \tag{6}$$

with $cov(A \cdot \hat{p}, e) = 0$ and $\beta = \frac{cov(\hat{w}, A \cdot \hat{p})}{var(A \cdot \hat{p})} > 0$, by definition of e. If industry prices were observed, we could simply test the model by checking that β is positive through an OLS estimation of (6). To get an expression of $\hat{w}$ as a function of observables, let us plug (5) into (6)

$$\hat{w} = -\beta\gamma OCX + \epsilon, \text{with} \quad \epsilon \equiv \beta A \cdot u + e. \tag{7}$$

As (7) makes apparent, a simple OLS regression of w on OCX is not enough to test the sign of β, since the obtained estimate $\widehat{\beta\gamma}$ could pick up some of the correlation between OCX and $A \cdot u$. As described in the empirical section, we deal with this issue through an instrumental variable strategy: we isolate variation in OCX which is plausibly orthogonal to $A \cdot u$. Following this strategy, we obtain a consistent estimator of $-\beta\gamma$ and are able to test the sign of β.

Figure 2: Import penetration of Chinese Imports in France



(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

$$CX_j = \frac{\Delta M^{FC}_{j,2015-1997}}{Y_{j,1997} + M_{j,1997} - E_{j,1997}}. \tag{8}$$

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 (8) 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.[22] The choice of our starting and final dates are constrained by data availability (see the discussion in Section 3.2).

[22] 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 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.

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.[23]

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 (8) with an analogous measure of industry-level change in import penetration from a set of comparable high-income countries,

$$CX_j^A = \frac{\Delta M^A_{j,2007-1997}}{Y_{j,1994} + M_{j,1994} - E_{j,1994}}, \tag{9}$$

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.[24] 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

[23] We show in Table A.2 in the appendix 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. To the best of our knowledge, this is the finest level of disaggregation available of sectoral prices.

[24] 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.

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

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.[25]

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).[26] 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 FICUS, 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.

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

[26] 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.

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.[27] 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.[28] 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 within that year, specifying its duration, start and end date, total gross and net wages,[29] hours worked, and the 2-digit occupation.[30] 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,[31] 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.

[27]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.

[28]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.

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

[30]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.

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

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.[32] 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.

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 suggests comparing outcomes in only two periods. Given that we use the increase in Chinese exports between 1997 and 2015 in our empirical setting, this would imply comparing workers' earnings in 1997 (pre-China shock) and 2015 (post-China shock). However, this is not our preferred specification. In our theoretical framework, there are only two time periods and there is no entry and exit of workers in the labor market. In practice, however, 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

$$\tilde{E}_n \equiv \frac{\sum_{t=1997}^{2015} E_{n,t}/19}{E_{n,1997}}, \tag{10}$$

where the numerator is the average annual earnings of a worker over the 1997-2015 period and the denominator, the worker's earnings in 1997 . The advantage of this formulation is that the dependent variable can be 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 results easier to compare

[32] 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.

with these studies.[33]

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 (11) that use value of shipments or value-added as denominators, the sample drops to 154,669. We use the latter sample to test the empirical prediction of our model, since we need to use the factor intensity measures to construct the occupational exposure index. 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 Socio-professionnelles - des Emplois Salariés des Employeurs privés et publics), which is the reference classification of occupations used by the French public administration.

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 to a relatively small number, consistent with the notion of broad occupation. 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

[33] This expression corresponds to a first-order Taylor approximation to the exact expression we would obtain from our theoretical framework, which would be $\ln\left(\frac{\sum_{t=1997}^{2015} E_t/19}{E_{1997}}\right)$ around the average accumulated earnings $\bar{E} = \sum_{t=1997}^{2015} E_t/19$ being equal to initial earnings. Taking a Taylor approximation around 1, we obtain $\ln\left(\tilde{E}_n\right) = \tilde{E}_n - 1 + o\left(\tilde{E} - 1\right)$.. We have also verified (and reported in a previous version) that our results go through if we compare worker earnings in 2015 relative to 1997.

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 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 as 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

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.

largest (3.5%). Within production workers, the skilled ones have relatively higher wages but a larger share of them work in highly exposed industries.[34]

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.

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-occupation intensity, corresponding to α_{ij} in our model, and the occupational exposure index (3), OCX_i.

[34] Finally, we note that we do not include occupation 34-35 (other managers) in our analysis 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). 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).

We start discussing 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

$$\alpha_{ij} = \frac{w_i o_{ij}}{p_j Y_j}, \tag{11}$$

where the numerator is total labor payments to occupation i in sector j, and the denominator is value of production. Our preferred measure of α_{ij} is the share of total payments to occupation i in industry j relative to total labor payments, which is implied by our theoretical framework. 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. Our baseline model assumes that labor payments coincide with 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) sectoral value added.[35] Tables D.1 and D.2 in the appendix report summary statistics for α_{ij} when using the wage bill over shipments and over the value added of the sector, respectively. We also find substantial variation in α_{ij} with these alternative measures.

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 (3) 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 com-

[35] 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.

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).

petition. 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 by the factor-proportions theory. Table D.3 and D.4 in the appendix report the occupation exposure indices 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 (9), and computing the weighted 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.[36]

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

4 Results: The Effect of Trade across Occupations

This section reports the main results of the paper. Using our baseline specification, we first show that on average, occupations 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 theoretical framework. We then document the robustness of this result through a series of sensitivity tests.

4.1 Baseline Results on Earnings

We use the model-implied measure of occupational exposure that we introduced in Section 2, $OCX_i \equiv \sum_j \alpha_{ij} CX_j$, in our regression setting. In particular, we estimate the following worker-level regression

$$\tilde{E}_n = \beta \cdot OCX_{i(n)} + \delta \cdot \text{Share Manuf}_{i(n)} + \rho \cdot \text{Controls}_n + FE_{j(n)} + FE_{r(n)} + \varepsilon_n, \tag{14}$$

where $\tilde{E}_n$ corresponds to our measure of changes in earnings of worker n, defined in Equation (10), $OCX_{i(n)}$ denotes the occupational index of occupation i corresponding to worker n's initial occupation. All our regressions include the same set of Controls_n and fixed effects to absorb differences across workers. 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.[37] 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.[38] In Section 4.2, we show that our results are robust to controlling also for firm capital and investment. Importantly, we augment this set of controls with $\text{Share Manuf}_{i(n)}$, the sum of manufacturing shares to address the "missing share" problem,

[37]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+.

[38]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.

following Borusyak et al. (2022).[39] To control for the direct effect of workers' initial industry or regional exposure to Chinese competition, we include fixed effects $FE_{j(n)}$ and $FE_{r(n)}$, based respectively on the 1994 industry and region of the worker.

We estimate our baseline regression, Equation (14), by Two Stage Least Square (2SLS). We use $OCX^A_{i(n)}$ as an instrument for $OCX_{i(n)}$. As explained by Borusyak et al. (2022), one can think of the identification assumption with shift-share instruments as a "quasi-random assignment of shocks." In our context, this amounts to assuming that, conditional on controls and fixed effects, the trade shock CX^A_j in industry j is uncorrelated to the average earning shocks ε_n of workers whose occupation is concentrated in industry j.

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 from regression (14). 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). To deal with the inference problems specific to shift-share instruments, we report standard errors computed according to the implementation of Borusyak et al. (2022) of the method proposed by Adao et al. (2019), clustered at the 3-digit industry level.[40]

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 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 20% of 1997 total earnings ($-0.0285 \cdot (7.16 - 0.18) = -0.199$) every year over the 1997-2015 period. Alternatively, increasing occupational exposure by one standard deviation in our worker

[39] We construct for each occupation the total weight of manufacturing Share $\text{Manuf}_i = \sum_{j \in manuf.} \alpha_{ij}^{1994}$.

[40] Specifically, we perform a weighted IV regression by collapsing our dataset at the industry level after partialling out our controls on the dependent and independent variables. The instrument is the industry shock CX^A. We use as weights the sum of α_{ij}, i.e., the "shift" component of OCX, across all workers in a given industry. As shown in Borusyak et al. (2022), this industry-level regression yields the same estimated coefficient, but with shift-share robust standard errors.

sample implies an annual loss of $0.0285 \cdot 2.15 = 6.13\%$ of 1997 total earnings. To give a point of comparison, we estimate the direct impact of industry exposure CX_j, controlling for occupation fixed effects (the results are reported in the appendix table A.4). A one standard deviation increase in Chinese exposure of manufacturing workers reduces their annual earnings over 1997-2017 by $0.296 \cdot 0.131 = 3.9\%$. In other words, the impact of occupational and industry exposure is of the same order of magnitude, with the impact of occupational exposure being, if anything, a bit larger. Through the lens of our theoretical framework, the occupational exposure 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 the occupational exposure index, so that the production function explicitly accounts for capital, intermediates and other factors of production.[41] Panel B defines occupation-intensity as the ratio of the wage bill of the occupation over shipments in the industry (Table D.3). In Panel C, we compute employment shares using value-added instead of shipments (Table D.4). In all specifications, the coefficient of the occupation exposure index is negative and significant. Quantitatively, the effects are similar.[42]

In sum, the negative β coefficient in Equation (14) 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. It is important to stress that we obtain this result having industry and region fixed effects as controls. Thus, the occupational effects that we uncover appear to be an additional important margin of adjustment to the China shock.

Cumulative Effect on Earnings Since 1994 Before further investigating the robustness of the relationship between occupational exposure and relative earnings, Figure 3 reports the cumulative effect of the China shock since 1994. Specifically, each point in the figure is the estimated coefficient β in Equation (14) where we construct our normalized variable, E_n, up to period T for $T \in [1994, 2015]$. Thus, the coefficient reported for year 2015 corresponds to our previous results.

[41] 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.

[42] According to the estimates in Panel B, moving from other middle-skilled occupation to skilled production workers implies losing 20% of (1997) earnings ($-0.0822 \cdot (2.52 - 0.07) = -20.1\%$) every year over the 1997-2015 period. In Panel C, the loss is 19%. Therefore, the magnitude of the earnings loss is robust to the different specifications.

Table 4: Occupation Exposure Index and Cumulative Earnings

Dep. Var. : Normalized Average Earnings, $\frac{\sum_{t=1997}^{2015} \text{Earnings}_t/19}{\text{Earnings 1997}}$		
	(1)	(2)
	OLS	IV
Panel A: α_{ij} constructed with Wage bill		
Occ. Exposure Index OCX_i	-0.0156***	-0.0285***
	(0.0018)	(0.0085)
Panel B: α_{ij} constructed with Gross Output		
Occ. Exposure Index OCX_i	-0.0399**	-0.0822**
	(0.0480)	(0.0398)
Panel C: α_{ij} constructed with Value Added		
Occ. Exposure Index OCX_i	-0.0195***	-0.0321***
	(0.0023)	(0.0126)
Occ. Manuf Share	Y	Y
Controls	Y	Y
Industry Fixed Effects	Y	Y
Region Fixed Effects	Y	Y
Observations	151,361	151,361

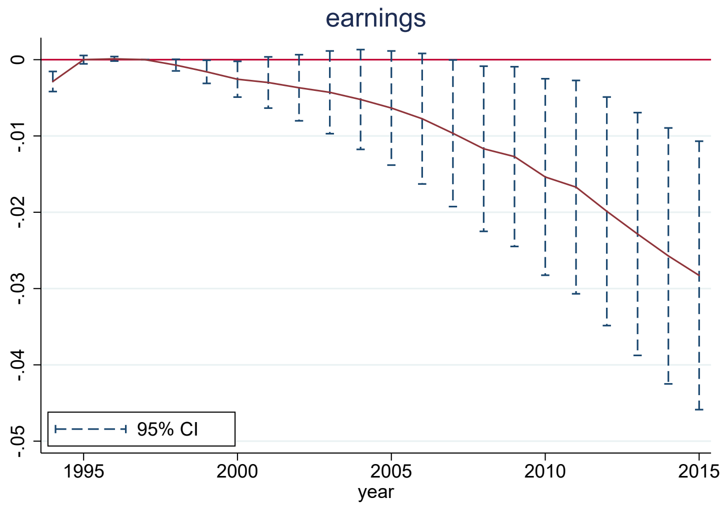
Notes: Shift-share robust standard errors in parenthesis, clustered at the 3-digit industry level. ***, **, * denotes significance at 1%, 5%, and 10%, respectively. All regressions include the same controls and fixed effects, as described in the main text.

The shape of this figure is consistent with the China shock literature (e.g., Autor et al., 2014). The negative effect on earnings is increasing over time. Note that this time pattern is not an impulse response to a one-time shock. The evolution of the effect should rather be interpreted as a combination of a build-up in the trade shock and the adjustment of workers to the shock. This finding underscores the importance of having long panels to capture trade adjustment.

4.2 Robustness Checks

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.

Figure 3: Cumulative Effect of Occupational Exposure on Earnings



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. The horizontal bars correspond to the 95% confidence interval.

Sensitivity to Baseline Controls and Fixed Effects In order to investigate the sensitivity of our baseline results, we re-estimate our main specification leaving out one set of controls at a time. The results are reported in table A.5. As it turns out, leaving out region fixed effects or industry fixed effects or worker-level pre-trends does not significantly change the quantitative results.

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.[43] 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.[44] As expected (and in line with Autor and Dorn),

[43]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.

[44] 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

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.[45] Panel A of Table A.6 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.[46]

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.6 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

(503-699) and Unskilled Production Workers (703-889).

[45]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.

[46]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.

Union. Dauth et al. (2014) 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).[47] According to our theoretical framework, increased import competition has a relative negative effect on occupations most intensively used in the exposed industries. Thus, a potential concern is that our Chinese exposure measure is also a proxy for trade with Eastern Europe countries—which arguably features an exporting strategy based on low-wages similar to China during this period. To check that our identification does not come from increased trade with Eastern Europe, we include an occupational exposure to Eastern European countries to our baseline specification.[48] Panel C in Table A.6 shows that the coefficient on occupational exposure to China remains negative and significant.

Specific-Factors Occupational Exposure Index In Appendix B, we derive an alternative expression for the occupational exposure index by specializing our model to a multi-occupation version of the specific-factor model in Kovak (2013). The main advantage of this approach is that, in contrast to the covariance result, it provides a direct link between the occupational exposure index and changes in wages (see equation B.4). Table A.7 in the Appendix reports the results of empirically testing our baseline equation with this new occupational exposure index instead of our baseline occupational index. Column (2) reports our two-stage least squares results. Consistent with our baseline results, we find that there is a significant, negative effect of occupational exposure on workers' earnings. The magnitude of the effect is larger than in our baseline. A one standard deviation increase in exposure leads to an annual loss of 29 percent of 1997 earnings over the period ($27.93 \cdot 0.0104 = 0.29$). This alternative occupational exposure index requires more stringent assumptions and, prima facie, is arguably a less plausible exercise. However, we find re-assuring that the analysis yields a negative effect, reinforcing the idea that workers' initial occupation exposure to Chinese competition is an important determinant of their earnings

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

[48] 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. Eastern countries included in the exercise 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.

Table 5: Decomposing the Effect on Earnings: Adjustment in Hours and Wages

Dep. Var:	Hours $\frac{\sum_{t=1997}^{2015} \text{Hours}_t/19}{\text{Hours 1997}}$		Wage $\frac{\sum_{t=1997}^{2015} \text{Wage}_t/19}{\text{Wage 1997}}$		log(Hours)		log(Wage)	
	(1) OLS	(2) IV	(3) OLS	(4) IV	(5) OLS	(6) IV	(7) OLS	(8) IV
Occ. Exposure Index OCX_i	-0.005***	-0.011***	-0.0123***	-0.005	-0.001	-0.010***	-0.007***	-0.007
	(0.001)	(0.003)	(0.002)	(0.011)	(0.001)	(0.002)	(0.001)	(0.013)
Occ. Exposure Index OCX_i VA	-0.007***	-0.014***	-0.0154***	-0.007	-0.002	-0.013**	-0.010***	-0.010
	(0.002)	(0.006)	(0.003)	(0.014)	(0.001)	(0.005)	(0.002)	(0.009)
Occ. Exposure Index OCX_i Shipments	-0.015***	-0.039***	-0.031***	-0.013	-0.003	-0.040**	-0.019***	-0.027
	(0.003)	(0.019)	(0.006)	(0.041)	(0.002)	(0.017)	(0.003)	(0.026)
Occ. Manuf Share	Y	Y	Y	Y	Y	Y	Y	Y
Controls	Y	Y	Y	Y	Y	Y	Y	Y
Industry Fixed Effects	Y	Y	Y	Y	Y	Y	Y	Y
Region Fixed Effects	Y	Y	Y	Y	Y	Y	Y	Y
Observations	151,361	151,361	151,361	151,361	151,361	151,361	151,361	151,361

Notes: Shift-share robust standard errors in parenthesis, clustered at the 3-digit industry level. ***, **, * denotes significance at 1%, 5%, and 10%, respectively. All regressions include the same controls and fixed effects, as described in the main text.

adjustment.

5 Additional Results on Adjustment: Hours, Wages and Mobility

This section presents additional 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 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

$$\frac{\text{Average Earnings 2015-1997}}{\text{Earnings 1997}} \equiv \frac{\text{Average Wage 2015-1997}}{\text{Wage 1997}} \cdot \frac{\text{Average Number Hours 2015-1997}}{\text{Number Hours 1997}}$$

and analyze the effect of the occupational exposure index on each of these two components separately. For these exercises, we run the same 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.

Columns (1) and (2) of Table 5 report the OLS and 2SLS coefficients of the effect of the occupational exposure index on hours, respectively. Both coefficients are negative and significant at 5%. Quantitatively, our 2SLS coefficient implies that increasing occupational exposure by one standard deviation reduces the average annual hours over 1997-2015 by 2.3 percent of 1997 hours ($0.011 \cdot 2.15 = 0.023$). Column (3) and (4) of Table 5 report the analogous coefficients for hourly wages. The 2SLS coefficient is negative but it is not statistically significant (at the conventional 95 percent confidence interval). This may either reflect a small economic impact on wages (possibly reflecting downward wage rigidity on the French labor market) or a lack of statistical precision. In order to discriminate between these two alternatives, in Columns (5) to (8) we present the same results as in Columns (1) to (4), except for the fact that we take the log transformation of the dependent variables. This makes it easier to compare the magnitude of the effect on hours and wages since their sum equals the effect on log(earning). Comparing Columns (6) and (8) reveals that the estimated effect on log(wages) is smaller than on log(hours) while the standard error on the estimate is larger. This suggests that the impact on wages is insignificant both because it is small and imprecise. Repating these exercises using our alternative definitions of the occupational exposure index yields the same conclusions, as can be seen from the second and third rows of Table 5.

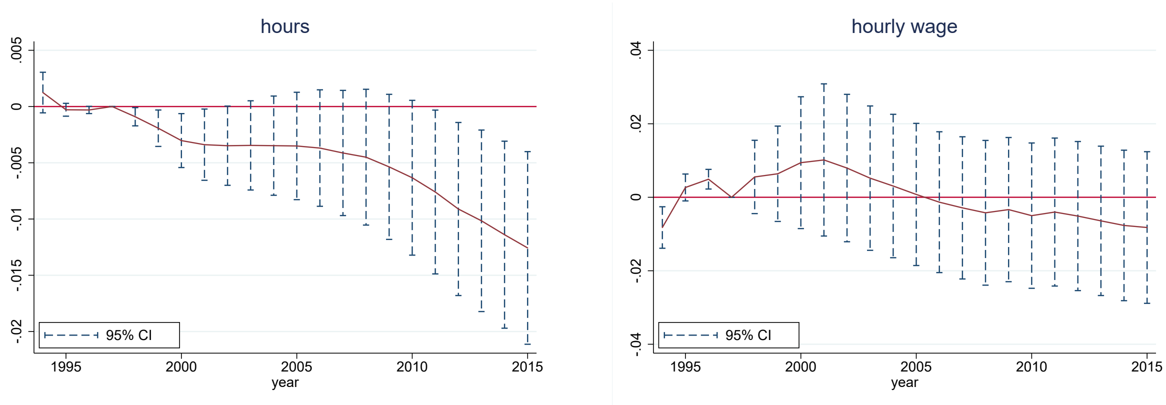
Cumulative Effect on Hours and Wages Since 1994 Figure 4 reports the dynamic effect for average annual hours and hourly wages, respectively. There exists a negative trend in hours and the coefficient becomes statistically significant around 2010. For wages, we do not observe any trend and the coefficient is not statistically different from zero in any year.

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.

To investigate industry mobility, we regress a dummy equal to one if a worker's final industry is different from her 1997 industry on the industry shock CX_j. We look at mobility at different levels of aggregation. Results reported in Column (1) to (6) of Table 6 reveal that workers respond

Figure 4: Cumulative Effect on Hours and Wages



(a) Hourly Wage (b) Wage

Table 6: Mobility Across Occupations and Industries

Dep. Var:	Move 4-digit Industry		Move 3-digit Industry		Move 1-digit Industry		Move 2-digit Occupation		Move Broad Occupation	
	(1) OLS	(2) IV	(3) OLS	(4) IV	(5) OLS	(6) IV	(7) OLS	(8) IV	(9) OLS	(10) IV
Industry Exposure CX_j	0.0927*	0.174**	0.105***	0.160***	0.0879**	0.141***	0.0572*	0.0345	0.0519	0.0271
	(0.054)	(0.078)	(0.037)	(0.050)	(0.0403)	(0.0523)	(0.0342)	(0.0519)	(0.0382)	(0.0559)
Controls	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Occupation Fixed Effects	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Region Fixed Effects	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Observations	151,367	151,370	151,367	151,370	151,367	151,370	151,367	151,370	151,367	151,370

Notes: Robust standard errors in parenthesis, clustered at the 3-digit industry level. ***, **, * denotes significance at 1%, 5%, and 10%, respectively. All regressions include the same controls as described in the main text.

to the trade shock by changing industry. The effect is larger (although not significantly) for finer industries. A one standard deviation increase in Chinese exposure increases the probability to move 4-digit industry between 1997 and 2015 by 1.5 percentage points. This effect is respectively 1.3% at the 3-digit level and 1.2% at the 2-digit level. This evidence is consistent with the view that workers initially working in industries hard-hit by the Chinese shock switched industries.

By contrast, Columns (7) to (10) of Table 6 reveal no effect of Chinese competition on the probability of workers changing their initial occupation. Compared to Columns (1) to (6), these columns only differs in terms of dependent variable, as we use 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. As the table shows, the estimated coefficient of the effect of Chinese competition on occupational mobility is not statistically different from zero

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, 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 Conclusions

Rising import competition from low-wage countries is of increasing concern for economists, policymakers, and the general public in advanced economies. In this paper, we have documented an additional margin of workers' adjustment to rising competition from Chinese exports. We show that workers' initial occupation plays a substantial role in accounting for their overall earnings adjustment. A one-standard deviation increase in occupational exposure implies a 6.1 percent annual decline of initial (1997) worker earnings over 19 years. Restricting our attention to manufacturing workers, we find that a one-standard deviation increase implies a 4.7 percent yearly decline of initial (1997) manufacturing workers' earnings. Importantly, in addition to a rich set of worker and firm controls, our estimation includes industry and region fixed effects to absorb the industry and regional effects of rising Chinese competition documented by Autor et al. (2014) and Autor and Dorn (2013) for the US. In fact, we find that the magnitude of the effect of occupational exposure is comparable to that of the effect of industry exposure. According to our estimates for France, a one standard deviation increase in industry exposure results in an annual loss of 3.9 percent percent of initial (1997) earnings.

We also show that our finding of heterogeneous earnings' adjustment across occupations can be rationalized through the lens of a simple theoretical framework in which *broad* occupations are treated as factors of production. This simplifying assumption of occupations as factors of production is meant to capture the notion that the knowledge and capabilities of workers in one broad occupation may be hard to transfer to other broad occupations (e.g., engineers and secretaries). Building on this assumption also allows us to provide a sharp characterization of worker earnings' adjustment in terms of an occupational exposure index, which motivated our empirical analysis. Perhaps surprisingly, we show that attached workers tend not to change their broad occupation after the rise in Chinese competition, lending support to the assumption of workers being fixed in their occupation, while switching industries. The policy implications of our findings suggest that accounting for the distributional effects of trade across occupations is quantitatively important. Simply focusing on the effect of trade competition on skilled versus unskilled workers may be too simplistic, since we do indeed find highly exposed occupations in both skilled and unskilled categories.

References

ABOWD, J. M., F. KRAMARZ, AND D. N. MARGOLIS (1999): “High Wage Workers and High Wage Firms,” *Econometrica*, 67, 251–333.

ADAO, R., C. ARKOLAKIS, AND F. ESPOSITO (2020): “General Equilibrium Effects in Space: Theory and Measurement,” Discussion Papers Series, Department of Economics, Tufts University 0835, Department of Economics, Tufts University.

ADAO, R., M. KOLESÁR, AND E. MORALES (2019): “Shift-Share Designs: Theory and Inference,” *Quarterly Journal of Economics*, 134, 1949–2010.

AUTOR, D. H. AND D. DORN (2013): “The Growth of Low-Skill Service Jobs and the Polarization of the US Labor Market,” *American Economic Review*, 103, 1553–1597.

AUTOR, D. H., D. DORN, AND G. H. HANSON (2013): “The China Syndrome: Local Labor Market Effects of Import Competition in the United States,” *American Economic Review*, 103, 2121–68.

AUTOR, D. H., D. DORN, G. H. HANSON, AND J. SONG (2014): “Trade Adjustment: Worker-Level Evidence,” *The Quarterly Journal of Economics*, 129, 1799–1860.

——— (2016): “The China Shock: Learning from Labor-Market Adjustment to Large Changes in Trade,” *Annual Economic Review*, 205–40.

BALSVIK, R., S. JENSEN, AND K. G. SALVANES (2015): “Made in China, sold in Norway: Local labor market effects of an import shock,” *Journal of Public Economics*, 127, 137–144.

BASCO, S. AND M. MESTIERI (2013): “Heterogeneous trade costs and wage inequality: A model of two globalizations,” *Journal of International Economics*, 89, 393–406.

BERNARD, A., J. JENSEN, AND P. SCHOTT (2006): “Survival of the best fit: Exposure to low-wage countries and the (uneven) growth of U.S. manufacturing plants,” *Journal of International Economics*, 68, 219–237.

BORUSYAK, K., P. HULL, AND X. JARAVEL (2022): “Quasi-experimental shift-share research designs,” *The Review of Economic Studies*, 89, 181–213.

BURSTEIN, A. AND J. VOGEL (2017): “International Trade, Technology, and the Skill Premium,” *Journal of Political Economy*, 125, 1356–1412.

CALIENDO, L., F. MONTE, AND E. ROSSI-HANSBERG (2015): “The anatomy of french production hierarchies,” *Journal of Political Economy*, 123, 809–852.

CURUK, M. AND G. VANNOORENBERGHE (2017): “Inter-sectoral labor reallocation in the short run: The role of occupational similarity,” *Journal of International Economics*, 108, 20–36.

DAUTH, W., S. FINDEISEN, AND J. SUEDEKUM (2014): "The Rise Of The East And The Far East: German Labor Markets And Trade Integration," *Journal of the European Economic Association*, 12, 1643–1675.

——— (2016): "Adjusting to globalization - Evidence from worker-establishment matches in Germany," DICE Discussion Papers 205, University of Düsseldorf, Düsseldorf Institute for Competition Economics (DICE).

——— (2017): "Trade and Manufacturing Jobs in Germany," *American Economic Review*, 107, 337–342.

DEARDORFF, A. (1993): "The Stolper-Samuelson Theorem: A Golden Jubilee; Chapter 2 Overview of the Stolper Samuelson Theorem," Working papers, Research Seminar in International Economics, University of Michigan.

DIX-CARNEIRO, R. AND B. K. KOVAK (2017): "Trade Liberalization and Regional Dynamics," *American Economic Review*, 107, 2908–46.

——— (2019): "Margins of labor market adjustment to trade," *Journal of International Economics*, 117, 125–142.

EBENSTEIN, A., A. HARRISON, M. MCMILLAN, AND S. PHILLIPS (2014): "Estimating the Impact of Trade and Offshoring on American Workers using the Current Population Surveys," *The Review of Economics and Statistics*, 96, 581–595.

ERTEN, B. AND J. LEIGHT (2017): "Exporting out of Agriculture: The Impact of WTO Accession on Structural Transformation in China," Working papers, CUNY.

ETHIER, W. (1984): "Higher dimensional issues in trade theory," in *Handbook of International Economics*, ed. by R. W. Jones and P. B. Kenen, Elsevier, vol. 1, chap. 03, 131–184, 1 ed.

GALLE, S., A. RODRÍGUEZ-CLARE, AND M. YI (2017): "Slicing the Pie: Quantifying the Aggregate and Distributional Effects of Trade," NBER Working Papers 23737, National Bureau of Economic Research, Inc.

HAKOBYAN, S. AND J. MCLAREN (2016): "Looking for Local Labor Market Effects of NAFTA," *The Review of Economics and Statistics*, 98, 728–741.

HARRIGAN, J., A. RESHEF, AND F. TOUBAL (2021): "The March of the Techies: Job Polarization Within and Between Firms," *Research Policy*, 50, 104008.

JACOBSON, L. S., R. LALONDE, AND D. G. SULLIVAN (1993): "Earnings Lossses of Displaced Workers," *Annual Economic Review*, 83, 685–709.

JONES, R. W. (1965): "The Structure of Simple General Equilibrium Models," *Journal of Political Economy*, 73, 557–572.

KAMBOUROV, G. AND I. MANOVSKII (2008): "Rising Occupational And Industry Mobility In The United States: 1968-97," *International Economic Review*, 49, 41–79.

——— (2009a): "Occupational Mobility and Wage Inequality," *Review of Economic Studies*, 76, 731–759.

——— (2009b): "Occupational Specificity Of Human Capital," *International Economic Review*, 50, 63–115.

KELLER, W. AND H. UTAR (2016): "International Trade and Job Polarization: Evidence at the Worker-Level," CEPR Discussion Papers 11311, C.E.P.R. Discussion Papers.

KONG, Y.-C., B. RAVIKUMAR, AND G. VANDENBROUCKE (2018): "Explaining cross-cohort differences in life-cycle earnings," *European Economic Review*, 107, 157 – 184.

KOVAK, B. K. (2013): "Regional Effects of Trade Reform: What Is the Correct Measure of Liberalization?" *American Economic Review*, 103, 1960–1976.

MALGOUYRES, C. (2017): "The impact of Chinese import competition on the local structure of employment and wages: evidence from France," *Journal of Regional Science*, 57, 411–441.

MENEZES-FILHO, N. A. AND M.-A. MUENDLER (2007): "Labor Reallocation in Response to Trade Reform," CESifo Working Paper Series 1936, CESifo Group Munich.

NEAL, D. (1995): "Industry-Specific Human Capital: Evidence from Displaced Workers," *Journal of Labor Economics*, 13, 653–677.

PARENT, D. (2000): "Industry-Specific Capital and the Wage Profile: Evidence from the National Longitudinal Survey of Youth and the Panel Study of Income Dynamics," *Journal of Labor Economics*, 18, 306–23.

PARRO, F. (2013): "Capital-Skill Complementarity and the Skill Premium in a Quantitative Model of Trade," *American Economic Journal: Macroeconomics*, 5, 72–117.

PIERCE, J. R. AND P. K. SCHOTT (2016): "The Surprisingly Swift Decline of US Manufacturing Employment," *American Economic Review*, 106, 1632–62.

POLETAEV, M. AND C. ROBINSON (2008): "Human Capital Specificity: Evidence from the Dictionary of Occupational Titles and Displaced Worker Surveys, 1984–2000," *Journal of Labor Economics*, 26, 387–420.

POSTEL-VINAY, F. AND J.-M. ROBIN (2002): "Equilibrium Wage Dispersion with Worker and Employer Heterogeneity," *Econometrica*, 70, 2295–2359.

TOPALOVA, P. (2007): "Trade Liberalization, Poverty and Inequality: Evidence from Indian Districts," in *Globalization and Poverty*, National Bureau of Economic Research, Inc, NBER Chapters, 291–336.

——— (2010): "Factor Immobility and Regional Impacts of Trade Liberalization: Evidence on Poverty from India," *American Economic Journal: Applied Economics*, 2, 1–41.

TOPEL, R. (1991): "Specific Capital, Mobility, and Wages: Wages Rise with Job Seniority," *Journal of Political Economy*, 99, 145–176.

TRAIBERMAN, S. (2019): "Occupations and Import Competition: Evidence from Denmark," *American Economic Review*, 109, 4260–4301.

UTAR, H. (2018): "Workers Beneath the Floodgates: Low-Wage Import Competition and Workers' Adjustment," Tech. Rep. Forthcoming, Review of Economics and Statistics.

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	2.37%	8.58%	151,361
Δ Imp. from China to France/Init. absorp. - Manufacturing	6.15%	13.07%	53,476
Panel B: Main outcome variables, 1997-2015			
100/19 * Cumulative earnings 1997-2015/Earnings 1997	83.00	59.54	151,361
100/19 * Total hours worked 1997-2015/Hours worked 1997	57.46	38.89	151,361
Average hourly wage 1997-2015/Hourly wage 1997	140.94	28.47	151,361
Panel C: Worker characteristics in 1997			
Female	.33	.47	151,361
Employed in manufacturing	.35	.48	151,361
Tenure 0-1 year	.09	.28	151,361
Tenure 2-5 years	.24	.43	151,361
Tenure 6-10 years	.24	.42	151,361
Firm size 1-99	.29	.45	151,361
Firm size 100-999	.33	.47	151,361
Firms size >1000	.38	.49	151,361

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: Industry Exposure Index and Cumulative Earnings

Dep. Var. : Normalized Average Earnings, $\frac{\sum_{t=1997}^{2015} \text{Earnings}_t/19}{\text{Earnings 1997}}$		
	(1)	(2)
	OLS	IV
Exposure Index CX_j	-0.191***	-0.311***
	(0.076)	(0.111)
Controls	Y	Y
Occupation Fixed Effects	Y	Y
Region Fixed Effects	Y	Y
Observations	151,367	151,370

Notes: Robust standard errors in parenthesis, clustered at the 3-digit industry level. ***, **, * denotes significance at 1%, 5%, and 10%, respectively. All regressions include the same controls as described in the main text. In terms of fixed effects, we replace the industry fixed effects from our baseline specification with broad occupation fixed effects, to absorb OCX_i.

Table A.5: Occupation Exposure and Earnings : Sensitivity Analysis

	Dep. Var. is Normalized Average Earnings, $\frac{\sum_{t=1997}^{2015} \text{Earnings}_t / 19}{\text{Earnings 1997}}$							
	No Industry FE		No Region FE		No Industry/Region FE		No Individual Pre-trends	
	(1) OLS	(2) IV	(3) OLS	(4) IV	(5) OLS	(6) IV	(7) OLS	(8) IV
Occ. Exposure Index OCX_i	-0.014***	-0.019***	-0.0142***	-0.028***	-0.016***	-0.021***	-0.014***	-0.024***
	(0.002)	(0.008)	(0.002)	(0.009)	(0.002)	(0.009)	(0.002)	(0.007)
Occ. Exposure Index OCX_i (VA)	-0.020***	-0.037***	-0.018***	-0.025**	-0.018***	-0.027**	-0.017***	-0.032***
	(0.002)	(0.012)	(0.003)	(0.012)	(0.003)	(0.012)	(0.002)	(0.012)
Occ. Exposure Index OCX_i (shipments)	-0.041***	-0.109***	-0.038***	-0.067*	-0.038***	-0.074**	-0.036***	-0.091***
	(0.005)	(0.035)	(0.006)	(0.035)	(0.006)	(0.036)	(0.005)	(0.034)
Individual Pre-trends	Y	Y	Y	Y	Y	Y	N	N
Industry Fixed Effects	N	N	Y	Y	N	N	Y	Y
Region Fixed Effects	Y	Y	N	N	N	N	Y	Y
Observations	151,361	151,361	151,361	151,361	151,361	151,361	151,587	151,587

Notes: Shift-share robust standard errors in parenthesis, clustered at the 3-digit industry level. ***, **, * denotes significance at 1%, 5%, and 10%, respectively. In each regression, we leave out different sets of controls/fixed effects, compared to our baseline specification. In column (1) and (2), we remove the industry fixed effects. In column (3) and (4), we remove the region fixed effects. In column (5) and (6), we remove both the industry and region fixed effects. In column (7) and (8), we remove the worker pre-trends.

Table A.6: Occupation Exposure Index and Earnings: Additional Robustness

Dep. Variable: Average norm. earnings, $\frac{\sum_{t=1997}^{2015} \text{Earnings}_t/19}{\text{Earnings 1997}}$	(1) OLS	(2) IV
Panel A: Computerization		
Occ. Exposure Index OCX_i	-0.0134***	-0.028***
	(0.002)	(0.013)
Occ. Exposure Index OCX_i (VA)	-0.0184***	-0.037***
	(0.002)	(0.013)
Occ. Exposure Index OCX_i (shipments)	-0.0383***	-0.103***
	(0.005)	(0.039)
Panel B: Firm Capital and Investment		
Occ. Exposure Index OCX_i	-0.015***	-0.032**
	(0.002)	(0.006)
Occ. Exposure Index OCX_i (VA)	-0.017***	-0.036***
	(0.003)	(0.014)
Occ. Exposure Index OCX_i (shipments)	-0.035***	-0.133***
	(0.006)	(0.047)
Panel C: Eastern Countries Competition		
Occ. Exposure Index OCX_i	-0.0197***	-0.0695***
	(0.005)	(0.011)
Occ. Exposure Index OCX_i (VA)	-0.0199***	-0.0366***
	(0.002)	(0.012)
Occ. Exposure Index OCX_i (shipments)	-0.0413***	-0.108***
	(0.005)	(0.035)
Controls	Y	Y
Industry Fixed Effects	Y	Y
Region Fixed Effects	Y	Y

Notes: The dependant variable is (normalized) average annual 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 44). In Panel B we include average firm capital and investment. In Panel C, we include East Countries Occupation Exposure Index, ECX_i^A, which is computed analogously to China Exposure OCX_i^A(see description in main text). Shift-share robust standard errors à la Borusyak et al. (2022) and clustered at the 3-digit industry level in parenthesis in panels A and B. Panel C reports std. err. clustered at 3-digit industry level. ***, **, * denotes significance at 1%, 5%, and 10%, respectively.

Table A.7: Specific-factor Occupational Exposure and Cumulative Earnings

Dep. Var. : Normalized Average Earnings, $\frac{\sum_{t=1997}^{2015} \text{Earnings}_t/19}{\text{Earnings 1997}}$		
	(1)	(2)
	OLS	IV
Specific-Factor Occ. Exposure OCX_i^{SF}	1.352***	-27.93***
	(0.264)	(6.55)
Occ. Manuf Share	Y	Y
Controls	Y	Y
Industry Fixed Effects	Y	Y
Region Fixed Effects	Y	Y
Observations	151,370	151,370

Notes: Shift-share robust standard errors in parenthesis, clustered at the 3-digit industry level. ***, **, * denotes significance at 1%, 5%, and 10%, respectively. All regressions include the same controls and fixed effects, as described in the main text.

B The Specific Factors Case

Consider the particular case of our baseline model in which factor markets are perfectly competitive, and there are decreasing returns to scale in labor, $\sum_{i=1}^{I} \alpha_{ij} < 1$ for all industries $j = 1, \cdots, J$. Since firms price at their marginal cost, this implies positive profits in each sector. Equivalently, and perhaps more conventionally, one can assume the existence of a "fixed" factor in each industry, Tj, with factor share $\theta_{Tj} = 1 - \sum_{i=1}^{I} \alpha_{ij}$, that absorbs these profits. Under this assumption, it is possible to invert the demand for input factors, and obtain a closed-form relationship between changes in output prices and workers' earnings,

$$\hat{w} = \left(1 + \Lambda \Theta_T^{-1} A'\right)^{-1} \Lambda \Theta_T^{-1} \hat{p}, \tag{B.1}$$

where $\hat{w}$ and $\hat{p}$ denote the difference of equilibrium log-wages and log-prices in two trade equilibria, A' denotes the transpose of A,[49] Θ_T denotes a $J \times J$ diagonal matrix whose jth entry contains θ_{Tj} defined above, Λ denotes a $I \times J$ matrix whose entry ij corresponds to the employment share of occupation i in industry j, and 1 denotes the $I \times I$ identity matrix.

Equation (B.1) implies that the effect of a change in prices on earnings of occupation i is a linear combination of the price changes in all industries. The change in earnings of occupation i is

$$\hat{w}_i = \sum_{j=1}^{J} \alpha_{ij}^{SF} \hat{p}_j, \tag{B.2}$$

where the weight of industry j log-price change on the log-change in the wage of occupation i, α_{ij}^{SF}, is given by the ijth entry of the matrix defined in Equation (B.1). Note that these weights are different from the weights in the covariance result, α_{ij}, derived above.[50]

We can make use of Assumption 1 and state the result for the specific-factors model, Equation (B.2), in terms of an occupation-specific exposure measure to the China shock, $OCX_i^{SF} \equiv \sum_{j=1}^{J} \alpha_{ij}^{SF} CX_j$, for each occupation i, to obtain that

$$\hat{w}_i = -\gamma \cdot OCX_i^{SF}. \tag{B.4}$$

Note that the result in Equation (B.4) is structural in nature. Meaning that conditional on this being

[49] That is, A' is a $J \times I$ matrix whose jith entry corresponds to the factor share of occupation i in industry j, α_{ij}.

[50] If there is only one occupation, Equation (B.1) becomes the one obtained in Kovak (2013) and it is more easily interpretable. The weights α^{SF} depend on the industry employment share normalized by the industry labor share,

$$\hat{w} = \frac{\lambda \Theta_T^{-1} \hat{p}}{1 + \lambda \Theta_T^{-1} \theta_O} = \sum_{j}^{J} \frac{\lambda_j / \theta_j}{\sum_{j'}^{J} \lambda_{j'} / \theta_{j'}} \hat{p}_j, \tag{B.3}$$

where $\lambda' = \begin{bmatrix} \lambda_1 & \lambda_2 & \cdots & \lambda_J \end{bmatrix}$, and λ_j is the share of workers in industry j. We note also that computing α_{ij}^{SF} requires additional information on employment shares relative to our baseline exercise. Also, α_{ij}^{SF} cannot be as easily interpreted, since it involves the product and inversion of matrices containing factor and industry-occupation employment shares.

the true model, it tells us by how much we would expect earnings to decline given the exposure of a given occupation. By contrast, (4) does not have this structural property. It only informs us of a sign restriction. Thus, the quantification of the magnitudes of the effects is based on the reduced form relationship and there is no structural model underlying it.

C Derivations of the Theoretical Results

This appendix provides the details to derive the two occupational exposure indices described in Section 2.

C.1 Factor-Proportions Model

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}, $i = 1, \cdots, I$, as

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

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

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

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

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

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

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

Equation (C.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 (C.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 (C.4), we find that

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

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 (1) 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).

C.2 Specific Factors Model

We now consider a particular case of our previous model. Let us assume that there are decreasing returns to scale to labor, $\sum_{i=1}^{I}\alpha_{ij}<1$. In particular, as it is standard in the trade literature, we assume that there "fixed" factors in each industry, Tj. We further assume that a_{Oij} and a_{Tj} denote the number of workers of occupation i and quantity of specific factor T_j needed to produce one unit of output in industry j. This model is a multi-occupation extension of Kovak (2013). We follow analogous steps to derive an equation that directly relates changes in industry prices to changes in earnings of workers in a given occupation.

Occupation i labor market clearing condition is,

$$\sum_{j=1}^{J}a_{Oij}Y_j=O_i, \tag{C.6}$$

where O_i is the supply of workers in occupation i. Note that occupation i is used in all industries j. This is in contrast to the specific factor, which, by defintion, is used only in one industry. Thus, the market clearing for that factor is,

$$a_{Tj}Y_j=T_j, \tag{C.7}$$

The zero-profit conditions in industry j can be written as,

$$P_j=c_j=\sum_{i=1}^{I}a_{Oij}w_i+a_{Tj}R_j, \tag{C.8}$$

where c_j is the unit cost of industry j, w_i is the wage of workers in occupation i and R_j is the return of the factor specific to industry j. Note that workers are mobile across industries and, thus, there is a unique wage for occupation.

If we apply Jones hat algebra (Jones, 1965) to this zero-profit condition, we obtain,

$$\hat{P}_j = \sum_{i=1}^{I} \theta_{Oij}\hat{w}_i + \theta_{Tj}\hat{R}_j, \tag{C.9}$$

where $\theta_{Oij}=\frac{a_{Oij}w_i}{c_j}$ for each occupation i and $\theta_{Tj}=\frac{a_{Tj}R_j}{c_j}$. Note that, by definition, $\sum_{i=1}^{I} \theta_{Oij}+ \theta_{Tj}=1$ in each industry j.

Then, we can apply Jones hat algebra to occupation i market clearing condition,

$$\hat{O}_i = \sum_{j=1}^{J} \lambda_{ij}[a\hat{O}_{ij} - a\hat{T}_j], \tag{C.10}$$

where λ_{ij} is the share of workers of occupation i employed in industry j. Note that we have already used the hat-version of the specific factor clearing condition, $\hat{Y}_j$=-$a\hat{T}_j$.

If we assume that the elasticity of substitution across factors is one, the same assumption as in Kovak (2013), occupation i market clearing equation can be re-written as,

$$\hat{O}_i = \sum_{j=1}^{J} \lambda_{ij}[\hat{R}_j - \hat{w}_i], \tag{C.11}$$

Note that the hat-version of the J zero-profit conditions (equations C.9) and the I occupation market clearing conditions (equation C.11) can be written in a matrix form.

$$\begin{bmatrix} \Theta_T & \Theta_O \\ \Lambda & -1 \end{bmatrix} \begin{bmatrix} \hat{R} \\ \hat{w} \end{bmatrix} = \begin{bmatrix} \hat{P} \\ \hat{O} \end{bmatrix}, \tag{C.12}$$

where $\Theta_T = \begin{pmatrix} \theta_{T1} & 0 & \cdots & 0 \\ 0 & \theta_{T2} & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \cdots & \theta_{TJ} \end{pmatrix}$, $\Theta_O = \begin{pmatrix} \theta_{O11} & \theta_{O21} & \cdots & \theta_{OI1} \\ \theta_{O12} & \theta_{O22} & \cdots & \theta_{OI2} \\ \vdots & \vdots & \ddots & \vdots \\ \theta_{O1J} & \theta_{O2J} & \cdots & \theta_{OIJ} \end{pmatrix}$, $\Lambda = \begin{pmatrix} \lambda_{11} & \lambda_{12} & \cdots & \lambda_{1J} \\ \lambda_{21} & \lambda_{22} & \cdots & \lambda_{2J} \\ \vdots & \vdots & \ddots & \vdots \\ \lambda_{I1} & \lambda_{I2} & \cdots & \lambda_{IJ} \end{pmatrix}$,
$\hat{R}' = \begin{bmatrix} \hat{R}_1 & \hat{R}_2 & \cdots & \hat{R}_J \end{bmatrix}$, $\hat{w}' = \begin{bmatrix} \hat{w}_1 & \hat{w}_2 & \cdots & \hat{w}_1 \end{bmatrix}$, $\hat{P}' = \begin{bmatrix} \hat{P}_1 & \hat{P}_2 & \cdots & \hat{P}_J \end{bmatrix}$ and $\hat{O}' = \begin{bmatrix} \hat{O}_1 & \hat{O}_2 & \cdots & \hat{O}_I \end{bmatrix}$.

It is straightforward to obtain from equation C.12 an expression of how changes in industry prices affect wages in each occupation. In particular, by assuming that the stock of workers in each occupation is fixed, it follows that,

$$\hat{w} = \left[1 + \Lambda\Theta_T^{-1}\Theta_O\right]^{-1} \Lambda\Theta_T^{-1}\hat{P}, \tag{C.13}$$

Equation C.13 implies that the effect of a change in prices on earnings of occupation i is a linear combination of the change in prices in all industries. The interpretation of which occupations should experience a larger fall in earnings after a decline in industry prices is much more nuanced given that it involves the product and inversion of matrices containing factor and industry-occupation employment shares.

D Supplemental Tables

Table D.1: Factor Specificity by Occupation α_{ij} using Gross output

	Mean	Std. Dev.	p25	p75
Executives	0.14	0.27	0.02	0.16
Engineers	0.07	0.08	0.02	0.1
Administrative Staff	0.27	0.64	0.03	0.25
Technician Staff	0.07	0.1	0.04	0.08
Other Middle-skill Occ.	0.67	1.58	0.22	0.44
Skilled Production Workers	0.16	0.14	0.07	0.21
Unskilled Production Workers	0.06	0.07	0.02	0.08

Notes: Factor specificity computed as the wage bill of occupation i in industry j divided by gross ouput in that industry (measured by value of shipments), both in 1997.

Table D.2: Factor Specificity by Occupation α_{ij} using Value Added

	Mean	Std. Dev.	p25	p75
Executives	0.25	0.55	0.05	0.23
Engineers	0.16	0.14	0.06	0.24
Other Engineers	0.19	0.09	0.14	0.2
Administrative Staff	0.28	0.68	0.08	0.25
Technician Staff	0.16	0.14	0.09	0.2
Other Middle-skill Occ.	0.39	0.19	0.29	0.52
Skilled Production Workers	0.31	0.15	0.21	0.39
Unskilled Production Workers	0.14	0.11	0.06	0.2

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

Table D.3: Occupation Exposure Index based on Shipments

	OCX_i	OCX_i^A
Executives	0.43	6.06
Engineers	1.91	9.13
Administrative Staff	0.92	12.03
Technician Staff	0.79	11.21
Other Middle-skill Occ.	0.07	0.76
Skilled Production Workers	2.52	22.79
Unskilled Production Workers	1.15	15.45

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

Table D.4: Occupation Exposure Index based on Value-Added Occupation Intensities

	OCX_i	OCX_i^A
Executives	1.14	16.66
Engineers	4.59	23.06
Administrative Staff	2.23	30.17
Technician Staff	1.98	29.18
Other Middle-skill Occ.	0.14	1.52
Skilled Production Workers	6.01	56.77
Unskilled Production Workers	2.78	38.22

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