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Sergi Basco[*] Maxime Liégey[†] Martí Mestieri[‡] Gabriel Smagghue[§]

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Abstract

This paper develops and implements a novel test of the Stolper-Samuelson theorem. We use nationally-representative matched employer-employee panel data from 1997 through 2015 to study the effect of the rise in China's exports on French worker earnings. Our version of the Stolper-Samuelson theorem states that there is a negative correlation between occupation exposure to Chinese competition and change in worker earnings. First, we document substantial heterogeneity in trade adjustment across occupations. Then, consistent with the Stolper-Samuelson prediction, we show that workers initially employed in occupations more intensively used in hard-hit industries experience larger declines in earnings. We also show that workers tend to move out of hard-hit industries, but they tend to remain in their initial occupation.

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[*]Universitat de Barcelona, BEAT and MOVE
[†]Université de Strasbourg
[‡]Federal Reserve Bank of Chicago, Northwestern University and CEPR
[§]Universidad Carlos III de Madrid
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1 Introduction

Do the returns to factors more intensively used in an industry decline after a negative shock to that industry? This is the prediction of the Stolper-Samuelson theorem and a fundamental result of the factor proportions theory.[1] Since its original publication by Stolper and Samuelson (1941), this theorem has played a central role in the analysis of the effect of trade on inequality. For example, it has been used to analyze the effect of trade on the returns to capital relative to labor and on the skill premium (e.g., Leamer, 1996, 2012, Feenstra and Hanson, 2008, Baldwin, 2008).

Despite playing a prominent role in the neoclassical theory of trade and inequality, there is little empirical evidence supporting the Stolper-Samuelson result. This is partly due to the fact that the sharpest results of the Stolper-Samuelson theorem apply for economies with only two sectors and two factors of production.[2] In this article, we develop a novel test of the Stolper-Samuelson theorem that allows for an arbitrary number of factors of production and industries. We build on the formulation of the Stolper-Samuelson theorem as a correlation developed in Ethier (1984). However, differently from Ethier, our formulation only requires information on observed equilibrium outcomes, which makes it readily amenable to empirical testing. In our setting, the testable prediction of the Stolper-Samuelson theorem is that, after a negative trade shock, there is a larger percent decline in the return to factors more intensively used in the industries affected by the shock.

To empirically test our formulation of the Stolper-Samuelson result, we use matched employer-employee panel data from French Social Security records spanning 1993 through 2015, supplemented with exhaustive firm-level balance-sheet information.[3] Our analysis focuses on the effect of the rise of Chinese exports on worker earnings across occupations. We thus establish a connection with the Stolper-Samuelson theorem by taking occupational categories as factors

[1] This general statement applies to both the Ricardo-Viner specific factors model and the Heckscher-Ohlin model. As pointed out by Neary (1978), the latter can be thought of as a long-run version of the former. That is, no factor is specific enough so that it cannot be used in another industry in the long-run. Within the Heckscher-Ohlin model, this empirical prediction is known as the Stolper-Samuelson theorem.

[2] Accordingly, most empirical tests of the Stolper-Samuelson Theorem have focused on the two-by-two formulation, facing the daunting task of mapping empirical settings to a two-by-two world. Typically, they have considered labor and capital or skilled and unskilled workers as the factors of production. See for example, the survey on empirical tests cited in Leamer (2012).

[3] A long panel allows us to circumvent a second empirical challenge for testing the Stolper-Samuelson theorem. Neoclassical trade theory assumes perfect factor mobility across sectors. However, in practice, reallocation may not be immediate and one needs to observe data for a sufficiently long period to allow production factors to adjust.

of production, and using the rise in Chinese exports over this period as a trade shock. In our empirical setting, the Stolper-Samuelson theorem implies that earnings declines should concentrate in workers initially employed in occupations more intensively used in industries highly exposed to Chinese competition.

Our identification strategy for the effect of the rise in Chinese competition builds on the previous work studying the "China shock," and it 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 on the rich set of worker and firm controls in our data, we compare "observationally equivalent" workers initially employed in the same occupation, but different industries. The underlying identifying assumption is that, absent industry-specific "China shocks," these workers would have experienced comparable earning trajectories.

As a first step in studying trade adjustment of French workers, we document the effect of the rise in Chinese exports in a reduced-form setting. We begin by showing that, on average, French workers experienced earning losses between 1997 and 2015 comparable to U.S. workers over the same period. We then show that these losses were substantially heterogeneous across occupations. Workers initially employed in occupations that are very specific to manufacturing (e.g., engineers or blue-collar workers with vocational training) experienced substantial earnings losses, while workers initially employed in occupations less specific to manufacturing such as administrative occupations (e.g., secretaries and accountants) hardly experienced a decline in earnings.[4]

We then turn our analysis to an empirical setting motivated by our theory, and show that the heterogeneity in changes of worker earnings across occupations is consistent with the prediction of the Stolper-Samuelson theorem. In particular, our theory implies that an index of occupation exposure to Chinese competition is a "sufficient statistic" for the effect of the trade shock on worker earnings. This index is constructed as a weighted average over industry exposure, where the weights for each occupation are given by the occupation's industry factor intensity. Our version of the Stolper-Samuelson result states that there is a negative correlation

[4] As noted in Autor et al. (2014), there is no information on occupations in the U.S. Social Security records. We are not aware of any study conducting an analogous analysis to ours for the U.S.

between this index of occupation exposure and the relative worker earnings pre- and post-trade shock.[5]

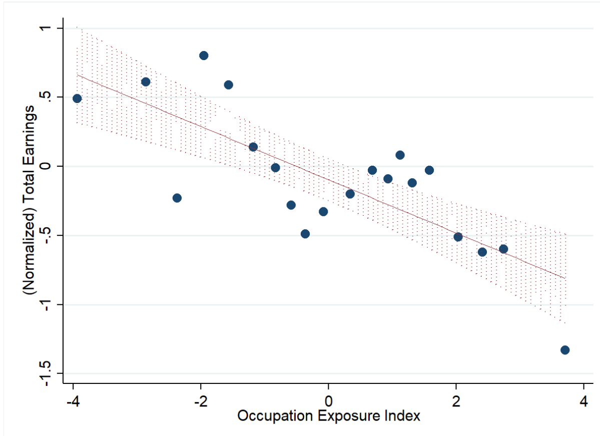
Figure 1 shows that, in our data, there is a strong, negative partial correlation between the increase in exposure to Chinese competition of each occupation, measured by the occupation index, and workers' change in relative earnings over the 1997-2015 period.[6] We show that this correlation persists (and becomes slightly larger) after instrumenting the occupation exposure index with an index constructed using lagged occupation factor intensities (from 1994) and Chinese exposure in other advanced economies (as in our reduced-form exercise). We find that the decline in relative earnings is the highest in occupations that were used intensively in highly-exposed industries and, thus, have a high occupation exposure index. The estimated magnitude of the effect across occupations is substantial. Moving from the occupation with the lowest occupation exposure index (which corresponds to middle-skill occupations such as retail workers) to the highest (which corresponds to skilled production workers such as metal welders and turners) implies losing almost two yearly (1997) total earnings over the 1997-2015 period. This result is robust to using different levels of aggregation of occupations and alternative definitions of factor intensity.

We also provide evidence that supports the mechanism underlying the Stolper-Samuelson prediction and our assumption of occupations as factors of production. We show that workers initially employed in industries that are highly exposed to Chinese competition move to other industries—and away from manufacturing, which has the highest exposure. Moreover, despite changing industry, we find that workers stay in their initial occupation: there is no effect of Chinese exposure on the probability of workers changing occupation. This result is consistent with our view of workers' broad occupations as factors of production. Finally, we also decompose the effect on total earnings between hours and wages and we show that even though trade adjustment operated through both margins, the effect on hours is larger. We also provide suggestive evidence on the role of labor market regulation in shaping trade adjustment differentially across industries.

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

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

Figure 1: Occupation Exposure Index and Change in Earnings



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

Detailed Overview of the Paper Section 2 presents our theoretical framework. We first present the Stolper-Samuelson (SS) result in a simple modern rendition of the classic two-by-two environment. Then, Section 2.2 presents our general result with an arbitrary number of factors and industries. The key innovation relative to the prior literature is to obtain a statement of SS that holds for any two trade equilibria without resorting to more information (e.g., in contrast to Ethier, 1984, which requires knowledge of an unobserved equilibrium outcome). This makes possible to empirically test the SS prediction using readily available data.

Section 3 presents our empirical strategy and data sources. Our identification strategy of the trade shock builds on the previous work that has used the China shock at the industry level, starting with Autor et al. (2014). France, like the vast majority of developed economies, has experienced a spectacular increase in imports from China—faster, if anything, than the U.S.[7] We use China's differential industrial growth in exports to France between 1997 and 2015 as a trade shock. We instrument the rise in Chinese exposure in France to isolate the supply shock coming from China using the rise in Chinese exports in other advanced economies outside the European Monetary Union.[8] We then infer the effect of Chinese competition on worker

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

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

adjustment by comparing observationally equivalent workers exposed to different levels of Chinese competition.

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

Section 4 presents our main results. We focus on workers that were attached to the labor market over the 1994-1996 period.[9] This allows us to examine workers that, absent the trade shock, would not have any problem participating in the labor market. The dependent variable that we use throughout our analysis is motivated by our theory. It corresponds to cumulative 1997-2015 worker earnings normalized by initial (1997) worker earnings. As a first step towards documenting heterogeneity in trade adjustment by occupation, Section 4.1 performs a reduced-form analysis. We estimate a log-linear specification where future worker earnings normalized by initial worker earnings are regressed on our industry-level measure of Chinese competition in the worker's initial (1997) industry. In this regression, we control for (1) a rich array of worker, initial firm and industry characteristics, and commuting zone fixed effects, (2) the initial trade exposure of the industry (separately controlling for Chinese and non-Chinese competition). The 2SLS coefficient on Chinese competition informs us of the effect of the China shock on relative earnings. Pooling all occupations together, we find that, for the average

et al. (2014, 2016, 2017, 2018).

[9] A worker is defined as attached if they earn at least the monetary equivalent of 1500 hours/year at the legal minimum wage, over 3 consecutive years prior to 1997. Building on the literature studying displaced workers and mass layoffs (e.g., (Jacobson et al., 1993)), our goal is to zoom in the effect of the trade shock by looking at workers with stable labor income prior to the shock. This way we can isolate it from other type of shock that less attached workers may have.

manufacturing worker, an increase of one standard deviation in Chinese exposure amounts to loosing 82.5% of the 1997 average worker earnings over the 1997-2015 period.[10]

We then estimate our reduced-form regression separately by occupation, and find that the pooled reduced-form regression masks substantial heterogeneity across occupations. Workers employed in 1997 as production workers, technical staff, engineers or executives experience a significant fall in (normalized) cumulative earnings over the 1997-2015 period. In contrast, Chinese exposure has a smaller negative but insignificant effect at conventional levels among unskilled production workers, administrative staff or other mid-level occupations. Quantitatively, a one standard deviation increase in Chinese competition implies a decline in cumulative earnings for engineers (the most affected occupation) by 332% of their initial earnings. In contrast, we cannot reject a zero effect for administrative and other middle-skill occupations. We also document that the effect of the trade shock builds over time. It takes between 5 and 10 years to generate a significant drop in earnings across occupations. This result echoes similar findings for the U.S. (Autor et al., 2014) and Brazil (Dix-Carneiro and Kovak, 2019).

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

We find that this negative relationship persists and becomes somewhat stronger when we instrument the occupation exposure measure to account for potential alternative drivers of the rise in Chinese competition in France. We instrument the occupation index with an occupation index constructed using industry-exposure to Chinese competition from other advanced economies outside the European Monetary Union and lagged (1994) factor-intensity as weights (to account for potential anticipation effects). Quantitatively, comparing the effect on the average worker initially employed in the occupation with the lowest exposure index (which corresponds to middle-skill occupations such as retail workers) to the highest (which corresponds to

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

skilled production workers such as metal turners) implies a difference in earnings lost of 180% of the 1997 worker total earnings over the 1997-2015 period.

We also show that the mechanism through which the shock operates is consistent with the SS logic. First, we show that workers initially employed in hard-hit industries tend to leave that industry *regardless* of their initial occupation. We also show that they tend to move towards sectors outside manufacturing, which have lower Chinese exposure. Perhaps more surprisingly, we also document that, despite changing jobs and leaving their initial industry, workers do not tend to change their initial occupation. We find no effect of Chinese competition on the probability that workers change occupation. This facilitates the interpretation of occupations as factors of production, even though it is not necessary for our results: if workers changed occupations as a reaction to the trade shock and moved to occupations experiencing a smaller decline in earnings, our estimate would be a lower bound on the Stolper-Samuelson effect (which assumes no occupational mobility).[11]

Section 5 exploits the richness of our data to explore different margins of adjustment. We first analyze whether the adjustment operates more on the extensive or intensive margin. To this end, we decompose the effect on relative earnings through changes in relative hours worked versus relative wages. We find evidence that both margins are operative. However, quantitatively, the extensive margin accounts for the larger part of the variation. A final contribution of this paper is to shed light on how trade adjustment interacts with labor regulation. The discontent with globalization in most developed countries has coincided with the large increase in Chinese competition. Arguably, one of the most critical policy questions is how labor institutions should be designed to mitigate the effects of international trade. In Section 5.2, we construct a measure of pre-shock labor regulation at the industry level (based on collective agreements) to provide suggestive evidence on this interaction and how it varies across occupations. We find that labor regulation exacerbated the negative effect of Chinese competition on cumulative earnings. We document that the negative effect of regulation is concentrated among skilled production workers and technical staff, whereas it is neutral for the rest of occupations. That is, it seems that labor regulation exacerbated the losses of workers in low-wage occupations.

[11] In the limit, if there were no occupational specificity (i.e., all industries have the same occupational composition), we should expect no differential change in earnings across occupations, which is counterfactual.

Related literature This paper relates to several strands of the trade literature. Even though the Stolper-Samuelson (SS) theorem is one of the most salient empirical predictions of the Factor Proportions/Heckscher-Ohlin model, there is scant direct evidence on its empirical validity (instead, most of the empirical literature has focused on the predictions of the pattern of trade, Leamer and Levinsohn, 1995). The SS theorem has been used to explain why North-South trade can induce an increase in wage inequality (typically measured as the skill premium) in the North. The idea is that, from the North's perspective, trade with Southern countries represents a positive demand shock for skill intensive industries (see, for example, Feenstra and Hanson, 1995, Leamer, 1996, and Basco and Mestieri, 2013). This paper follows this tradition of studying trade and labor inequality through the lens of a factor proportion model. Unlike these papers, we consider a more disagreggated set of workers and industries and derive a new test of the SS theorem.

Our paper relates to other studies of the SS predictions, e.g., Goldberg and Pavcnik (2007), Baldwin (2008), Chiquiar (2008), Amiti and Cameron (2012), and Bernhofen et al. (2014). Our paper is closest to Bernhofen et al., who test the SS theorem in the context of the opening of Japan to international trade during the XIXth century. Their test is based on the covariance formulation of Ethier (1984). There are two important methodological differences between the papers. First, Bernhofen et al., to avoid the dependence on unobserved equilibrium prices that appear in Ethier's formulation, assume that all sectors in the economy produce according to Leontief production functions, so that the factor demands are independent of prices. Instead, we allow for a positive elasticity of substitution in production. Second, Bernhofen et al.'s test of SS consists of directly constructing the covariance between changes in factor and goods prices and testing its sign. Instead, we show how to test the SS theorem using a regression analysis, and use this fact to control for other potential drivers of changes in factor prices.

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 in a context of specific factors model. Our approach is similar. The most important difference is that we examine the effect of trade across different occupational groups.[12] Our paper is also related to the rel-

[12] Another strand of the literature has used trade policy to indirectly show the validity of the factor specificity assumption. See, for example, Goldberg and Maggi (1999) for an application for the United States in a lobbying model.

atively 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 from this literature is to examine the effect across occupations and make the connection with a test of the SS theorem.

We emphasize the importance of the initial occupation to understand the trade adjustment. This finding is consistent with previous studies, e.g., Ebenstein et al. (2014), Bernard et al. (2006), Utar (2018), and Traiberman (2018).[13] Ebenstein et al. use CPS data for 1984-2002 to document that the effect of globalization operates mostly through occupational exposure rather than industry exposure. Traiberman 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.[14] Our findings provide complementary evidence on the importance of occupations in shaping trade adjustment. In our case, the mechanism operates through heterogeneous factor intensity across industries.

Our identification strategy builds on the "China industry Shock" introduced in Autor et al. (2014) and subsequently used in Dauth et al. (2014), among others.[15] The main difference with this literature is that we analyze the differential effect of the "China Shock" across occupations and relate this heterogeneous effect to occupation specificity, which allows us to test the SS theorem. In addition, we investigate other margins of adjustment (changing wages, hours worked, etc.), which help us to understand this heterogeneous effect and are consistent with

[13]Utar uses the expiration of the Multi-fiber Arrangement (MFA) quotas for China due to its accession to the WTO as a quasi-natural experiment for Danish textile and clothing. Following workers initially in the textile sector over 10 years, she documents large earnings losses. She also finds that the initial effect on earnings is uniform across all skill levels, but that low-skill workers experience more job instability. In a complementary paper, Utar (2014) also uses the expiration of the Multi-fiber Arrangement (MFA) quotas for China (due to its accession to the WTO) as a quasi-natural experiment for Danish textile and clothing. She finds that employment and firm sales and value-added are negatively affected by the intensified competition from China.

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

[15]Pierce and Schott (2016) provide an alternative instrument for China shock for the U.S. and show that it accounts for the decline in the U.S. manufacturing employment. Dauth et al. (2018) 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.

the occupation specificity narrative.[16]

2 Theoretical Framework

This section presents a theoretical analysis of the Stolper-Samuelson (SS) theorem. We first review the standard neoclassical small-economy, two-industries two-factors of production SS result, which corresponds to a modern textbook rendition of the original derivation (Stolper and Samuelson, 1941). As we discussed in the introduction, our key departure from the original interpretation, which focused on capital and labor as factors of production, is to think of occupations as factors of production. That is, we think of different industries using engineers, secretaries, etc., in different intensities (but we allow for a positive elasticity of substitution between them). In our view, this is a natural extension of the often used skilled vs. unskilled interpretation of the SS theorem (e.g., Leamer, 1996) to more than two factors of production.[17]

We then provide a novel generalization of the SS theorem to an arbitrary number of industries and factors. Our result is stated in terms of the correlation between relative changes in labor earnings and occupation exposure to a trade shock. Thus, the correlation interpretation of our result is similar to Ethier (1984). However, our result is starker since it holds for any two equilibria, and it does not rely on the intermediate value theorem that needs to invoke an (unobserved) third equilibrium. Finally, we discuss how to test the implications of our theoretical framework and bring the model to the data.

2.1 The Textbook Two-by-Two Case

We consider a neoclassical small-open economy. There are two perfectly competitive industries A and B, indexed by j. Each industry produces one good, which sells at world price p_j.

[16] A recent and fast-growing stream of the literature has been focusing 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 (2016), and Dix-Carneiro and Kovak (2017). These studies focus on the effects of trade across different regional labor markets. In this paper, we study the impact of trade at the worker level while controlling for regional differences.

[17] In this theory section we make the stark assumption that workers are fixed in their initial occupation and cannot change it (i.e., engineers remain engineers and secretaries remain secretaries), but they are allowed to change industries. Our empirical exercise relaxes this assumption and allows for workers to change occupation. However, we show that the assumption of lack of occupation mobility in response to the China shock is not rejected in our data, perhaps not surprisingly since we focus on attached workers prior to the shock. In fact, in our theory, relaxing the assumption of workers being fixed in the initial occupation would attenuate the resulting wage differential as workers would move across occupations. Indeed if the mobility cost was zero all wages would be equalized.

Production requires workers performing two different occupations, o_{1j} and o_{2j}, according to

$$Y_j = A_j o_{1j}^{\alpha_j} o_{2j}^{1-\alpha_j}, \quad \text{for} \quad j = A, B, \tag{1}$$

and $A_j = \tilde{A}_j \alpha_j^{-\alpha_j}(1-\alpha_j)^{1-\alpha_j}$ with $\tilde{A}_j > 0$. Without loss of generality, we assume $1 \geq \alpha_A \geq \alpha_B \geq 0$. This assumption implies that occupation 1 is more specific to industry A. In the extreme case that $\alpha_A = 1$ and $\alpha_B = 0$, occupation 1 is only used in industry A and it is specific to industry A. This would be the assumption in the Ricardo-Viner specific factors model.

Each worker supplies inelastically one unit of labor. We assume that workers cannot switch occupations, but they can freely offer to perform their occupation to any industry.[18] Perfect competition implies that the price of the good produced by industry j equals the cost of production. Since we are assuming that workers can offer to perform their occupations to either industry, no-arbitrage implies that the wage per occupation is equalized across industries. Denoting by w_1 and w_2 the equilibrium wages for each occupation, we have that

$$\ln p_j = \alpha_j \ln w_1 + (1-\alpha_j) \ln w_2 - \ln \tilde{A}_j. \tag{2}$$

Consider now two equilibria, denoted by superscripts 0 and 1. Building on our empirical application, consider a China-trade shock that increases competition and puts downward pressure on domestic producers in equilibrium 1. In particular, suppose that Chinese exposure is positive in industry A, CX_A>0, but it is zero in industry B, CX_B=0, so that the change in equilibrium log prices $\Delta \ln p_j \equiv \ln p_j^1 - \ln p_j^0$ satisfies $\Delta \ln p_A = -\beta CX_A < 0 = \Delta \ln p_B$ with $\beta > 0$. Using Equation (2), we find that[19]

$$\Delta \ln w_1 = \frac{-(1-\alpha_B)\beta CX_A}{(\alpha_A - \alpha_B)} < 0 < \Delta \ln w_2 = \frac{\alpha_B \beta CX_A}{(\alpha_A - \alpha_B)}. \tag{3}$$

This result implies that the decline in earnings due to Chinese competition is larger for the occupation more specific to the industry most exposed to Chinese competition. In this case,

[18] Of course, in practice, occupations are chosen by workers and, indeed, workers change occupations over their life-cycle. In our empirical setting, we will be tracing the effect across occupations of an unexpected industry-specific shock happening *after* the initial choice of occupations has been made by attached workers. We show that our assumption cannot be rejected in our data: workers respond to the industry shock by changing industry they work in but not occupation.

[19] Extending this result to $\Delta p_1 < \Delta p_2$ is straightforward. The proof follows from $0 = \alpha_B \Delta \ln w_1 + (1-\alpha_B)\Delta \ln w_2$ and $\Delta \ln p_A = \alpha_A \Delta \ln w_0 + (1-\alpha_A)\Delta \ln w_1$. Thus, $\Delta \ln w_0 = \Delta \ln p_A / (\alpha_A - (1-\alpha_A)\alpha_B(1-\alpha_B)^{-1}) = (1-\alpha_B)\Delta \ln p_A/(\alpha_A - \alpha_B) < 0$, which implies that w_1 has to decline and w_2 has to increase.

this corresponds to occupation 1, since it is more intensively used in industry A given our assumption that $\alpha_A > \alpha_B$. The intuition for the result comes from the fact that, as Chinese competition increases in sector A, the producer of good A has to cut back its production to break even. This implies a reduction in the relative demand of the occupation more intensively used in the production of sector A. In equilibrium this results in a decline of its wage.

2.2 Generalized Model: I occupations and J industries

We now extend our analysis to an arbitrary number of industries and occupations. This will help connect the SS result to our empirical application, which has several (more than two) occupations and industries. The literature has provided different types of extensions of the SS result (Deardorff, 1993). The two most prominent are the "friends and enemies" formulation and the correlation formulation of Ethier (1984).[20] Here, we build on the latter and state a generalization of the SS in terms of correlations. Differently from Ethier (1984), we formulate the problem in terms of elasticities of the cost functions. Using this formulation with Cobb-Douglas production functions allows us to provide a sharper characterization of the SS result that holds when comparing *any* two equilibria without resorting to a third unobserved equilibrium (as in Ethier, 1984) or providing a local result (as in Deardorff, 1993).

Consider a production function for industry $j = 1, \cdots, J$ that uses occupations $i = 1, \cdots, I$,

$$Y_j = A_j \prod_{i=1}^{I} o_{ij}^{\alpha_{ij}}, \tag{4}$$

with, $\alpha_{ij} \geq 0$, $\sum_{i=1}^{I} \alpha_{ij} = 1$ and $A_j = \tilde{A}_j \prod_i \alpha_{ij}^{-\alpha_{ij}}$ with $\tilde{A}_j > 0$.[21] Following the same steps as in the previous section, the elasticity of the equilibrium price to each wage is constant

$$\frac{\partial \ln p_j}{\partial \ln w_i} = \alpha_{ij}. \tag{5}$$

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

[20] See Jones and Scheinkman (1977) and the references therein for the friends and enemies formulations.

[21] A_j and α_{ij} can capture in reduced form any patterns of complementarity across factors of production on the wage bill, see Comin et al. (2019). Also, since we are abstracting from other factors of production, $\tilde{A}_j$, not only captures Hicks-neutral technical change but also stands-in for capital, land, and any other omitted factors.

that

$$\boldsymbol{P} = \boldsymbol{A}'\boldsymbol{W}. \tag{6}$$

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 $\boldsymbol{W}^0$. It follows that

$$(\boldsymbol{P}^1 - \boldsymbol{P}^0)'\boldsymbol{A}'(\boldsymbol{W}^1 - \boldsymbol{W}^0) = (\boldsymbol{P}^1 - \boldsymbol{P}^0)'(\boldsymbol{P}^1 - \boldsymbol{P}^0) > 0. \tag{7}$$

Equation (7) 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), the type of result in Equation (7) is a statement about an inner product. To recast this result in terms of correlations, 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 (7). 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 (7), we find that

$$\text{Cov}\left(\boldsymbol{A} \cdot \Delta\boldsymbol{P}, \Delta\boldsymbol{W}\right) > 0, \tag{8}$$

where Δ is the difference operator, $\Delta\boldsymbol{P} = \boldsymbol{P}^1 - \boldsymbol{P}^0$. To interpret this result, 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 (8) 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.

Despite its simplicity, this is a novel result to the best of our knowledge. The key difference with Ethier (1984) is that, in his formulation, the equivalent term to $\boldsymbol{A}$ in Equation (8) depends on equilibrium prices evaluated at an intermediate equilibrium point between 0 and 1. These equilibrium prices are thus unobserved and not pinned down by the theory.[22] As a consequence, his result remained mainly as an elegant theoretical derivation. The proposed

[22] This is the case because Ethier's proof comes from the intermediate value theorem.

empirical attempts to test Ethier's result so far either considered an infinitesimal change in prices (e.g., Deardorff, 1993) or Leontieff production functions to eliminate the dependence of the cost function on equilibrium input prices (Bernhofen et al., 2014). In contrast, our formulation holds for any two equilibria and allows for a positive elasticity of substitution across factors of production.

To build a connection with our empirical exercise, we make the analogous assumption to the previous section. We assume that in equilibrium 1 there is a rise in Chinese competition that is heterogeneous across domestic industries.[23] As a result, the world price vector changes from $\boldsymbol{P}^0$ to $\boldsymbol{P}^1 = \boldsymbol{P}^0 - \beta \boldsymbol{CX}$, with $\beta > 0$. That is, there is a negative relationship between Chinese exposure and change in prices, $\Delta \boldsymbol{P} = -\beta \cdot \boldsymbol{CX}$. Given this assumption, Equation (8) becomes

$$\mathrm{Cov}(\boldsymbol{A} \cdot \boldsymbol{CX}, \Delta \boldsymbol{W}) < 0. \tag{9}$$

Equation (9) implies that occupations more intensively used in more exposed industries experience, on average, a larger decline in earnings.

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

$$OCX_i \equiv \sum_{j=1}^{J} \alpha_{ij} CX_j. \tag{10}$$

Using this notation, Equation (9) can be equivalently stated as $\mathrm{Cov}(\boldsymbol{OCX}, \Delta \boldsymbol{W}) < 0$.[24] Equation (9) constitutes the core of our test of the SS theorem and we summarize it below.

Empirical Prediction *The decline in relative earnings $\Delta \boldsymbol{W}$ is, on average, larger in occupations that are more intensively used in industries more exposed to Chinese competition. Formally, as stated in Equation (9), this implies that there is a negative correlation between changes in worker earnings and their occupation exposure to Chinese competition.*

The intuition for this result is the same as in the two-industry two-occupations model. After

[23] As we discuss further below, the French national statistical agency (INSEE) does not produce industry price indices at a fine industry level (4-digit).

[24] Note that, as a reduced form, this formulation is very similar to the approach used in Ebenstein et al. (2014) who also use an occupation exposure index to assess the impact of offshoring.

an increase in Chinese competition, the change in the rewards to a given occupation depends on how specific this occupation is to the industries most exposed to Chinese competition. If an occupation is mainly used in industries highly exposed to Chinese competition, workers performing this occupation will experience a large decline in earnings because output and, consequently, labor demand will fall the most for these industries.[25] Similarly, if an occupation is mainly used in industries with zero (or very low) exposure to Chinese competition, the earnings of workers performing this occupation will not be affected.

2.3 Bringing the Model to the Data

This section discusses how to operationalize the previous theoretical result in our empirical setting. In particular, we show how our main result can be tested by means of regression analysis. We also discuss how, guided by the previous theory, we construct key regression variables.

2.3.1 Operationalizing the SS Test through OLS

One appealing property of the SS Theorem in Equation (9) is that it is stated in terms of the sign of a covariance. This immediately suggests testing for this result using standard OLS techniques with the occupation exposure index OCX_i derived from our theory (Equation 10) as independent variable. In particular, we consider the following regression in which the dependent variable is the log-change in earnings between two equilibria of worker n in occupation i and industry j (in the initial equilibrium),[26]

$$\Delta \ln w_n = \gamma + \beta \cdot OCX_{i(n)} + \varepsilon_n. \tag{11}$$

where $OCX_{i(n)}$ is the occupation exposure index for the initial occupation $i(n)$ of worker n and γ is an intercept.

[25] We can derive a similar correlation result between the price change and the change in output. As noted in Ethier (1984), we can use the fact that optimality implies that income is maximized so that, holding endowments constant, $\sum_{j=1}^{J} p_j^2 Y_j^2 \geq \sum_{j=1}^{J} p_j^2 Y_j^1$ and $\sum_{j=1}^{J} p_j^1 Y_j^1 \geq \sum_{j=1}^{J} p_j^1 Y_j^2$. Taking the logarithm of these expressions, and denoting $\boldsymbol{Y} \equiv (\ln Y_1, \cdots, \ln Y_J)'$, we have that both inequalities imply that $\Delta \boldsymbol{p} \Delta \boldsymbol{Y} \geq 0$.

[26] 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 log-wages in the empirical section and document similar results.

The estimated OLS coefficient of this regression is $\hat{\beta} = \text{Cov}(\Delta \ln w_n, OCX_i)/\text{Var}(OCX_i)$. This covariance term corresponds to the covariance defined in Equation (9) with wages averaged at the i cell. Since the variance is always positive, the sign of $\hat{\beta}$ coincides with the covariance term. Thus, a negative sign of β is consistent with the SS theorem, while a positive coefficient would reject it. In the neoclassical SS theory, it is assumed that labor is homogeneous and that wages are equalized within and across industries for any occupation. In practice, however, workers may be heterogeneous in their earnings capacity for reasons not included in the model. We will include a rich set of controls that absorb some of these observable differences across workers (age, experience, gender, tenure, location, industry, and firm characteristics). After these differences are partialed out, our empirical covariance measure will infer the average changes at the averaged i or ij cell. The result of this exercise corresponds to Figure 1 in the Introduction, where we have documented a negative correlation between the ratio of relative earnings and the occupation exposure.

Finally, a central concern in implementing our regression approach in (11) is that there may be unobserved factors driving both the occupation exposure index and earnings (despite including a rich vector of controls). For this reason we will follow an instrumental variable approach that we will discuss at length in Section 3.2

2.3.2 Construction of Relative Earnings and Sectoral Occupation Intensity

Measurement of Changes in Earnings ΔW A literal interpretation of our model would suggest using a measure of total labor earnings in the final year of our data (2015) and at our initial date (1997) and computing as outcome variable the change in earnings $\ln\left(\frac{E_{2015}}{E_{1997}}\right)$ for each worker in our sample (where E_t denotes *E*arnings at time t). While we report the results of this exercise in our empirical exercises, this is not our preferred specification.

In our theoretical framework, there were only two periods and no entry and exit of workers in the labor market. However, in practice, the China trade shock may put workers with positive earnings in 1997 in different earnings trajectories over the 19-year period that we consider. Some of them may enter and exit the labor force, generating periods of zero earnings, or reduce the number of hours they work. Taking the log of initial and final labor earnings would preclude us from using this information. Given these considerations, we interpret the final equilibrium point of our model as an average of these worker earning trajectories.

To obtain our preferred measure, we start constructing the average earnings between 1997 and 2015 for worker n in our sample, $\overline{E_n} = \sum_{t=1997}^{2015} E_{n,t}/19$. We take this as a measure of the "final period" earnings. We further simplify the log-relative earnings variable by first taking a first order Taylor approximation of the logarithm of the ratio of earnings,[27] and, second, rescaling it by the length of our panel—which does not affect the sign of the covariance term of interest in Equation (8).[28] We obtain

$$\frac{\sum_{t=1997}^{2015} E_{n,t}}{E_{n,1997}}. \tag{12}$$

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

Measurement of occupation intensity at the industry level The first order condition of the firm problem implies that

$$\alpha_{ij} = \frac{w_i o_{ij}}{p_j Y_j}, \tag{13}$$

where the numerator is total labor payments to occupation i in sector j and the denominator is the value of production. Our preferred measure is based on the share of total payments to occupation i in industry j relative to total labor payments, which is implied by our theoretical framework. However, our model implies that labor payments coincide with the value of total sectoral output. This implicitly assumes that there are no intermediates or other factors of production. To account for these additional factors, as a robustness check, we also compute occupation intensity measures as the occupation labor payments relative to (1) the value of total sectoral output (measured as value of total shipments) and (2) sectoral value added.[29] Finally, as we discuss further below, we note that we use "pre-shock" data (from 1994 and 1997)

[27] Taking a Taylor approximation of the logarithm term around 1, we obtain $\ln\left(\frac{\overline{E_n}}{E_{n,1997}}\right) = \frac{\overline{E_n}}{E_{n,1997}} - 1 + o\left(\frac{\overline{E_n}}{E_{n,1997}} - 1\right)$.

[28] Since we are interested in assessing the sign of the covariance term in Equation (8) in a linear regression analysis, we can scale up the first term of the Taylor expansion by the number of years in the panel without affecting the sign of the coefficient. In particular, we multiply the term by the number of years in our panel and ignore the constant term (which will be captured in the intercept of our regression) to obtain our preferred normalized measure of earnings, $\frac{19 \cdot \overline{E_n}}{E_{n,1997}} = \frac{\sum_{t=1997}^{2015} E_{n,t}}{E_{n,1997}}$.

[29] 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.

to compute the industry intensities α_{ij} for each occupation i in each industry j.

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 our regression analysis.

3.1 Identification

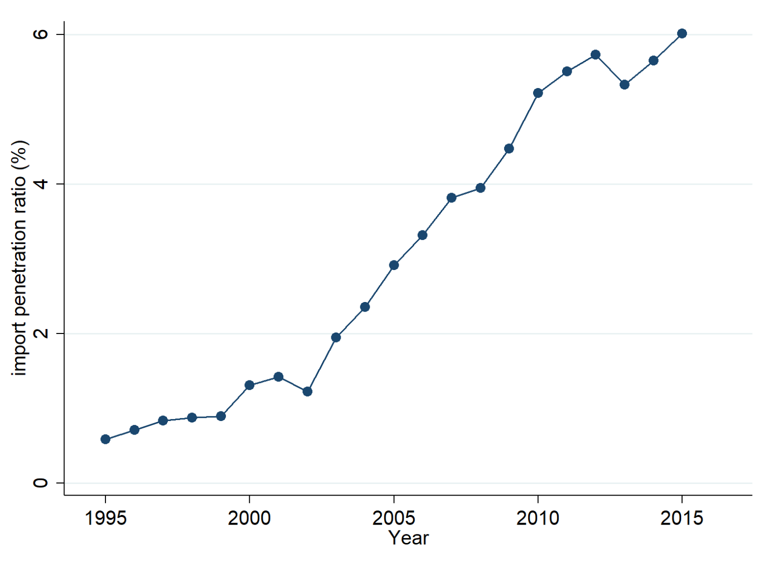
In our analysis, we use the industry-specific variation in the rise of Chinese exports to France between 1997 and 2015 to document heterogeneous impacts across occupation and test the SS theorem. During this period, Chinese exports to high-income countries (including France) increased steeply. Much of 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 differed substantially across industries (see Table 1 below). To exploit this variation, we use industry-level measures of Chinese competition as our measure of industry-specific shock. We follow the empirical strategy developed in Autor et al. (2014), and proxy industry exposure by the evolution of the import penetration rate of goods imported from China. More concretely, we define our measure of industry j's Chinese eXposure, CX_j, as

$$CX_j = \frac{\Delta M^{FC}_{j,2015-1997}}{Y_{j,1997} + M_{j,1997} - E_{j,1997}}. \tag{14}$$

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

Figure 2: Import penetration of Chinese Imports in France



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 (14) 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.[30] The choice of our starting and final dates are constrained by data availability (see the discussion in Section 3.2).

An important feature of our empirical exercise is that it leverages the substantial amount of heterogeneity in Chinese exposure across narrowly defined industries. This allows us to credibly compare observationally equivalent workers that work in different narrowly defined industries within the same broad sector of the economy. For this reason, we conduct our analysis at the four-digit industry level (which corresponds to 577 industries), and always add broad sector fixed effects in our analysis. The downside of this approach is that France does not produce sectoral price indices at this level of disaggregation, which would allow us to proxy for the importance of the trade shock at industry level (as suggested by our theory). For this

[30]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.

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.[31]

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

$$CX_j^A = \frac{\Delta M_{j,2007-1997}^A}{Y_{j,1994} + M_{j,1994} - E_{j,1994}}, \tag{15}$$

where $M_{j,2007-1997}^A$ 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.[32] We also note that we use a three-year lag on the numerator to minimize anticipation concerns. We assign our instrumental industry exposure variable CX_j^A to workers based on their lagged industry of affiliation, so as to minimize the potential downward bias arising from workers' sorting into industries in expectation of rising competition from China.

This instrumental-variable strategy relies on the pervasive nature of the "China shock" across high-income countries. China's increased comparative advantage in manufacturing industries should affect industries similarly across high-income countries. As in Autor et al. (2014), industries in France and in the group of other high-income countries experienced very similar trends in import penetration of Chinese goods, vindicating the identification strategy for our purposes: an OLS regression between the two measures of industry exposure, CX and CX^A, adjusted for the size difference between France and the group of countries, results in a coefficient equal to 1.19, with a t-statistic equal to 23.8 and a R^2 equal to 0.72.[33]

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

[32] 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.

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

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

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).[34] In order to measure market absorption at the NACE 4-digit level, we need a measure of industry-level shipments. For this purpose we aggregate firm-level sales from the BRN/FARE,[35] 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.

3.2.1 Chinese Exposure and Industry Prices

In our empirical application, we are interested in documenting how the China export supply shock (i.e., the increase of Chinese exposure) affects returns to different occupations in France. As we have discussed, our theory suggested using industry price data to assess the magnitude

[34] 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.

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

of the export shock. Unfortunately, French sectoral price indices exist at a much more aggregated level than the 4-digit industry for which we have our trade flows data. For this reason, we use Chinese exposure of different French industries directly as a reduced-form proxy for the export shock, as in Autor et al. (2016).

Anticipating this fact, our derivation of the SS theorem operated under the assumption that Chinese exposure imposes downward pressure on French prices, $\Delta \boldsymbol{P} = -\beta \boldsymbol{C}\boldsymbol{X}$. While we cannot test this assumption at the 4-digit industry level (577 industries in our matched dataset), we document a negative correlation between changes in log-prices and Chinese exposure at a more aggregate level (52 industries) for the 2000-2015 period.[36] Table 6 in Appendix A shows that the coefficient of running the change of French sectoral log-prices on Chinese exposure (defined as in Equation 14) is negative and statistically significant. Moreover, this finding is robust to instrumenting Chinese exposure with our instrument based on Chinese exposure in other advanced economies (Equation 15).

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 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.[37] 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.[38] 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

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

[37]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.

[38]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.

Table 2: Summary Statistics

	Mean	Std. Dev.	Nb. Obs.
Panel A: Trade exposure, 1997-2015			
Δ Imports from China to France/Initial absorption	0.88%	8.51%	154,667
Δ Imp. from China to France/Init. absorp. - Manufacturing	2.63%	16.29%	59,764
Panel B: Main outcome variables, 1997-2015			
100* Δ ln (Earnings 2015/Earnings 1997)	23.6	103.7	46,023
100* Cumulative earnings 1997-2015/Earnings 1997	1580.1	1136.3	154,667
100* Total hours worked 1997-2015/Hours worked 1997	1093.2	741.5	154,667
100* Average hourly wage 1997-2015/Hourly wage 1997	141.0	28.5	154,667
Panel C: Worker characteristics in 1997			
Female	.36	.13	154,667
Employed in manufacturing	.35	.12	154,667
Tenure 0-1 year	.09	.01	154,667
Tenure 2-5 years	.25	.06	154,667
Tenure 6-10 years	.23	.05	154,667
Firm size 1-99	.29	.08	154,667
Firm size 100-999	.33	.11	154,667
Firms size >1000	.39	.15	154,667

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,[39] hours worked, and the 2-digit occupation.[40] 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,[41] 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

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

[40]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).

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

into an intensive margin, the hourly wage rate, and an extensive margin, total hours worked.

To study the effects of the rise in Chinese exports on French workers, we focus our analysis on workers attached to the labor market prior to this trade shock. The rationale for focusing on these workers is to capture the effect of the trade shock on workers that were "settled" in their jobs and would otherwise have no problem participating in the labor market.[42] We define attached workers as those who, in each of the four consecutive years from 1994 to 1997, received a wage income higher than the equivalent to 1500 annual hours paid at the national minimum wage. Note that the focus on attached workers makes our outcome variables as comparable as possible across observationally identical workers, as their situation prior to the shock is more likely to reflect a stationary state, rather than a transient one.

In our sample, we count 163,207 attached workers, who were born between 1942 and 1976. When we match this dataset with firm level-data BRN/FICUS to compute the measures of factor intensity (13) that use value of shipments or value-added as denominators, the sample drops to 154,667. We use the former sample to estimate the effect of Chinese exposure across occupations, since we do not need this industry information. We use the latter sample to conduct the test of the Stolper-Samuelson theorem, since we need to use the factor intensity measures. For ease of exposition, Table 2 reports the summary statistics only for the latter one. The summary statistics are almost identical in both cases.

3.4 Occupational Groups

To document the heterogeneous effect across occupations of the rise of Chinese exports, we use the information on the occupation of the employee in 1997 reported in the DADS Panel. Occupations are reported according to the PCS-ESE classification (Professions et Catégories Socioprofessionnelles - des Emplois Salariés des Employeurs privés et publics), which is the reference classification of occupations used by the French public administration.[43]

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 posi-

[42] 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.

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

tion in the firm, and their required level of education. The advantage of this relatively coarse classification is that it goes beyond the 1-digit classification of occupations and, as we show below, it captures substantial heterogeneity in occupational exposure that is muted at the 1-digit level of aggregation, while it still maintains the total number of occupations in a number that is easier to interpret and digest. The occupational groups that we consider are defined as follows:

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

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

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

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

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

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

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

Table 3 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.

Table 3: 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.

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 the exposure to Chinese competition than the average executive. The second broad 1-digit group corresponds to Mid-Level Occupations (CS1-4 and CS1-5) and it is the largest in size. The hourly wage (in 1997) was substantially lower than that of managers, 10.4€on average. There is substantial heterogeneity in exposure to Chinese competition within the group. The average exposure among technical staff is twice the exposure among administrative stuff (2.8% vs 1.4%), whereas the other occupations are hardly exposed to Chinese competition (0.2%). Finally, the last broad 1-digit occupational group corresponds to Production workers. The hourly wage of production workers is the lowest (8.2€) and the average exposure to Chinese competition is the largest (3.5%). Within production workers, the skilled ones have relatively higher wages but a larger share of them work in highly exposed industries.[44]

[44]Finally, we note that we do not report the coefficients for occupation 34-35 (other managers) when we break down our analysis by occupation because it is a very small (1.9%) and heterogeneous group. Similarly, we have excluded from our sample workers that were initially employed in occupations with PCS code starting with 2 (Business Heads and CEOs) because they represent a very small share of sample (2.2%) that is an extremely heterogeneous (it includes craftsmen, small business owners, and CEOs). We do, however, include both groups of workers when we estimate pooled regressions that do not do not distinguish by occupation. Also, as we have discussed, we focus on workers employed in private firms. In practice, this implies that we exclude from our sample occu-

Taken together, the evidence presented in Table 3 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 Occupation Exposure

Before turning to our regression analysis, we discuss the empirical counterparts of our measure of industry specificity of an occupation (13), α_{ij}, and the occupation exposure index (10), OCX_i. As discussed in Section 2.3, our preferred measure of specificity of occupation i in industry j, α_{ij}, is the ratio between the wage bill of occupation i in industry j and the total wage bill of industry j in 1997. Table 7 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.[45]

Specificity by itself does not need to be correlated to changes in earnings. As our version of the SS theorem states, it is the product between factor specificity and industry exposure that should be correlated with the change in earnings across occupations. We use Equation (10) 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,

$$OCX_i = \sum_{j=1}^{J} \alpha_{ij} CX_j. \tag{16}$$

Table 4 reports the value of OCX_i for each of our occupations. According to this measure, Engineers and Skilled production workers are the most exposed occupations to Chinese competition. Conversely, Other middle-skill occupations appear to have the lowest exposure. Table A.3 and A.4 in the online appendix report the occupation exposure indexes when using alternative measures of occupation-intensity based in gross output and value added. As it can be

pations 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).

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

Table 4: 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 (16) and (17).

readily observed, the ranking of OCX_i is consistent throughout. Even though the occupation index in Table 4 is our preferred measure, we show that our 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 (15), and computing the weighted sum using industry-occupation intensities in 1994 as weights,

$$OCX_i^A = \sum_{j=1}^{J} \alpha_{ij}^{1994} CX_j^A. \tag{17}$$

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.[46]

4 Effect of Trade Across Occupations and a Stolper-Samuelson Test

This section reports the main results of the paper. First, we present reduced-form evidence on the negative effect of Chinese competition and its heterogeneity across occupations. We then show that this heterogeneity across occupations is consistent with the empirical prediction of the Stolper-Samuelson theorem presented in Section 2. Occupations that are used more intensively in highly-exposed sectors experience a larger drop in earnings relative to their 1997 level.

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

4.1 A Reduced-Form Look at Heterogeneous Effects Across Occupations

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

$$E_n = \gamma_0 + \beta \cdot \text{Chinese Exposure}_{j(n)} + \gamma_1 \cdot \text{Controls}_n + \varepsilon_n, \tag{18}$$

where worker n was employed in occupation *i(n)* in 1997 and was working in industry *j(n)* in 1997, and $E_n = \left(\sum_{t=1997}^{t=2015} E_n^t\right) / E_n^{1997}$ denotes cumulative earnings between 1997 and 2015 normalized by the earnings in 1997 for worker n.[47] This measure imputes zero earnings at time t if a worker does not have any earnings in that year (e.g., they drop out of the labor force). Thus, this measure captures both the extensive and intensive margins of adjustment. We decompose these margins (hours worked and wages) in the next section.[48]

All our regressions include the same set of $\text{Controls}_{ij(n)}$ to absorb differences at the worker, industry, and geographical level. As worker controls, we include a dummy for being a woman, birth-year fixed effects, dummy bins for labor market experience, tenure at the initial (1997) firm, and initial (1997) firm size.[49] 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. We also control for the average and variance of log wages paid at the firm in which worker i was employed in 1997.[50]

To control for industry trends and heterogeneity, for each industry four-digit sector j, we include as controls the total wage bill, average wage and hours worked in 1997, and the change in these variables between 1994 and 1997. We also include ten broad sector fixed effects.[51] We also add as two separate controls the level of initial (1997) Chinese and non-Chinese import

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

[48] We find similar results when using the log-ratio between the final and initial year earnings, $\ln\left(E_n^{2015}/E_n^{1997}\right)$ as dependent variable.

[49] 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+.

[50] 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.

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

penetration. Finally, to account for geographical heterogeneity, we include workers' initial (1997) commuting zone fixed effects.[52]

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

Figure 3 reports the 2SLS coefficients of the effect of Chinese exposure on the cumulative earnings, β in Equation (18), for the pooled regression and for a regression that we estimate separately by occupations, according to the initial worker occupation in 1997.[53] The first column in the figure reports the estimated effect on the pooled regression across occupations and thus corresponds to the effect on the average worker in our sample. The coefficient on Chinese Exposure is negative and statistically significant, implying a decline in earnings for the average worker. Quantitatively, the coefficient means that a one standard deviation increase in Chinese exposure reduces cumulative earnings of a manufacturing worker by $5.07 \cdot 16.29 = 82.5\%$ of the initial earnings. Alternatively, moving from an industry in the 10th to the 90th percentile of the Chinese exposure distribution results in a reduction in cumulative earnings of 82 percent of initial income (since a one standard deviation in exposure corresponds almost exactly to the 90-10 gap). This calculation can be used to benchmark the effect of Chinese competition relative to the US, as this pooled specification is very similar to the main specification in Autor et al. (2014). Our estimated average effect for France is around three-quarters of the effect reported by Autor et al. (2014) for the US.[54] This suggests that the effect of Chinese competition in France is of a similar order of magnitude to the US, albeit somewhat smaller.

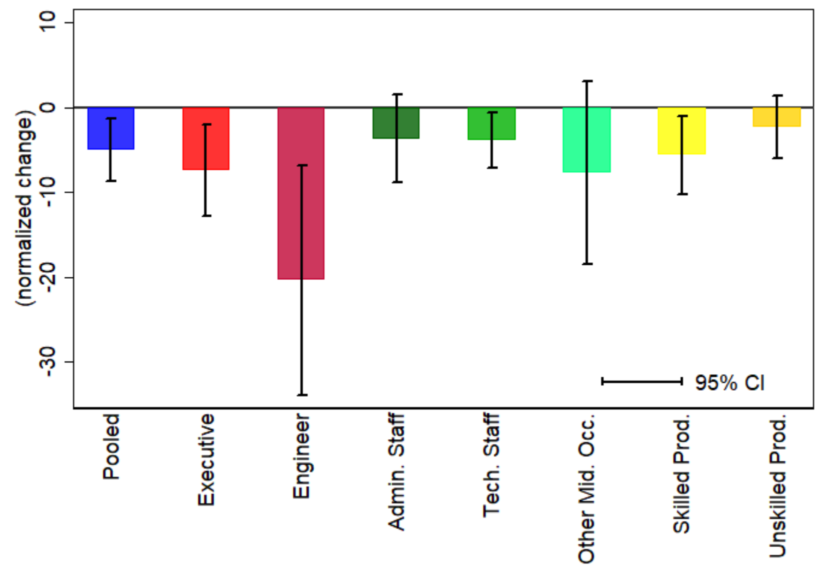
If the adjustment were different across occupations, the average effect that we have documented would be masking substantial heterogeneity across occupations. The core of the Stolper-Samuelson logic is precisely that the adjustment in earnings should be heterogeneous across occupations, with the occupations more intensively used in highly-exposed industries experiencing larger falls in normalized earnings. The second to seventh columns in Figure 3

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

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

[54] According to their estimates, a one standard deviation increase in Chinese exposure would translate, 18 years after the shock, into a fall in cumulative earnings of 114 percent (=13.85*6.9864*(18/15)).

Figure 3: Cumulative Effect on Earnings Across Occupations

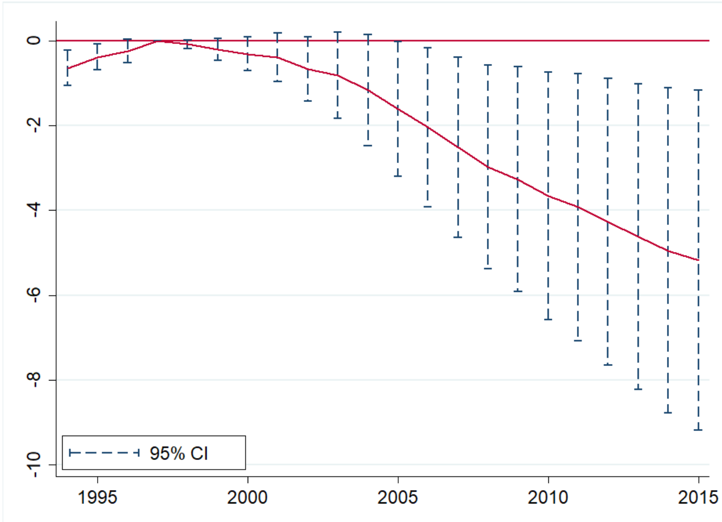


Notes: Each bar corresponds to the coefficient of "Chinese exposure" for a separate 2SLS regression. The dependant variable is cumulative (normalized earnings) of each occupational group between 1997 and 2015. Standard errors are clustered at the industry level. The lines correspond to the 95% confidence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

report the 2SLS coefficient on Chinese exposure, β in Equation (18), when we estimate separately the effect of Chinese exposure for each of our occupational groups. Note that with this empirical strategy, we allow the coefficient of each control variable appearing in Equation (18) to be different across occupations. The picture that emerges from the estimated effects across occupations is that the effect of Chinese exposure on cumulative earnings varies substantially across occupations.

We find that the effect is negative and significant for executives, engineers, technical staff and skilled production workers. In contrast, we find a negative but insignificant effect for administrative staff, other middle-level occupations, and unskilled production workers. This is consistent with the Stolper-Samuelson paradigm. Using the average Chinese exposure by occupation reported in Table 3, we see that the effect is significant in the occupations that have the highest values of Chinese exposure and have a higher fraction of workers employed in highly exposed sectors. Workers in occupations related to engineering, technical staff or skilled production are highly concentrated in manufacturing sectors that are highly exposed. This implies that, after the Chinese shock, workers in these occupations appear to have less transferable

Figure 4: Dynamic Effect on Earnings for the Average Worker



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

skills to the less affected industries relative to, say administrative staff or unskilled production workers. As a result, they experience the largest decline in earnings.

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

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

Dynamic Effect on Earnings Before further investigating the relationship between the effect on relative earnings and the Stolper-Samuelson result, we document the dynamic response of trade adjustment. We show that, consistent with previous studies for other countries, trade adjustment also builds up slowly over time in France. This finding underscores the importance of having long panels to capture trade adjustment. As we discussed in the Introduction, the slow adjustment that we document is in line with the interpretation of Factor Proportions Theory as one of "long-run" outcomes suggested by Neary (1978). Specifically, we plot the estimated coefficient β in Equation (18) when we construct our normalized variable, E_{ij}, up to period T for $T \in [1994, 2015]$. Thus, the coefficient reported for year 2015 corresponds to our previous results.

Figure 4 and 5 plot the cumulative effect of Chinese exposure over our sample period for the pooled regression and the different occupational groups, respectively. The general pattern that emerges is similar in all panels. We do not observe any clear trend before the China shock (1997). However, after the shock, the coefficient becomes negative and follows a negative trend throughout. Within this general picture, there are some particularities across occupations. First, the negative slope is the largest for engineers, who experienced a significant decline in (normalized) earnings since 2002. Second, unskilled production workers have an almost zero trend for the whole period. Third, skilled production workers, technical staff, and executives have a similar trend and the coefficient does not become negative until the late 2000s.

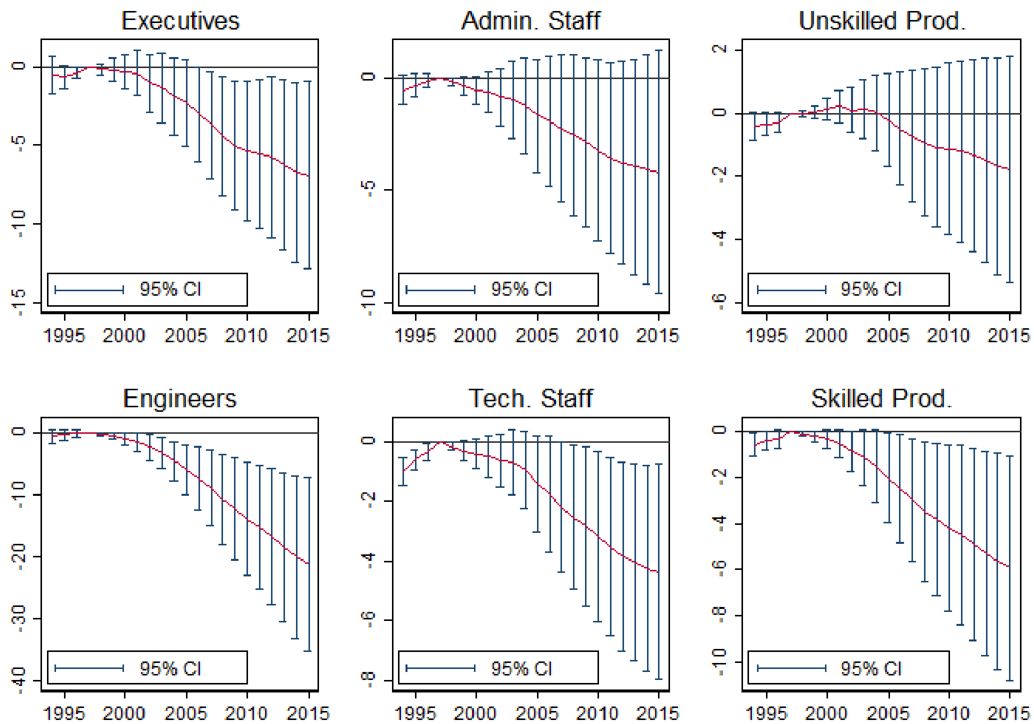
4.2 Occupation Specificity and Earnings: A Test of the Solper-Samuelson theorem

In the previous section, we showed that the effect of the China shock differed across occupations. We also pointed out that occupations more intensively used in exposed industries (as measured by employment shares) seemed to be the ones experiencing the largest declines in relative earnings.

Next, we formally test our version of the Stolper-Samuelson theorem. We use the model-implied measure of occupation specificity that we introduced in Section 2, $OCX_i = \sum_j \alpha_{ij} CX_j$, in our regression setting. In particular, we estimate

$$\tilde{E}_n = \gamma_0 + \beta \cdot OCX_{i(n)} + \gamma_1 \cdot \text{Controls}_n + \varepsilon_n, \tag{19}$$

Figure 5: Dynamic Effect on Earnings Across Occupations



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

where we augment our baseline set of controls with the initial (1997) worker's occupation specificity measure $\alpha_{ij(n)}$ and initial sectoral Chinese exposure (i.e., the term Chinese Exp.$_{j(n)}$) to control for potential direct effects that these variables could be capturing separately (e.g., differential adjustment costs to leave an industry depending on the occupation specificity of the occupation in the industry or the level of exposure to Chinese competition). The empirical prediction of the Stolper-Samuelson theorem is that β<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 5 reports the estimated β coefficients from regression (19). 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 17). Panel A reports the coefficients for our preferred measure of occupation exposure, based on factor 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 Stolper-Samuelson theorem prediction. 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 suggests that there is some mild negative demand shock co-existing with the supply shock that we identify. In terms of magnitude, moving from the occupation with the lowest occupation exposure index (other middle-skill occupations) to the highest (skilled production workers) implies losing almost two years of (1997) total earnings ($-0.27 \cdot (7.16 - 0.18) = -1.88$) over the 1997-2015 period. Columns (3) and (4) report the same exercises for the log change in earnings between 1997 and 2015 (for workers that remain in the sample). Moving again from the least to the most exposed occupation, implies a 10% decline in 2015 earnings relative to 1997 ($\exp(-0.015 \cdot (7.16 - 0.018)) - 1 = -0.10$). Note that the implied magnitude of the loss is similar if we assume that this loss is accrued each year over the 1998-2015 years ($-10\% \cdot 18 = -1.80$).

We report a battery of robustness checks on our baseline specification. Panels B and C in Table 5 report the coefficients of the occupation exposure index when we use two alternative measures of occupation exposure index. Panel B defines occupation-intensity as the ratio of the wage bill of the occupation over shipments in the industry (Table A.3). In Panel C, the denominator is value-added instead of shipments (Table A.4). In all specifications, the coefficient of the occupation exposure index is negative and significant. Quantitatively, the effects are similar.[55] We also show in Table 9 in the appendix that we obtain similar results if we only include our baseline controls (i.e., do not include the initial occupational specificity and industry exposure of the worker), when we only include industry exposure or if we extend our analysis to 2-digit occupations rather than our baseline occupational groups.

In sum, the negative β coefficient in Equation (19) documented in this section confirms the empirical prediction of the Stolper-Samuelson theorem. Given a negative industry shock, the occupation more specific to that industry experiences a larger decline in earnings. The intuition is that if there is a shock to an industry and the occupation is very specific to that industry, the worker will be tied to that industry and will experience a large decline in earnings. In contrast,

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

Table 5: Stolper-Samuelson Theorem Test

	Dependent Variable is:			
	$\frac{\sum_{t=1997}^{2015} \text{Earnings}_t}{\text{Earnings 1997}}$		$\ln\left(\frac{\text{Earnings 2015}}{\text{Earnings 1997}}\right)$	
	(1) OLS	(2) IV	(3) OLS	(4) IV
Panel A: α_{ij} constructed with Wage bill				
Occ. Exposure Index OCX_i	-0.21***	-0.27***	-0.011***	-0.015***
	(0.03)	(0.03)	(0.003)	(0.003)
Panel B: α_{ij} constructed with Gross Output				
Occ. Exposure Index OCX_i	-0.61***	-0.80***	-0.039***	-0.050***
	(0.07)	(0.09)	(0.009)	(0.009)
Panel C: α_{ij} constructed with Value Added				
Occ. Exposure Index OCX_i	-0.26***	-0.33***	-0.015***	-0.019***
	(0.03)	(0.04)	(0.004)	(0.004)
Controls	Y	Y	Y	Y
Observations	154,666	154,666	46,023	46,023

Notes: Standard errors clustered at the industry level shown in parenthesis.*** denotes significance at 1%.

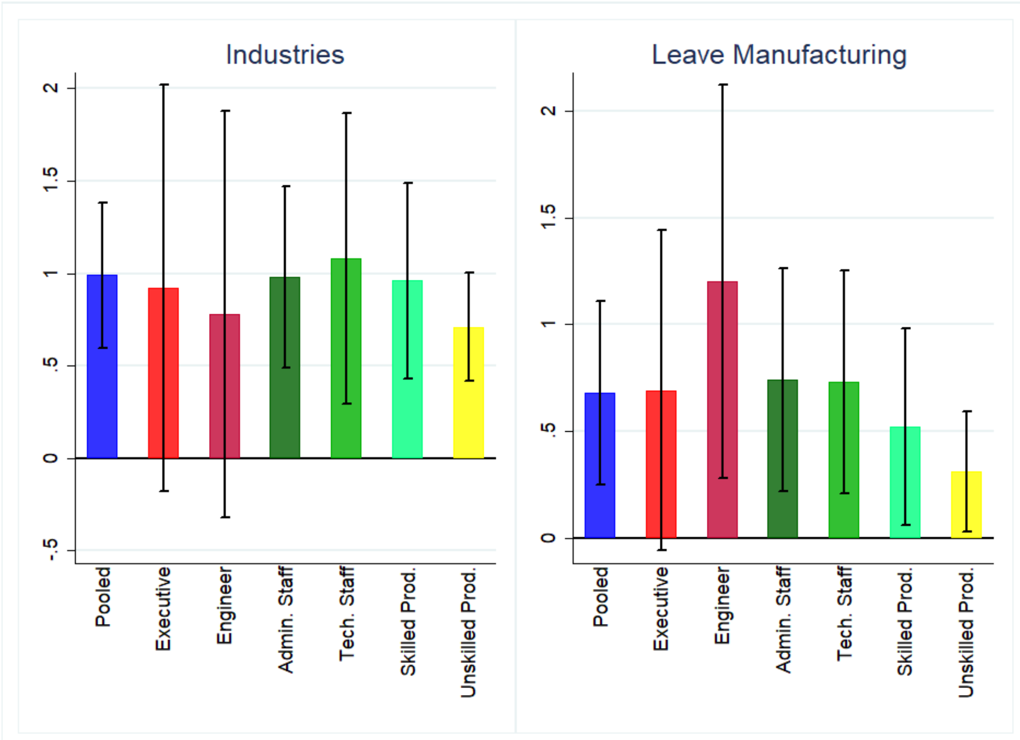
if the occupation is not specific to the industry that experiences the shock, the worker can switch industry and soften the shock. In the next section, we provide evidence on mobility across industries consistent with this argument.

4.3 Mechansim: Mobility Across Industries and Occupations

This section investigates the effect of Chinese competition on the mobility of French workers across industries and occupations. The goal is twofold. First, these adjustment results allow us to validate some of the assumptions made in the theoretical framework. Second, these results help us better understand the effects on earnings we have documented so far, and shed light on additional dimensions of workers' adjustment.

Mobility Across Industries The left panel in Figure 6 reports the effect of Chinese competition on mobility across industries. We run the same reduced-form specification as in 18, changing the dependent variable on the left-hand side to the number of different industries

Figure 6: Mobility Across Industries



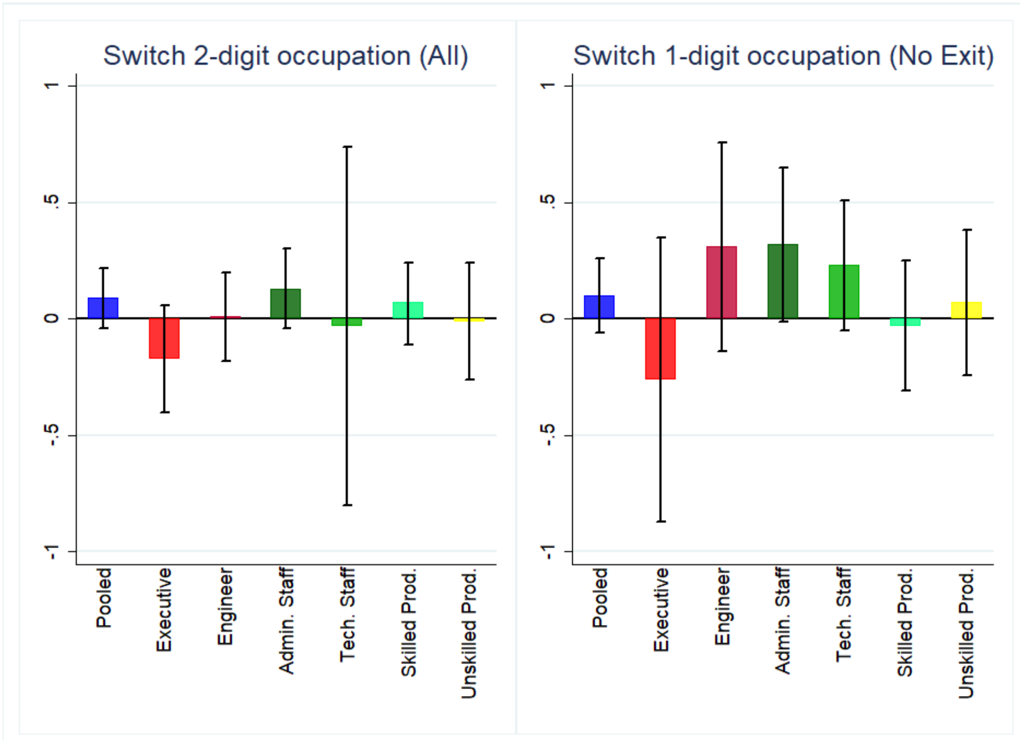
Notes: Each bar corresponds to the coefficient of "Chinese exposure" for a separate 2SLS regression. The dependant variable in the left-hand side is (normalized) number of different industries between 1997 and 2015, respectively. In the right hand side, it is a dummy equal to one if the worker leaves manufacturing by 2015. Standard errors are clustered at the industry level. The lines correspond to the 95% confidence interval. See Appendix for the coefficients of each regression.

in which workers were employed between 1997 and 2015. We find a significant positive effect on the pooled regression across occupations. The coefficient is insignificant for engineers and mildly significant (90 percent) for executives. However, it is positive and significant for the rest of the occupational groups.[56] It is remarkable that, within these occupations, we do not find substantial differences in the effect of changing occupation.

In the right hand-side panel of Figure 6, we complement this evidence on industry mobility by analyzing the probability that these workers leave the manufacturing sector. In this case, we again run specification (18), but with the dependent variable as a dummy equal to one if the worker is still active but not employed in the manufacturing sector in 2015. We notice that the effect for the average worker is once again positive and statistically significant. The coefficient

[56]We exclude other mid-level occupations from this analysis because they are a small group with very low exposure to Chinese competition, which translates into very large standard deviations.

Figure 7: Mobility Across Occupations



Notes: Each bar corresponds to the coefficient of "Chinese exposure" for a separate 2SLS regression. The dependant variable in the left-hand side is (normalized) number of different industries between 1997 and 2015, respectively. In the left hand side, it is a dummy equal to one if the worker switches between 2-digit occupations. In the right hand-side, the dependent variable is equal to one if workers changes 1-digit occupation. In the left-hand side we consider all workers. In the right-hand side we select workers who remain active in 2015. The lines correspond to the 95% confidence interval. See Appendix for the coefficients of each regression.

varies across occupations but it is positive and statistically significant for all occupations (it is only mildly significant for executives with p-value of 10%). This evidence is consistent with the view that workers hit by Chinese shock switched industries and tended to move outside the manufacturing sector.

Mobility Across Occupations Figure 7 shows that there is no effect of Chinese competition on the probability of a worker changing their initial occupation. The left-hand panel reports the result of using specification (18), but having as the dependent variable a dummy equal to one if the occupation of worker in the last period in which they appear in the sample is different from their initial occupation. Here, we define occupation as a 2-digit occupation. Notice that this classification allows for changes within our broad 7-group classification and is thus more demanding than using only variation at our baseline 7-group. The coefficient is not different from zero for either the average worker (pooled regression) or for any of the occupational groups. As complementary evidence, the right-hand side of Figure 7 focuses on workers that remain in the sample in 2015. We again use specification (18) and use as dependent variable a dummy indicator for a worker changing occupation at 1-digit level. This broader classification is meant to capture, for example, changes between low-, mid-level, and high-level workers. The coefficients are not statistically different from zero. They are mildly significant (90 percent) for administrative staff.

To conclude, the evidence presented in the section paints a picture consistent with our interpretation of the factor proportion model. Most workers hit by the Chinese shock were able to switch industry but they did not change occupation. Thus, these results are consistent with our assumptions in the theoretical framework of thinking about occupations as factors of production that are mobile across industries.

5 Additional Results: Hours, Wages, and Labor Market Regulation

In this section, we report additional reduced-form results on the adjustment of French workers to the increase in Chinese competition and its heterogeneity across occupations. First, we decompose the effect on earnings between hourly wages and hours. Then, we investigate how French labor market institutions shaped the effects of Chinese competition and whether these effects are also heterogeneous across occupations.

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

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

$$\frac{\text{Cum. Earnings 2007-1997}}{\text{Earnings 1997}} = \frac{\text{Average wage 2007-1997}}{\text{Wage 1997}} \cdot \frac{\text{Number hours 2007-1997}}{\text{Number hours 1997}}$$

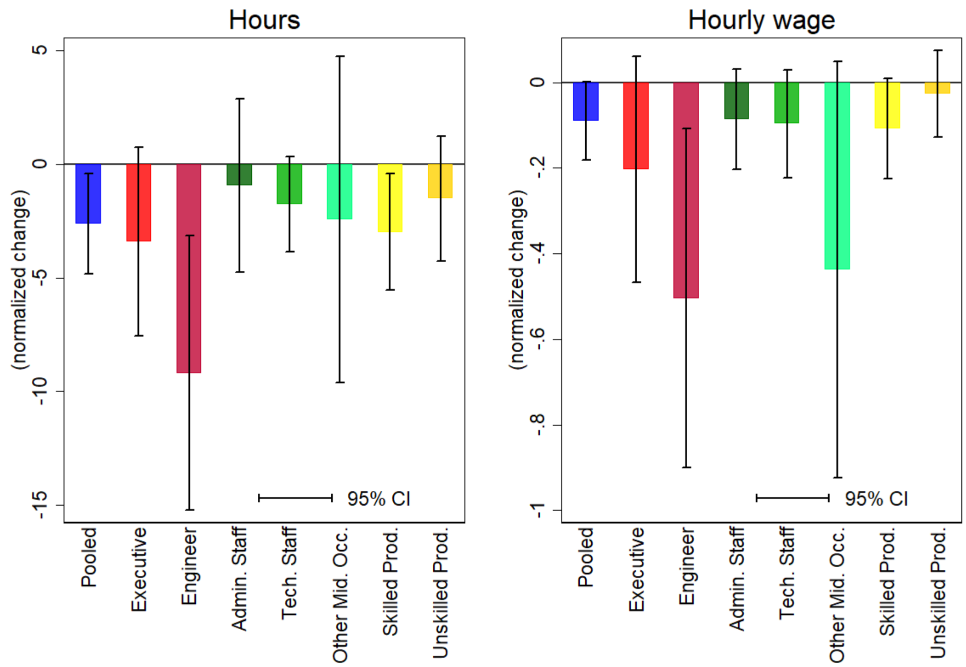
and analyze the effect of Chinese competition on each of these two components separately.

Extensive Margin: Hours The left-hand side of Figure 8 reports the coefficients of the effect of Chinese exposure on hours. For the average worker, the coefficient is negative and significant at 5%. Quantitatively, a one standard deviation increase in Chinese Exposure translates into a reduction on (normalized) cumulative of hours of 42 percent (2.609·16.29) of hours. Once again, these coefficients hide substantial heterogeneity across occupations. When we run the regression separately for each occupation, we observe that this negative effect on hours is driven only by engineers and skilled production workers, whose respective coefficients are -9.185 and -2.990, respectively. Quantitatively, for engineers starting in an industry with one standard deviation more in Chinese exposure translates into a fall in (normalized) cumulative hours of 149.62(9.185·16.29) percent. For the rest of the occupations, none of the coefficients is statistically different from zero.

Intensive Margin: Wages The right-hand side of Figure 8 reports the coefficients for the effect of Chinese exposure on normalized average hourly wages. For the average worker, the coefficient is negative but it is not statistically significant (at the conventional 95 percent confidence interval). However, this non-effect is misleading because there is one occupational group that experiences a large drop in wages. The coefficient of exposure for engineers is -0.504. Quantitatively, it implies that, for engineers, being in an industry that experiences a one standard deviation increase in Chinese competition in 1997, reduced their average wage by 8.14 percent (0.504·16.29). Therefore, engineers experienced a fall in both hours and wages. For the other groups, even though the coefficients are negative, they are not statistically different from zero. For skilled workers, the coefficient is smaller and only significant at 10 percent. A possible explanation why skilled production workers did not experience a significant fall in wages is that their wage was closer to the minimum and, thus, it was more rigid. We documented in Table 3 that the average hourly wage of engineers was 20.2, compared with 8.6 for skilled production workers.

Dynamic Effect on Hours and Wages Figures A.1 and A.3 reports the dynamic cumulative effects for hours and average hourly wages, respectively. For the average worker, there exists a negative trend in hours starting with the trade shock, and the coefficient becomes statistically significant around 2008. For wages, we do not observe any trend and the coefficient is not statistically different from zero in any year. This is the general pattern for the occupation groups

Figure 8: Decomposing Effect on Earnings



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

but there are significant exceptions. Engineers experience a declining trend in both hours and wages right after the trade shock. For hours, the coefficient becomes significant in 2003 and for wages in 2008. For occupations with seemingly more specific skills (technical staff, skilled production workers, and executives), the pattern is similar to that for engineers but the negative slope of the trend is smaller. This difference in the trends implies that, for these occupations, the effect of Chinese competition on hours became significantly negative later and it did not become negative for hourly wages. Finally, we want to emphasize that for unskilled production workers there is no trend in neither hours nor wages.

5.2 Labor Market Institutions and Trade Adjustment

One of the most salient features of the French labor market compared to, for example, the United States is the role of collective agreements. Collective agreements are the most prevalent rent-sharing mechanism and play a key role in wage determination (Venn, 2009). We investigate whether collective agreements can shape the effects of a trade shock by analyzing the evolution of cumulative earnings of employees across industries with different degrees of collective bargaining. To the best of our knowledge, this interaction has not been examined before.

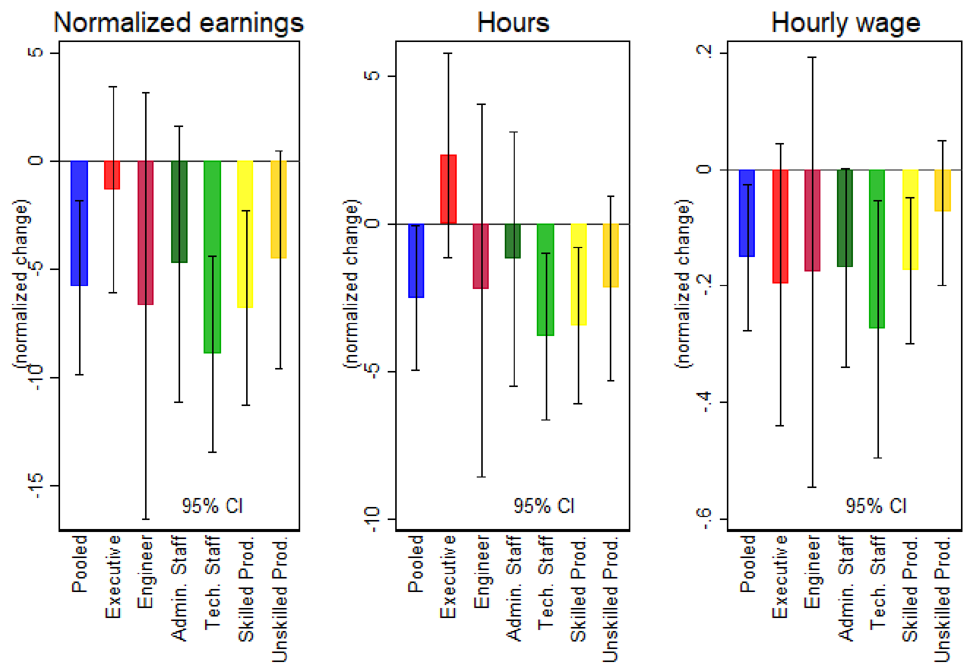
Our measure of market regulation is based on the number of collective agreements before the China shock. We obtain these data from Avouyi-Dovi et al. (2013), who have digitized the universe of collective agreements in France from 1992 onwards.[57] These authors also note that the most important topic in the vast majority of collective agreements is wage setting. In our data, around 71% of workers are covered by collective agreements (a very similar number to the one reported by Avouyi-Dovi et al., 2013). We follow Avouyi-Dovi et al., 2013 and Carluccio et al. (2015) and proxy the intensity of regulation in the industry by the number of collective agreements in a given period.[58] In particular, we define an industry as regulated if the number of collective agreements in that industry is above the median number of agreements from 1992 to 1997. We then re-estimate our baseline regressions introducing the interaction of industry exposure to Chinese imports with this regulation dummy variable (and also include the regulation dummy as a control).

Cumulative Earnings Panel A of Figure 9 reports the 2SLS regression results of our reduced-form regression (18), when we introduce the interaction between industry exposure and regulation as explanatory variable. The dependent variable is normalized cumulative earnings between 1997 and 2015. We only report the coefficient of the interaction term (but also include as regressors separately the terms appearing in the interaction). A negative coefficient implies that the negative effect of trade in cumulative earnings is exacerbated with regulation. The coefficient of the interaction term for the average worker is negative and statistically significant. Once again, this average effect masks substantial heterogeneity. Indeed, the negative coefficients are only statistically significant for technical staff (-6.66) and skilled workers (-6.77). Therefore, from this figure we can conclude that labor regulation did not help workers to cope better with the trade shock and it penalized low-paid workers like skilled production workers relatively more.

[57] They have used it to estimate the effect of collective agreements in France in Avouyi-Dovi et al. (2013) and Carluccio et al. (2015).

[58] Labor law in France is such that if no agreement is reached, firms are allowed to set their own contracting conditions, see Avouyi-Dovi et al., 2013.

Figure 9: Interaction Effect of Regulation and Chinese Exposure



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

Decomposing Change in Earnings Panel B and C of Figure 9 report the coefficients of decomposing the effect of regulation on earnings between hours and hourly wages, respectively. Since collective agreements are mainly concerned with wages, one would expect that regulation has a larger incidence in wages than hours. On the other hand, one could also argue that since collective agreements represent a constraint on wages, they give incentives to employers to use hours to adjust to the trade shock. From the coefficients in both panels, the two interpretations seem right. For the average worker, we observe that the coefficient of the interaction term is negative and statistically significant for both hours and hourly wages. When we run the regression for each occupation, a similar picture emerges. For wages, the coefficient is negative and significant only for technical staff and skilled workers. The coefficient is much larger (in absolute terms) for technical stuff (-0.27 vs -0.17). An explanation for this difference may be that the wage of skilled workers is closer to the minimum wages and, thus, there is less margin of adjustment. For hours, once again, the negative coefficient is only significant for technical staff and skilled workers. In this case, the two coefficients are more similar (-1.01 vs -0.81) than for wages. These coefficients on hours reinforce the interpretation that one of the reasons why the effect on wages is substantially larger for technical staff is that wages are lower for skilled production workers.

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

6 Concluding Remarks

The idea that the rewards of factors more specific to an industry decline after a negative trade shock to that industry is one of the cornerstones of the international trade literature. However, the empirical relevance of this result, known as the Stolper-Samuelson theorem, is scant. In this paper, we developed and implemented a simple test of the Stolper-Samuelson theorem by interpreting occupations as factors of production and using the increase in Chinese competition as a trade shock to the French economy.

We proceeded in two steps. First, we were agnostic on the relative specificity of each occupation and just examined how the effects of Chinese competition on workers' adjustment varies across occupations. We performed this exercise by using matched employer-employee data for French workers between 1997 and 2015. We documented substantial heterogeneity across occupations. Even though the average worker in France has a similar (albeit a bit smaller) loss in cumulative earnings to the average worker in the United States, this masks substantial heterogeneity. We find that only engineers, executives, technical staff, and skilled production workers experience a significant reduction on earnings. On the other hand, unskilled production workers, administrative workers, and other mid-level occupation do not experience any loss.

Second, we formally tested the Stolper-Samuelson theorem. Guided by our theoretical framework, we constructed a new measure of the occupation exposure index. This index is a weighted-average of industry exposure to Chinese competition where industry-specific occupation factor-intensity is used as a weight. According to our version of the Stolper-Samuelson theorem, there should be a negative correlation between the occupation exposure index of the worker and the change in (normalized) cumulative earnings during the period. We find that this is indeed the case both in the OLS regression and when we instrument our occupation exposure index along the lines of Autor et al. (2014). These results are robust to using different measures of the occupation exposure index and more disaggregated (2-digit) occupations.

We also report additional results consistent with the SS mechanism. We show that workers in hard-hit industries tend to change their industries and move away from manufacturing. Moreover, they do not appear to change their occupation when switching industries. Lastly, we provide two additional sets of results. First, we decompose the adjustment in worker earnings between hours worked and wages, and find a larger average effect for hours worked. Second, we document suggestive evidence that labor regulation exacerbates the negative effects of Chinese competition on earnings. In fact, the negative effect of regulation is concentrated among relatively low-income occupations, such as skilled production workers and technical staff. This latter result opens up the question of the design of an optimal labor regulation, which we leave for future research.

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A Additional Tables and Figures

Table 6: 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 7: 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 8: Effect of Chinese Exposure on Earnings Across Occupations

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

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

Table 9: Stolper-Samuelson Theorem: Robustness

	(1) OLS	(2) IV
Panel A: Only OCX_i		
Occ. Exposure Index OCX_i	-0.23***	-0.28***
	(0.02)	(0.03)
Panel B: OCX_i and CX_j		
Occ. Exposure Index OCX_i	-0.23***	-0.28***
	(0.02)	(0.03)
Panel C: 2-digit occupations		
Occ. Exposure Index OCX_i	-0.10***	-0.15***
	(0.03)	(0.03)
Controls	Y	Y

Notes: Standard errors clustered at the industry level shown in parenthesis. *** denotes significance at 1%.