Three Essays on Networks and Trade

Adam Jakubik

Thesis submitted for assessment with a view to obtaining the degree of Doctor of Economics of the European University Institute

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European University Institute
Department of Economics

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Adam Jakubik

December 8, 2017

Dedication

To my advisors:

Fernando Vega-Redondo

&

Bernard Hoekman

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Abstract

This thesis comprises three chapters that contribute to the fields of industrial organisation and international trade. The first chapter presents an application of network games to modelling the complex market structures in spatial competition, the second chapter studies how various sources of value added in China's exports to the US affect employment in import competing sectors, and the third chapter reveals how the use of services in these sectors attenuates the employment effects of import competition.

Although they follow different methodologies – the first chapter is applied theory and the latter two are empirical – the chapters have in common an underlying network structure to economic interactions, be it competitive relationships or input-output linkages, that shapes the outcomes of various forms of competition, spatial competition between firms and competition due to exposure to international trade.

The first chapter models complex market structures as networks based on geographic or product space proximity. Firms set prices given the information they have of the network structure. I study how the network structure and firms' knowledge of the network structure jointly determine equilibrium pricing behaviour.

The second chapter studies the relationship between increased trade with China and the decline of manufacturing jobs in the US. Value added decomposition of bilateral trade flows allows to differentiate between effects of Chinese and third country drivers of the trade shock. We find that the negative labour market effects of imports are not driven by GVC integration and have greatly diminished by now. Evolving Chinese comparative advantage has extended the adjustment period. We contribute a novel trade exposure measure that accounts for exposure faced by upstream industries.

The third chapter presents evidence that the use services inputs by manufacturing industries attenuates the impact of import competition. Potential mechanisms for this finding are explored, revealing significant heterogeneity across different services.

Contents

Chapter 1

Competition Networks[1]

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Abstract

I present a model of spatial competition where the market structure is represented as a network. Two firms sharing a link represents a notion of proximity in the geographic or product space. A price setting game is played on this network, in which firms simultaneously set prices taking into account their information about the network structure. The question of interest is, how does the particular pattern of locations influence pricing? If the structure of the market is very complex or in constant flux, firms might not be aware of the entire market. How would they behave when limited to observing only their closest competitors? If firms are limited in their information of the competition network, equilibrium prices are decreasing in the intensity of local competition while profits will be non-monotonic in the intensity of local competition. Thus both the opposing relocation incentives in the industrial organisation literature – Hotelling's law and product differentiation – are present. On the other hand, when a firm has complete information about the competition network it has to account for the cumulative effect of all externalities exerted on it though its neighbours, those exerted on its neighbours by their neighbours, and so on. In equilibrium, prices will be set proportional to a measure of centrality that captures this propagation of externalities.

Keywords: Network games, Spatial competition, Incomplete information, Bonacich centrality
JEL Classification: C7; D4; L11; R32

1.1 Introduction

In many markets the structure of competition is spatially dispersed. We can think of location as either geographic coordinates or location in a multidimensional product space. Gas stations are Chamberlin's famous example of a 'chain-linked' market where competition is localised, so that more proximate competitors have larger cross-price effects. The structure of spatially dispersed markets is often complex, with non-trivial topological features, and volatile in nature, therefore market participants often have incomplete information about it. Recent innovations in big data analysis of consumers' behaviour and the use of geographic information systems (GIS) to understand spatial movement patterns have been adopted by firms to help guide product design or location choice. The aim of this paper is to provide a tractable framework to study price competition under complex market structures and under two different assumption on the informational sophistication of participants. The model yields predictions of distinct pricing behaviour depending on informational sophistication that can be empirically tested. Furthermore, it highlights the benefits to firms of being as informationally sophisticated as possible relative to their competitors.

Imagine a rather dull city where all the bars are identical: they have the same interior, the same music, the same selection of beers, and even the bartenders in all of them are close cousins. They do, however, set their own prices. As a bar raises its prices, patrons will start migrating to other nearby bars; whereas if nearby bars become more expensive, the bar might gain some new patrons. These are the basic mechanics of price competition when firms are dispersed geographically. Taking location as given, in this paper I explore how the particular pattern of locations influences pricing. Furthermore, if the structure of the market is very complex or in constant flux, firms might not be aware of the entire market. I study how firms behave depending on how limited they are in their information about the structure of the market. I choose to model the spatial distribution of firms, whether in the geographic or product space, by a network which keeps track of the nearest competitors based on a notion of proximity. A price setting game is played on this network, in which firms simultaneously set prices taking into account their information about the network structure.

If firms are limited in their information of the competition network, equilibrium prices are decreasing in the intensity of local competition. Profits on the other hand are non-monotonic in the intensity of local competition, thus both the opposing relocation incentives in the literature are preset: Hotelling's law and product differentiation, depending on the region of competition intensity a firm is presently in. The intuition is that a firm with many direct competitors relative to the market average will expect an additional competitor to have on average fewer direct competitors (by reversion to the mean) and thus also a higher price. The expected gain in demand thus dominates the price effect. Conversely, a firm with only a few direct competitors relative to the market average will expect an additional competitor to have on average more direct competitors and thus a lower price. Now a larger price decrease is required to avoid a loss of demand, and thus the price effect dominates. A boundedly rational firm that fails to understand the the spatial nature of competition or that its structure is irregular performs worse than its rational competitors. Indeed, a firm would benefit from acquiring deeper network information then its direct competitors. I leave it for future research to study endogenous choices of informational sophistication.

If firms have complete information about the competition network the entire network structure becomes relevant for pricing decisions. In equilibrium a firm has to account for the cumulative effect of all externalities exerted on it though its neighbours, those exerted on its neighbours by their neighbours, and so on. The equilibrium effect of these bilateral externalities is captured by the relevant measure of centrality, and firms set prices in proportion to this.

The rest of the paper is structured as follows: Section 2 discusses the related literature, Section 3 presents the theoretical model, Section 4 characterises the equilibria under incomplete information and Section 5 under complete information. Section 6 concludes.

1.2 Related literature

The present model builds on traditional spatial models of competition in the industrial organisation literature. In the earliest of which, much like the bar example, a homogeneous product is sold at various geographic locations represented by a line segment and firms may compete with others within a given distance. Customers are usually uniformly distributed along the segment and their utility decreases with distance to their chosen vendor. (Hotelling, 1929) Here geographic location can be seen as a metaphor for product differentiation along a single dimension. In Salop (1979) the product space is the circumference of a circle. By introducing periodic boundary conditions to the Hotelling model he abstracts from "corner difficulties" in order to study its undistorted qualitative properties. However, when multiple characteristics of goods are considered in spatial models a multidimensional product space leads to the contested markets between firms becoming polytopal and they quickly lose tractability. The present model avoids this curse of dimensionality while allowing for complexity of market structure by describing interactions on a graph rather than in a space. Location in a product space according to subjective characteristics may not always be obvious, but a competitive relationship with another product is something managers who follow their market closely are aware of, thus helping identify the set of neighbours in this framework.

Firms are in direct competition if the prices of their products directly affect each others' demands. However, the complexity and transience of these links can mean that firms are restricted in their information about the contemporaneous network structure, while their long term experience in the marketplace justifies them having some statistical knowledge of the network structure. Thus my approach to the informational framework naturally follows the approach introduced by Galeotti et al. (2010) and Galeotti and Vega-Redondo (2011), where strategically interacting agents in a network have a combination of local knowledge, that is, they only observe the network around them, and global knowledge, that is, a beliefs over the statistical properties of the network structure in order to be able to draw conclusions about their peers' likely actions.

Chen and Riordan (2007) present a particular model of product differentiation which could be seen as a star network in my setup, some vertices left empty. It is worth noting their justification for each consumer caring for only two products is along the lines of Hart (1985) and Wolinsky (1986): if a consumer is informed about her local brand but must conduct a costly search to obtain information about additional brands then she will be interested in a finite number of brands even if other brands are desirable.

There is a separate literature stemming from the tradition of operational research that deals with location games on graphs. (Hakimi, 1983; ReVelle, 1986; Fournier and Scarsini, 2016; Heijnen and Soetevent, 2014) In this paper I consider fixed locations under different informational assumptions and focus on the problem of optimal pricing.

On the empirical side, Bloch and Wills-Johnson (2010) present a methodology for using data to construct a network which summarises the structure of competition. Firgo et al. (2015) use a data set to test the effects of centrality on prices in the Viennese retail gasoline market. The data contains a set prices for diesel from petrol stations in the Vienna metropolitan area and the geographic location of these petrol stations (complete with drive times between locations, which is arguably a more appropriate measure of distance). This is an example of a dataset that may be suitable to test implications of the model because it fulfils some basic requirements: as diesel is a homogeneous good, product differentiation is largely based on location on the road network; direct competitors are easily identifiable; the competition network has a high degree of complexity, which suggests the limited information assumption is valid; and finally, location is fixed in the short run so that competition takes place largely along prices.

1.3 The model

Let $N = \{1, 2, ..., n\}$ be a set of price setting firms which produce one type of good. To allow for complexity and thus incomplete information, n is assumed to be large. Firms choose their price $x_i \in X = [0, M]$ to maximise their expected profits. If we exclude the possibility of monopolies then a bounded strategy space is a purely technical assumption and results coincide with those of the unbounded case. The prevailing market structure is given by a realisation of a random competition network, that is, by a network which is chosen uniformly from the collection of all networks with the given degree distribution p. The realised network is represented by a symmetric adjacency matrix g where if firms i and j are in direct competition then $g_{ij} = 1$, otherwise $g_{ij} = 0$. A firm cannot compete with itself. The firms competing with firm i are called its neighbours and denoted $N_i = \{j \in N : g_{ij} = 1\}$. Firms who are neighbours are proximate in the product space, that is, less differentiated from each other than. The number of neighbours firm i has is called degree and is denoted $k_i = |N_i|$. The degree distribution is given by $p : \{0, 1, ..., n-1\} \to [0, 1]$ where $p(k)$ is in any realised network also the proportion of firms who have a certain degree k and $\sum_{k=0}^{n-1} p(k) = 1$.

Lemma 1 (Newman, 2003) *Let $\tilde{p} : \{1, 2, ..., n-1\} \to [0, 1]$ be the degree distribution of a neighbouring node $j \in N_i$.*

$$\tilde{p}(k) = p(k)k / \sum_{l=1}^{n-1} p(l)l$$

The underlying degree distribution can be freely chosen to match observed characteristics of markets of interest, whether this is the scale free property, skewness, multimodality, or any distinctive asymmetry.

The idea of a complex or volatile market is captured by modelling the interaction as a one-shot game. This precludes learning opponents' types from their actions, which would gradually expand the boundaries of local knowledge.

Under *complete information* the network structure g is common knowledge. Under *local information* each firm has only incomplete information of the environment: a combination of local knowledge and global knowledge as in the framework of Galeotti et al. (2010). In particular, they are limited to observing their set of neighbours N_i as opposed to the whole network structure. Nonetheless, they do have some general or statistical knowledge about the marketplace in which they operate, namely the degree distribution p is common knowledge. Note that the identity of a neighbour carries no relevant information before prices are set.

For any vector of prices $\mathbf{x} \in X^n$ each firm i faces a demand which is a special case of demand in a n-firm Bertrand oligopoly with differentiated products. Consider the following demand system upon which certain restrictions are made:

$$\mathbf{D} = \begin{bmatrix} \alpha_1 \\ \vdots \\ \alpha_n \end{bmatrix} + \begin{bmatrix} \beta_{11} & \cdots & \beta_{1n} \\ \vdots & \ddots & \vdots \\ \beta_{n1} & \cdots & \beta_{nn} \end{bmatrix} \begin{bmatrix} x_1 \\ \vdots \\ x_n \end{bmatrix}.$$

Firstly, note that $\beta_{ii} \leq 0$ and $\beta_{ij} \geq 0 \ \forall i, j \in N : i \neq j$ simply ensures non-increasing demand in own price, and non-decreasing demand in competitors' prices. Specific to this model is localised competition, which requires $\beta_{ij} = 0 \forall j \notin N_i$. In other words, the network topology is accounted for by setting cross-price elasticities of demand of non-neighbouring firms to zero. In addition, we are considering a case of competition for customers where aggregate market demand is inelastic, that is to say, all consumers have a valuation for a single unit of the good which exceeds the monopoly price. This leads to the condition that any customers lost by firm i are gained by its neighbours, so that $-\beta_{ii} = \sum_{j \in N_i} \beta_{ji}$. Further assuming that this happens symmetrically requires $\beta_{ij} = \beta_i \forall i, j \in N : j \in N_i$. For further symmetry let $\beta_i = \beta \forall i \in N$. This implies $\beta_{ii} = -k_i \beta$. Lastly, for clarity let $\beta = 1$ and $\alpha_i = \alpha \forall i \in N$. It is also assumed demands are nonnegative for any feasible price vector, or equivalently that α is always large enough to ensure this. This means that we essentially care about changes in demand as a consequence of price competition rather than the absolute level of demand. If we consider geographic competition as an example, α can be thought of as the measure of maximum local demand, so firms being homogenous in α is realistic in the case where entry and exit considerations have resulted in a density of firms that is in fixed proportion to the population density throughout the region studied.

Given these restrictions the demand function for each firm is $D_i : X^{k_i+1} \to \mathbb{R}_+$ given $D_i\left[x_i, (x_j)_{j\in N_i}\right] = \alpha - k_i x_i + \sum_{j\in N_i} x_j$. The demand function can be obtained from representative consumers or discrete choice models where consumers choose between the two firms in each contested market à la Hotelling.

The resulting payoffs for firms with positive degree are then a special case of payoffs in an n-firm Bertrand oligopoly with differentiated products.

The payoff functiuon $\pi_i : X^{k_i+1} \to \mathbb{R}$ is defined as

$$\pi_i\left[x_i, (x_j)_{j\in N_i}\right] = (x_i - c)\left(\alpha - k_i x_i + \sum_{j\in N_i} x_j\right)$$

$$= -\alpha c + (\alpha + c k_i)\, x_i - k_i x_i^2 + \sum_{j=1}^{n} g_{ij}\,(x_i - c)\, x_j,$$

Each firm sets their own price x_i, has a unit cost $c < M$ of production and faces a demand linear in their own and neighbours' prices. There will be a constant measure $n\alpha$ of aggregate demand in the whole market.

Note that these payoffs violate a common assumption in the network games literature (Property A in Galeotti et al., 2010) thus many of the standard results do not apply. This assumption requires payoffs to be invariant to the addition of a neighbour who plays $x_j = 0$; in this model setting the price to zero is not a neutral action, in fact, it is quite the opposite.

1.4 Equilibria under incomplete information

First note that any firm i with $N_i = \varnothing$ has monopoly power over their measure α of customers and it is immediate that under any information structure the optimal monopoly price is the upper bound M.

Under the local information hypothesis each firm i seeks to maximise payoffs by choosing an optimal price $x_i \in X$ knowing only their set of neighbours N_i and the economy-wide degree distribution p. Because of ex-ante symmetry of neighbours in fact the only relevant information is own degree k_i, and p, which is common knowledge. Hence in the Bayesian game players' Harsanyi types are their degrees.

We consider symmetric Bayes-Nash equilibria, where agents with the same information sets act identically. As each firm i of a given type faces an identical decision problem and will have a unique best response due to strict concavity of payoffs, all Bayes-Nash equilibria must be symmetric. It follows that equilibrium prices depend only on a firm's degree k and are given $\{x^*(k)\}_{k=0}^{n-1}$. Formally, the objective functions are identical for the same types, that is

$$\mathbb{E}\,\pi_i\left[x(k_i), x^*(l_1), x^*(l_2), ..., x^*(l_{k_i})\right] = \mathbb{E}\,\pi_j\left[x(k_j), x^*(l_1), x^*(l_2), ..., x^*(l_{k_j})\right] \forall i, j \in N : k_i = k_j.$$

Knowledge of the degree distribution induces firms' beliefs over the degree (and thus action) of others. As discussed above, for firms of degree zero the equilibrium price is given as $x^*(0) = M$.

Let $\mathbb{E}\;\hat{\pi}_k \equiv \mathbb{E}\;\pi_i$ where $k_i = k$.

The price choices for firms with positive degree in equilibrium can now be characterised by $\{x^*(k)\}_{k=1}^{n-1}$ such that

$$x^*(k) \in \arg\max_{x(k)\in X} \mathbb{E}\;\hat{\pi}_k\left[x(k), x^*(l_1), x^*(l_2), ..., x^*(l_k)\right] \quad \forall\; k \in \{1, 2, ..., n-1\}\,.$$

The existence and uniqueness of the equilibrium are given by standard theorems. The Bayesian game is *smooth supermodular* as X is compact, $\mathbb{E}\hat{\pi}_{k_i}$ is twice continuously differentiable with $\frac{\partial^2 \mathbb{E}\hat{\pi}_{k_i}}{\partial x(k_i)\partial x(k_j)} \geq 0 \quad \forall\; i \neq j$. Then by applying Tarski's fixed point theorem there exists a largest and a smallest symmetric Bayes-Nash equilibrium in pure strategies. Moreover, since expected payoffs are strictly concave in own-action and the contraction condition $\frac{\partial^2 \mathbb{E}\hat{\pi}_{k_i}}{\partial x(k_i)^2} + \sum_{j\in N_i}\left|\frac{\partial^2 \mathbb{E}\hat{\pi}_{k_i}}{\partial x(k_i)\partial x(k_j)}\right| < 0$ holds, the extremal equilibria coincide meaning there exists a unique equilibrium in pure strategies.

Other desirable properties of the equilibrium due to Theorems 5 and 8 of Milgrom and Roberts (1990) are dominance solvability and global stability under adaptive learning rules. Dominance solvability rules out other equilibria in mixed or correlated strategies. A discussion of why this is not a general property of network games under incomplete information is presented in Cimini et al. (2015).

The expectation in the payoffs is over the realisations of the possible combinations of the degrees of the firm's k neighbours which follows a multinomial distribution. The set of all vectors describing the possible combinations, S_k, and the probability associated to each element $r \in S_k$ are defined as

$$S_k = \left\{(r_1, r_2, ..., r_{n-1}) \in \mathbb{Z}_+^{n-1} : \sum r_l = k\right\}$$

$$P_k(r) = \frac{k!}{r_1! r_2! \cdots r_{n-1}!}\ \tilde{p}(1)^{r_1} \tilde{p}(2)^{r_2} \cdots \tilde{p}(n-1)^{r_{n-1}}.$$

This allows the expected profit function to be written as

$$\mathbb{E}\ \hat{\pi}_k[x(k), x^*(l_1), x^*(l_2), ..., x^*(l_k)] =$$

$$\sum_{r \in S_k} P_k(r)\,(x(k) - c)\left(\alpha - kx(k) + \sum_{l=1}^{n-1} r_l x^*(l)\right).$$

As the above function is strictly concave in own price $x(k)$, the first order conditions $\frac{\partial \mathbb{E}\hat{\pi}_k}{\partial x(k)}\Big|_{x(k)=x^*(k)} = 0$ for each k obtain the system of linear equations which yields a unique solution.

Proposition 1 *Equilibrium prices under local information are given*

$$x^*(k) = c + \frac{\alpha}{2}\left[\frac{1}{k} + \frac{1 - p(0)}{\langle k \rangle}\right] \quad \forall\ k \in \{1, 2, ..., n-1\}\,.$$

Here $\langle k \rangle$ denotes the first moment of the degree distribution. It will be useful to note that the expression $\frac{1-p(0)}{\langle k \rangle}$ denotes the inverse of the conditional mean degree given that degree is positive, that is $\langle k \mid k > 0 \rangle^{-1}$.

Corollary 1.1 *It follows that equilibrium expected profits for firms with positive degree are given by*

$$\mathbb{E}\ \pi_i\,[x^*(k), x^*(l_1), x^*(l_2), ..., x^*(l_k)] =$$

$$\frac{\alpha^2}{4}\left[k\left(\frac{1 - p(0)}{\langle k \rangle}\right)^2 + \frac{1}{k} + 2\frac{1 - p(0)}{\langle k \rangle}\right] \quad \forall\ k \in \{1, 2, ..., n-1\}\,.$$

Under the incomplete information framework the symmetric Bayes-Nash equilibrium prices are monotonically decreasing in degree, reflecting the fact that maintaining higher prices in the face of more direct competition would lead to a loss of customers. However, equilibrium expected profits are increasing in degree for all degrees greater or equal to certain threshold, which by concavity of the continuous approximation can be shown to be $\overline{k} = \lceil \langle k \mid k > 0 \rangle \rceil$. The implication is that for networks with a degree distribution that has a high enough conditional mean $\langle k \mid k > 0 \rangle$, equilibrium expected profits sharply decrease in degree in a range below $\overline{k}$ and subsequently increase in degree approximately linearly. This non-monotonicity means that for firms with few direct competitors, the necessary price reductions due to additional competitors outweigh the gains from access to more contested markets, whereas for firms with degrees $k \geq \overline{k}$ the gains from access to markets outweigh the effects of lower prices. To put it another way, since the threshold value is a function of the conditional mean $\langle k \mid k > 0 \rangle$, it can be said that a firm with many direct competitors relative to the market average will expect their competitors to have higher prices on average since by reversion to the mean they will have fewer competitors, and thus they end up gaining customers by contesting additional markets, and thus additional demand outweighs the lower equilibrium price. On the other hand, a firm with few direct competitors relative to the market average will expect their competitors to have lower prices on average, because, again by reversion to the mean they are expected to have more direct competitors. Because of this, a larger price decrease is required to avoid a loss of demand, and thus additional competitors in this range of k imply lower profits. Of course, in this model, the market structure follows an exogenous stochastic process, but clearly both the opposing incentives in the spatial product differentiation literature are present were firms to choose to add or delete an edge: increasing differentiation to avoid intense price competition dominates below the threshold, and decreasing differentiation to capture competitors' customers dominates above it.

What can be said about comparative statics hinges crucially on the conditional mean of the degree distribution $\langle k \mid k > 0 \rangle$. When comparing two degree distributions $p(k)$ and $p'(k)$ the implications of first-order stochastic dominance or mean preserving spread on the value of $\langle k \mid k > 0 \rangle$ are ambiguous. It can instead be said that equilibrium prices for firms with positive degree are decreasing in the probability of zero degree $p(0)$ and also in the first moment $\langle k \rangle$. In terms of the model, this means that if firms expect neighbours to be on average of higher degree, and thereby have lower prices, it is optimal for them to set prices lower; and vice versa. Thus, increased average connectedness, which in this context is equivalent to lower levels of product differentiation, will have a positive impact on consumers' surplus.

Expected equilibrium profits are also decreasing in the conditional mean $\langle k \mid k > 0 \rangle$. This is consistent with standard result of competitive forces lowering profits by loss of market power: higher average connectedness in the competition network unambiguously decreases expected equilibrium profits by forcing prices of all firms down, irrespective of degree. This generates the tension that while a firm would prefer to be of high degree in a market of low connectedness, if all firms followed suit it would increase average connectedness and drive profits down. In a relocation game this would favour relocation as a monopoly and might drive the creation of a new disconnected network component. In other words, once a market becomes too saturated and approaching perfect competition, the incentives to make big leaps in differentiation increase. Notice also that as $p(n-1) \to 1$, the degree distribution degenerates to that of a complete network, and since n is large we approach asymptotically a perfect competition scenario where prices are equal to marginal costs and profits are zero.

Corollary 1.2 *The realised profits will in turn depend on the actual degrees of a firm and its neighbours, and are given by*

$$\pi_i[x^*(k_i),(x^*(k_j))_{j\in N_i}] =$$

$$\frac{\alpha^2}{4}\left[\frac{1}{k_i}+\frac{1-p(0)}{\langle k\rangle}\right]\left[1+\sum_{j\in N_i}\frac{1}{k_j}\right] \quad \forall \ k \in \{1,2,...,n-1\}.$$

In equilibrium play the realised profits of a firm under the incomplete information framework depend on its own degree and the degrees of all of its neighbours. It is clear that neighbours with a high enough degree are detrimental to profits as their presence decreases $\frac{1}{k_i}$ and this is not offset by a compensatory increase in $\sum_{j\in N_i}\frac{1}{k_j}$. Firms would prefer their neighbours to have as small a degree as possible. In this setting the most profitable firms are middle-of-the-road ones who are positioned in a way that they are able to attract customers through lower priced from many separate isolated markets, that is, firms whose position most closely resembles that of the central node in a star network.

Detailed proofs of these results are relegated to the Appendix.

1.4.1 Asymmetric informational sophistication

The motivation for the baseline incomplete information assumption which combines local knowledge with global knowledge stems from the high degree of complexity and volatility in the structure of competition. Under these circumstances it is natural to ask what would happen to a firm whose managers are either more or less informationally sophisticated than their competitors characterised by the baseline case. A less sophisticated firm could be irrational in a formal sense, and may not fully understand the game being played. It may not understand that there is a wider complex network of interactions beyond its immediate neighbourhood, or less restrictively, it may only fail to understand that this structure of interaction is complex and does not follow globally the same regularities the firm observes locally. Alternatively, the firm may be fully rational, and furthermore, may have gathered deeper information about the local structure of competition than its competitors. The question of interest is how such asymmetries would be reflected in the firm's price setting behaviour and its expected and realised profits. We quantify these difference in expected and actual profits based on an individual firms' level of information and rationality under the assumption that all other firms have local information as previously defined, and find that more informational sophistication pays off. This implies that given the choice, firms would have incentives to invest in their capacity to fully understand the functioning of the market they are in, and to attain an informational advantage with respect to their peers. Given the these benefits, there is a potential market for third parties who attain economies of scale by specialising in information gathering and data analysis such as a business analytics firm focusing on big data and GIS in order to better understand demand dynamics in the product space or geographic mobility and consumption patterns.

The section proceeds by considering each informational setup as a separate case. Case A and B study situations where a firm's limited rationality with respect to understanding the networked structure of interactions is detrimental to its profits when compared to fully rational firms in a local information setting. Case C studies the benefits of acquiring deeper network information in a local information setting.

A: The myopically naive firm

In this case a firm believes, incorrectly, that its neighbours are only competing with it, and therefore believes $k_j = 1 \forall j \in N_i$, that is to say $\tilde{p}_i(1) = 1$. Because the firm believes, incorrectly, that it knows the degree of its neighbours, it also believes that its neighbours know its degree. Assuming otherwise, i.e. that the firm believes its neighbours to be myopic and thus unaware of each other would, upon reflection, reveal its own myopicity. This line of reasoning will mean the firm plays a best response to the anticipated actions of its neighbours. All other firms are fully rational, and therefore, by definition, are aware that one firm in the market is irrational, however, since n is large they attribute zero probability to a firm of this type belonging to their set of neighbours.

Proposition 2 *A myopically naive firm will set its price to be*

$$x_i = c + \frac{\alpha}{3}\left(\frac{4}{k_i} + 1\right)$$

and receive the actual profits

$$\pi_i = \frac{\alpha^2}{3}\left[\frac{2}{3k_i} + \left(\frac{1}{k_i} + \frac{1}{2}\right)\left(\sum_{j\in N_i}\frac{1}{k_j} + k_i\frac{1-p(0)}{\langle k\rangle}\right) - \frac{1}{3}\left(k_i + 1\right)\right].$$

This can take negative values provided that k_i is high enough relative to $\langle k\rangle$ and $\sum_{j\in N_i}\frac{1}{k_j}$, that is to say, the myopic calculations were erroneous enough and that at the same time the firm is plentifully exposed to competitors.

B: Projection bias

In this case a firm is aware that its competitors may have other competitors and that it is part of a larger competition network. It erroneously assumes that all participants are like itself, in that they face the same number of competitors, so that $k_j = k_i \forall j \in N$, that is to say $\tilde{p}_i(k_i) = 1$. Projecting one's private type onto others is similar in spirit to the model of Madarász (2011) where agents project their private information onto others.

Proposition 3 *A firm with projection bias will set its price to be*

$$x_i = c + \frac{\alpha}{k_i}$$

and receive the actual profits

$$\pi_i = \frac{\alpha^2}{2}\left[\frac{1}{k_i}\sum_{j\in N_i}\frac{1}{k_j} + \frac{1-p(0)}{\langle k\rangle}\right].$$

For firms whose degree exactly equals the conditional mean degree, that is, $k_i = \langle k \mid k > 0\rangle$, price and profits coincide with the canonical rational incomplete information case. This is also the case if the firm's projections about its neighbours' inverse degrees are on average accurate, or $\frac{1}{k_i}\sum_{j\in N_i}\frac{1}{k_j} = \frac{1}{k_i}$.

Corollary 3.1 *Profits of a firm with projection bias will be strictly lower than profits* *of a rational firm if and only if*

$$\left(\frac{1}{k_i} - \frac{1}{\langle k \mid k > 0 \rangle}\right)\left(1 - \sum_{j \in N_i} \frac{1}{k_j}\right) > 0$$

This condition places the requirement that for firms with a degree below (above) the conditional mean degree its neighbours must have relatively high degrees so that the sum of their inverse degrees is below one, that is, the firms' projections turn out to be too low (high) which is quite likely given they were based on its own relatively low (high) degree. In fact, this has the probability of $1 - \sum_{k<k_i} \tilde{p}(k)$ which increases as the firm's degree gets smaller ($\sum_{k<k_i} \tilde{p}(k)$ which increases as the firm's degree increases).

C: Expanded radius of local knowledge

In this case, a firm has expanded local knowledge, such that in addition to the local knowledge framework it also knows $\{k_j\}_{j \in N_i}$. Equivelently, a firm may have even deeper network knowledge, or even complete information of Γ, here it only matters that it knows the types of its direct neighbours, because other firms' behaviour is predicated on local knowledge.

Proposition 4 *With expanded local knowledge a firm will set its price to be*

$$x_i = c + \frac{\alpha}{2}\left[\frac{1}{k_i} + \frac{1 - p(0)}{2\langle k \rangle} + \frac{\sum_{j \in N_i} \frac{1}{k_j}}{2k_i}\right]$$

and receive the actual profits

$$\pi_i = \frac{\alpha^2}{4}\left[\frac{k_i}{2}\left(\frac{1-p(0)}{\langle k \rangle}\right)^2 + \frac{1-p(0)}{2\langle k \rangle}\sum_{j \in N_i}\frac{1}{k_j} + \frac{1}{4k_i}\left(\sum_{j \in N_i}\frac{1}{k_j}\right)^2 + \frac{1}{k_i}\sum_{j \in N_i}\frac{1}{k_j} + \frac{1}{k_i} + \frac{1-p(0)}{\langle k \rangle}\right]$$

which are always strictly higher than in the canonical local knowledge case.

Corollary 4.1 *The expected profit in this case is are given*

$$\mathbb{E}\ \pi_i\left[x_i^*, x^*(l_1), x^*(l_2), ..., x^*(l_{k_i})\right] =$$

$$\frac{\alpha^2}{4}\left[\frac{5k-1}{4}\left(\frac{1-p(0)}{\langle k \rangle}\right)^2 + \frac{1}{k} + \frac{8 + \sum_{l=1}^{k} p(l)\frac{1}{l}}{4}\frac{1-p(0)}{\langle k \rangle}\right].$$

Corollary 4.2 *It follows that the expected gain from obtaining this deeper degree of network information is given by*

$$\frac{\alpha^2}{4}\left[\frac{k-1}{4}\left(\frac{1-p(0)}{\langle k\rangle}\right)^2+\frac{\sum p\left(l\right)\frac{1}{l}}{4}\frac{1-p(0)}{\langle k\rangle}\right].$$

Notice that this is increasing in degree, so depending on how the cost of gathering network information is structured, potentially higher degree firms would opt for collecting additional information while lower degree firms would not, leading to some equilibrium asymmetry. If some positive proportion of firms have deeper network knowledge, this of course changes the expected benefits as described above. An interesting subject for future research will be to analyse games where information acquisition is also an endogenous choice.

1.5 Equilibria under complete information

Under incomplete information, equilibrium prices and expected payoffs depend only on firms' own degree and the conditional mean degree given that degree is positive; under complete information the entire network structure becomes relevant for pricing decisions. Ballester and Calvó-Armengol (2010) provide valuable methods for the characterisation of the equilibrium and the intuition behind it. Nash equilibrium prices can be solved for fairly easily from the system of equations given by the first order conditions, however Ballester and Calvó-Armengol (2010) point out that this equilibrium coincides with a specific measure of centrality, and therefore is related to the network characteristics in a meaningful manner.

Some technical notes specific to this section follow. The assumption that n is large plays no role anymore. We exclude monopolies from the analysis, thus $k_i \geq 1 \ \ \forall\, i \in N$. We let the strategy space be unbounded from above, so that $X = \mathbb{R}_{+}$.

Recall that $\pi_i\left[x_i,(x_j)_{j\in N_i}\right] = -\alpha c + (\alpha + ck_i)\,x_i - k_i x_i^2 + \sum_{j=1}^{n} g_{ij}\,(x_i - c)\,x_j$.

Definition 1 *The vector of potential pure strategy Nash equilibria* $\mathbf{x}^*$ *of the game can be characterised by the following linear complementarity problem given by the Karush–Kuhn–Tucker conditions:*

$$\begin{cases} \mathbf{x} \geq 0 \\ \mathbf{u}^0 - \mathbf{\Gamma x} \leq 0 \\ \mathbf{x}^T \left(\mathbf{u}^0 - \mathbf{\Gamma x}\right) = 0 \end{cases}$$

Here $u_i^0 = \alpha + ck_i$ describes incentives at the origin and the interaction matrix $\mathbf{\Gamma} = 2diag\left(\mathbf{k}\right) - g$ describes the relationship between firms' actions. Note that $\gamma_{ii} = 2k_i \geq 0$ gives concavity in own-action and for $i \neq j$ $\gamma_{ij} = -g_{ij}$ describes the externality firm j's price exerts on firm i.

Lemma 2 (Ballester and Calvó-Armengol, 2010) *For the game to yield a unique pure strategy equilibrium it is sufficient that, in case of concavity in own-actions,* $\mathbf{\Gamma}$ *be* signed *and* moderate.

A signed interaction matrix indicated that actions are stretegic complements. A moderate interaction matrix indicates that the positive externalities exerted on a firm and its own price balance each other out so that there is no escalation of best responses with positive externalities, given that the action space is unbounded from above.

Definition 2 (Ballester and Calvó-Armengol, 2010) $\mathbf{\Gamma}$ *is signed if* $\gamma_{ij} \leq 0 \ \ \forall\, i \neq j$ *and moderate if* $\exists \mathbf{z} \geq 0 : \mathbf{\Gamma z} > 0$.

In the model studied here it is immediate that $\mathbf{\Gamma}$ is signed, and easy to verify that $\mathbf{\Gamma}$ is moderate (take for example $\mathbf{z} = \mathbf{1}$).

Moreover, we will see that the unique pure strategy equilibrium prices are related to firms' centrality in the competition network in a fundamental way.

Definition 3 (Katz, 1953; Bonacich, 1987) *For a weight vector* $\mathbf{w} \in \mathbb{R}_+^n$ *and a decay parameter* $\phi \geq 0$ *the vector of weighted Katz-Bonacich centralities for a network with adjecency matrix* $\mathbf{A}$ *is given*

$$\mathbf{b_w}\left(\phi \mathbf{A}\right) = \left[\mathbf{I} - \phi \mathbf{A}\right]^{-1} \mathbf{w} = \sum_{p=0}^{+\infty} \phi^p \mathbf{A}^p \mathbf{w}$$

where $\phi \rho\left(\mathbf{A}\right) < 1$ *guarantees the inverse exists and is non-negative.*

Here $\rho\left(\mathbf{A}\right)$ denotes the spectral radius of $\mathbf{A}$, which measures the network's density. Note that in the general case the matrix $\mathbf{A}$ can represent a network that is weighted, directed, and may contain self-loops. The matrix $\mathbf{A}^p$ keeps track of all paths of length p in the network, thus the weighted Katz-Bonacich centrality of node i counts all paths of any length stemming from i weighted by a geometrically decaying factor ϕ and paths reaching j are weighted by w_j. In this way it captures the network feedback effects of the strategically complementary actions, which inevitably influence equilibrium behaviour.

Note that as $\mathbf{\Gamma}$ is signed it may be decompose as $\mathbf{\Gamma} = s\mathbf{I} - \mathbf{G}$ where $\mathbf{G}$ is a nonnegative matrix and s is a scalar. In our case one such decomposition is given by

$$s = 2(n-1)$$
$$\mathbf{G} = g + 2diag\left((n-1) - k_1, ..., (n-1) - k_n\right).$$

Note also that since $\mathbf{\Gamma} = 2(n-1)\mathbf{I} - \mathbf{G}$ is signed it follows that moderation is equivalent to $\rho(\mathbf{G}) < 2(n-1)$ by Lemma 1 of Ballester and Calvó-Armengol (2010).

Given that $\mathbf{\Gamma}$ is both signed and moderate and $\mathbf{u}_0 \geq 0$ then by Theorem 2 of Ballester and Calvó-Armengol (2010) the unique pure strategy Nash equilibrium actions are proportional to the vector of $\mathbf{u}_0$-weighted Katz-Bonacich centralities of decay parameter $\frac{1}{2(n-1)}$ in a network with adjecency matrix $\mathbf{G}$.

Proposition 5 *Equilibrium prices under complete information are given*

$$\mathbf{x}^* = \frac{1}{2(n-1)}\mathbf{b}_{\mathbf{u}_0}\left(\frac{1}{2(n-1)}\mathbf{G}\right),$$

and the equilibrium profits are therefore denoted

$$\boldsymbol{\pi}^* = diag(\mathbf{x}^* - \mathbf{c})\left[\boldsymbol{\alpha} + (g - diag(\mathbf{k}))\mathbf{x}^*\right].$$

As the uniqueness conditions are met, the proof requires to show that $\mathbf{x}^*$ satisfies the equations of the linear complementarity problem. Note also that $\mathbf{G}$ is merely the adjacency matrix of the competition network with some heterogenously weighted self-loops. Profits are a function of a firm's own weighted Katz-Bonacich centrality and that of its direct neighbours, which are of course dependent.

Under the complete information framework we no longer have monotonicity of equilibrium actions in degree because the whole network structure is relevant for pricing decisions in a specific manner. In equilibrium firms set prices proportional to a measure of weighted centrality in the competition network. In fact, a firm has to account for the cumulative effect of all externalities exerted on it though its neighbours, those exerted on its neighbours by their neighbours, and so on. The equilibrium effect of these bilateral externalities is captured by the relevant measure of centrality which accounts for all paths in the network stemming from a firm weighted by the length of the path, such that shorter paths have more influence. As prices are strategic complements, more central firms are better able to exploit the feedback from positive externalities.

1.6 Conclusions

This paper aims to present a model of spatial competition where implications of limited information about the complexities of the market beyond its local structure can be readily distinguished.

In order to do this parsimoniously, some stylised assumptions on markets and the nature of information are necessary. The main results are quite intuitive: under incomplete information prices are found to be decreasing in the number of direct competitors, and also in the market average number of competitors because a higher mean degree means that the expected prices of competitors will be lower. Expected profits will be increasing in the number of competitors beyond a certain threshold which is a function of mean degree, and may be decreasing below this threshold. This is because a firm with many direct competitors relative to the market average will expect an additional competitor to have on average fewer direct competitors (by reversion to the mean) and thus also a higher price. The expected gain in demand thus dominates the price effect. Conversely, a firm with only a few direct competitors relative to the market average will expect an additional competitor to have on average more direct competitors and thus a lower price. Now a larger price decrease is required to avoid a loss of demand, and hence the price effect dominates. Under complete information prices are found to depend mainly on a measure of weighted centralities which captures all the possible feedback from externalities on the competition network. The two informational assumptions yield distinct empirically testable predictions.

The model can serve as a basis for further theoretical and empirical research. This could be studying the effects of other informational specifications, for example, where firms have to decide whether to acquire local knowledge which extends beyond their immediate neighbours. It can also serve to study franchise competition where one firm controls and sets identical prices at multiple vertices, the effects of price regulations and how these propagate in a network, and collusion among firms in price setting and repositioning. Furthermore, given suitable data on prices and locations, it could be empirically tested whether certain markets' behaviour aligns more with the predictions of the local information hypothesis or the complete information hypothesis.

Chapter 2

The China Shock revisited: Insights from value added trade flows[1]

joint work with Victor Kummritz

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Abstract

We study the relationship between increased trade with China and the decline of manufacturing jobs in US local labour markets. We exploit value added decomposition of bilateral trade flows in order to distinguish the effects of Chinese and third country drivers of the trade shock, as well as to identify the groups of industries driving the adjustment based on revealed comparative advantage. Our identification and instrumentation strategy follows closely the nascent literature on local labour market trade exposure. We find evidence for Chinese value added driving adverse relative employment effects in the 2000-2008 period, contrary to an assembly hub or GVC integration explanation. However, these effects have greatly diminished by the 2008-2015 period, as labour market adjustment has largely concluded. This obviates labour market related justifications for bilateral trade policy interventions. The negative effects that persist in the latter period are found to be driven by recently-gained Chinese comparative advantage industries. As a methodological contribution we improve on the local trade exposure measure by calculating it using value added industries, as doing so based on exporting industries obscures the exposure faced by upstream suppliers.

Keywords: value added trade, labor-market adjustment, local labor markets
JEL Classification: E24; F14; F16; J23; L60; R23

2.1 Introduction

The reintegration of China into the world trading system has been an extraordinary historical achievement that has lifted millions of people out of poverty. It has also set in motion monumental shifts in world trading pattens which provide a unique opportunity to examine how predictions of classic trade theory hold up. Trade liberalisation is expected to be on the whole welfare improving, but it also necessitates adjustments in factor markets which will not always be favourable to all groups, be it the owners of a specific type of capital or workers in a specific industry. Without government intervention, some groups are left worse off than before, and individuals face significant adversities in transitioning from job to job. Recent research has largely corroborated the view that aggregate gain and localised pain are two sides of the same coin. For instance, Amiti et al. (2017) estimate that China's WTO entry has caused consumer price of manufacturing goods to fall 7.6% in between 2000-2006. On the other hand, highly influential research by Autor et al. (2013) shows that US local labour markets more exposed to increased import competition from the Chinese manufacturing sector, what is commonly referred to as the China shock, have seen significant losses in jobs and earnings. They find that over a decade a $1000 increase in per worker exposure to Chinese imports leads to a 0.6 percentage point reduction in the share of manufacturing in total employment. Although recent research by Magyari (2017) suggests that these negative effects are not present at the national industry level, and that the costs savings made possible by trade with China have actually helped US manufacturing industries retain workers on aggregate, this does not diminish the significance of the fact that in many location US manufacturing industries have suffered. Autor et al. (2016b) present a historical overview of the rise of China and the subsequent adjustment in labour markets. These effects have also been shown to be present in other advanced economies such as Spain, Norway, and France (Donoso et al., 2015; Balsvik et al., 2015; Malgouyres, 2016). What is special about the China shock, however, is its scale. The localised pain felt by those adversely impacted has started to feed into the political process and has shaped the discourse on trade at a national level. Colantone and Stanig (2016) show that the vote for Brexit was influenced by import competition from China, and Autor et al. (2017) present evidence on trade with China contributing to the polarisation of US politics.

Given these developments it is important to clarify the implications of the China shock research agenda for trade policy. Firstly, it is well known that changes in trade patterns lead to adjustment costs during the transition to a new equilibrium.

Such costs are important and should be addressed by policy makers, but they do not outweigh net gains from trade such as the reduction of prices faced by consumers and increases in productivity.[2] It is clear that a policy response to these concerns should not come in the form of barriers to trade but rather as policies that facilitate adjustment and attenuate adjustment costs.

In this paper, we use value added decomposed trade flows to shed light on two aspects of adjustment to the China shock. The first is to distinguish between the impact of Chinese drivers of the trade shock and that of third countries who use China in final stages of their production but provide much of the value added. Autor et al. (2016b) discuss extensively the domestic reforms which took place in China that finally enabled it to take its place in the globalised economy as a major manufacturing powerhouse. On the other hand, Johnson and Noguera (2016) and Koopman et al. (2012) research the proliferation of Global Value Chains (GVCs) and in particular the participation of China. Implication for US policy response are different depending on the extent to which employment effects are driven by (i) China increasing its productivity and moving up the value chain as a result of successful development policies, and (ii) third countries such as Japan and Korea gaining a cost advantage and competing indirectly with US manufacturers by making use of China's comparative advantage in labour intensive stages of production. In the former case, given the structural reasons for the differences in comparative advantage between the US and China, it would make little sense to protect or subsidise those manufacturing sectors in which China has a clear comparative advantage. The priority should be on using transfers financed by the gains from trade to facilitate workers' adjustment out of these industries. In the latter case, it is competition between structurally similar advanced economies that is behind the negative employment effects, however, adjusting bilateral trade policy towards China would have a limited impact as GVCs would increasingly shift to rely on alternative low-wage countries for the final stages of production. Instead, policy should focus on findings ways to improve the competitiveness of US manufacturers in the industries affected. Facilitating the GVCs integration of these industries would permit them to benefit from the cost advantage afforded by Chinese or Mexican inputs and compete on equal terms with their Japanese or Korean counterparts.

The other main contribution of this paper is to explore the length of adjustment and how changes in Chinas comparative advantage over time may have prolonged

[2]Further evidence on temporary adjustment costs are provided by Trefler (2004) and Dix-Carneiro and Kovak (2015) for Canada and Brazil respectively, while evidence on gains from trade with China is presented in Handley and Limão (2017) and Bloom et al. (2016a).

the employment effects. Autor et al. (2016b) show that the negative effects of the China Shock on US local labor markets have been fairly persistent. For designing appropriate policies, it is important to understand if the negative effects of Chinese import competition are temporary but prolonged due to the large size of the new trading partner or if the China shock is unique in that it has a permanent effect. We aim to answer the question, to what extent has the US labour market successfully adjusted by now? If adjustment has already concluded, there is no case for policies aimed at limiting import exposure.

We address these two points by exploiting data from Inter-Country Input-Output tables (ICIOs) covering the time period from 2000 to 2015. This expands the time-period analysed by Autor et al. (2013) to shed light on whether the negative effect of Chinese import competition persists, and therefore whether the China shock is fundamentally different from other trade shocks with regard to adjustment time. The tables allow splitting gross imports from China into their individual value added components by origin and, thus, separate Chinese value added (which we refer to as domestic value added, DVA) in exports to the US from third country value added (foreign value added, FVA) that enters the US via China. This approach entails two important methodological improvements over the use of gross export data.

First, it allows us to create a more precise measure of local labour market exposure by taking into account input-output linkages on the supply side. The reason is that goods exported from a downstream industry such as consumer electronics contain inputs from upstream industries such as plastics and fabricated metal products. Therefore, a rise in US consumer electronics imports might actually affect local labor markets which depend on plastics or fabricated metal products. By looking at the value added content of US imports from China, we can correctly assign the imports to the local labour markets that are ultimately affected. Furthermore, we can remove the portion of export value due to double counting, since a part or component crossing the US border more than once due to ever lengthening value chains has no significance for its potential to displace local production.

Second, it allows us to better control for the endogeneity of import exposure by removing the US value added component in Chinese exports. Since US employment is a major contributor to US value added in Chinese exports it causes a mechanical correlation between import exposure and employment in manufacturing. Moreover, it is problematic for the instrumentation strategy since US value added is also present in Chinese exports to other high-income countries. By removing this part of Chinese exports, we improve the validity of the instrument. Johnson and Noguera (2012) show that the US value added content in Chinese exports is considerable and can reduce the bilateral trade deficit between China and the US by up to 40%, which highlights that this adjustment is quantitatively meaningful and relevant.

We find that in the period 2000-2008 increased exposure to Chinese value added is associated with a decline in local manufacturing employment, whereas exposure to foreign value added in Chinese exports has a positive effect, albeit not robustly statistically significant. This means that the China shock is indeed caused by China-specific changes as suggested by Autor et al. (2013) and not by indirect imports consistent with a GVC-driven explanation. It also shows that the results by Autor et al. (2013) are robust to a specification that takes into account input-output linkages at the local labor market level. The result for foreign value added suggests that other advanced economies such as Japan and Korea re-routing exports via China does not harm US manufacturing. This is potentially explained by lower prices of goods that have been previously imported by the US directly from these countries boosting total demand without requiring significant new labour market adjustment in the industries affected. This hypothesis is in line with the fact that most of foreign value added in Chinese exports to the US stems from high-income countries which have traded intensively with the US before the rise of China. An alternative hypothesis is that foreign value added is associated more with horizontal intra-industry trade and Chinese value added with vertical intra-industry trade as defined by Greenaway et al. (1995), and hence the former necessitates relatively little labour market adjustment.

We also find that in the period from 2008-2014 the negative effects of local exposure to Chinese value added are greatly diminished. The corresponding coefficients suggest that the magnitude of the effect has decreased by 66% implying that the China shock today only plays a minor role. We further split our DVA exposure along three industry groups to determine if the remaining negative impact of DVA in the second period is driven by a particular subset of industries. Specifically, the three groups comprise industries in which China has had a comparative advantage since 1995, industries in which China had gained a comparative advantage between 1995 and 2008, and industries in which China has had a comparative disadvantage between 1995 and 2008. We find that in the period 2000-2008 exposure to DVA from the first two groups is associated with negative effects on local manufacturing employment. However, in 2008-2014 only the second group shows a significant, although smaller, effect. This implies that while adjustment is still taking place in some industries in which China has only relatively recently gained a competitive edge, it has mostly concluded. Exposed occupations and firms have contracted or adapted successfully, leaving the surviving manufacturing occupations and firms largely resistant to a further increase in import competition. We conclude that the China shock is not special in that it has no permanent negative effects. While the adjustment period estimated by Autor et al. (2013) of about 10 years from the mid-1990s to 2007 is fairly long, this can be explained by the concurrent evolution of China's comparative advantage to encompass more complex and skill intensive manufacturing industries.

The rest of this paper is organised as follows. Section 2.2 reviews the related literature, Section 2.3 discusses the empirical strategy followed by a discussion of the data in section 2.4, Section 3.4 presents the econometric results, and Section 3.5 concludes.

2.2 Related Literature

Our work is directly related to the seminal paper by Autor et al. (2013) and papers that replicate their methodology. Our methodological contribution to this line of research is to improve upon the precision of the exposure measure by considering also the upstream industries that contribute value added to the final product whose industry is recorded in the gross trade statistics.

In addition, our work is similar in spirit to Shen and Silva (2016). Rather than studying the value added decomposition of bilateral gross trade flows as does the present paper, they view the impact of the rise of China through a different lens, focusing on all the Chinese value added that is eventually absorbed by the US, that is, they consider also the Chinese value added embedded in third country exports to the US. For instance, China might export processed rare earth elements to Japan for the production of semiconductors which are then exported to the US. In technical terms, the value added decomposition we use employs backward linkages whereas theirs employs forward linkages. They ask whether all the absorbed Chinese value added taken together has a negative labour market impact, and find that it does not. A potential reason for this is that using forward linkages, their measure of Chinese value added is often embedded in goods that will go through several additional production stages after leaving China, that is, upstream goods. Most of these goods, such as rare earths or other raw materials, do not compete with US goods but are rather complementary, or even necessary inputs to US production processes. As such, the presence of this type of value added might attenuate the effects of more downstream, substitutable value added found in bilateral exports which directly competes with US production. Indeed, their paper finds that it is the downstreamness of industries that is associated with negative labour market consequences. Ultimately their decomposition is not suited to study implications of bilateral trade policy and it prevents a direct comparison to the results by Autor et al. (2013) who, like us, look at bilateral trade flows. Instead, they study the overall (direct and indirect) impact of the rise of China including its participation in third countries' production chains.

More recent work on the impact of Chinese imports emphasises the importance of input-output linkages. Acemoglu et al. (2016a) use industry level data to study the effects of direct industry exposure, exposure which propagate downstream from a given industry's suppliers, and exposure which propagate upstream from a given industry's buyers. As one would expect, direct and upstream effects of exposure are found to be negative, however downstream effects are statistically insignificant. The key difference to our approach is that they generate upstream and downstream exposure by using US national input-output tables to create a weighted average of what is direct Chinese import exposure measured by exporting industry. In contrast, we use data on the value added industry content of each exporting industry generated from inter country input-output tables to correctly allocated exposure to the affected industries, which encompasses both direct exposure, i.e coming from the value added by the exporting industry itself, and upstream exposure industries.

Like Autor et al. (2013), we are interested in precisely identifying the negative employment effects of Chinese import exposure which necessitate labour market adjustment, so we do not seek to simultaneously include a treatment variable for downstream exposure which would have to be constructed using US national input-output tables. Industries which are downstream from the imported product presumably benefit, so the expected effect identified here would be positive. This hypothesis is consistent with Topalova and Khandelwal (2011), who show that trade liberalisation leads to some firm level efficiency gains due to import competition, but much bigger gains due to increased access to foreign inputs.

The effects we identify here are but one side of the coin of trade liberalisation: the necessary local labour market adjustment. Magyari (2017) broadens the focus by studying the effects on US manufacturing employment at a firm level, cutting across local labor markets. She finds that US firms involved in manufacturing record net gains in jobs in response to increased Chinese import competition. While specific units of production within the firm shrink, others, in sectors where the US has a comparative advantage relative to China experience employment growth. These results are attributed to firms reorganising production and a favourable cost shock in the form of cheaper Chinese inputs. This does not contradict the significant effects found at a local labour market level or indeed the adjustment costs faced by individual workers, rather, this methodology is suited to assess the aggregate effects of a trade shock, which are equally important to consider from a policy perspective.

In one of the earliest papers in trade to apply this type of identification strategy, Topalova (2007) emphasises that this methodology is suited to identify short- and medium-run effects at the local level. Rather than identifying the effects of the treatment, in our case the China shock, on the overall levels of the outcome variable, the focus is on identifying differential regional effects based on regional variation in the level of treatment exposure. The fact that manufacturing employment is reduced more in local labour markets that are more exposed to import competition is a good indicator of the locally borne costs of trade adjustment, which are greatly important for domestic policy, as discussed earlier. However, it is not informative about the causal effects of the China shock on the manufacturing employment share at a national level, much less about aggregate welfare implications in general equilibrium, which are more relevant questions from a trade policy angle.

2.3 Empirical Strategy

2.3.1 Identification and Instrumentation

Our empirical approach builds on the methodology developed by Autor et al. (2013) with the aim to extend and deepen our understanding of the local labour market effects of the US-China trading relationship. In this approach, the identification strategy relies on the fact that the US can be divided into 722 regional markets, termed commuting zones (CZs). Within commuting zones labour is mobile and across them it is highly immobile. This is a key assumption, because if labour were mobile also across CZs, the effects of trade shocks will not be identifiable at a local labour market level. It is thus worth noting that the literature finds support for this assumption (Topel 1986; Blanchard and Katz 1992; Glaeser and Gyourko 2005). These CZs are then subject to differential trade shocks determined by their initial patterns of industry specialisation. In order to identify differential effects of exposure to domestic and foreign value added, it must be the case that the two are sufficiently different in their industry composition, that is, the proportion of value added contributed by each manufacturing industry.

We use a measure of CZ trade exposure created in the spirit of Autor et al. (2013)

with several key differences. As a useful reference point, let us first describe their exposure measure, which is based on gross imports of Chinese goods to the US:

$$\Delta EXP_{it} = \frac{1}{L_{it}} \sum_{s} \frac{L_{ist}}{L_{st}} \Delta IMP_{st}. \tag{2.1}$$

The above expression represents the change in exposure, EXP, for a particular CZ i with the base year t. It is normalised per worker. The change in imports, IMP, from each exporting sector s is weighted by the national prominence of the CZ in the sector, using the CZ's share of total US employment, L, in that sector.

The issue of potential endogeneity stemming from the correlation of both employment outcomes and imports with unobservable and omitted demand shocks is addressed by instrumenting this exposure measure with an analogous one where employment is lagged by one period and US imports from China are replaced by imports by a group of other developed countries.

In contrast to the gross imports used by Autor et al. (2013) our trade data originates from ICIOs and has additional layers of richness that we exploit in our analysis. Trade flows are decomposed according to the bilateral trade accounting framework proposed by Koopman et al. (2014) and adapted to bilateral-sector level by Wang et al. (2013). In particular our bilateral trade flows are net of double counting, which is important, since whether an intermediate good passes through customs more than once at various stages of production is irrelevant from a labour displacement perspective. Using backwards linkages, we can decompose trade flows based on source country and industry of value added.[3] Therefore, we are able to create separate exposure measures based on the distinct sources of exposure and evaluate their relative importance. As discussed above, this is how we evaluate competing hypotheses as to the drivers of the China shock.

$$\Delta MANUF_{it} = b_1 + b_2 \Delta EXP_{it} + b_3 \Delta EXP_{it} \times D_t + \mathbf{X'}_{it} b_4 + e_{it} \tag{2.2}$$

In our general specification shown above we regress the share of manufacturing employment in the working-age population by CZ on its trade exposure. We depart from Autor et al. (2013) in that we allow time interactions rather than using their stacked first differences model in order to test whether adjustment is taking place so that the effects of exposure differ in the two time periods analysed. In the example specification (2) above this means that the effects of exposure are captured by b_2 in

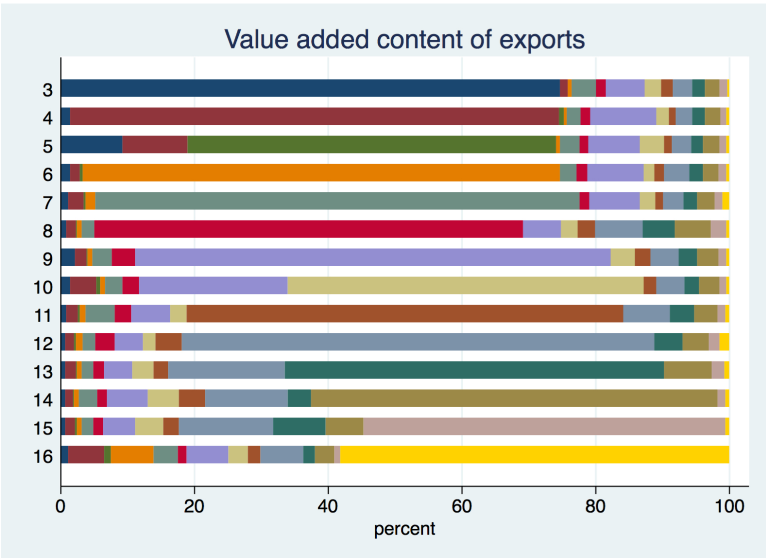
[3] See Baldwin and Lopez-Gonzalez (2015) for a general discussion on value-added trade.

the first period and $b_2 + b_3$ in the second period.

2.3.2 Value Added Exposure

We make a methodological contribution to the growing literature that employs this style of identification strategy. Our richer trade data enables us to improve upon the way local exposure is calculated. We provide a measure which more accurately reflects the threat of displacement to workers in various manufacturing industries. First, we want to draw attention to the fact that the value added content, and hence the labour content, of exports does not generally originate from the exporting industry. This point is well illustrated by Figure 1 below, where different colours represent the manufacturing value added industry content for each exporting manufacturing industry (in the same order). The industry (colour) with the largest share is usually the nominal exporting industry, however it is clear that a significant share of value added – and labour – content is contributed by other industries.

Figure 2.1: Industry-level value added content of exports

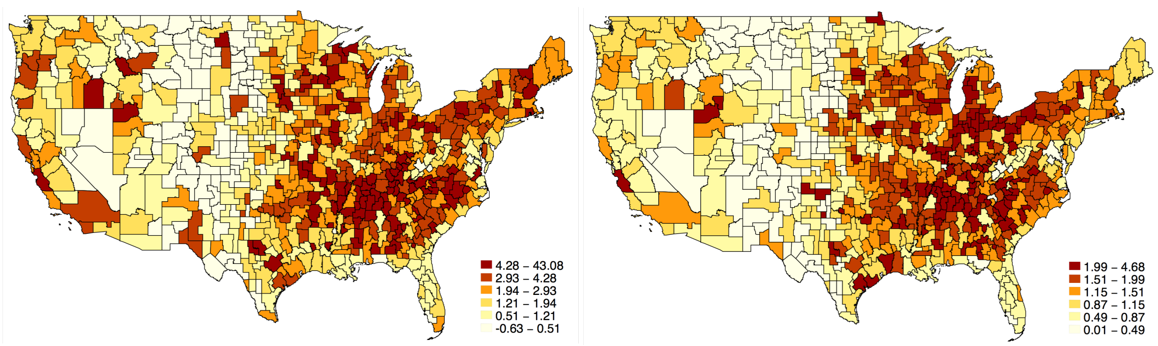


We therefore calculate our exposure measure described in equation (1) with s representing value added industries, in contrast to previous work where local exposure is calculated using exporting industries. While this has been made possible due to more detailed data, note that using exporting industries obscures the true set of industries affected by the increase in trade and thus skews the correct attribution of trade shocks to CZs. For example, if a third of motor vehicle imports' value added increase comes from the steel sector and these domestic industries are located in different CZs, one should allocate a third of the trade shock to the CZ where iron and steel are prominent.

Figure 2 provides a graphical representation of how the geographic distribution of exposure differs when it is calculated based on the two different methodologies. In Washington, Oregon, and California we observe several CZs that display high exporting industry exposure and much lower value added exposure. Their industry structure is such and even though they appear directly exposed to import competition, it is actually jobs located elsewhere that are at risk. Since manufacturing employment losses have been less severe in these areas, misallocating exposure to them leads to underestimating its effect on employment. Therefore, we hypothesise that our exposure measure will yield a negative coefficient much greater in magnitude than Autor et al. (2013). This expected difference is moderated by the fact that upstream industries to a given manufacturing industry are not uniformly distributed across the country but exhibit patterns of geographic clustering. (Ellison and Glaeser, 1997) In terms of causal inference, our methodology yields a more precise estimate of the ideal treatment variable (true exposure to import competition) and is thus better at identifying the true effects of import competition at a local labour market level. It bears repeating that we do not claim to identify any other effects of Chinese imports, such as beneficial downstream effects of cheaper inputs, or more aggregate industry or economy wide employment effects which propagate in general equilibrium though the price-demand channel. As such, this methodology is well suited to studying the labour market adjustment process following a trade shock, but poorly suited to study aggregate welfare implicated that should guide trade policy.

Figure 2.2: Comparison of import exposure measures for 2000-2007

(a) Exposure in Autor et al. (2013) (b) Value added exposure



2.4 Data Description

We use value added decomposed trade flow data covering the years 2000, 2008, and 2015 which has been generated from the Asian Development Bank multi-regional input-output tables (ADB-MRIO) and provided by the Research Centre on GVCs at the University of International Business and Economics in Beijing. The decomposition uses the accounting framework proposed by Koopman et al. (2014) and further disaggregated to a bilateral-sector level by Wang et al. (2013). For some robustness exercises we also use equivalent data from the 2016 release of the World Input-Output Tables (WIOT 2016). For future research we plan to run value added decompositions also on the OECD/WTO Trade in Value Added database (TiVA). The ADB-MRIO is our preferred source because compared to WIOD 2016 it contains 5 additional Asian economies, and since the focus of this research is on the sources of value added in Chinese exports, accurately measuring input-output linkages in the region is critical. It should be noted that ICIOs rely on exporter reporting rather than importer reporting, so while we maintain the terminology of Autor et al. (2013) when referring to import exposure, in Table 1 which makes a direct comparison with their results we apply a scaling correction based on the import/export discrepancy in the UN Comtrade Database.

Our employment data is sourced from the publicly available County Business Patterns (CBP) series of the United States Census Bureau and covers the years 1990, 2000, 2007, 2008, and 2014. This data is cleaned using code made public by David Dorn[4]. Data on working-age population used to compute the dependent variables is sourced from the Population Estimates Program (PEP) of the United States Census Bureau. We concord our employment data to the more aggregated industry classification of our trade flow data using correspondence tables made available by the United Nations Statistics Division[5].

Control variables at the CZ level, with the exception of lagged percentage of employment in manufacturing, are the ones made public by David Dorn.

[4] http://www.ddorn.net/

[5] ISIC Rev.3 - US SIC 87 correspondence, https://unstats.un.org/unsd/cr/registry/regdnld.asp?Lg=1

2.5 Econometric Results

2.5.1 Comparison with Autor et al. (2013)

We begin our analysis by conducting a comparison and validation exercise where we fit the model of Autor et al. (2013) using our value added data and value added exposure measure but without splitting it into its foreign and Chinese value added components and without extending the analysis to the most recent time period. We evaluate at this stage only whether the results of Autor et al. (2013) are robust to redefining import exposure using the value added origins of imports and the differences between the two. The specification we use is given by equation (3) and is equivalent to the preferred specification of Autor et al. (2013) with the full set of controls.

$$\Delta MANUF_{it} = b_1 + b_2 \Delta EXP_{it} + \mathbf{X}'_{it} b_3 + e_{it} \tag{2.3}$$

For ease of comparison we use data for the time period 2000-2008 and adjust variables to be 10-year equivalent. We use data and code made available by Autor et al. (2013) to run an equivalent regression for the 2000-2007 period, as single period analyses are not reported in their paper.[6] The dependent variable is the change in the share of working-age population employed in manufacturing in each CZ. Each observation is weighted by population. The export exposure measure is instrumented according to the strategy described in Section 2.3.

Table 1 focuses exclusively on the time period of overlap between our data and that of Autor et al. (2013). In columns 1-6 we replicate their Table 3 and in column 7 we use their data to replicate column 6, since they only publish results for a stacked first differences specification involving also the prior time period. Table 1 shows qualitatively similar findings to Autor et al. (2013) on export exposure with our novel data sources and exposure methodology, with some differences in the significance of controls. We observe a clear difference in the coefficients of exposure depending on the methodology used. From column 7 we see that over the decade in question a \$1000 increase in per worker exporting industry based exposure to Chinese imports leads to a 0.47 percentage point reduction in the share of local manufacturing employment, whereas column 6 shows that a \$1000 increase in per worker value added exposure leads to a 0.96 percentage point reduction. We posit

[6] Autor et al. (2013) report results from a stacked first differences specification using two time periods, the earlier of these does not overlap with out data.

that this difference is due to our exposure measure more accurately identifying the causal effect of imports. We also conclude that our data and methodology are validated and we can have confidence in further results to follow.

Table 1 — Comparison with Autor et al. (2013) using 2000-2008 trade flows

Dependent Variable: 10-year equivalent change in manufacturing employment / working-age population in % pts

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Local exposure to Chinese exports / worker	-2.142***	-1.683***	-1.436***	-1.145***	-1.017***	-0.958***	-0.469***
	(0.225)	(0.380)	(0.363)	(0.296)	(0.295)	(0.285)	(0.123)
% manufacturing employment t-1		-0.0481	-0.0680**	-0.132***	-0.126***	-0.138***	-0.083***
		(0.0380)	(0.0347)	(0.0392)	(0.0331)	(0.0358)	(0.025)
% college educated population t-1				-0.0319		-0.00726	-0.000
				(0.0246)		(0.0204)	(0.021)
% foreign born t-1				-0.0470***		-0.000	0.057***
				(0.0112)		(0.0214)	(0.013)
% employment among women t-1				-0.0268		0.0349	-0.064
				(0.0396)		(0.0414)	(0.039)
% employment in routine occupations t-1					-0.229***	-0.220***	-0.142***
					(0.0742)	(0.0739)	(0.093)
avg offshorability of occupations t-1					-0.511	-0.628	-0.670*
					(0.351)	(0.519)	(0.344)
Constant	0.0651	0.204	-0.364	4.608**	7.334***	5.152	-1.182
	(0.334)	(0.364)	(0.516)	(2.066)	(2.385)	(3.798)	(3.270)
Observations	722	722	722	722	722	722	722
R-squared	0.437	0.453	0.532	0.589	0.638	0.642	0.532
Census division dummies	NO	NO	YES	YES	YES	YES	YES

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

2.5.2 Extending the analysis until 2014

We proceed to analyse the persistence of local labour market effects in the more recent period 2008-2014. We use a two period setup with each period adjusted to 8-year equivalent period lengths. Instead of using the stacked first differences technique as in Autor et al. (2013) we include a time interaction term with a dummy variable for the second period $D_t = \mathbf{1}_{\{t=2008\}}$ because we do not want to ex-ante restrict the exposure impact coefficients to be identical in both periods. The coefficient of exposure will thus be b_2 in the first period and $b_2 + b_3$ in the second. This is done because we hypothesise that the latter period is fundamentally different. It is far enough from the start of the China shock for local labour market adjustment to have potentially taken place, and additionally there may be an interaction with the after-effects of the 2008 global financial crisis.

$$\Delta MANUF_{it} = b_1 + b_2\Delta EXP_{it} + b_3\Delta EXP_{it} \times D_t + \mathbf{X'}_{it}b_4 + e_{it} \tag{2.4}$$

Column 1 in Table 2 is equivalent to column 6 in Table 1 without the necessary adjustments for quantitative comparability with Autor et al. (2013). From column 2 we learn that the interaction of exposure with time is significant, so we may reject that hypothesis that exposure has equal effects in both time periods. Furthermore, we cannot reject that this effect is zero in the second period. This is consistent with our hypothesis that the manufacturing industries most vulnerable to import competition have on the most part already adjusted, leaving behind an industry structure that is more resilient to increasing volumes of import competition.

Bloom et al. (2015) posit that firms accelerate technological and organisational innovation to inoculate themselves against import competition, which could explain our findings. In some recent research Magyari (2017) presents evidence showing that firms reorganise their production activities towards less exposed industries in response to trade shocks. While this may happen across CZ boundaries, leaving certain CZs no better off, it may to some extent attenuate the average local negative effects estimated. Further, given some degree of reorganisation response in the prior period, persistent effects can be expected to be diminished in the latter period presuming the the industry composition of increased import competition does not change significantly. We later show that the industry composition does evolve over time, which may account for the persistent of negative effects from some components once trade flows are decomposed in subsequent analysis.

Table 2 — Results using trade data from 2000-2015

Dependent Variable: 8-year equivalent change in manufacturing employment / working-age population in % pts		
	(1)	(2)
Local exposure to Chinese exports / worker	-1.219***	-1.905***
	(0.363)	(0.321)
Time Dummy × Local exposure to Chinese exports / worker		1.425***
		(0.305)
Time Dummy		-0.568**
		(0.281)
% manufacturing employment t-1	-0.111***	-0.0629***
	(0.0286)	(0.0224)
% college educated population t-1	-0.00581	0.000820
	(0.0163)	(0.00990)
% foreign born t-1	-7.28e-05	0.00460
	(0.0172)	(0.00726)
% employment among women t-1	0.0279	0.0239
	(0.0331)	(0.0158)
% employment in routine occupations t-1	-0.176***	-0.121***
	(0.0591)	(0.0300)
avg offshorability of occupations t-1	-0.502	-0.487**
	(0.416)	(0.230)
Constant	4.121	2.067
	(3.038)	(1.663)
Chinese Export Exposure Coefficient + Coefficient of Time Interaction		-0.480
		(0.378)
Observations	722	1,444
R-squared	0.642	0.574
Census division dummies	YES	YES

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

2.5.3 Trade flows decomposed

In this section our aim is to shed light on the drivers of China shock by decomposing our exposure measure based on the origin of the value added. DVA represents Chinese domestic value added and FVA represents foreign, third-country value added, with the US excluded. Figure 3 presents two maps contrasting the geographic distribution of DVA and FVA. The specification used in this section is described in equation (5).

$$\Delta MANUF_{it} = b_1 + b_2 \Delta DVAEXP_{it} + b_3 \Delta DVAEXP_{it} \times D_t + b_4 \Delta FVAEXP_{it} + b_5 \Delta FVAEXP_{it} \times D_t + \mathbf{X'}_{it} b_6 + e_{it} \quad (2.5)$$

In order to separately identify the causal effects of these two treatment variables on manufacturing employment, it is a prerequisite that the industry compositions of DVA and FVA are sufficiently different. Even though DVA exposure is generally much greater in magnitude, we can confirm from Figure 3 that the geographic pattern of these two exposures is sufficiently different to allow identification. The reason for this variation in the industry composition of DVA and FVA is an interesting topic of research in its own right. This could be attributed to comparative advantage stemming from the varying resource endowments of China and FVA contributors, China moving up the value chain as its economy develops, strategic consideration by the Chinese government to facilitate the growth of certain sectors, or a combination of factors. We further note that the exposure pattern of FVA changes significantly from the first period to the second reflecting both changes in the industry composition of FVA and changes in the US local industry composition. The exposure pattern of DVA remains fairly stable.

Figure 2.3: Comparison of DVA and FVA exposure 2000-2008

(a) DVA exposure (b) FVA exposure

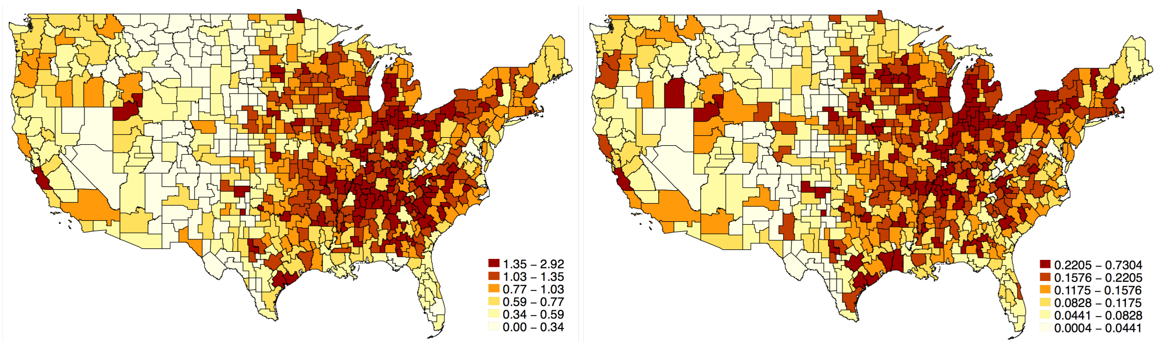


Table 3 — Local labour market exposure by origin of value added for periods 2000-2008 and 2008-2015
Dependent Variable: 8-year equivalent change in manufacturing employment / working-age population in % pts

	(1)	(2)
Local exposure to the Chinese value added content of Chinese exports / worker	-4.298***	-4.801***
	(1.314)	(0.856)
Local exposure to the Foreign value added content of Chinese exports / worker	7.609**	8.356***
	(3.591)	(2.741)
Time Dummy × Local exposure to the Chinese value added content of Chinese export		3.189***
		(0.618)
Time Dummy × Local exposure to the Foreign value added content of Chinese export		-5.334
		(5.035)
Time Dummy		-0.558*
		(0.290)
% manufacturing employment t-1	-0.0307	-0.00661
	(0.0413)	(0.0256)
% college educated population t-1	-0.0129	-0.00355
	(0.0161)	(0.0104)
% foreign born t-1	0.000785	0.00536
	(0.0181)	(0.00770)
% employment among women t-1	0.0211	0.0166
	(0.0346)	(0.0170)
% employment in routine occupations t-1	-0.140**	-0.0962***
	(0.0638)	(0.0315)
avg offshorability of occupations t-1	-0.554	-0.518**
	(0.458)	(0.255)
Constant	3.622	1.837
	(3.247)	(1.711)
Chinese value added content Coefficient + Coefficient of Time Interaction		-1.613***
		(0.626)
Foreign value added content Coefficient + Coefficient of Time Interaction		3.022
		(3.782)
Observations	722	1,444
R-squared	0.645	0.583
Census division dummies	YES	YES

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 3 reports results from the first period in column 1 and with time interactions in column 2. We see that the coefficient of DVA exposure is negative in both periods, although significantly smaller in the latter period, reflecting local labour market adjustment to the domestic component of the trade shock. The coefficient of FVA exposure is positive and we cannot reject that there it is constant across the two periods. However, in robustness exercises using ICIO tables from WIOD 2016 the coefficient of FVA is positive but no longer significant. We may conclude that there are no negative local labour market effects from this component of the trade shock.

While this type of reduced form analysis cannot identify the exact source of the shock, whether it is a Chinese productivity increase or simply the political decision to integrate more deeply into the world economy, we can say that the drivers of the shock are Chinese in origin, and we can discount the hypothesis that it is driven by other advanced economies rerouting production through China via global value chains. In fact, the negative effect of DVA indicates that manufacturing has shrunk the most in CZs whose industry structure corresponds to industries in which China has expanded, highlighting a degree of substitutability. However, manufacturing has expanded in CZs whose industry structure mirrors the industry composition of increased FVA. This could indicate a broad shift across developed countries to expand manufacturing sectors where they maintain a comparative advantage in response to increased import competition from other sectors. It is also the case that the FVA component does not necessitate new adjustment as countries such as the US have been previously exposed to direct imports from Japan and Korea in these industries which are now rerouted via China. The hypothesis that the US had already adjusted to competition from these industries prior to the China shock is supported by Wang et al. (2017) who describe how Japan and the four Asian Tigers constituted 75% of the US trade deficit in manufactured goods in 1990, but this share declined to just 13% by 2015.

2.5.4 Comparative advantage sectors

Recent work by Hanson et al. (2015) has shown evidence for comparative advantage industries changing dynamically over time. It is well known that since the early 1990s China has expanded its set of comparative advantage manufacturing industries rapidly. We investigate the impact of Chinese value added exposure coming from exporting industries grouped by the dynamics of their revealed comparative advantage.[7]

Specifically, the three groups used in our specification shown in equation 6 ($DVA1$, $DVA2$, and $DVA3$ respectively) comprise exporting industries in which China has had a comparative advantage since 1995, industries in which China has gained a comparative advantage between 1995 and 2008, and industries in which China has had a comparative disadvantage between 1995 and 2008.

[7]We compute comparative advantage industries using the methodology of Balassa (1965) based on value added exports provided by TiVA.

$$
\begin{aligned}
\Delta MANUF_{it} = b_1 + b_2\Delta DVA1EXP_{it} + b_3\Delta DVA1EXP_{it} \times D_t \\
+ b_4\Delta DVA2EXP_{it} + b_5\Delta DVA2EXP_{it} \times D_t \\
+ b_6\Delta DVA3EXP_{it} + b_7\Delta DVA3EXP_{it} \times D_t \\
+ b_8\Delta FVAEXP_{it} + b_9\Delta FVAEXP_{it} \times D_t + \mathbf{X'}_{it}b_{10} + e_{it} \quad (2.6)
\end{aligned}
$$

Table 4 — Local labour market exposure by origin of value added for periods 2000-2008 and 2008-2015

Dependent Variable: 8-year equivalent change changes in manufacturing employment / working-age population in % pts

	(1)	(2)
Local exposure to the Chinese G1 industry value added content of Chinese exports	-3.189**	-4.020***
	(1.351)	(1.068)
Local exposure to the Chinese G2 industry value added content of Chinese exports	-4.882***	-5.718***
	(1.364)	(0.998)
Local exposure to the Chinese G3 industry value added content of Chinese exports	1.275	-1.510
	(5.022)	(4.498)
Local exposure to the Foreign value added content of Chinese exports / worker	9.075**	10.50***
	(3.535)	(3.058)
Time Dummy × Local exposure to the Chinese G1		2.861***
		(0.609)
Time Dummy × Local exposure to the Chinese G2		4.313***
		(1.204)
Time Dummy × Local exposure to the Chinese G3		3.086
		(6.046)
Time Dummy × Local exposure to the Foreign value added content of Chinese export		-8.132*
		(4.685)
Time Dummy		-0.568*
		(0.300)
% manufacturing employment t-1	-0.0634	-0.0275
	(0.0475)	(0.0337)
% college educated population t-1	-0.00755	-0.00102
	(0.0173)	(0.0115)
% foreign born t-1	0.000393	0.00519
	(0.0177)	(0.00744)
% employment among women t-1	0.0203	0.0176
	(0.0343)	(0.0173)
% employment in routine occupations t-1	-0.162***	-0.107***
	(0.0584)	(0.0301)
avg offshorability of occupations t-1	-0.432	-0.458*
	(0.424)	(0.234)
Constant	4.075	2.021
	(3.148)	(1.636)
Chinese G1 value added content Coefficient + Coefficient of Time Interaction		-1.159
		(0.866)
Chinese G2 value added content Coefficient + Coefficient of Time Interaction		-1.405*
		(0.796)
Chinese G3 value added content Coefficient + Coefficient of Time Interaction		1.577
		(4.813)
Foreign value added content Coefficient + Coefficient of Time Interaction		2.369
		(3.721)
Observations	722	1,444
R-squared	0.656	0.592
Census division dummies	YES	YES

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

We find in Table 4 that in the first period 2000-2008 exposure to DVA from the first two groups is associated with negative effects on local manufacturing employment. However, in 2008-2014 only the second group shows a significant, although smaller, effect. The effects of FVA exposure are qualitatively similar to the previous specification. We take these results as evidence that adjustment has largely taken place to exposure to China's original comparative advantage industries, and is still taking place due to some industries in which China has only relatively recently gained a competitive edge. This type of rolling adjustment necessitated by China's concurrent development and movement up the value chain could explain why it has taken a several decades for US labour markets to adjust to the rise of China. It is furthermore evidence that this adjustment is winding down despite the growth in imports.

2.6 Conclusion

The literature on the local labour market effects of Chinese import competition has been cited extensively as an argument for limiting trade with China despite the fact that the results do not support this conclusion. While the differential effects of trade at a local labour market level are clear, its aggregate negative effects on manufacturing employment are subject to debate.

In this paper we provide explicit evidence that even if policy were narrowly focused on averting or reversing the aforementioned local labour market effects, there is no case for limiting trade with China. Using recent trade data, we show that rising US local labor market exposure to Chinese imports in the recent period 2008-2014 has significantly smaller effects than in the period 2000-2008 and is driven exclusively by industries in which China has gained a comparative advantage only recently. This suggests that US local labour market adjustment to the China shock has largely concluded.

Furthermore, by exploiting value added decomposition of trade flows, we can analyse the relative impact on US local labour markets of value added components of Chinese imports originating from China and from third countries. We provide evidence that confirms the thesis of Autor et al. (2016b) that the local labour market effects are driven by changes specific to China rather than the proliferation of GVCs which have increasingly incorporated China in downstream production stages.

Moreover, we contribute an important methodological innovation that complements the empirical strategy of Autor et al. (2013) with a cleaner identification of the causal effects of import exposure. We show that the results of Autor et al. (2013)

are qualitatively robust to using our value added based exposure measure, but that more precisely identifying treated local labour markets yields a quantitatively larger effect of trade exposure on local manufacturing employment.

We leave for future research to attempt to identify at a local labour market level the downstream effects of exposure to imports of intermediate products from China, which are predicted to be positive. We find it important to emphasise and to make clear that while the focus of this line of research has so far been on the effects of import competition which necessitate labour market adjustment in the short run, there are other channels in general equilibrium through which bilateral trade relations with China have welfare improving effects, and evaluation of policy should take into account both sides of the coin. While the China shock was a unique historical event, we can expect future disruptive technology shocks to be of similar magnitude and therefore, lessons from the China shock and how it has affected various countries around the world could potentially inform domestic labour market policies aimed at facilitating adjustment.

Chapter 3

Services Input Intensity and US Manufacturing Employment Responses to the China Shock[1]

joint work with Omar Bamieh, Matteo Fiorini, and Bernard Hoekman

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Abstract

We present evidence that the negative effect of the China shock on US manufacturing employment is lower for industries that use services inputs more intensively. Different potential mechanisms for this finding are analyzed. This reveals significant heterogeneity across different types of services and their potential role in affecting labor demand and supply responses to greater import competition.

Keywords: manufacturing employment, China shock, import competition, servicification, services inputs use
JEL Classification: F16; L8

3.1 Introduction

The rapid rise in China's share of global trade since the early 1990s has generated significant adjustment pressures in countries around the world. Recent research on the impact of the steep rise in exports of manufactures from China to the United States on US manufacturing employment has documented the regionally differentiated effects of the "China shock" (Autor et al., 2013, 2016a). Of particular note is the finding that the negative effects on manufacturing employment in local labor markets (commuting zones) are substantial and that in the time period investigated other economic sectors within commuting zones do not provide alternative employment opportunities to affected manufacturing workers (Acemoglu et al., 2016b), implying that much of the adjustment to the shock takes the form of exit from the labor market.

The United States is a services economy. Aggregate employment and productivity growth in the US and other high-income advanced economies is increasingly intertwined with the performance of the service sector. The share of manufacturing in total employment has been falling since the late 1970s, with a concomitant steady increase in the services content of production, consumption and employment. At the level of the economy as a whole, competition from China and other emerging economies is just one, albeit important, factor inducing shifts in employment away from manufacturing and towards services sectors. These shifts in US comparative advantage are driven by technical change and investment responses to policies in both the US and in the rest of the world (China). Services account for an increasing share of US exports (34 percent in 2016, up from 27 percent in 2000); in 2016 the services trade balance registered a surplus of $248 billion, compared to a merchandise trade deficit of $752 billion.[2] US comparative advantage in services reflects human capital endowments and the ability to take advantage of services agglomeration externalities (Gervais and Jensen, 2014).

These broader features of structural transformation of the US economy are important in assessing the determinants of the impact of the China shock. In this paper we focus on one specific dimension of the 'servicification' of the US economy: the role of cross-sectoral variation in services input use (arms-length purchases of services) by manufacturing sectors as a factor influencing the resilience of the latter to

[2] Data are from US Bureau of the Census, at https://www.census.gov/foreign-trade/statistics/historical/index.html and reflect balance-of-payments figures. Thus they do not include services sold by foreign affiliates of US multinationals, which are an important additional channel for international provision of services by US-owned companies (Francois and Hoekman, 2010).

greater import competition from China. Services such as transport, telecommunications and financial intermediation are intermediate inputs for manufacturing sectors and their cost and quality will have an impact on the productivity of manufacturing industries that use such services (see for instance Barone and Cingano, 2011; Bourlès et al., 2013; Beverelli et al., 2017). Given that the US has a revealed comparative advantage in services, downstream industries that are relatively intensive users of services in which the US has a comparative advantage may be better able to withstand import competition from China because the associated embodied services increase the quality or otherwise help to differentiate the goods that are produced.

What is of specific interest in this regard is the role of producer services such as R&D, management consulting, engineering, supply chain logistics, and business process outsourcing as intermediate inputs into the output of manufacturing industries. Such business services support (are associated with) outsourcing of tasks and activities, which can improve manufacturing firms' productivity and thus help them to meet competitive pressures from imports and attenuate the downward shift in labor demand following a trade shock. Conversely, the intensity with which business or producer services are used as part of processes of outsourcing service activities to specialized providers may enhance the operational flexibility of manufacturing industries, resulting in greater sensitivity of manufacturing employment to trade shocks by increasing the elasticity of labor supply for the industries concerned.

In this paper we analyze the heterogeneity of local manufacturing employment effects of the China shock, focusing specifically on the question whether differences in the intensity of use of externally purchased services inputs across US manufacturing industries is associated with greater resilience of employment to import competition from China. We use the empirical approach developed by Autor et al. (2013) to identify the employment response of manufacturing sectors at the commuting zone level in the US and distinguish between two mechanisms that affect employment effects: (1) the role that greater services intensity may play in attenuating reductions in the demand for labor following a trade shock and (2) the role that services intensity may play by increasing the elasticity of labor supply for a manufacturing sector. In the Autor et al. (2013) framework it is assumed that workers are immobile across different zones. Thus, the analysis centers on the short-run employment effects of a shock, with reallocation of factors being limited to intra-zone dynamics. Considering local labor markets to be an independent unit of analysis that is not connected to the rest of the economy permits the use of a partial equilibrium framework and a focus on local employment effects and local labor market adjustment. We do not take a stance on whether it is appropriate to limit analysis of Chinese competition to a relatively short-run setting in which worker mobility is assumed to be very limited. Our goal is simply to deepen the understanding of the factors that determine the cross-sectoral variation in employment effects at the level of local labor markets (commuting zones) by investigating the relationship between the intensity of services input use and manufacturing industries' employment responses to trade shocks. We find that more intensive use ('outsourcing') of producer services appears to be positively associated with resilience to greater import competition.

Our analysis extends the literature in several respects. The main contribution is to assess the role of services input intensity as a determinant of the local manufacturing employment response to greater import penetration. We complement Acemoglu et al. (2016b) by showing that labor demand impacts within a commuting zone is a function of the degree of sectoral exposure to Chinese imports, but that the services intensity of production is an additional factor that should be considered. We also complement Magyari (2017), who shows that at the firm level, trade with China generates cost savings which enables expansion of employment in manufacturing sectors in which the US has a comparative advantage relative to China, even as specific establishments shrink. She finds that the firms hire more services workers that are complementary to high-skilled and high-tech manufacturing. More generally, our paper contributes to the debate on the employment effect of services outsourcing and offshoring. The literature has identified different theoretical channels with ambiguous predictions regarding the effects of services outsourcing on employment.[3] To the best of our knowledge the role of services outsourcing on the response of manufacturing employment to trade shocks has not been investigated.

The remainder of the paper is organized as follows. Section 3.2 discusses the economic rationale for focusing on the intensity of services input use in assessments of labor market adjustment following a trade shock, as well as the related literature on services as a driver of productivity and performance at the industry level. Section 3.3 presents the econometric framework. Results are reported and discussed in Section 3.4. Section 3.5 concludes with some implications for further work.

[3] On the one hand, offshoring lowers input prices and increases profits, in turn potentially increasing manufacturing production and labor demand. On the other hand, higher quality and cheaper service inputs may substitute for labor used in production, leading to a decrease in labor demand (Amiti and Wei, 2006; Milberg and Winkler, 2010b and Winkler, 2010). Consistent with the theoretical ambiguity, the results of empirical analyses are mixed (see Amiti and Wei, 2005, 2006; Schöller, 2007; Winkler, 2010; Michel and Rycx, 2012; Milberg and Winkler, 2010a, 2015). Services offshoring tends to be associated with higher demand for skilled labor at the firm-level (Crinò, 2010; Andersson et al., 2016).

3.2 Services input use, manufacturing employment, and trade shocks

Autor et al. (2013) find that a local labor market's degree of exposure to imports of goods from China has a negative effect on the size of its manufacturing sector relative to geographic areas that are less exposed to imports. In what follows we hypothesise that the services input intensity of an industry will affect its response to changes in local trade exposure, i.e., for a given level of local labor market exposure to imports of manufactured goods, industries within that local labor market that are more intensive users of services are less affected.

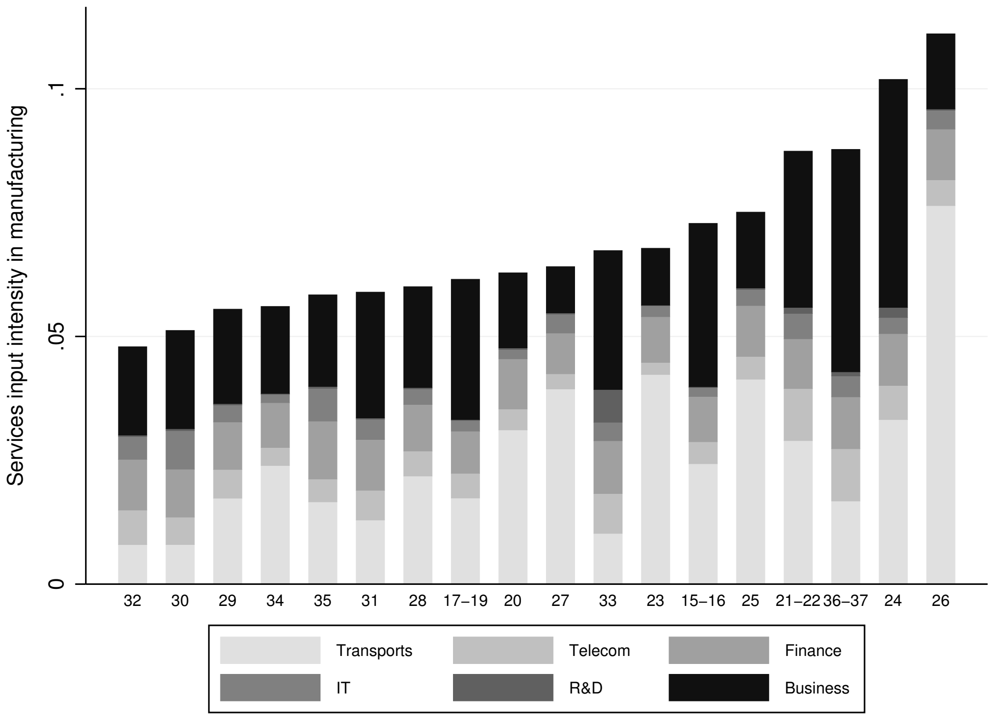
Figure 3.1 ranks US manufacturing sectors (denoted with their two-digit ISIC Rev. 3 codes) in terms of their services input intensity as defined by the sum of technical input-output coefficients for six services sectors that are particularly salient intermediate inputs into production (so called 'producer services').[4] The pattern of services input intensity is relatively heterogeneous across manufacturing sectors. Transport, business and financial services tend to be relatively significant for most manufacturing industries. Conversely, R&D services tend to be small or absent in the input consumption bundle of downstream sectors, with the notable exception of medical, precision and optical instruments (ISIC sector 33).

Various (related) mechanisms motivate the hypothesis that the effects of local exposure to import competition on employment will be heterogeneous across manufacturing sectors as a function of their services input intensity.

One is that more services intensive industries are likely to include more firms that are integrated into global value chains (GVCs). GVC participation requires many services inputs, ranging from transport and logistics to communications (Baldwin, 2016). Firms that participate in GVCs are more productive on average than firms that do not (Constantinescu et al., 2017). Greater services input intensity implies greater specialization, as the tasks and activities that are outsourced allow firms to concentrate on core areas of competitive advantage, while sourcing services from the most efficient providers in the market. This may be reflected in production of more

[4] Technical coefficients in Figure 3.1 capture the technical relationship between US industries as of the early 1990s. Formally, technical coefficients are the elements of the square matrix A defined as $A \equiv YM$ where Y is a dimension n square matrix of zeros, except along the main diagonal, that includes the inverse output of each industry and M is the intermediate demand matrix. For each services-manufacturing sector pair (s, j), the technical coefficient is the element a_{sj} of A and represents the cost of the intermediate inputs from services sector s per dollar of total production of manufacturing sector j.

Figure 3.1: Services input intensity in manufacturing sectors



Notes: Manufacturing sectors are denoted on the horizontal axis with their 2 digit ISIC Rev. 3 codes. The mapping between sectors codes and labels is as follows. 15-16: food products, beverages and tobacco; 17-19: textiles, textile products, leather and footwear; 20: wood and products of wood and cork; 21-22: pulp, paper, paper products, printing and publishing; 23: coke, refined petroleum products and nuclear fuel; 24: Chemicals and chemical products; 25: rubber and plastics products; 26: other non-metallic mineral products; 27: basic metals; 28: fabricated metal products except machinery and equipment; 29: machinery and equipment n.e.c; 30: office, accounting and computing machinery; 31: electrical machinery and apparatus n.e.c; 32: radio, television and communication equipment; 33: medical, precision and optical instruments; 34: motor vehicles, trailers and semi-trailers; 35: other transport equipment; 36-37: manufacturing n.e.c. and recycling. For each services sector the vertical axis reports its technical coefficient in the respective manufacturing sector. Technical coefficients are computed from the earliest observation of the US input-output table sourced from the OECD IO STAN capturing the technical relationship between industries prevailing at the beginning of the 1990s.

sophisticated, higher quality, and brand differentiated products that compete less directly on price with Chinese imports. Higher services input intensity is likely to reflect greater investment in R&D, product development, innovation, and marketing, helping firms to compete with foreign firms both in terms of satisfying market demand and anticipating trends in consumer preferences (see Bloom et al., 2016b).

The importance of services input use and associated outsourcing as a channel to boost the performance of manufacturing sectors is not new to the literature. Services outsourcing as a driver of firm performance has been the subject of numerous papers, with research identifying a positive effect of services outsourcing (and offshoring) on productivity at both the firm level (see for instance Görg et al., 2008; Hijzen et al., 2010) and at the sector level (see Amiti and Wei, 2009; Winkler, 2010). For example, Görg and Hanley (2011) identify a positive impact of (international) outsourcing of services on innovation practices in a sample of Irish manufacturing firms. The use of ICT services in a broad range of industries has been a driver of US output and productivity growth since the mid-1990s (van Ark et al., 2008).

Services play a more complex role as intermediate inputs into production than sourcing of manufactured parts and components from specialized suppliers. A key property of services inputs is the role they play in coordinating and controlling economic activities and supporting the process of specialization. For instance, information and communications, transport and logistics services are needed to connect labor and/or capital units across space; financial and insurance services allow firms to manage the risks of routine operations as well as risks inherent in innovation and experimentation. As "facilitators" of geographically fragmented production processes, the quality and cost of a variety of "margin" services directly influence the feasible degree of specialization and scale of downstream economic activities (Francois, 1990; Francois and Hoekman, 2010). In a world of GVCs where production involves the coordination across space and time of intermediate inputs produced by firms located in different regions or countries, this coordination function is particularly important. Baldwin et al. (2015) note that transport, telecommunications, logistics and distribution services account for an increasing share of total value added in manufacturing because of the increasing fragmentation of the production process and outsourcing of non-core activities. In the increasingly complex value chains that characterise modern manufacturing, parts have to be shipped and activities coordinated in ways that minimize the need for (cost of) storage.[5]

The coordination and 'connectivity' functions provided by many of the services purchased by businesses apply irrespective whether services are performed in-house or outsourced to the market (both domestic and international). Our analysis uses US Input Output tables to capture the intensity of services input use and thus we are unable to capture the value of services that are performed in-house by firms. While this limitation biases downward our measure of the services-intensity of production, there is a well-established and long-standing trend toward outsourcing of services functions and activities, and thus a concomitant reduction in the share of services provided in-house.[6]

[5]Berlingieri (2015) finds that firms increase their services input intensity in order to manage coordination complexity (proxied by the number of contested export destination markets).

[6]Mancher (2014) presents data from a survey finding that a high share of manufacturing firms outsource many of the services they need to operate, including financial, legal, facilities management, human resources, customer relations and IT services.

Differences across manufacturing sectors in services input intensity in part reflect differences in the ability/willingness of industries to outsource services intermediates. An increasing use of services is part and parcel of the general pattern of the "servicification"[7] of manufacturing in high-income countries (Miroudot and Cadestin, 2017).[8] Recent research has highlighted the positive effects of selling services alongside manufactured products: servicification is associated with better production technology features (Crozet and Milet, forthcoming) as well as stronger export performance (Ariu et al., 2017) for manufacturing firms. Servicification may also reflect a strategy of diversification and differentiation: a good with services embedded or attached to it is different from the good by itself.

3.2.1 Services input use in a labor supply and demand framework

Although the literature has found that the performance (productivity) of services industries is important for manufacturing performance; that services productivity tends to grow at a rate that is lower but not that much different from that of other sectors of the economy (Young, 2014); and that outsourcing of services by manufacturing industries is a factor driving the reduction in manufacturing employment (Schettkat and Yocarini, 2006; De Backer et al., 2015) we are not aware of research on the effects of differences in services input intensity (outsourcing) on labor demand and supply responses for manufacturing sectors following a major trade shock.

Given the partial equilibrium model that is implicit in the framework used by Autor et al. (2013) (reflected in the assumption there is no factor mobility between US commuting zones), a basic supply and demand framework suggests there will be two mechanisms through which services outsourcing may affect the response of a manufacturing firm to increased import competition. The first is the impact on labor demand as plotted in Figure 3.2a. Given that the trade shock will displace some demand for the output of the domestic firm, there will be an associated downward

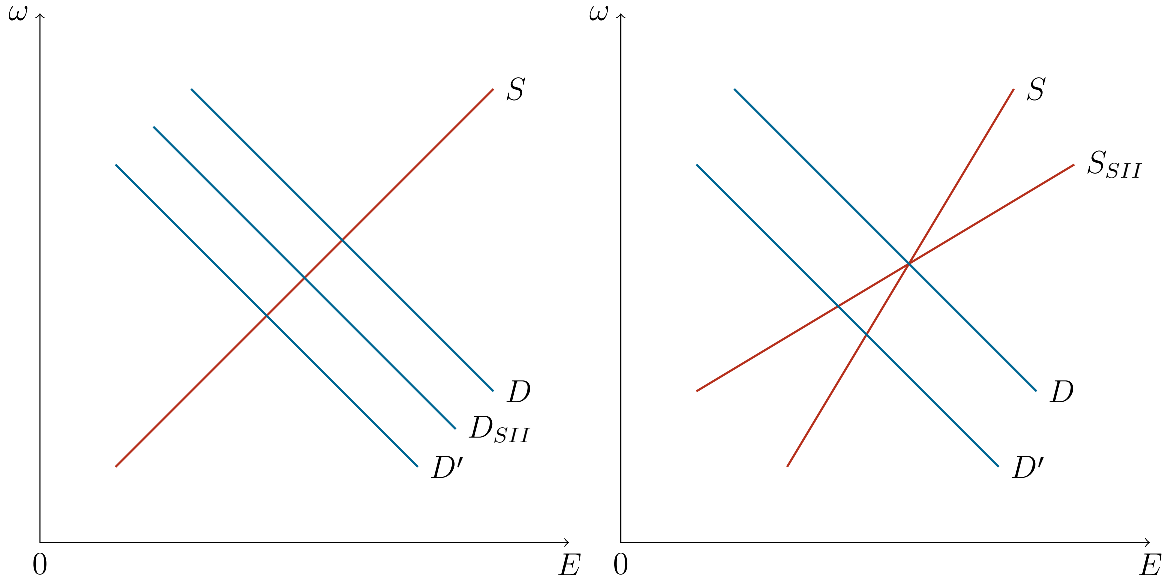
[7]The term servicification is generally used to describe a shift by firms/industries in non-services sectors to perform and sell services as part of their output, with an increasing share of their revenues coming from the provision of services to clients.

[8]Evidence of this pattern is presented in Bernard et al. (2017) for the case of Danish firms, many of which have undergone a shift from manufacturing into services sectors by abandoning actual production but retaining many of their manufacturing-related services activities such as design and distribution. These authors find higher employment and a larger share of high-tech workers in firms that 'switch' sectors. Similar patterns are highlighted in Dauth et al. (2017) for the case of Germany, where labor transition from manufacturing to services occurs via unemployment spells and through young workers entering the labor market.

shift in the labor demand schedule (from D to D'). In industries with higher services input intensity this downward shift may be attenuated insofar as consumer demand for the domestic product is less affected (shift from D to D_{SII}). This may be due to greater ability to compete on price or to product differentiation along the vertical or horizontal dimension. If the downward shift in labor demand is mitigated, greater services input use (intensity) helps to cushion the employment effects of the trade shock.

Figure 3.2: Labor supply and demand framework

(a) SII affecting the labor demand shift (b) SII affecting labor supply elasticity



The second mechanism works on the supply side (Figure 3.2b). Higher services input intensity may increase the elasticity of supply of labor and thus exacerbate the employment effects of a given trade shock. The aggregate labor supply elasticity in a sector is higher when there are fewer barriers and fixed costs to employment, e.g. training, educational attainment, certification, firm or sector specific experience. It is also the case when a sector has a larger pool of potential workers to draw from, which may also be due to their geographic mobility or the ability to work remotely. Business and IT services in particular facilitate the outsourcing of tasks at manufacturing firms which require relatively little firm or industry specific skills. These workers will have contracts with other companies that will manage personnel-related issues, training and certification costs and contract workers at remote sites. Because there is a large market for such workers spanning many industries, they have relatively more employment opportunities than workers who are directly employed by manufacturing firms and perform tasks which require a high level of firm-specific knowledge capital. An implication is that the business and IT services input intensity of a sector is associated with a more wage sensitive labor force. The upshot is a higher labor supply elasticity, so that a given downward shift in demand will result in a greater decrease in employment by manufacturing establishments in equilibrium.

If both mechanisms are active, the net effect of a SII in shaping the employment response to a trade shock is ambiguous. It is an empirical matter which of these mechanisms dominates.[9] We provide an analysis of this question in Section 3.4.

3.3 Econometric framework

We focus on the role of services input intensity in moderating the local labor market effects of exposure to imports of manufactured goods from China as assessed in the empirical framework developed by Autor et al. (2013). We do so by augmenting their empirical specification with a sectoral dimension in the spirit of Acemoglu et al. (2016b). This allows us to explicitly introduce a measure of services input intensity which is used as a moderator of the effect of the treatment variable.

3.3.1 Empirical specification

To investigate the role of differences in services input intensity in moderating the impacts of an increase in import competition on manufacturing employment, we interact the change in import exposure at the commuting zone (CZ) level with a measure of services input intensity across sectors:[10]

$$\Delta E_{ist} = \delta_{st} + \beta \Delta IP_{it} + \mu(\Delta IP_{it} \times SII_s) + \gamma' \mathbf{X}_{ist-1} + \epsilon_{ist}. \tag{3.1}$$

where ΔE_{ist} is the change in employment of sector s in CZ i at time t, expressed in percentage points of working–age population, ΔIP_{it} is the change in import penetration (exposure) to Chinese competition at the local labor market level as defined in Autor et al. (2013), and SII_s is a measure of the services input intensity of sector s. More precisely, SII_s is the manufacturing sector-specific sum over services sectors

[9] A detailed discussion and empirical test of role of SII in moderating the wage effect of the China shock goes beyond the scope of the present analysis and it is left for further research.

[10] We define local labor markets according to Autor et al. (2013) to be 722 non-overlapping commuting zones (CZs) which represent areas with a high degree of labor mobility within and very little mobility across zones. Our empirical specification follows closely Section 6 of Acemoglu et al. (2016b). We refer the reader to these papers for an in depth discussion of identification and instrumentation strategies.

of their technical coefficients. We restrict the focus to six categories of producer services: (1) transport and storage, (2) telecommunications, (3) finance, (4) computer and related services (IT), (5) R&D, and (6) business services.[11] To rule out the possibility that the change in exposure to Chinese import competition affects the degree of service input intensity, we measure SII_s using data for the late 1990s, i.e. before the time period considered in the rest of the analysis. $\mathbf{X}_{ist-1}$ is a vector of controls, including lagged variables varying at the CZ-time level and census divisions dummies interacted with sector fixed effects.[12] δ_{st} are sector-time fixed effects, which flexibly capture any sector specific time effect. ϵ_{ist} is the error term.

The marginal effect of changes in exposure to Chinese import competition on local employment is given by:

$$ME_s = \beta + \mu \times SII_s. \tag{3.2}$$

3.3.2 Data and estimation sample

The analysis distinguishes between the two time periods analysed by Autor et al. (2013), i.e., 1990-2000 and 2000-2007, with the latter adjusted to be a 10-year equivalent. For our dependent variable, changes in sectoral employment, we use County Business Patterns (CBP) data from the U.S. Census Bureau for the years 1990, 2000 and 2007. Data on working-age population are sourced from the Population Estimates Program (PEP) of the U.S. Census Bureau. We follow Autor et al. (2013) in controlling for unobserved demand shocks affecting at the same time changes in local employment levels and Chinese import competition. We also use their instrument, an exposure variable where bilateral trade flows from China to the US are replaced by trade flows from China to a basket of other advanced economies (Australia, Denmark, Finland, Germany, Japan, New Zealand, Spain, and Switzerland). These data were made available by David Dorn. For the services input intensity measure we use US Input Output tables from the OECD STAN database for the beginning of the 1990s. Summary statistics for the main variables used in the estimation are reported in Table 3.1.

[11]The business services category includes professional services such as legal, accounting, management consulting, and engineering.

[12]The 9 census divisions are identified by 8 dummies grouping together subsets of CZs.

Variable	Mean	Median	sd	Min	Max
ΔE_{ist}	-0.099	-0.001	0.706	-18.57	14.035
ΔIP_{it}	1.906	1.179	2.582	-0.629	43.085
SII_s	0.069	0.063	0.017	0.048	0.111

Table 3.1: Summary statistics for the main variables

3.4 Results

Table 3.2 reports the results of 2SLS estimation of equation (3.1) using the same instruments and controls as Autor et al. (2013). This confirms at a sector-local labor market level previously known results about a negative relative effect of import exposure on employment share. We confirm that our results are invariant to progressively adding control variables capturing relevant features of the local labor markets.[13] Note that we observe the effects in terms of percentage point changes, not levels, of employment share, and that the methodology permits analysis of relative effects, that is, the performance of more exposed local sector versus less exposed ones.

[13]The remarkable stability of the point estimate for the coefficient of the interaction term is due to the empirical relationship between the interaction term and CZ-level controls, once conditioning for the main effect of CZ-level import penetration and all the heterogeneity embedded in the fixed effects. Indeed services input intensity only varies at the sectoral level and it is constant across CZs.

Dependent variable: 10 year change in manuf empl / working-age pop (%)					
	(1)	(2)	(3)	(4)	(5)
Change in Import Exposure per worker	-0.107***	-0.0927***	-0.0875***	-0.0904***	-0.0918***
	(0.0250)	(0.0279)	(0.0259)	(0.0261)	(0.0261)
Change in Import Exposure per worker × SII	0.856***	0.856***	0.856***	0.856***	0.856***
	(0.30195)	(0.30195)	(0.30197)	(0.30196)	(0.30198)
% Employed in Manufacturing t-1		-0.00379***	-0.00635***	-0.00505***	-0.00490***
		(0.00132)	(0.00123)	(0.00103)	(0.000991)
% College Educated t-1			-0.00309**		-0.000702
			(0.00120)		(0.000853)
% Foreign Bornt-1			-0.00170***		0.00168**
			(0.000573)		(0.000698)
% Females Employed t-1			-0.00163		0.00257*
			(0.00170)		(0.00149)
% Employed in Routine Occupations t-1				-0.0105**	-0.0116***
				(0.00435)	(0.00430)
Average Offshorability Index t-1				-0.0395*	-0.0582***
				(0.0213)	(0.0194)
Observations	25,992	25,992	25,992	25,992	25,992
R-squared	0.258	0.264	0.269	0.272	0.272
Census division×Sector FE	YES	YES	YES	YES	YES
Sector×Decade FE	YES	YES	YES	YES	YES

Notes: The dependent variable is the 10-year equivalent change in manufacturing employment / working-age population in percentage points. All models are estimated using 2SLS. SII is a measure of services input intensity in the downstream sector. Standard errors in parenthesis are clustered by trading–pair. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table 3.2: Services input intensity mediates the effect of Chinese import competition

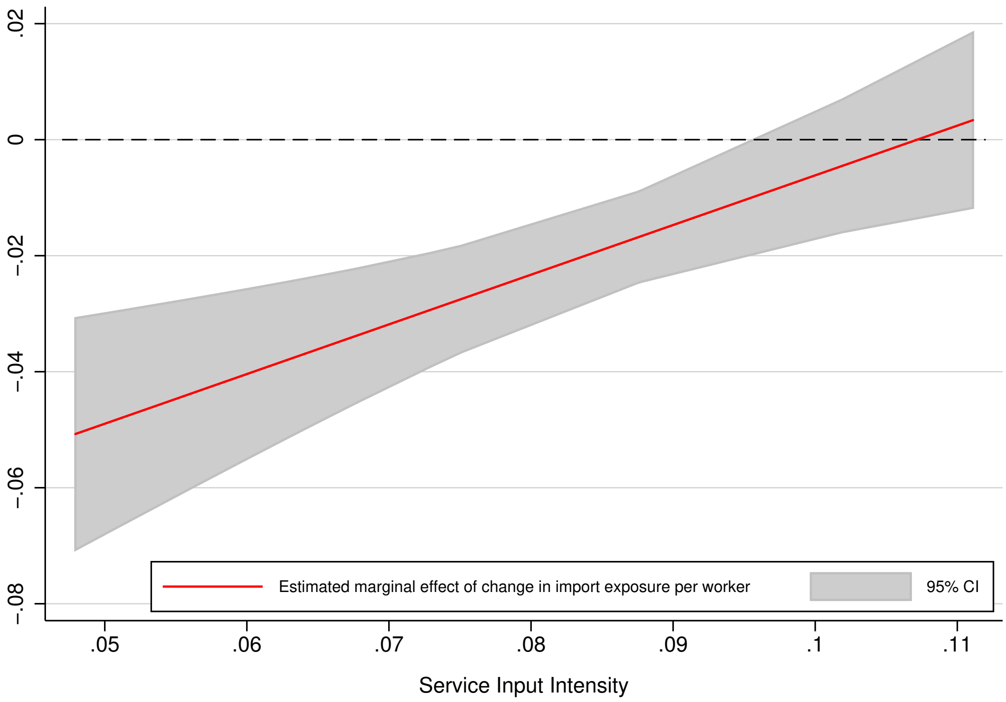
A novel finding from our analysis is the significant positive coefficient on the interaction between import exposure and services input intensity of the local manufacturing sector. This supports the hypothesis that greater use of services inputs may act to moderate adverse employment effects of an increase in import penetration.[14]

To illustrate this finding graphically, Figure 3.3 plots the marginal effect of the treatment on the dependent variable as a linear function of the moderator variable SII. The estimated marginal effect of exposure to manufactured imports is less negative the more the sector makes use of service inputs. For the highest values of

[14] Controling for endogeneity due to potential unobserved demand shocks using the instrumentation strategy is important as the OLS point estimates (not reported) of β and μ are -0.0420*** and 0.387* respectively, significantly underestimating this impact.

service input use observed in the sample the effect is not statistically different from zero.

Figure 3.3: Marginal effect of trade shock as a function of services input intensity



Notes: The figure shows the estimates and the corresponding 95% confidence intervals of equation (3.2) computed for different values of services input intensity.

The point estimates in column (5) show that, at the mean value of SII of 0.069, a \$1,000 exogenous decadal rise in CZ's import exposure per worker reduces sectoral manufacturing employment per working–age population by approximately 0.033 percentage points ($= -.0918 + 0.856 \times 0.069 = -0.033$). The same increase in import competition generates different effects depending on the sectoral SII. At the highest level of SII (0.111) the same increase in import exposure leads to an almost negligible increase in sectoral manufacturing employment. At the lowest level of SII (0.048), the same increase in import exposure leads to a reduction in sectoral manufacturing employment of 0.051 percentage points.

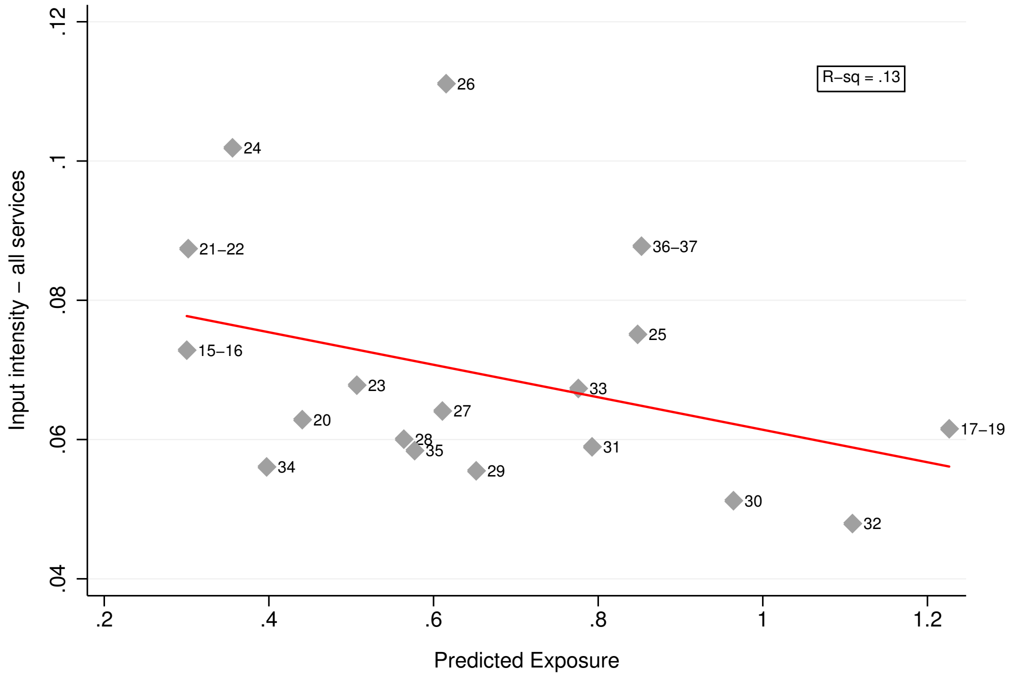
3.4.1 Services input intensity and sectoral import exposure

The foregoing demonstrates that services input intensity is a moderator of the China shock. SII is a "pre-treatment" sector-level characteristic of manufacturing sectors that potentially affects not only a sector's employment response to import competition but also the extent to which it is subject to exposure. As discussed previously, the employment effect of a trade shock will be sector-specific, depending on the degree of exposure, which is determined in part by the services intensity of different manufacturing industries. SII moderates the employment effect of the trade shock through its influence on the degree to which it attenuates the level of import competition it is confronted with, which is reflected in the magnitude of the shift of the labor demand curve across manufacturing sectors. Given the degree of sectoral exposure to import competition, services intensity may also affect a sector's response to greater import competition. This effect can operate both through a further shift in sector-specific labor demand and/or through variations across sectors in the elasticity of labor supply. In cases where labor supply is more elastic the net result may be to further reduce in labor demand.

Our empirical framework allows to precisely identify a sector's response to the China shock as long as services input intensity and sectoral import exposure are uncorrelated. In the spirit of Acemoglu et al. (2016b), to guarantee exogeneity, we use predicted sectoral exposure computed by regressing US sectoral exposure on the sectoral exposure of other high-income advanced economies. As Figure 3.4 shows, the estimated correlation between SII and predicted sectoral exposure is negative and equal to -0.36 (see Table 3.3). This suggests that the moderating effect of SII is at least partly driven by the lower values of sectoral exposure associated with higher SII.

In order to isolate the extent to which SII determines a manufacturing sector's ability to withstand a trade shock rather than merely reduce the extent to which it is subject to import competition, we construct an alternative measure of services input intensity that is independent of sector-level import competition from China. We do this by regressing SII on sectoral exposure and using the vector of residuals, denoted as $SIIres$, as the moderator in our main specification (equation (3.1)). $SIIres$ captures the portion of variability in SII which is orthogonal to sectoral import exposure. Any moderating effect of $SIIres$ can then be attributed solely to a manufacturing sector's response to import competition and not to variation across sectors in their exposure to import competition. For ease of comparison, Column (1) of Table 3.4 repeats the coefficent estimate for model 5 in Table 3.2. Column (2) of Table 3.4 reports the coefficient of $\Delta IP_{it} \times SIIres_s$. Since the coefficient is statistically not different from zero, we conclude that the properties of SII which determine its moderating role must be embedded in the portion of its variation that co-moves with sectoral exposure. Since the properties of SII that determine the

Figure 3.4: Correlation between exposure and service input intensity



Notes: The red line shows the fitted values of the univariate regression of SII on our measure of predicted exposure. Both variables are measured at the sectoral level and manufacturing sectors are denoted with their 2 digit ISIC Rev. 3 codes. The mapping between sectors codes and labels is as follows. 15-16: food products, beverages and tobacco; 17-19: textiles, textile products, leather and footwear; 20: wood and products of wood and cork; 21-22: pulp, paper, paper products, printing and publishing; 23: coke, refined petroleum products and nuclear fuel; 24: Chemicals and chemical products; 25: rubber and plastics products; 26: other non-metallic mineral products; 27: basic metals; 28: fabricated metal products except machinery and equipment; 29: machinery and equipment n.e.c; 30: office, accounting and computing machinery; 31: electrical machinery and apparatus n.e.c; 32: radio, television and communication equipment; 33: medical, precision and optical instruments; 34: motor vehicles, trailers and semi-trailers; 35: other transport equipment; 36-37: manufacturing n.e.c. and recycling.

response of manufacturing sectors to import competition could well be the same ones that result in a sector being less exposed, we are unable to distinguish between the role played by SII in determining the extent of sectoral exposure to import competiton and its role in determining the response to the trade shock.

In order to further investigate this question, we unpack SII at the level of each individual producer service component, generating six different services-specific measures of input intensity, denoted as SII^k, where k is the index for different categories of producer services inputs. Figure 3.5 plots the estimated correlation between manufacturing sector import exposure and the relevant SII^k variable. There is substantial heterogeneity across individual services sectors. For Finance and R&D we find that the correlation is equal to 0. In these two cases all of the moderating effect of SII^k (see Columns A:(5) and B:(3) of Table 3.5) can be attributed solely to

	Predicted Exposure
Input intensity - all services	-0.362
Input intensity - transport	-0.371
Input intensity - telecom	0.115
Input intensity - finance	-0.017
Input intensity - IT	0.284
Input intensity - R&D	0.003
Input intensity - business	-0.076
Observations	18

Notes: The table reports the Pearson correlation coefficient between sectoral service input intensity and sectoral exposure. The first row refers to all service sectors, whereas each of the remaining rows refers to one of the 6 service sectors.

Table 3.3: Correlation between service input intensity and exposure

	(1)	(2)
$\Delta IP_{it} \times SII_s$	0.856***	
	(0.302)	
$\Delta IP_{it} \times SIIres_s$		-0.397
		(0.396)
Observations	25,992	25,992

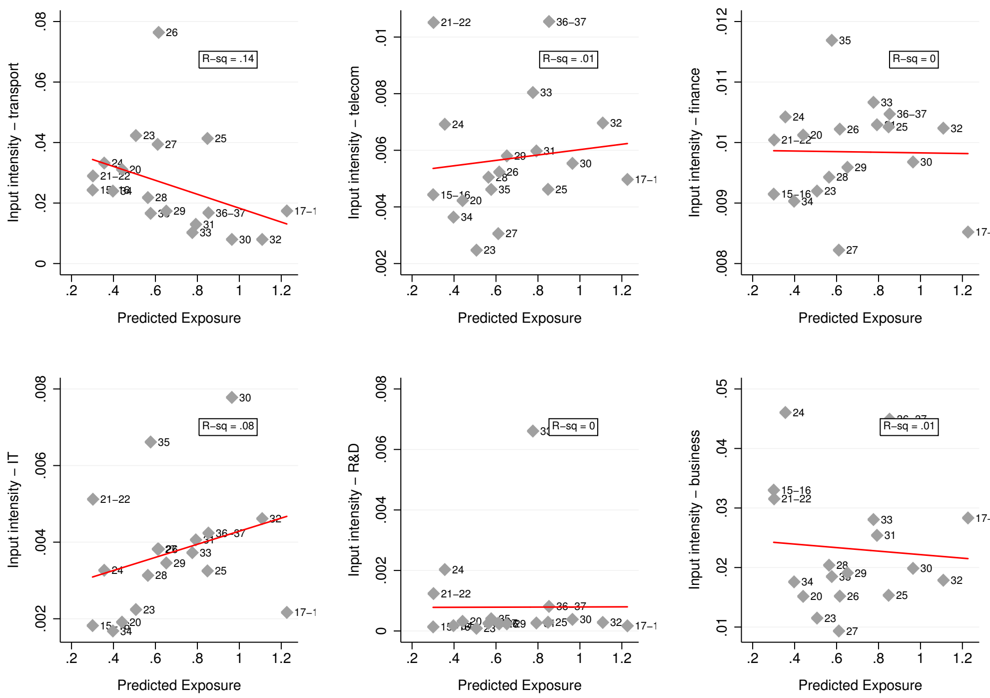
Notes: The table compares the moderating role of service input intensity, SII_s, in column (1) to the moderating role of the residual variation of service input intensity not explained by the variation in predicted exposure, $SIIres_s$, in column (2). The latter is obtained from a univariate regression of service input intensity on our measure of predicted exposure. Standard errors in parenthesis are clustered by trading–pair. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table 3.4: The role of service input intensity orthogonal to exposure

manufacturing sectors capacity to respond to import competition.

When the correlation is different from 0, we cannot distinguish between the effect of services intensity on import exposure and the effect on the employment response. For these cases, we substitute SII^k with $SIIres^k$ in the regression model in order to isolate the component of services input intensity that is orthogonal to predicted sectoral exposure. As shown in Column A:(2) the moderating properties of $SII^{Transport}$ are completely absorbed by the portion of its variability that co-moves with sectoral exposure to imports. In this case we replicate the result obtained using the aggre-

Figure 3.5: Correlation between import exposure and services sector-specific SII



Notes: The red lines show the fitted values of the univariate regressions of SII on our measure of predicted exposure. Both variables are measured at the sectoral level and manufacturing sectors are denoted with their 2 digit ISIC Rev. 3 codes. Each graph refers to the 6 different types of services. The mapping between sectors codes and labels is as follows. 15-16: food products, beverages and tobacco; 17-19: textiles, textile products, leather and footwear; 20: wood and products of wood and cork; 21-22: pulp, paper, paper products, printing and publishing; 23: coke, refined petroleum products and nuclear fuel; 24: Chemicals and chemical products; 25: rubber and plastics products; 26: other non-metallic mineral products; 27: basic metals; 28: fabricated metal products except machinery and equipment; 29: machinery and equipment n.e.c; 30: office, accounting and computing machinery; 31: electrical machinery and apparatus n.e.c; 32: radio, television and communication equipment; 33: medical, precision and optical instruments; 34: motor vehicles, trailers and semi-trailers; 35: other transport equipment; 36-37: manufacturing n.e.c. and recycling.

gate SII variable: higher services intensity reduces the negative impact on labor demand, but we cannot disentangle the mechanism through which this works. In the case of IT services, Column B:(1) reveals no statistically significant moderating effect of SII^{IT}, suggesting that IT plays no role in attenuating import exposure of manufacturing sectors or the response to increased import exposure. Finally, in the case of telecommunications and business services, higher values of $SII^{Telecom}$ and $SII^{Business}$ are associated with larger negative employment effects of the China shock. This is consistent with a situation where the supply side (elasticity) effect augments the demand side impact, resulting in a greater decline in manufacturing employment. In the case of telecommunications, these properties are again completely absorbed by the portion of the variation that co-moves with sectoral exposure. In contrast, in the case of business services, this effect is at least partly driven by variation that is orthogonal to predicted sectoral import exposure.

Panel A:	Transport		Telecom		Finance	
	(1)	(2)	(3)	(4)	(5)	(6)
$\Delta IP_{it} \times SII_s^k$	1.463***		-6.905*		25.018*	
	(0.464)		(3.919)		(14.466)	
$\Delta IP_{it} \times SIIres_s^k$		0.208		-3.988		23.875
		(0.497)		(3.867)		(14.404)
Panel B:	IT		R&D		Business	
	(1)	(2)	(3)	(4)	(5)	(6)
$\Delta IP_{it} \times SII_s^k$	-0.388		6.365*		-1.337*	
	(8.228)		(3.623)		(0.689)	
$\Delta IP_{it} \times SIIres_s^k$		10.588		6.484*		-1.768**
		(9.297)		(3.630)		(0.737)
Observations	25,992	25,992	25,992	25,992	25,992	25,992

Notes: The table compares the moderating role of service input intensity, SII_s^k, in column (1) to the moderating role of the residual variation of service input intensity not explained by the variation in predicted exposure, $SIIres_s^k$, in column (2). The latter is obtained from a univariate regression of service input intensity on our measure of predicted exposure. Each pair of columns refers to one of the 6 service sectors k. Standard errors in parenthesis are clustered by trading–pair. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table 3.5: Unpacking services-specific SII effects

These results should not be over-interpreted but are nonetheless informative. They suggest there are services sector-specific differences that are masked by the finding that at the aggregate level greater services intensity is associated with a smaller decline in manufacturing labor demand (employment) following the trade shock. This aggregate result is driven by transport, finance and R&D, with the last two service categories representing cases where the effect is independent of variation across manufacturing industries in exposure to import competition. Our unpacking of SII also reveals that for some types of services, business services in particular, the labor supply elasticity effect is significant: higher levels of $SII^{Business}$ are associated with a greater decline in labor demand. These findings illustrate the need for more disaggregated analysis of the role of specific types of services as opposed to a focus on broader categories of “services inputs” or servicification of manufacturing.

3.5 Conclusions

The evidence presented in this paper suggests that services intensity is a factor differentiating local US manufacturing employment responses to the China shock.

We find that the manufacturing sectors that have borne the brunt of the adjustment costs associated with import competition from China are those that are less services intensive, whereas those that use services inputs more intensively experienced less reductions in employment.

The decline in US manufacturing employment has been ongoing for decades, largely reflecting continued technological change. The share of services has expanded, reflecting a mix of inter-industry productivity differences, inter-industry shifts in the division of labor (outsourcing), and increasing final demand for services as per capita incomes rise Schettkat and Yocarini (2006). Looking forward, manufacturing jobs will continue to become more skill intensive and sophisticated and be associated with further servicification of production. The implications of servicification of the economy has long been a subject of research. Less well understood is how the rise in services outsourcing (and offshoring) impacts on the employment responses of manufacturing industries to trade shocks. This paper finds that services input intensity is a factor moderating the negative employment impacts of the China shock, but also shows that it is important to "unpack" this result. Different services play different roles and functions in making manufacturing employment more or less resilient to trade shocks. This suggests that future research needs to focus on disaggregating services further and analyzing the distinct roles different services may play in influencing the employment response to greater import competition.

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Appendices

Competition Networks: Proof of Proposition 1

$$\mathbb{E}\ \hat{\pi}_k[x(k), x^*(l_1), x^*(l_2), ..., x^*(l_k)] = \sum_{r \in S_k} P_k(r)\,(x(k) - c)\left(\alpha - kx(k) + \sum_{l=1}^{n-1} r_l x^*(l)\right) =$$

$$= (x(k) - c)\left(\alpha - kx(k) + \sum_{l=1}^{n-1} x^*(l) \sum_{r \in S_k} P_k(r) r_l\right)$$

First we define

$$\{r \in S_k : r_l > 0\} = \left\{(r_1, r_2, ..., r_{n-1}) \in \mathbb{Z}_+^{n-1} : \sum\ r_l = k \wedge r_l > 0\right\} =$$

$$\left\{(r_1, r_2, ..., r_l + 1, ..., r_{n-1}) \in \mathbb{Z}_+^{n-1} : \sum\ r_l = k - 1\right\} \equiv \hat{S}_{k-1}$$

and note that

$$= \sum_{r \in \hat{S}_{k-1}} \frac{(k-1)!}{r_1! r_2! \cdots (r_l - 1)! \cdots r_{n-1}!}\ \tilde{p}(1)^{r_1} \tilde{p}(2)^{r_2} \cdots \tilde{p}\,(l)^{\,r_l - 1} \cdots \tilde{p}(n-1)^{r_{n-1}} =$$

$$= \sum_{r \in S_{k-1}} \frac{(k-1)!}{r_1! r_2! \cdots (r_l)! \cdots r_{n-1}!}\ \tilde{p}(1)^{r_1} \tilde{p}(2)^{r_2} \cdots \tilde{p}\,(l)^{\,r_l} \cdots \tilde{p}(n-1)^{r_{n-1}} = 1$$

It follows that for all $l \in \{1, ..., n-1\}$ we have

$$\sum_{r \in S_k} P_k(r) r_l = \sum_{r \in S_k} \frac{k!}{r_1! r_2! \cdots r_{n-1}!}\ \tilde{p}(1)^{r_1} \tilde{p}(2)^{r_2} \cdots \tilde{p}(n-1)^{r_{n-1}} r_l =$$

$$= k\tilde{p}(l) \sum_{r \in S_k : r_l > 0} \frac{(k-1)!}{r_1! r_2! \cdots (r_l - 1)! \cdots r_{n-1}!}\ \tilde{p}(1)^{r_1} \tilde{p}(2)^{r_2} \cdots \tilde{p}\,(l)^{\,r_l - 1} \cdots \tilde{p}(n-1)^{r_{n-1}} = k\tilde{p}(l)$$

Therefore

$$(x(k) - c)\left(\alpha - kx(k) + \sum_{l=1}^{n-1} x^*(l) \sum_{r \in S_k} P_k(r) r_l\right) = (x(k) - c)\left(\alpha - kx(k) + k\sum_{l=1}^{n-1} x^*(l)\tilde{p}(l)\right)$$

This formulation allows to obtain a system of equations by taking first order conditions which characterises the equilibrium prices

$$\left.\frac{\partial(\cdot)}{\partial x(k)}\right|_{x(k)=x^*(k)} = 0$$

$$\alpha - 2kx^*(k) + ck + k\sum_{l=1}^{n-1} x^*(l)\tilde{p}(l) = 0 \Rightarrow x^*(k) = \frac{\alpha}{2k} + \frac{c}{2} + \frac{1}{2}\sum_{l=1}^{n-1} x^*(l)\tilde{p}(l)$$

$$\Rightarrow x^*(1) = \frac{\alpha}{2} + \frac{c}{2} + \frac{1}{2}\sum_{l=1}^{n-1} x^*(l)\tilde{p}(l) \Rightarrow \sum_{l=1}^{n-1} x^*(l)\tilde{p}(l) = 2x^*(1) - \alpha - c$$

$$\Rightarrow x^*(k) = x^*(1) + \frac{\alpha}{2k} - \frac{\alpha}{2}$$

$$\Rightarrow x^*(1) = \frac{\alpha}{2} + \frac{c}{2} + \frac{1}{2}\sum_{l=1}^{n-1} \tilde{p}(l)\left[x^*(1) + \frac{\alpha}{2l} - \frac{\alpha}{2}\right]$$

$$\Rightarrow x^*(1) = \frac{\alpha}{2} + \frac{c}{2} + \frac{1}{2}\sum_{l=1}^{n-1} \frac{p(l)l}{\sum_{q=1}^{n-1} p(q)q}\left[x^*(1) - \frac{\alpha}{2} + \frac{\alpha}{2l}\right]$$

$$\Rightarrow x^*(1) = \frac{\alpha}{2} + \frac{c}{2} + \frac{1}{2}\left[\sum_{l=1}^{n-1} \frac{p(l)l}{\langle k\rangle}\left(x^*(1) - \frac{\alpha}{2}\right) + \sum_{l=1}^{n-1} \frac{p(l)l}{\langle k\rangle}\frac{\alpha}{2l}\right]$$

$$\Rightarrow x^*(1) = \frac{\alpha}{2} + \frac{c}{2} + \frac{1}{2}\left[x^*(1) - \frac{\alpha}{2} + \sum_{l=1}^{n-1} \frac{p(l)}{\langle k\rangle}\frac{\alpha}{2}\right]$$

$$\Rightarrow x^*(1) = \frac{\alpha}{2} + \frac{c}{2} + \frac{1}{2}x^*(1) - \frac{\alpha}{4} + \frac{\alpha}{4}\frac{1-p(0)}{\langle k\rangle}$$

$$\Rightarrow x^*(1) = \frac{\alpha}{2} + c + \frac{\alpha}{2}\frac{1-p(0)}{\langle k\rangle}$$

$$\Rightarrow x^*(k) = \frac{\alpha}{2} + c + \frac{\alpha}{2}\frac{1-p(0)}{\langle k\rangle} + \frac{\alpha}{2k} - \frac{\alpha}{2} = c + \frac{\alpha}{2}\left[\frac{1}{k} + \frac{1-p(0)}{\langle k\rangle}\right] \blacksquare$$

It remains to determine $\mathbb{E}\hat{\pi}_k^*$, first we look at the demand component $\hat{D}_k^*$

$$\hat{D}_k^* = \alpha - k\left[c + \frac{\alpha}{2}\left(\frac{1}{k} + \frac{1-p(0)}{\langle k\rangle}\right)\right] + \frac{k}{\langle k\rangle}\sum_{l=1}^{n-1} p(l)l\left[c + \frac{\alpha}{2}\left(\frac{1}{l} + \frac{1-p(0)}{\langle k\rangle}\right)\right] =$$

$$= \alpha + k \left[\underbrace{-\frac{\alpha}{2k} - c - \frac{\alpha}{2} \frac{1 - p(0)}{\langle k \rangle}}_{\text{own price effect}} + \underbrace{c + \alpha \frac{1 - p(0)}{\langle k \rangle}}_{\text{others' price effect}} \right]$$

$$\mathbb{E}\hat{\pi}_k^* = \left(\frac{\alpha}{2k} + \frac{\alpha}{2} \frac{1 - p(0)}{\langle k \rangle} \right) \left(\frac{\alpha}{2} + \frac{\alpha k}{2} \frac{1 - p(0)}{\langle k \rangle} \right) = \frac{\alpha^2}{2} \left[\frac{k}{2} \left(\frac{1 - p(0)}{\langle k \rangle} \right)^2 + \frac{1}{2k} + \frac{1 - p(0)}{\langle k \rangle} \right]$$

The China Shock revisited: Insights from value added trade flows: Value added decomposition of gross trade flows at bilateral-sector level

In this section we aim to familiarise the reader with the basics of value added decomposition frameworks in order to provide some insight on how our more detailed trade data is generated. Getting to the value added structure of gross trade at a disaggregated level requires taking into account the differences between final and intermediate goods using more techniques that go beyond the standard Leontief decomposition. Wang et al. (2013) propose an accounting framework which builds on Koopman et al. (2014) using additional information found in ICIOs on the subsequent uses and final destinations of foreign value added inputs to domestic industry. For a detailed exposition we refer the reader to original papers. Our data applies their framework to the ADB-MRIO table and completely decomposes gross exports into four major categories: domestic value added absorbed abroad, domestic value added that returns home, foreign value added, and double-counted intermediate trade.

Below is the final decomposition for a simple two country one industry model (equation 22 in Wang et al. (2013)).

$$
\begin{aligned}
E^{kl} = {} & \left(V^k B^{kk}\right)^T * F^{kl} + \left(V^k L^{kk}\right)^T * \left(A^{kl} B^{ll} F^{ll}\right) \\
& + \left(V^k L^{kk}\right)^T * (A^{kl} \sum_{t \neq k,l}^{G} B^{lt} F^{tt}) + \left(V^k L^{kk}\right)^T * (A^{kl} B^{ll} \sum_{t \neq k,l}^{G} F^{lt}) \\
& + \left(V^k L^{kk}\right)^T * (A^{kl} \sum_{t \neq k}^{G} \sum_{l,u \neq k,t}^{G} B^{lt} F^{tu}) + \left(V^k L^{kk}\right)^T * \left(A^{kl} B^{ll} F^{lk}\right) \\
& + \left(V^k L^{kk}\right)^T * (A^{kl} \sum_{t \neq k,l}^{G} B^{lt} F^{tk}) + \left(V^k L^{kk}\right)^T * \left(A^{kl} B^{lk} F^{kk}\right) \\
& + \left(V^k L^{kk}\right)^T * (A^{kl} \sum_{t \neq k}^{G} B^{lk} F^{kt}) + \left(V^k B^{kk} - V^k L^{kk}\right)^T * \left(A^{kl} X^l\right) \\
& + \left(V^l B^{lk}\right)^T * F^{kl} + \left(V^l B^{lk}\right)^T * \left(A^{kl} L^{ll} F^{ll}\right) + \left(V^l B^{lk}\right)^T \\
& * \left(A^{kl} L^{ll} E^{l*}\right) + (\sum_{t \neq k,l}^{G} V^t B^{tk})^T * F^{kl} + (\sum_{t \neq k,l}^{G} V^t B^{tk})^T \\
& * \left(A^{kl} L^{ll} F^{ll}\right) + (\sum_{t \neq k,l}^{G} V^t B^{tk})^T * \left(A^{kl} L^{ll} E^{l*}\right),
\end{aligned}
\tag{3.3}
$$

Here E^{kl} represents exports from country k to l, F^{kl} is the final demand in l for goods of k, L^{ll} refers to the national Leontief inverse as opposed to the Inter-Country inverse B, and T indicates a matrix transpose operation. As can be seen from equation (3.3), this decomposition splits gross exports into 16 linear terms with four main categories which are subdivided by final destination, as described below.

- Domestic value added absorbed abroad (*vax_ g*, T1-5)
  - Domestic value added in final exports (*dva_fin*, T1)
  - Domestic value added in intermediate exports (*dva_ intt*, T2-5)
    - Domestic value added in intermediate exports absorbed by direct importers (*dva_ int*, T2)
    - Domestic value added in intermediate exports re-exported to third countries (*dva_ intrex*, T3-5)
      - Domestic value added in intermediate exports re-exported to third countries as intermediate goods to produce domestic final goods (*dva_ intrexi1*, T3)
      - Domestic value added in intermediate exports re-exported to third countries as final goods (*dva_ intrexf*, T4)
      - Domestic value added in intermediate exports re-exported to third countries as intermediate goods to produce exports (*dva_ intrexi2*, T5)
- Domestic value added returning home (*rdv*, T6-8)
  - Domestic value added returning home as final goods (*rdv_fin*, T6)
  - Domestic value added returning home as final goods through third countries (*rdv_fin2*, T7)
  - Domestic value added returning home as intermediate goods (*rdv_ int*, T8)
- Foreign value added (*fva*, T11-12/14-15)
  - Foreign value added in final good exports (*fva_fin*, T11/14)
    - Foreign value added in final good exports sourced from direct importer (*mva_fin*, T11)

    - Foreign value added in final good exports sourced from other countries (*ova_fin*, T14)
  - Foreign value added in intermediate good exports (*fva_ int*, T12/15)
    - Foreign value added in intermediate good exports sourced from direct importer (*mva_ int*, T12)
    - Foreign value added in intermediate good exports sourced from other countries(*ova_ int*, T15)
- Pure double counting (*pdc*, T9-10/13/16)
  - Pure double counting from domestic source (*ddc*, T9-10)
    - Due to final goods exports production (*ddf*, T9)
    - Due to intermediate goods exports production (*ddi*, T10)
  - Pure double counting from foreign source (*fdc*, T13/16)
    - Due to direct importer exports production (*fdf*, T13)
    - Due to other countries' exports production (*fdi*, T16)

It is due to this decomposition that we are able to disregard double counted terms in our analysis, and to split our bilateral exports into country-industry level DVA and FVA components. Note that Koopman et al. (2014) split the PDC term further into domestic and foreign content based on the origins of the double counted terms whereas here the entire PDC term is kept intact and apart from domestic value-added in order to allow total bilateral DVA to remain net of double counting.