



^b
**UNIVERSITÄT
BERN**

Faculty of Business, Economics
and Social Sciences

Department of Economics

**Estimating the Gains from Trade in Frictional Local
Labor Markets**

Germàn Pupato, Ben Sand, Jeanne Tschopp

19-09

August 2019

DISCUSSION PAPERS

Schanzeneckstrasse 1
CH-3012 Bern, Switzerland
<http://www.vwi.unibe.ch>

Estimating the Gains from Trade in Frictional Local Labor Markets *

Germán Pupato[†] Ben Sand[‡] Jeanne Tschopp[§]

August 2019

Abstract

We develop a theory and an empirical strategy to estimate the welfare gains of economic integration in economies with frictional local labor markets. The model yields a welfare formula that nests previous results in the literature and features an additional adjustment margin, via the employment rate, that generates new insights. We show that the quantitative impact of this new channel depends on the goods market structure and on the degree of firm heterogeneity. To obtain causal estimates of the two key structural parameters needed for the welfare analysis, the trade elasticity and the elasticity of substitution in consumption, we propose a theoretically-consistent identification strategy that exploits exogenous variation in production costs driven by differences in industrial composition across local labor markets. As an application, we exploit Germany's rapid trade integration with China and Eastern Europe between 1988 and 2008 to assess the quantitative importance of accounting for unemployment changes when computing the gains from trade across local labor markets in West Germany. Under monopolistic competition with free entry and firm heterogeneity, the median welfare gains in the frictional setting are 6% larger relative to the frictionless setting. The relative welfare gains are typically more modest under alternative market structures.

Keywords: Welfare gains from trade, trade elasticity, local labor markets, unemployment, wages, search and bargaining. **JEL Codes:** F12, F16, J31, J60.

* We are grateful to The Social Sciences and Humanities Research Council of Canada for its financial support and to the Research Data Centre of the German Federal Employment Agency at the Institute for Employment Research for providing data access. We also thank Wolfgang Dauth, Sebastian Findeisen and Jens Suedekum for sharing their data. We thank, without implicating, Paul Beaudry, Mauro Caselli, Marc Muendler, Tomasz Świącki and participants at the Canadian Economics Association, Sardinia Empirical Trade Conference, Empirical Investigations in International Trade, European Association of Labour Economists, Midwest International Trade Conference and the Conference of Swiss Economists Aborad, as well as seminar participants at Brock University, the University della Svizzera italiana, the University of Bern, York University, McMaster University, the University of St-Gallen and Ryerson University for helpful comments and suggestions. Busra Ariduru provided outstanding research assistance.

[†]Department of Economics, Ryerson University, 350 Victoria Street, Toronto, ON, M5B 2K3, Canada; gpupato@economics.ryerson.ca; +1 (416) 979-5000 (ext 3143).

[‡]Department of Economics, York University, 4700 Keele Street, Toronto, ON, M3J 1P3, Canada; bmsand@yorku.ca; +1 (416) 736-2100 (ext 20587)

[§]Department of Economics, University of Bern, Schanzeneckstrasse 1, 3001 Bern, Switzerland; jeanne.tschopp@vwi.unibe.ch; +41 31 631 45 05.

1 Introduction

The looming global trade war has reinvigorated the public debate on the merits of international economic integration. The media focus and the political discourse revolve largely around the impact of international trade on labor market outcomes, particularly on jobs and wages. Interest in this topic among economists has not lagged behind. For example, recent empirical research examines the effects of import penetration and export expansion on unemployment and wages in US local labor markets ([Autor et al. \(2013\)](#), [Acemoglu et al. \(2016\)](#) [Pierce & Schott \(2016\)](#), and [Feenstra et al. \(2017\)](#)). Concurrently, the literature has increasingly acknowledged the prominent empirical role that individual firms play in shaping the impact of trade shocks on the labor market ([Card et al. \(2013\)](#), [Helpman et al. \(2017\)](#) and [Song et al. \(2018\)](#)).

What do these findings imply for the outcome of ultimate interest, social welfare? Perhaps surprisingly, we know relatively little about the quantitative impact of trade-induced changes in unemployment on welfare and the role that firms play. Our objective in this paper is to develop a theory and an empirical strategy to estimate the welfare gains from trade in economies with frictional local labor markets.

The theory introduces search frictions and wage bargaining into a general equilibrium model with two open economies – one of them composed of many local labor markets – and multiple industries populated by potentially heterogeneous firms. Our first contribution is to derive a simple formula that enables a comparison of the gains from trade across models with alternative market structures (perfect and monopolistic competition) featuring either frictional or frictionless labor markets. Our welfare formula nests well-known results in the literature and establishes new insights.

For a class of workhorse models that assume full employment of factor endowments, [Arkolakis et al. \(2012\)](#) – henceforth, ACR – show that the welfare gains from trade can be inferred from the share of expenditure on domestic goods and the trade elasticity; i.e. the elasticity of imports with respect to variable trade costs. In our model, however, labor market frictions imply that trade liberalization impacts real income via an additional channel, the employment rate. Importantly, the quantitative impact of this adjustment margin depends on the goods market structure and on the existence of firm heterogeneity. Under monopolistic competition with free entry, the welfare gains of changes in the employment rate depend inversely on the elasticity of substitution in consumption. Intuitively, for a given share of domestic expenditure, changes in the employment rate generate two effects: on aggregate income and on consumer prices. The second effect operates via product variety, driven by entry and exit decisions of firms responding to changes in aggregate expenditure. We show that, condi-

tional on the trade elasticity, the magnitude of this second effect depends on whether firms are homogeneous ([Krugman \(1980\)](#)) or heterogeneous ([Melitz \(2003\)](#) and [Chaney \(2008\)](#)). Moreover, when the measure of consumption goods is fixed, only the first effect remains active and our welfare formula nests two additional cases of interest: monopolistic competition with restricted entry and perfect competition (i.e. a multi-industry extension of [Heid & Larch \(2016\)](#), for the [Armington \(1969\)](#) model with search and bargaining frictions).

Our second contribution is to obtain causal estimates of the two structural parameters that regulate the welfare gains from trade in our model, the elasticity of substitution and the trade elasticity. As we discuss below, these parameters also play crucial roles in a wide range of models and applications in the literature and hence our empirical methodology can, in principle, be applied well beyond the scope of this paper. We show that the two key structural parameters can be identified from two wage elasticities: the wage elasticity of firm-level domestic revenue and the wage elasticity of bilateral trade flows in a gravity equation that holds at the local-labor-market level. To address the endogeneity of wages in the two estimating equations, we propose an identification strategy that exploits exogenous variation in production costs driven by differences in industrial composition across local labor markets. Strategic bargaining between firms and workers implies that the local equilibrium wage depends on the industrial composition of the labor market: local labor markets with greater concentration of high-paying industries improve workers' outside option and, *ceteris paribus*, imply relatively higher costs for producers in any given industry. This property of the model naturally leads us to use Bartik-style instruments for the local wage in the estimating equations.

We implement our empirical methodology using firm-level data for Germany, spanning 24 local labor markets and 58 industries during 1993-2010. The Bartik instruments are computed from a weighted average of national-level industrial wage premia, with weights reflecting local industry employment composition in the initial year. Identification, therefore, stems from within-industry, across-city variation in local wages. For the instruments to be valid, we require shocks to local labor markets as well as technological innovations to be independent from local industrial composition in employment in the initial year. The validity of our instruments therefore hinges on the exogeneity of the base-period local industrial employment shares ([Goldsmith-Pinkham et al., 2017](#)). To evaluate the quality of our identification strategy, we propose a series of data-driven tests that consist in assessing the relevance of our instruments and the correlation of our instruments with observables in the base year. We also perform Hansen's test of overidentifying restrictions. Overall, the results from these tests support our instrumental variable strategy and the estimates we obtain are remarkably stable over a variety of specifications.

We estimate wage elasticities of -8 and -0.78 in the gravity and domestic revenue equations, respectively. From these, we recover an elasticity of substitution in consumption of 1.78 and a trade elasticity that ranges from 3.5 to 7, depending on the underlying micro details of the model. We find that OLS produces substantial biases, particularly in the gravity equation. Moreover, since welfare is inversely related to the elasticity of substitution, our IV estimate of 1.78 hints at the possibility that omitting labor market frictions and firm heterogeneity might lead to a substantial underestimation of the welfare gains from trade.

Finally, we exploit the rise of trade with China and Eastern Europe between 1988 and 2008 to assess the quantitative importance of accounting for firm heterogeneity and changes in unemployment when computing the gains from trade for local labor markets in West Germany. Our ex-post welfare evaluations take the trade elasticity and changes in local employment rates, domestic trade shares and industry composition as given by the data and ask: how do the measured gains from trade between 1988 and 2008 differ when changes in the employment rate are accounted for? The answer depends on the underlying market structure and on the existence of firm heterogeneity. Indeed, under monopolistic competition with free entry and firm heterogeneity, welfare gains in the frictional setting are 6% greater than those predicted by ACR's formula, for the median local labor market in West Germany. In contrast, accounting for changes in the employment rate in frameworks with homogeneous firms, monopolistic competition with restricted entry or perfect competition yield gains that are around 3% larger.

The paper belongs to a growing literature that studies the interrelationship between labor market outcomes and international trade. Our theoretical framework is related to papers that introduce search frictions, as in [Pissarides \(2000\)](#), into the heterogeneous firms model of [Melitz \(2003\)](#). [Helpman & Itskhoki \(2010\)](#) and [Helpman et al. \(2010\)](#) theoretically examine the impact of trade liberalization on unemployment, wages and welfare but do not attempt a quantitative assessment of the gains from trade. [Helpman et al. \(2017\)](#) structurally estimate their model but focus on wage inequality rather than welfare. Our model departs from [Felbermayr et al. \(2011\)](#) by considering asymmetric locations in terms of trade costs and distributions of firm productivity. This feature allows us to escape from a separability result established in Lemma 1 of [Felbermayr et al. \(2011\)](#), under which productivity cutoffs and industry exports do not depend on local wages. In contrast, that link plays a central role in our empirical strategy. [Świącki \(2017\)](#) extends ACR's welfare formula in a Ricardian model that features labor misallocation across industries. Since full employment still prevails in equilibrium, welfare changes are independent of the employment rate – whereas their dependence is a key feature of our theory.

A widely popular approach to estimating the trade elasticity relies on the gravity equa-

tion for bilateral trade. In a broad class of models that comply with structural gravity assumptions, [Head et al. \(2014\)](#) show that the trade elasticity can, in principle, be identified from variation in either bilateral trade costs (e.g. distance or tariffs) or, closer to our approach, export “competitiveness” (e.g. wages or productivity). In both cases, the central empirical challenge is finding reliable instruments that can be excluded from the gravity equation. Similarly, the standard approach to estimating elasticities of substitution, developed by [Feenstra \(1994\)](#), [Broda & Weinstein \(2006\)](#) and [Soderbery \(2015\)](#), requires no correlation between the error terms in bilateral import demand and export supply equations, a restrictive yet necessary assumption in the absence of exogenous supply shifters.

The novelty of our empirical approach is to propose model-based, Bartik-style instruments that exploit wage and employment variation across industries and local labor markets to identify the elasticity of substitution and the trade elasticity. Moreover, since our approach relies exclusively on within-country variation, the resulting estimates are less prone to identification challenges that plague cross-country estimation of the gravity equation, including reverse causality due to endogenous tariff protection and omitted variable bias due to unmeasured institutional features of countries that are potentially correlated with trade flows, tariffs and factor prices. As long as trade policy and institutions do not vary across local labor markets within a country, their effects can be controlled for with an appropriate set of fixed effects.

The remainder of the paper is organized as follows. Section 2 develops the theoretical framework. Section 3 discusses the empirical strategy. Section 4 describes the data. Section 5 reports the estimation results. Section 6 presents our counterfactual exercises. The final section concludes. The Online Appendix contains theoretical derivations, details on the linear approximations and additional empirical results.

2 Theoretical Framework

2.1 Setup

There are two countries, Home and Foreign. Home (Germany) is composed of local labor markets called cities, indexed by $c \in \{1, \dots, C\}$. Since we do not observe export destinations in the data, we assume that Foreign is a single economy with no internal barriers (the extension is straightforward). We will use subscript n to denote a particular location irrespective of its country and subscript F when referring specifically to Foreign.

Demand. Each location n is populated by a continuum of infinitely-lived individuals of mass \bar{L}_n with identical risk-neutral preferences, represented by a time-separable and stationary Cobb-Douglas instantaneous utility function defined over the consumption of I differentiated goods. Time is discrete and denoted by $t \geq 1$. The normative representative consumer in market n maximizes $\sum_{t=1}^{\infty} \prod_{i=1}^I (Y_{int})^{\alpha_i} / (1 + \rho)^t$, where α_i is the share of expenditure on good i , $\rho > 0$ is the discount factor and

$$Y_{int} = \left[\int_{\omega \in \Omega_{int}} q_{int}(\omega)^{\frac{\sigma_i-1}{\sigma_i}} d\omega \right]^{\frac{\sigma_i}{\sigma_i-1}}, \quad \sigma_i > 1,$$

is a CES index of the aggregate consumption $q_{int}(\omega)$ of varieties $\omega \in \Omega_{int}$ of good i . σ_i is the elasticity of substitution. The set Ω_{int} may contain varieties produced in any city (intranational trade) and Foreign (international trade). The composition and measure of Ω_{int} is determined endogenously if and only if there is free entry.

In a standard setting with sequential trading in complete one-period Arrow securities, the aggregate consumption and equilibrium price of every differentiated good are time-invariant if the aggregate consumer income is time-invariant. As in [Hopenhayn \(1992\)](#) and [Melitz \(2003\)](#), our analysis is restricted to stationary equilibria and thus we henceforth suppress the time subscript to ease notation.¹ For good i in market n , the aggregate demand for variety ω with price $p_{in}(\omega)$ is

$$q_{in}(\omega) = A_{in} p_{in}(\omega)^{-\sigma_i}, \quad (1)$$

where $A_{in} = X_{in} P_{in}^{\sigma_i-1}$ is the demand shifter, X_{in} is total expenditure and

$$P_{in} = \left[\int_{\omega \in \Omega_{in}} p_{in}(\omega)^{1-\sigma_i} d\omega \right]^{\frac{1}{1-\sigma_i}}$$

is the price index.

Product Markets. For ease of exposition, we focus on analyzing a monopolistically competitive setting with free entry and heterogeneous firms. We briefly discuss the special cases of homogeneous firms with free or restricted entry and defer the details to the Online Appendix. The latter also contains a complete treatment of the case of perfect competition in the goods market under constant returns to scale.

¹At this point, the reader may wonder about the rationale for setting up a dynamic, rather than static, model if the analysis is restricted to stationary equilibria. Essentially, the dynamic setting allows us to have a microfounded outside option for workers that depends on the probability of future transitions to alternative jobs in the economy. This property plays a key role in our empirical strategy. In contrast, in a static search framework outside options do not depend on the industrial composition of the economy.

A competitive fringe of risk-neutral firms can acquire a blueprint to produce a unique variety of good i in city c by incurring a sunk per-period investment f_{ic}^E that terminates in any period with exogenous probability δ_c . To serve any market n , the firm must incur an additional fixed cost f_{icn} per period and a variable iceberg trade cost, such that τ_{icn} units of the firm's output must be produced per unit that arrives in market n . We assume $\tau_{icn} \geq \tau_{icc} = 1$ and that variable trade costs respect the triangular inequality for any three locations. Fixed and entry costs are measured in units of (non-production) workers hired in the domestic labor market.

Upon entry (but before incurring any fixed and variable costs), the firm discovers the time-invariant productivity of its production workers, denoted φ , an independent draw from a known distribution $G_{ic}(\varphi)$ with positive support. Firms thus operate under constant but heterogeneous marginal returns to the variable input. All firms with the same productivity behave symmetrically in equilibrium, hence we index firms and varieties by φ from now onward. Prior to the beginning of the following period, the firm is hit by an i.i.d. shock that forces it to exit with probability δ_c .

For the case of homogeneous firms, we consider a degenerate productivity distribution and set $f_{ic}^E = f_{icn} = 0$. In addition, under free entry, there is a fixed startup cost f_{ic} that depends on the industry and location of the producer. Alternatively, under restricted entry, the mass of producers is exogenous.

Labor Market Frictions and Bargaining. Each individual in city c is endowed with one unit of labor. In addition, we assume that workers are not mobile across cities, hence \bar{L}_c represents the exogenous labor endowment in c .² The local labor market is characterized by search frictions and wage bargaining, modeled as in [Felbermayr et al. \(2011\)](#). In each period, firms post vacancies and all unemployed workers search. Matching is random and determined by a linearly homogeneous matching function. $m_c(\theta_c)$ denotes the vacancy filling rate, a decreasing function of the vacancy-unemployment ratio (or labor market tightness) θ_c . The job finding rate is $\theta_c m_c(\theta_c)$. Let k_{ic} denote the number of units of the numeraire that firms must expend to post one vacancy; we henceforth refer to k_{ic} as the (unit) cost of posting vacancies. The recruitment cost per matched worker is $[k_{ic}/m_c(\theta_c)]$.³ Matched workers enter

²This modelling approach is motivated by the lack of response of city-specific population size to trade shocks in our empirical application (Section 6). [Autor et al. \(2013\)](#) report a similar finding across US local labor markets. [Redding & Rossi-Hansberg \(2017\)](#) review a literature that allows for endogenous migration in a class of quantitative spatial models similar to ours.

³We allow search costs to vary across cities through labor market tightness and across cities and industries through the cost of vacancy postings. [Mühlemann & Leiser \(2015\)](#), using detailed establishment-level survey data from Switzerland, empirically show that costs associated with vacancy postings make up a significant proportion of recruiting costs and vary substantially by industry.

production in the following period. Before production takes place, wages are determined by an intra-firm bargaining process that assumes the absence of binding employment contracts, as in [Stole & Zwiebel \(1996\)](#).⁴ All payments are made at the end of each period. Workers earn no income while unemployed.

2.2 The Firm's Problem

We analyze the problem of a firm with productivity φ producing good i in city c . As anticipated, we restrict attention to stationary equilibria in which firm productivity distributions and all aggregates remain constant through time. We proceed in three steps. First, taking employment and export decisions as given, the firm seeks to maximize revenue by allocating output optimally across destinations. This is a static problem that yields firm revenue as a function of employment. Second, the firm solves a dynamic vacancy posting problem to determine the profit-maximizing employment level, anticipating the effect of this decision on the wage bargaining outcome. Finally, the firm makes entry and exit decisions, supplying all locations that generate non-negative profits.

The (Conditional) Revenue Function. A firm with productivity φ and l production workers allocates output to equalize marginal revenues across any two markets it serves. With CES demand (1), the c.i.f. price in market n is then proportional to the domestic price; i.e., $p_{icn}(\varphi) = \tau_{icn} p_{icc}(\varphi)$. This property enables a convenient aggregation of destination-specific revenues that allows us to express the firm's total revenue, $r_{ic}(l; \varphi)$, as a function of l :

$$r_{ic}(l; \varphi) = \left[\sum_n I_{icn}(\varphi) A_{in} (\tau_{icn})^{1-\sigma_i} \right]^{\frac{1}{\sigma_i}} (l\varphi)^{\frac{\sigma_i-1}{\sigma_i}}, \quad (2)$$

where $I_{icn}(\varphi)$ is an indicator function equal to one when the firm supplies good i in market n .

Optimal Vacancy Posting. Firms post vacancies, denoted v , in order to maximize the present value of expected profits. Firm φ currently employing l production workers solves:

⁴Wage agreements can be renegotiated any time before production begins. A firm may fire an employee or the latter may quit, in which case the worker immediately returns to the unemployment pool. During the bargaining process, the firm cannot recruit additional workers. Once production begins, wage agreements become binding. In equilibrium, wages are immune to intra-firm pairwise renegotiations.

$$\Pi_{ic}(l; \varphi) = \max_v \frac{1}{1 + \rho} \left\{ r_{ic}(l; \varphi) - w_{ic}(l; \varphi)l - w_{ic} \sum_n I_{icn}(\varphi) f_{icn} - k_{ic}v + (1 - \delta_c) \Pi_{ic}(l'; \varphi) \right\},$$

s.t. $l' = l + m_c(\theta_c)v,$

(3)

where l' is the mass of production workers in the following period. $w_{ic}(l; \varphi)$ is the wage bargaining outcome, characterized below. Note that we allow the firm to internalize the effect of employment size on the cost of recruiting production workers. For tractability, however, we assume that the firm takes the wage of non-production workers w_{ic} as given when solving (3) and impose $w_{ic} = w_{ic}(l; \varphi)$ in equilibrium.⁵

The first-order condition in problem (3),

$$(1 - \delta_c) \frac{\partial \Pi_{ic}(l'; \varphi)}{\partial l'} = \frac{k_{ic}}{m_c(\theta_c)},$$
(4)

equates the expected marginal profit of hiring an additional worker to the recruitment cost per worker. Equation (4) has two important implications. First, optimal employment size is independent of current employment l and constant over time as long as the firm is not forced to exit the market. In other words, employment in a firm that starts with no workers reaches its optimal long-run level in the following period.⁶ Second, the marginal profit of hiring an additional worker, $\partial \Pi_{ic}(l; \varphi) / \partial l$, is equalized across firms, despite heterogeneity in labor productivity. This result plays an important role in the outcome of the wage bargaining process.

Bargaining. The firm and its workers engage in strategic wage bargaining as in [Stole & Zwiebel \(1996\)](#), a generalization of Nash bargaining to the case of multiple workers. The value of employment in a firm with productivity φ and l production workers, denoted $E_{ic}(l; \varphi)$,

⁵This condition ensures a closed-form solution for $w_{ic}(l; \varphi)$ in the bargaining game while adhering to the usual practice in the trade literature of measuring fixed costs in terms of domestic labor (e.g. [Melitz \(2003\)](#) and [Melitz & Redding \(2014\)](#)). The assumption holds if, upon matching, an unemployed worker observes the industry of the match and then chooses either (i) to work in a random firm in the industry as a production worker or (ii) to competitively supply one unit of a homogeneous, non-tradable ‘market access’ service to local firms as a non-production worker. In equilibrium, matched workers must be indifferent between the two options, hence the (city-industry) wage for non-production workers will be equal to the expected wage of production workers across firms in a given city-industry cell. Below we show that all firms in a given city-industry cell pay the same wage, denoted w_{ic} , to production workers.

⁶The absence of transitional dynamics ensures sufficient analytical tractability to nest the ACR formula, one of the key objectives of our theory. In particular, we rely on this property in the derivation of sufficient statistics for welfare changes due to trade liberalization. We leave the study of transitional dynamics for a future dedicated paper on this important topic.

satisfies

$$(\rho + \delta_c) [E_{ic}(l; \varphi) - U_c] = w_{ic}(l; \varphi) - \rho U_c, \quad (5)$$

where U_c is the value of unemployment or outside option. The surplus splitting rule that solves the bargaining game can then be written as:

$$(1 - \beta_i) [E_{ic}(l; \varphi) - U_c] = \beta_i \frac{\partial \Pi_{ic}(l; \varphi)}{\partial l}, \quad (6)$$

where $\beta_i \in (0, 1)$ denotes the bargaining power of workers.⁷ Combining the revenue function (2), the envelope condition from (3), the first-order condition (4) and the value of employment (5), we can express the surplus-splitting rule (6) as a differential equation for the wage schedule. Its solution is the Wage Curve:

$$w_{ic} = \rho U_c + \frac{\beta_i}{(1 - \beta_i)} \left(\frac{\rho + \delta_c}{1 - \delta_c} \right) \frac{k_{ic}}{m_c(\theta_c)}. \quad (7)$$

Three remarks are in order. First, the equilibrium wage does not vary across firms within city-industry cells. Intuitively, firms adjust their labor force until the marginal profit of hiring an additional worker is equalized across firms. By (6), this equalizes the value of employment across firms. Wage equalization then follows from (5). Second, the city-industry wage w_{ic} depends on the industrial composition of the labor market (quality of jobs) and on the tightness of the labor market (quantity of jobs), via the worker's outside option U_c . To see this, let η_{ic} denote the share of employment of industry i in city c . Then

$$\rho U_c = \frac{\theta_c m_c(\theta_c)}{\rho + \delta_c} \sum_i \eta_{ic} (w_{ic} - \rho U_c). \quad (8)$$

By (8), cities with greater concentration of high-wage industries improve workers' outside option and display, *ceteris paribus*, a higher bargained wage in any given industry i . Finally, note that inter-industry wage differentials within local labor markets are driven by cross-industry variation in bargaining power (β_i) and costs of posting vacancies (k_{ic}).

Firm-level Outcomes. The stationarity of the vacancy posting problem implies that firms face a constant cost per employee each period, denoted μ_{ic} , equal to the wage plus the

⁷Note that the marginal surplus of the firm, $\partial \Pi_{ic}(l; \varphi) / \partial l$, accounts for the impact of employing an additional worker on the wage of the remaining production workers, a key feature of [Stole & Zwiebel \(1996\)](#). Also note that the surplus is expressed in units of the numeraire.

recruitment cost expressed on a per-period basis. In the Online Appendix, we show that

$$\mu_{ic} = w_{ic} + \left(\frac{\rho + \delta_c}{1 - \delta_c} \right) \frac{k_{ic}}{m_c(\theta_c)}. \quad (9)$$

Henceforth, we refer to μ_{ic} as the *cost of labor* in industry i of city c .

Under CES demand, the profit maximizing revenue per worker is a fixed proportion $(\sigma_i - \beta_i) / (\sigma_i - 1)$ of the cost of labor.⁸ This property enables closed-form solutions for all firm-level equilibrium outcomes in terms of the cost of labor μ_{ic} and demand shifters A_{in} . In particular, the firm's per-period revenue, denoted $r_{ic}(\varphi)$, can be written as

$$r_{ic}(\varphi) = \left(\frac{\sigma_i - 1}{\sigma_i - \beta_i} \right)^{\sigma_i - 1} \left[\sum_n I_{icn}(\varphi) A_{in} (\tau_{icn})^{1 - \sigma_i} \right] \left(\frac{\varphi}{\mu_{ic}} \right)^{\sigma_i - 1}. \quad (10)$$

Note that the partial elasticity of firm-level revenue with respect to the local cost of labor is fully determined by the elasticity of substitution, a property that we exploit in the empirical analysis.

In turn, the per-period profit (gross of the entry cost) is

$$\pi_{ic}(\varphi) = \left(\frac{1 - \beta_i}{\sigma_i - \beta_i} \right) r_{ic}(\varphi) - \mu_{ic} \sum_n I_{icn}(\varphi) f_{icn}. \quad (11)$$

The per-period profit generated by entering any particular market n is computed by switching the corresponding entry decision on ($I_{icn}(\varphi) = 1$) and off ($I_{icn}(\varphi) = 0$) in (11). The existence of fixed costs of market access and the monotonicity of revenue in firm productivity imply that there is a cutoff productivity level, denoted φ_{icn}^* , such that a firm with productivity φ enters market n if and only if $\varphi \geq \varphi_{icn}^*$. The cutoff satisfies

$$\left(\frac{1 - \beta_i}{\sigma_i - \beta_i} \right) r_{icn}(\varphi_{icn}^*) = \mu_{ic} f_{icn} \Leftrightarrow \Lambda_i^0 A_{in} (\tau_{icn})^{1 - \sigma_i} (\varphi_{icn}^*)^{\sigma_i - 1} (\mu_{ic})^{-\sigma_i} = f_{icn}, \quad (12)$$

where $r_{icn}(\varphi)$ denotes the sales of firm φ in market n and $\Lambda_i^0 > 0$ is a function of parameters σ_i and β_i .⁹

It is worth highlighting that with symmetric cities/locations, productivity cutoffs would be independent of the tightness in the labor market, a separability result established in [Felbermayr et al. \(2011\)](#).¹⁰ By relaxing symmetry across cities, we can circumvent this

⁸This is a usual property in static monopolistic competition models with CES demand and competitive labor markets that leads to a constant mark-up pricing rule. In the Online Appendix section A.2, we verify that it also holds in the current stationary setup with search and bargaining frictions.

⁹More specifically, $\Lambda_i^0 = (1 - \beta_i) (\sigma_i - 1)^{\sigma_i - 1} / (\sigma_i - \beta_i)^{\sigma_i}$.

¹⁰To see this, assume for a moment that countries are symmetric. In this case, equation (12) pins down the

result and allow the cost of labor (and hence outside options and the industrial composition of the labor market) to have a feedback effect on equilibrium productivity distributions and firm selection into export markets. As we show below, this property plays a crucial role in our empirical approach to identifying key structural parameters that regulate the gains from economic integration in our model.

2.3 Gravity

In this section, we show that the model delivers a sectoral gravity equation relating bilateral trade flows to the cost of labor at the city level when firm productivity follows a Pareto distribution. In the empirical analysis, we use the gravity equation to estimate key structural parameters that regulate the welfare gains of economic integration.

We start by aggregating firm sales in industry i from city c to location n , denoted X_{icn} . Letting M_{ic}^e denote the mass of *entrants* in cell ic , we have $X_{icn} = M_{ic}^e \int_{\varphi_{icn}^*}^{\infty} r_{icn}(\varphi) dG_{ic}(\varphi) / \delta_c$.¹¹ To eliminate M_{ic}^e from the gravity equation, we focus on the share of exports in sectoral revenue, X_{icF} / R_{ic} , where $R_{ic} \equiv \sum_n X_{icn}$. Assume that $G_{ic}(\varphi)$ follows a Pareto distribution with positive lower bound $\varphi_{\min,ic}$ and shape parameter κ_i , where $\kappa_i > \sigma_i - 1$.¹² Using equation (10), we obtain

$$\frac{X_{icF}}{R_{ic}} = \frac{(\varphi_{icF}^*)^{-\kappa_i} f_{icF}}{\sum_n (\varphi_{icn}^*)^{-\kappa_i} f_{icn}}. \quad (13)$$

We can simplify this expression using the free entry and cutoff conditions. For cell ic , the free entry condition equates the expected per-period profit for entrants to the expected per-period entry cost, i.e. $\int_0^{\infty} \pi_{ic}(\varphi) dG_{ic}(\varphi) = \mu_{ic} f_{ic}^E$. Under Pareto productivity, this fixes the denominator of (13).¹³ Using the export cutoff condition (12) to eliminate φ_{icF}^* from the numerator of (13), the latter becomes

$$\frac{X_{icF}}{R_{ic}} = \Lambda_i^1 (f_{ic}^E)^{-1} (f_{icF})^{1 - \frac{\varepsilon_i}{\sigma_i - 1}} \left(\frac{\varphi_{\min,ic}}{\tau_{icF}} \right)^{\varepsilon_i} (A_{iF})^{\frac{\varepsilon_i}{\sigma_i - 1}} (\mu_{ic})^{-\frac{\varepsilon_i \sigma_i}{\sigma_i - 1}}, \quad (14)$$

ratio of the export and domestic cutoffs in any industry independently of the cost of labor. In turn, it can be shown that the (industry-specific) free entry condition provides a second equation for the two productivity cutoffs that is independent of the cost of labor (e.g. the next section illustrates this for the case of Pareto productivity distributions).

¹¹This expression relies on the aggregate stability condition, which requires that the mass of successful entrants $(1 - G_{ic}(\varphi_{icc}))M_{ic}^e$ exactly replaces the mass $\delta_c M_{ic}$ of producers who exit in each period.

¹²Note that we allow for Ricardian comparative advantage by letting the lower bound vary across cities and industries.

¹³Under Pareto productivity, the free entry condition in cell ic simplifies to

$$\left(\frac{\sigma_i - 1}{\kappa_i - \sigma_i + 1} \right) (\varphi_{\min,ic})^{\kappa_i} \sum_n (\varphi_{icn}^*)^{-\kappa_i} f_{icn} = f_{ic}^E.$$

where $\varepsilon_i \equiv \kappa_i$ is the *trade elasticity*; i.e. (the absolute value of) the partial elasticity of the export share with respect to the variable trade cost. $\Lambda_i^1 > 0$ is a function of parameters β_i , ε_i , σ_i and ρ .¹⁴ Conditional on the demand shifter in Foreign, A_{iF} , a higher cost of labor in industry i in city c reduces its share of exports of this good by tightening firm selection into the export market.¹⁵

The Wage Elasticity and Market Structure. The partial elasticity of the export share with respect to the cost of labor μ_{ic} plays an important role in the rest of this paper. In the empirical section, we refer to it as the *wage elasticity* of the gravity equation, for reasons that will become clear.

Under monopolistic competition, free entry and heterogeneous firms, the wage elasticity depends on two structural parameters, the elasticity of substitution σ_i and the trade elasticity ε_i . More generally, however, the structural interpretation of the wage elasticity depends on the underlying market structure. Under the alternative market structures considered in the Online Appendix, the wage elasticity is a sufficient statistic for the trade elasticity. For example, we show that under monopolistic competition and homogeneous firms (with free or restricted entry) the trade elasticity is equal to the wage elasticity minus one.

2.4 Welfare

In this section, we study the consequences of economic integration on the welfare of consumers in city c . Holding intracity variable trade costs constant, we analyze otherwise arbitrary shocks to variable trade costs, therefore spanning various forms of intranational and international integration. We show that, when frictions in the local labor market are small, the welfare consequences of economic integration can be approximated by a parsimonious generalization of ACR's welfare formula that features an additional adjustment margin, via the employment rate.

Consumer preferences satisfy the Gorman form, hence there exists a normative representative consumer in every city. Recall that aggregate consumption and aggregate income are constant in any stationary equilibrium. Therefore the indirect utility of the representative

¹⁴Specifically, $\Lambda_i^1 = \left(\frac{\sigma_i - 1}{\varepsilon_i - \sigma_i + 1} \right) \left(\frac{1 - \beta_i}{\sigma_i - \beta_i} \right)^{\frac{\varepsilon_i \sigma_i}{\sigma_i - 1}}$.

¹⁵Note that if μ_{ic} increases (e.g. due to higher bargained wages or recruitment costs), not all cutoffs φ_{icn}^* in a given cell ic can increase because that would reduce profitability in all destinations, violating the free entry condition. However, if Foreign's demand shifter does not change (e.g. if the city is small relative to the rest of the world), the export cutoff φ_{iF}^* indeed increases, reducing the city's export share of good i . This observation underscores the importance of controlling for the demand shifter of the export market when estimating the elasticity of the export share with respect to the cost of labor.

consumer in city c , denoted V_c , is proportional to the per-period real income in the city:

$$V_c = \rho^{-1} \left(\prod_{i=1}^I (\alpha_i)^{\alpha_i} \right) \frac{\sum_{i=1}^I L_{ic} w_{ic}}{\prod_{i=1}^I (P_{ic})^{\alpha_i}},$$

where L_{ic} is the mass of workers employed in industry i .¹⁶

Trade Liberalization. Consider the effects of an arbitrary shock to the vector of variable trade costs, $\{\tau_{ivn}\}$ for any industry i and any two different locations n and v , on the welfare of city c . For any endogenous variable x , let \dot{x} denote the ratio of x after the shock to x before the shock; i.e. the proportional change in the stationary equilibrium value of x .

To enhance both comparability and analytical tractability, we focus on small deviations from the benchmark frictionless settings typically considered in the literature. In particular, suppose that the cost of posting vacancies in city c , k_{ic} , is small in all industries. Equation (7) implies that interindustry wage differentials are small in city c ; that is, $w_{ic} \approx w_c$ for all i , where w_c is the average wage in c . Then

$$\dot{V}_c \approx \frac{\dot{e}_c \dot{w}_c}{\prod_{i=1}^I (\dot{P}_{ic})^{\alpha_i}}, \quad (15)$$

where e_c is the employment rate in city c , i.e. $e_c = \sum_i L_{ic}/L_c$.¹⁷ Note that \dot{V}_c is the equivalent variation expressed as a fraction of the per-period income in the initial equilibrium.

The price index of any good i in city c depends on trade costs, costs of labor, technology and mass of producers of good i in all other locations that supply city c . We follow ACR and use city c 's domestic trade share, $\lambda_{icc} \equiv X_{icc}/\sum_v X_{ivc}$, as a sufficient statistic for the impact of all these external effects on P_{ic} . In the Online Appendix, we show that the proportional change in the price index following the shock to variable trade costs is approximately

$$\dot{P}_{ic} \approx \left(\frac{\dot{\lambda}_{icc}}{\dot{\eta}_{ic}^{\mathbb{1}}} \right)^{\frac{1}{\varepsilon_i}} (\dot{e}_c)^{-\Upsilon_i} \dot{w}_c, \quad (16)$$

where η_{ic} is industry i 's share of employment in city c . Υ_i and $\mathbb{1}$ are reduced-form parameters

¹⁶Under MC-RE, real income also includes positive aggregate profits. See Online Appendix.

¹⁷The Online Appendix shows that (15) also holds under monopolistic competition with restricted entry if we impose $\beta_i \approx \beta$ and $\sigma_i \approx \sigma \forall i$. The latter ensure that the share of aggregate profits in aggregate labor income is (approximately) constant across sectors and thus play the same role as macro-level restriction R2(MS) in Arkolakis et al. (2012).

that depend on the micro details of the model. In particular,

$$\Upsilon_i = \begin{cases} \frac{1}{\sigma_i - 1}, & \text{under MC-FE-HET,} \\ \frac{1}{\varepsilon_i}, & \text{under MC-FE-HOM,} \\ 0, & \text{under PC or MC-RE,} \end{cases}$$

where MC-FE-HET and MC-FE-HOM denote monopolistic competition settings with free entry and either heterogeneous or homogeneous firms, respectively. MC-RE denotes monopolistic competition with restricted entry, with or without firm heterogeneity. PC denotes the multi-industry extension of the perfectly competitive Armington model with search frictions of [Heid & Larch \(2016\)](#); see Online Appendix. The exponent $\mathbb{1}$ in (16) is equal to one if there is free entry (MC-FE-HET or MC-FE-HOM) and zero otherwise.

Equations (15) and (16) show that, conditional on $\dot{\lambda}_{icc}$, $\dot{\eta}_{ic}$ and ε_i , changes in the employment rate \dot{e}_c impact both aggregate income and consumer prices. The latter operates via product variety as a function of the structure of the goods market and the existence of firm heterogeneity, as summarized by Υ_i . Under MC-FE, product variety is driven by entry and exit decisions of firms responding to changes in domestic expenditure. Conditional on the trade elasticity, however, the magnitude of this effect depends on whether firms are homogeneous (HOM) or heterogeneous (HET). Moreover, under PC or MC-RE, the measure of consumption goods is fixed and hence changes in domestic expenditure have no effects on product variety.

Substituting (16) in (15), we obtain the main result of this section.

Proposition 1. *Suppose that the cost of posting vacancies, k_{ic} , is small in all industries of city c . Then the welfare gains in city c associated with an arbitrary shock to the vector of variable trade costs can be approximated as*

$$\dot{V}_c \approx (\dot{e}_c)^{1 + \sum_{i=1}^I \alpha_i \Upsilon_i} \prod_{i=1}^I \left(\frac{\dot{\lambda}_{icc}}{\dot{\eta}_{ic}^{\mathbb{1}}} \right)^{-\frac{\alpha_i}{\varepsilon_i}}. \quad (17)$$

Expression (17) nests the multi-sector welfare formula derived by ACR for versions of the models considered in this paper that feature frictionless labor markets. In these cases, $\dot{e}_c = 1$ because variable trade costs have no impact on aggregate employment. In our theory, however, frictions in the labor market generate equilibrium unemployment and hence enable an additional adjustment margin for welfare changes, via the employment rate.¹⁸ Note

¹⁸A closed-form characterization of this effect is not generally possible. In a symmetric version of our model, however, Proposition 2 in [Felbermayr et al. \(2011\)](#) establishes conditions under which a bilateral trade liberalization increases the steady-state employment rate. Note that the limited analytical tractability

that quantifying welfare changes in the standard case of frictionless labor markets requires estimating two structural parameters per industry, the expenditure share α_i and the trade elasticity ε_i . This also applies to (17) except under MC-FE-HET, which additionally requires an estimate of the elasticity of substitution σ_i , the crucial parameter that regulates the impact of employment rate changes on welfare.

Extension: Trade Liberalization and Labor Endowments. Next, consider the welfare implications of arbitrary changes to the vectors of variable trade costs, $\{\tau_{ivn}\}$, and labor endowments, $\{L_n\}$. The latter capture exogeneous patterns of migration or population growth across locations.

We now focus on the equivalent variation *per-capita* to measure welfare changes in city c , denoted $\dot{V}_c^{PC} \equiv \dot{V}_c/\dot{L}_c$. When the costs of posting vacancies are small, proportional changes in per-capita income are still approximated by $\dot{e}_c\dot{w}_c$, the numerator in (15). A change in the local endowment of labor \dot{L}_c , however, has an identical impact on domestic expenditure -and, hence, on domestic price indexes- as a change in the employment rate. In the Online Appendix, we show

$$\dot{V}_c^{PC} \approx (\dot{e}_c)^{1+\sum_{i=1}^I \alpha_i \Upsilon_i} \left(\dot{L}_c\right)^{\sum_{i=1}^I \alpha_i \Upsilon_i} \prod_{i=1}^I \left(\frac{\dot{\lambda}_{icc}}{\dot{\eta}_{ic}^{\frac{1}{\varepsilon_i}}}\right)^{-\frac{\alpha_i}{\varepsilon_i}}. \quad (18)$$

This extension of (17) enables the welfare analysis of episodes of economic integration that trigger regional and/or international migration, in addition to changes in trade costs.

3 Empirical Strategy

The goal of this section is to develop the methodological steps required to take our welfare formula to the data. Equation (17) depends on four variables that are, in principle, observable (the employment rate in city c , the industrial shares of employment and domestic trade in city c , and the industrial shares of expenditure) and on two structural parameters (σ_i and ε_i).¹⁹ Therefore, estimating the gains from trade first requires recovering these two structural parameters. In a nutshell, we propose identifying them from the estimated wage elasticities

of our model is comparable to the literature; e.g. in quantitative trade models, it is not possible to sign changes in labor allocations or domestic trade shares in response to an arbitrary change in variable trade costs.

¹⁹Note that our empirical strategy does not rely on direct observation of the four above-mentioned variables. In our empirical application, for example, we only observe the employment rate in city c and the share of industrial employment in city c . Observability is a dataset-specific constraint that will nevertheless determine the set of counterfactual exercises that may be implemented in a given dataset.

of the firm-level domestic revenue and local gravity equations. In what follows, we discuss this empirical strategy in detail.

In the model, the elasticity of substitution and the trade elasticity are industry-specific. However, estimating industry-specific coefficients places too high of a demand on our data. We therefore estimate weighted average values of these parameters, which we simply refer to as σ and ε . Later, when we discuss our results, we will be more formal about how our IV estimates of these coefficients approximate a weighted average of heterogeneous treatment effects, in line with the interpretation in [Borusyak et al. \(2018\)](#).

To make progress toward an empirical specification of our main equations, we first use equation (9) to establish a log-linear approximation to the unobservable cost of labor μ_{ic} , around the point where the latter is constant across cities. Using the Beveridge curve to express the tightness of the labor market θ_c as a one-to-one function of the employment rate e_c , we obtain:

$$\ln \mu_{ic} = \psi_{i0} + \ln w_{ic} + \psi_{i1}k_{ic} + \psi_{i2}e_c, \quad (19)$$

where ψ_{i0} , ψ_{i1} and ψ_{i2} are industry-specific parameters obtained in the linear approximation.²⁰

Expression (19) allows us to rewrite the gravity equation (14) as a log-linear function of the observable industry-city specific log wage. Adding time subscripts (since we use data at the city-industry-year level) and first-differencing over time yields:

$$\Delta \ln \left(\frac{X_{icFt}}{R_{ict}} \right) = \Delta d_{it}^G + \phi_1^G \Delta \ln w_{ict} + \phi_{i2}^G \Delta e_{ct} + \Delta u_{ict}^G, \quad (20)$$

where ϕ_1^G is the wage elasticity of the local gravity equation; e.g. $\phi_1^G = -\frac{\kappa\sigma}{(\sigma-1)}$, under MC-FE-HET, and where $\phi_{i2}^G = \phi_1^G \psi_{i2}$.

To capture the industry specificity of ϕ_{2i}^G , we interact changes in the employment rate with industry fixed effects. The term Δd_{it}^G is a full set of industry-year effects to capture changes in the demand shifter in Foreign, A_{iFt} . Moreover, the inclusion of Δd_{it}^G allows to control for time-varying industry-specific unobserved variables, such as changes in the industry component of the cost of posting vacancies, fixed costs, trade policy, non-tariff barriers to trade or (national-level) comparative advantage. The error term, Δu_{ict}^G , is a log-linear function of shocks to the industry-city-specific *residual* components in k_{ict} , f_{ict}^E , f_{icFt} , $\varphi_{\min,ict}$ and τ_{icFt} , which are collected in the error term after controlling for Δd_{it}^G . The time

²⁰Details of the linear approximation of the cost of labor can be found in the Online Appendix C.1.

differencing operator Δ eliminates time-invariant industry-city effects; e.g. local or industrial fixed comparative advantage stemming from geography, institutions or technology.

Given this specification, the estimated effects of our wage variable exploit within-industry, over-time variation, conditional on the local employment rate. Intuitively, this means that we identify the impact of local wage costs, ϕ_1^G , by comparing changes in the ratio of exports to revenues for firms in the same industry in two different cities that are experiencing different changes in wages. The fact that we hold the employment rate constant in this specification implies that the type of variation in wages that we want to use comes from shifts in the wage curve, equation (7), at a fixed labor market tightness. This ensures that shifts in wages correspond to changes in the cost of labor, μ_{ic} , that firms face (ie, not an equilibrium wage-tightness response). In the model, shifts in the cost of labor will induce firm entry and exit responses, as implied by equations (12) and (13). These responses will be reflected by shifts in the ratio of exports to revenues at the city-industry level, captured by the coefficient ϕ_1^G .

The domestic revenue equation at the firm level can be obtained similarly using equations (10) and (19):

$$\Delta \ln r_{ict}(\varphi) = \Delta d_{it}^R + \phi_1^R \Delta \ln w_{ict} + T(\varphi) + \phi_{i2}^R \Delta e_{ct} + \Delta \ln \tilde{A}_{ict} + \Delta u_{ict}^R(\varphi), \quad (21)$$

where $\phi_1^R = 1 - \sigma$, $\phi_{i2}^R = \phi_1^R \psi_{i2}$. $T(\varphi)$ denotes firm fixed effects that capture firm-specific linear trends in (log) productivity $\ln \varphi_t$. As in the gravity equation, we interact Δe_{ct} with industry fixed effects to capture the fact that ϕ_{2i}^R varies across industries. $\tilde{A}_{ict} \equiv \sum_{n \neq F} A_{int} (\tau_{icnt})^{1-\sigma}$ is an aggregate domestic demand shifter. We proxy for it using the traditional Bartik variable, defined as in [Bartik \(1991\)](#) and popularized in [Blanchard & Katz \(1992\)](#), interacted with industry fixed effects.²¹ $\Delta u_{ict}^R(\varphi)$ is an error term that collects residual variation in the cost of posting vacancies k_{ict} after accounting for industry-year fixed effects Δd_{it}^R .²²

Identification of ϕ_1^G and ϕ_1^R requires isolating variation in industry-city log wages that is orthogonal to the composite error terms, Δu_{ict}^G and $\Delta u_{ict}^R(\varphi)$, respectively. Under search and bargaining frictions, wages are necessarily endogenous in equations (20) and (21) because wages, domestic revenues and export shares all depend on idiosyncratic changes in the vacancy posting cost. Thus, estimating (20) and (21) by ordinary least squares would yield inconsistent estimates of ϕ_1^G and ϕ_1^R . Next, we show how to exploit the structure of the model to obtain instruments for wages.

²¹We interpret the traditional Bartik variable as a predictor of changes in city c 's income. To motivate our proxy, we note that \tilde{A}_{ict} can be written as the product of an industry-specific term and city c 's income, when cities are symmetric.

²²The domestic revenue equation is obtained by setting $I_{icn} = 1$ for $n \neq F$ and zero otherwise in (10) and then inserting (19).

3.1 Industrial Composition and Wages

The first step is to link the industry-city wage to the industrial composition of the local labor market. In our search and bargaining framework, this link is captured by the worker's outside option. To simplify the exposition, we impose constant exit rates and bargaining power, i.e. $\delta_c = \delta$ and $\beta_i = \beta$. The latter implies that inter-industry wage differentials within local labor markets stem solely from differences in recruitment costs, k_{ic} . Substituting equation (8) in equation (7) yields

$$w_{ic} = \tilde{\gamma}_{1c}\bar{w}_c + \gamma_{2c}k_{ic}, \quad (22)$$

where $\bar{w}_c = \sum_j \eta_{jc}w_{jc}$ is the local average wage and the coefficients $\tilde{\gamma}_{1c} = \frac{\theta_c m_c(\theta_c)}{\rho + \delta + \theta_c m_c(\theta_c)} \in \{0, 1\}$ and $\gamma_{2c} = \left(\frac{\beta}{1-\beta}\right) \left(\frac{\rho+\delta}{1-\delta}\right) \frac{1}{m_c(\theta_c)}$ are both dependent on the tightness of the local labor market. The latter coefficient is increasing in labor market tightness – workers benefit more from hiring costs when firms find it harder to hire. The equation shows that workers in any sector benefit from working in a city with higher wages (quality of jobs) due to the strategic complementarity of wages across industries generated by search frictions and bargaining in the labor market (Beaudry et al., 2012). Since the coefficient $\tilde{\gamma}_{1c}$ is an increasing function of labor market tightness, this benefit depends on the quantity of jobs.

We can rewrite equation (22) by decomposing the vacancy posting cost, k_{ic} , without loss of generality, as $k_{ic} = \tilde{k}_i + \tilde{k}_c + \tilde{\xi}_{ic}$, where \tilde{k}_i represents a common (across cities) industry component, \tilde{k}_c represents city-specific component, and $\tilde{\xi}_{ic}$ is an idiosyncratic component that sums to zero across industries, within cities. Using this decomposition, solving for \bar{w}_c and substituting back in equation (22), we obtain:

$$w_{ic} = \gamma_{1c}\tilde{K}_c + (\gamma_{1c} + \gamma_{2c})\tilde{k}_c + \gamma_{1c} \sum_j \eta_{jc}\tilde{\xi}_{jc} + \gamma_{2c}\tilde{k}_i + \gamma_{2c}\tilde{\xi}_{ic}, \quad (23)$$

where $\tilde{K}_c = \sum_j \eta_{jc}\tilde{k}_j$ captures the weighted city-average of national-level vacancy posting costs and $\gamma_{1c} = \frac{\tilde{\gamma}_{1c}\gamma_{2c}}{1-\tilde{\gamma}_{1c}}$. Note that γ_{1c} and γ_{2c} vary by city because of equilibrium differences in the rate at which workers find jobs. These coefficients can be written as an increasing function of the observable employment rate, which is a one-to-one function of the unobservable tightness of the labor market (Beveridge curve).

To derive an empirical specification in logs, we take a log-linear approximation of equation (23) around an expansion point in which the cost of posting vacancies is small. Adding the time subscript, industry-city wages are related to industrial composition in the following

way:

$$\ln w_{ict} = \gamma_0 + \frac{\gamma_1}{\gamma_2} K_{ct} + \gamma_2 k_{it} + \gamma_3 k_{ct} + \gamma_4 e_{ct} + \gamma_2 \xi_{ict}, \quad (24)$$

where γ_0 - γ_4 are constant parameters obtained from the linear approximation, $k_{it} = \frac{\tilde{k}_{it}}{\bar{w}}$, $k_{ct} = \frac{\tilde{k}_{ct}}{\bar{w}}$ and $\xi_{ict} = \frac{\tilde{\xi}_{ict}}{\bar{w}}$, where \bar{w} is the average wage in an arbitrary industry.²³ Equation (24) shows that, at the national level, inter-industry wage differentials are given by $\gamma_2 k_{it}$, which expresses the average wage in industry i relative to the average wage in an arbitrary omitted industry. Finally, $K_{ct} = \sum_j \eta_{jct} \nu_{jt}$, where $\nu_{jt} = \gamma_2 k_{jt}$ denotes the national industry wage premium. Thus, K_{ct} is a weighted average of industrial wage premia, weighted by industry-city-specific employment shares.

The term K_{ct} plays an essential role in our identification strategy. Since the probability that an unemployed worker finds a job in industry i and city c is proportional to η_{ict} , the term K_{ct} can be thought of as capturing variation in workers' outside option driven by the industrial composition of city c ; i.e., by city c 's specialization pattern across industries that pay intrinsically different wage premia. When the composition of jobs shifts toward higher-paying industries, workers are able to extract more surplus from firms when bargaining through an increase in their threat point. Crucially for the identification strategy, conditional on the employment rate and demand shifter, variation in industrial composition influences trade flows and firm revenues only through their impact on local wages. [Beaudry et al. \(2012\)](#) show that outside options are important determinants of industry-city wages in the U.S.. [Tschopp \(2015, 2017\)](#) finds similar results in Germany. Next, we discuss how to exploit variation in K_{ct} to construct model-based instruments for the industry-city wage in equations (20) and (21).

3.2 Instrumental Variables

Our identification strategy exploits variation in K_{ct} and hinges on the following decomposition:

$$\Delta K_{ct} = \sum_j \eta_{jct-1} (\nu_{jt} - \nu_{jt-1}) + \sum_j \nu_{jt} (\eta_{jct} - \eta_{jct-1}).$$

This decomposition is the starting point for our instruments, which, by exploiting the inner structure of the index K_{ct} , are, essentially, Bartik-type instruments, as defined by [Goldsmith-Pinkham et al. \(2017\)](#). The first term captures shifts in national-industrial pre-

²³See Online Appendix C.2 for details on the linear approximation and specific expressions of γ_0 - γ_4 .

mia, weighted by the beginning-of-period importance of an industry to the local economy. The second term captures changes in workers' outside options from shifts in the local industrial composition, weighed by the national industrial wage premia.

In order to construct instruments using the decomposition of ΔK_{ct} , we must confront two issues: (1) the national industrial premia, ν_{it} , are not directly observed, and (2) the observed industrial employment shares, η_{ict} , are potentially correlated with the error terms in (20) and (21). We tackle these two issues next.

Estimating National Wage Premia. Equation (24) shows that wages vary because of an industry-specific component (ν_{it}), a city-specific component ($\gamma_0 + \frac{\gamma_1}{\gamma_2} K_{ct} + \gamma_3 k_{ct} + \gamma_4 e_{ct}$) and an idiosyncratic term ($\gamma_2 \xi_{ict}$). An implication is that the inclusion of a set of city fixed effects in a wage regression at the industry-city level would allow us to recover national industrial wage premia from the estimated coefficients on industry fixed effects, without directly observing local industrial composition, K_{ct} , and the local component of the vacancy posting cost, k_{ct} .

However, in order to take the model's wage equation to the data, we must confront the fact that workers are heterogeneous in our data but not in the model. Our approach is to treat individuals as representing different bundles of efficiency units of labor, and assume these bundles are perfect substitutes in production. We interpret w_{ict} in (24) as the cost per effective labor unit and index worker characteristics by H_n . Let effective labor units be $\exp(H'_n \beta + a_n)$, where H_n and a_n capture observable and unobservable skills of worker n , respectively. Adding industry, city and time subscripts, workers log wages, $\ln W_{nict}$, are given by:

$$\ln W_{nict} = H'_{nt} b_t + \ln w_{nct} + a_{nict}.$$

This implies that we can estimate national industrial wage premia using the following procedure. First, we estimate, separately by year:

$$\ln W_{nict} = H'_{nt} b_t + D_{ict} + a_{nict}, \tag{25}$$

where D_{ict} are a complete set of city-industry dummies. In our empirical application, H'_{nt} includes age, the square of age, a gender dummy, a nationality dummy, a categorical variable for education and a full set of education-gender, education-nationality and education-age interactions. The estimated vector coefficients on the city-industry fixed-effects, D_{ict} , are regression-adjusted city-industry average wages, which we denote by $\widehat{\ln w_{ict}}$.

Pooling across years, we then estimate an empirical version of (24), regressing $\widehat{\ln w_{ict}}$ on

a set of city-year and industry-year fixed effects. The inclusion of the city-year fixed effects absorbs local economic conditions given by $\gamma_0 + \frac{\gamma_1}{\gamma_2}K_{ct} + \gamma_3k_{ct} + \gamma_4e_{ct}$ in equation (24) and the coefficients on the industry-year fixed-effects estimate the national-level industrial wage differentials, $\hat{\nu}_{it}$.

Predicting Shares. Since we have many industries within each city-year, we pursue a generalized leave-one-out method that purges a common city component from the national-level industry growth. The procedure that we use closely follows [Greenstone et al. \(2015\)](#). Consider the following equation for local industry-city employment growth:

$$\Delta \ln L_{ict} = g_{it} + g_{ct} + \tilde{g}_{ict}, \quad (26)$$

where g_{ct} are city-time fixed effects and g_{it} are industry-year effects. This equation describes local industry employment growth as stemming from national-level factors common across cities (g_{it}), city-level factors that are common across industries (g_{ct}), and an idiosyncratic city-industry factor (\tilde{g}_{ict}). The inclusion of g_{ct} is meant to absorb growth due to conditions in the local economy, such as demand shocks. The vector of coefficients on the g_{it} fixed-effects are associated with national-level forces. We use their estimates, denoted \hat{g}_{it} , to predict local industry size based on local base-period employment:

$$\hat{L}_{ict} = L_{ic0} \prod_{s=1}^t (1 + \hat{g}_{is}),$$

for $t \geq 1$, where L_{ic0} is a base-period level of employment in industry i in the local economy c . We then convert predicted employment into shares.

In order to alleviate any concerns that the correlation between our instruments and manufacturing wages is mechanical (since equations 20 and 21 are estimated using industries in the tradables sector), we exploit variation in the decomposition of ΔK_{ct} that originates outside the tradable sectors and construct instruments based on the non-manufacturing sector only. For this reason, we construct industrial shares within the non-manufacturing sector so the shares across industries within the non-manufacturing sector of a city sums to one:

$$\hat{\eta}_{jct} = \frac{\hat{L}_{jct}}{\sum_{i \in S} \hat{L}_{ict}},$$

where S denotes the set of non-manufacturing industries.

Constructing Instruments. With $\hat{\eta}_{jct}$ and $\hat{\nu}_{jt}$ at hand, we construct

$$IV_{ct}^W = \sum_{j \in S} \hat{\eta}_{jct-1} \Delta \hat{\nu}_{jt},$$

$$IV_{ct}^B = \sum_{j \in S} \hat{\nu}_{jt} \Delta \hat{\eta}_{jct},$$

where $\hat{\eta}_{jct}$ are only functions of base period shares and national growth rates. Variation in both IV_{ct}^W (the ‘within’ instrument) and IV_{ct}^B (the ‘between’ instrument) across cities comes from differences in initial local non-manufacturing industrial composition.

Each one of our instruments takes the form of the popular Bartik-type instruments that combine observed shocks (common across local labor markets) with exposure weights at the local level. Recently, several papers have examined these types of instruments in detail and formalized the conditions under which they are valid (Goldsmith-Pinkham et al., 2017; Borusyak et al., 2018; Beaudry et al., 2012, 2018). Following this research, we outline the conditions under which our instruments are valid in our context. First, notice that the inclusion of industry-by-year fixed effects in our specifications imply that the identifying variation we are using is across cities, within-industry variation. The implication is that instrument validity concerns the cross-city correlation between IV_{ct}^W or IV_{ct}^B and the error Δu_{ict}^G . Second, note that, by construction of $\hat{\eta}_{jct}$, all of the cross-city variation in the instruments stems from differences in the initial industrial composition, $\eta_{ic,t=0}$. Thus, a sufficient condition for our instruments to be valid is that cross-city differences in base-period industrial composition are uncorrelated with the error term – a condition emphasized in Goldsmith-Pinkham et al. (2017) and Beaudry et al. (2018).

More formally, consider the sample covariance between our within-instrument and the error of the gravity equation:

$$\frac{1}{I} \frac{1}{C} \sum_c \sum_{i \notin S} \left(\sum_{j \in S} \hat{\eta}_{jct-1} \Delta \nu_{jt} \right) \Delta u_{ict}^G = \frac{1}{I} \frac{1}{C} \sum_{i \notin S} \sum_{j \in S} \Delta \nu_{jt} \sum_c \hat{\eta}_{jct-1} \Delta u_{ict}^G \quad (27)$$

where the last summation on the right-hand-side is the city-level covariance between predicted non-manufacturing shares and the error term. Predicted shares are only a function of base-period non-manufacturing industrial composition and national-level industrial growth rates. The error term contains changes in the residual component of a number of model parameters, and can be generally interpreted in our framework as changes in city-industry unobservable comparative advantage. A sufficient condition for consistency is that $\frac{1}{C} \sum_c \hat{\eta}_{jct-1} \Delta u_{ict}^G \rightarrow^p \mathbf{E}[\hat{\eta}_{jct-1} \Delta u_{ict}^G] = 0$ as $C \rightarrow \infty$. In words, if base-period non-manufacturing industrial composition does not predict future *changes* in comparative ad-

vantage in manufacturing industries, our instrument is valid. Thus, our instruments would be valid, for example, under a random-walk type assumption for Δu_{ict}^G , as emphasized in [Beaudry et al. \(2012, 2018\)](#). Recently, [Borusyak et al. \(2018\)](#) have shown that even if this condition breaks down, Bartik-style instruments may still be valid. In their paper, they emphasize the conditions under which $\frac{1}{C} \sum_c \hat{\eta}_{jct-1} \Delta u_{ict}^G$ is asymptotically non-zero, but the industry shocks are uncorrelated to this covariance term. They show that if the industry-level shocks are as-good-as-randomly assigned, conditional on $\mathbf{E}[\hat{\eta}_{jct-1} \Delta u_{ict}^G]$, the condition for instrument validity is still satisfied. In our framework, this condition would hold if $\hat{\eta}_{jct-1}$ predicted Δu_{ict}^G , but the industry wage shock, $\Delta \nu_{it}$, is uncorrelated with these predictions, so that $\sum_{j \in S} \Delta \nu_{jt} \mathbf{E}[\hat{\eta}_{jct-1} \Delta u_{ict}^G]$ is zero.

The sufficient conditions for IV consistency are therefore either an assumption that base-period non-manufacturing industrial composition does not predict future changes in comparative advantage or an assumption that the industry level shocks are as-good-as-random with respect to $\mathbf{E}[\hat{\eta}_{jct-1} \Delta u_{ict}^G]$. While we cannot test these assumptions directly, we do attempt to assess their plausibility in several ways. [Goldsmith-Pinkham et al. \(2017\)](#); [Borusyak et al. \(2018\)](#) suggest checking whether observable baseline city-level characteristics are correlated with the instruments as an indirect exogeneity assessment. The idea is that if the Bartik-style instruments are correlated with baseline local characteristics that might be correlated to the structural error term in the estimating equation, then the consistency condition might not be met. In addition, [Goldsmith-Pinkham et al. \(2017\)](#); [Borusyak et al. \(2018\)](#) suggest controlling for base-period observable characteristics interacted with time trends when estimating 2SLS using the Bartik instruments. [Borusyak et al. \(2018\)](#), in particular, recommends an analysis at the industry level and controlling for industry level controls. Since our specification is at the city-industry level, we control for a full set of industry-by-year fixed effects, and specifically control for baseline or lagged manufacturing share.

Finally, we leverage the fact that we have two instruments and perform an over-identification test as done in [Beaudry et al. \(2012, 2018\)](#). As they discuss, each instrument uses a different type of variation, but are valid under the same identification assumption. In particular, each instrument can be seen as combining an industry-level shock with a local measure of exposure. Consistency depends on the orthogonality of the local measure of exposure (base-period non-manufacturing composition) and the error term. Given that each instrument weights potential violations of this assumption differently, if our orthogonality condition is not satisfied, estimates using either IV^W or IV^B should diverge. Using this insight, performing a standard over-identification test tests whether the instruments produce statistically different estimates. Note that this test is consistent with the theoretical framework. Each instrument should have the same impact on wages, because they both influence the outside options of

workers in the same way regardless of whether the variation stems from shifts in industrial premia, IV^W , or because of shifts in industrial composition, IV^B . Likewise, what matters for firms is the bargained wage, so that each instrument should produce the same response on the firms' side. Thus, we expect that each instrument should produce similar estimates of the wage response in our structural equation.

4 Data

This study uses two different data sources: the weakly anonymous Sample of Integrated Labour Market Biographies (SIAB) [Years 1975 - 2010] and the Linked-Employer-Employee Data (LIAB) [cross-sectional model 2 1993-2010 (LIAB QM2 9310)] from the Institute of Employment Research (IAB). Data access was on-site at the Research Data Centre (FDZ) of the German Federal Employment Agency (BA) at the University of Michigan, the Cornell Institute for Social and Economic Research and subsequently via remote data access.²⁴

SIAB Data. The SIAB data is a 2% random sample of individual accounts drawn from the Integrated Employment Biographies (IEB) data file assembled by the IAB. These data cover all employees registered by the German social insurance system and subject to social security. Civil servants and self-employed workers are not covered. The SIAB provide spell-data information on individual characteristics as such as gender, year of birth, nationality or education, and document a worker's entire employment history, e.g. an individual's employment status, full- or part-time status, occupational status, occupation and daily wage. Hours of work are not included in the IEB. Earnings exceeding the contribution assessment ceiling for social insurance are only reported up to this limit.²⁵ Administrative individual data are supplemented with workplace basic information taken from the Establishment History Panel (BHP). Establishment variables are measured on June 30 of each year and include information on location, industry, year of first and last appearance of the establishment, total number of employees, number of full employees, number of part-time employees and median wage of the establishment. Establishment and individual data are merged using employment spells which cover June 30.

LIAB Data. The LIAB data matches the IAB Establishment Panel data with individual social security data from the IAB on June 30 and comprises data from a representative annual establishment survey, stratified according to establishment size, industry and federal

²⁴See [Heining et al. \(2013\)](#), [Fischer et al. \(2009\)](#) and [Heining et al. \(2014\)](#) for further data documentation.

²⁵We drop top coded observations.

state. The survey provides information on establishment-level exports, employment and other performance-related measures, such as sales. For consistency with theory, we refer to these establishments as firms in the empirical analysis.

Cities and Industries. We define cities according to [Kropp & Schwengler \(2011\)](#) definition of labor markets. There are 24 cities; 19 in West Germany and 5 in East Germany.²⁶ There are 58 industries (“Abteilungen”), of which 29 belong to the manufacturing sector, grouped according to the 1993 time-consistent 3-digit classification of economic activities. In compliance with the FDZ guidelines, each industry-city cell includes at least 20 workers’ observations.

Construction of the Main Variables. We use the LIAB data to construct industry-city-specific export shares in revenues and firm-level domestic revenues. We first compute firm-level export values using sales and the share of exports in sales, which are both available at the firm level in the LIAB data. Firm-level domestic revenues are obtained by subtracting exports from sales. The industry-city export shares are obtained by aggregating firm revenues and exports by industry-city-year, weighting each observation using the weights provided in the establishment survey.

The SIAB data are used to construct industry-city wages, national industrial wage premia, predicted and observed local industrial employment shares, instruments, local employment rates, demographic controls and our proxy for local demand. These variables are then merged to the LIAB data by the Institute of Employment research.

Adjusted wages, predicted employment shares and instruments are constructed following the procedure described in Section 3.2. To estimate log industry-city wages from the wage regression at the worker level we first transform wages into real wages using the consumer price index, base 2005, provided by the German federal statistical office. Among the variables included in the vector of individual characteristics, our educational variable includes the following categories: without vocational training, apprenticeship, high school with *Abitur*, high school without *Abitur*, polytechnic, university. The nationality variable is restricted to two categories; German nationals and foreigners. In the second step which estimates the national industrial wage premia, we weigh observations by the size of the city-industry in the base-period so that the influence of each observation is proportional to its importance in that year.

To predict local industry size, we average industry-city employment over the period 1992-

²⁶[Kropp & Schwengler \(2011\)](#) correspondence table between districts, labor markets and regions can be downloaded at <http://www.iab.de/389/section.aspx/Publikation/k110222301>.

1993, i.e. $L_{ic0} = (L_{ic1992} + L_{ic1993})/2$. We then leave one year out and first predict employment, \hat{L}_{ict} , in 1995, which restricts our sample to the period 1996-2010 since IVB_{ct} and IVW_{ct} both use $t - 1$ predicted employment shares.

Finally, we proxy changes in local demand, $\Delta \ln A_{ict}$, in the domestic revenue equation by interacting industry fixed effects with the traditional Bartik variable, constructed as a weighted sum of national-level industrial employment growth, where the weights are past local industrial shares.

5 Results

Gravity Equation Table 1 presents the estimation results for the gravity equation (20) that relates the change in log share of exports in sectoral revenue to log changes in local sector wages. As this equation is derived from theory, the coefficient on Δw_{ict} has a structural interpretation that depends on the market structure; e.g. equal to $\frac{\kappa\sigma}{(\sigma-1)}$ under MC-FE-HET. Note that all specifications in Table 1 contain a full set of industry-by-year fixed effects and the local employment rate fully interacted with industry fixed effects. Given this specification, the estimated structural parameter is identified from within-industry, over-time variation in wages, holding local labor market tightness constant. The first column of Table 1 shows the OLS estimates of the gravity equation. As discussed above, wages are mechanically endogenous in this equation and under no circumstances would we expect to recover consistent estimates of the parameter of interest; we present them only for completeness. Thus, we turn our attention to columns (2)-(7) which contain the second-stage results of the gravity equation when we instrument for wages.

Before discussing the second-stage estimates in Table 1, it is useful to briefly discuss our first-stage estimates and identification. Our instrumental variable strategy identifies movements in $\Delta \ln w_{ict}$ from shifts in workers' outside options proxied by IV_{ct}^B and IV_{ct}^W . Intuitively, this means that we identify the sensitivity of trade to wages by comparing firms in the same industry in different cities that experienced different changes in their predicted industrial composition, and therefore costs of labor via bargaining. Since our instruments use a different level of variation than our dependent variable (city-year versus industry-city-year), all of our estimates in Table 1 report standard errors that are clustered. We report standard errors based on two choices of clustering: at the city-year level, the lowest level of clustering that would potentially be appropriate given the variation of our instruments, and two-way clustered standard errors at the city-year and industry-city level.²⁷ The stars (*) in

²⁷While city-year clustering takes into account the level of variation that we use, this choice neglects potential serial correlation in our dependent variable. Thus, our two-way clustered standard errors also

the table refer to city-year clustering.

[TABLE 1 ABOUT HERE]

Panel II of Table 1 reports our first-stage estimates from a variety of specifications. Both IV_{ct}^W and IV_{ct}^B are statistically significant in all columns. The bottom panel of the table shows the F -statistic of the test that our instruments jointly have no explanatory power; the null hypothesis of this test can easily be rejected. For example, the lowest F -statistic of the test of instrument relevancy across all specifications is 58.9 and, thus, we do not suffer from weak instrument problems. This can be viewed as a direct test of our model; i.e. it tests that our proxies for outside options in a city matter for industry-city wage growth which is implied by our search and bargaining model of the labor market. This result is in line with [Tschopp \(2015, 2017\)](#) who extensively examines the relationship between local industrial composition and wage formation in Germany. In column (3), we add a full set of city-fixed effects which, in our differenced specification, are equivalent to city-specific trends. Once these are added, the coefficients on IV_{ct}^W and IV_{ct}^B are nearly the same magnitude, and this does not change across additional specifications in the table. This result is intuitive and implied by our framework – shifts in outside options stemming from shifts in industrial composition or national-level wage premia should have the same impact on wages.

Panel I of Table 1 contains the second-stage results for the gravity equation. In column (2), the estimated coefficient on wages is -7.98 and this magnitude remains relatively stable across all of our specifications and is statistically significant at the 1-percent level. In column (3) we add a full set of city-fixed effects. These are meant to capture any variation in within-city exports that are city-specific over time; for example, trends in exports that are driven by secular factors such as increasing global integration that differentially impacts cities. Column (4) adds linear city trends which are meant to pick up trends in export growth across cities. Columns (5) and (6) control for either lagged manufacturing share or linear trends base-period manufacturing share. Recall that we restrict variation in our instruments by only using information on industries outside the tradables sector. Thus, these specifications assess whether we are inadvertently picking up wage movements due to shocks correlated to city-level manufacturing concentration. Finally, in column (7) we include a set of demographic controls interacted with time trends. These demographic controls are constructed at the city-level in the base time period (1992/93) and include the local share of college graduates, female workers and native Germans, and the log employment rate and log size of the labour force.

cluster at the industry-city level to take into account potential serial correlation, in addition to city-year. Standard errors based on clustering at the city level yield smaller standard errors, in general, than reported in our table. Since city-clustered standard errors are based on few clusters and are generally smaller, we take the more conservative approach and choose not to report them (available upon request).

Since our identification strategy relies on exploiting base-period differences in industrial composition across cities, any trend or shock that is correlated to these city characteristics could also be correlated with the instruments, therefore potentially violating the exclusion restriction. For example, if base-period industrial employment is correlated with the local share of highly educated workers, this specification addresses potential concerns that other trends associated with education confound our results.²⁸ These additional controls do not have an appreciable effect on our coefficient estimates.

It is useful to interpret these results through the lens of our model. Our 2SLS estimates of the gravity equation instrument changes in city-industry wages with measures of the change in the value of workers’ outside options. These outside options depend on predicted shifts in the industrial structure (IV_{ct}^B) and shifts in the national-level industry premia (IV_{ct}^W). Improvements in workers’ outside options lead to higher bargained wages and, thus, higher unit costs faced by producers at fixed labor market tightness. Conditional on foreign demand, export shares in industry i in city c fall when unit costs increase. The magnitude of this effect is governed by the wage elasticity, and our estimates suggest that a one percent increase in labor costs reduces export shares by about 8 percent. Given that we expect the response of trade to wages to vary across industries (ie, that ε and σ have i subscripts as in the model), we interpret this estimate as a weighted average of the wage response across industries.²⁹

This interpretation of our results, of course, relies on the idea that our instruments are exogenous. As discussed in section 3.2, a sufficient condition for our instruments to be valid is that base-period industrial composition is orthogonal to the error term in the gravity equation. The identification strategy we exploit is analogous to difference-in-differences with a continuous treatment exposure. The ‘treatment’ in our setup comes from national-level shocks in industrial growth rates (g_{it} from equation (26)) and industrial premia, $\hat{\nu}_{it}$, interacted with the exposure to these shocks given by base-period industrial structure. Thus, all of the cross-city variation in our instruments comes from differences in initial industrial composition. We combine this variation with two different types of national-level shocks to produce two different weighted averages, each corresponding to a component in ΔK_{ct} which proxies for the value of workers’ outside options. According to our theoretical framework, each instrument should have the same impact on wages since each influences worker outside

²⁸Following Goldsmith-Pinkham et al. (2017), we conduct a more detailed investigation of city initial characteristics and industrial composition in the Online Appendix D.2.

²⁹As Borusyak et al. (2018) show, our Bartik-style or shift-share IV approach estimates a weighted average of unit specific treatment effects. As the coefficient on wages only varies across industries, our approach is analogous to estimating our gravity equation by industry and then averaging. Thus, what we estimate is an average of an industry specific effect. Since our regressions are weighted by the number lagged number of establishments in each city-industry cell, this is a weighted average. Section E of the Online Appendix formally shows this result.

options in the same way. In fact, in Panel II of Table 1 we do find that each instrument has a similar impact on wages. Likewise, what matters for firms is the cost of labor, suggesting that using variation either instrument should produce the same export response. This intuition can be formalized by performing a standard Hansen’s- J over-identification test which tests whether estimates using either IV_{ct}^W or IV_{ct}^B are statistically different. In the bottom panel of Table 1 we present the p -value of this test. In every specification we fail to reject the null that our instruments are exogenous, which lends support for our identifying assumption.³⁰

Revenue Equation In table 2 we present our results from the estimation of the domestic revenue equation (21). This equation is estimated at the firm level using the same sample of cities and industries over the 1996-2010 period as above. Each specification again includes a full set of industry-by-year fixed effects, but also includes a full-set of firm fixed effects. The inclusion of the firm fixed effects is intended to capture the extra term in the error component of (21), denoting time-varying firm productivity, that is not present in (20). One complication of estimating the revenue equation, relative to the gravity equation, is that equation (21) contains a domestic demand shifter that cannot be absorbed by a fixed effect. We attempt to control for this demand shifter by including the traditional Bartik instrument, which is a proxy for local labor demand, interacted with a full-set of industry indicators.³¹ In this specification, the coefficient on wages has the structural interpretation of one minus the elasticity of substitution in consumption, $1 - \sigma$, and identification again comes from within-industry, over-time variation in the price of labour.

The layout of Table 2 is similar to Table 1 above, with columns 2-7 containing the results from two-stage least squares and each column controlling for the same set of controls as in Table 1. Panel II of the table displays the first-stage coefficients of our instruments and indicates that we do not face weak instrument problems. In column (2) of Panel I, the estimate of σ is about 1.75 and highly statistically significant and very stable across

³⁰When we estimate the specifications in Table 1 using either IV_{ct}^W or IV_{ct}^B as an instrument, the results are very similar to those presented the table. For example, in our baseline specification using IV_{ct}^B , the coefficient on wage is -8.07 (3.86). The corresponding result using IV_{ct}^W is -7.73 (2.78). Given that the correlation between our instruments in the data is low (0.3, after removing year effects as we do in all of our estimations), we view this as supportive of our identification assumptions. The over-identification test is that $\hat{\phi}_1^{IV^B} = \hat{\phi}_1^{IV^W}$. In Section E of the Online Appendix, we show the conditions under which this would asymptotically hold in our setup. Intuitively, the validity of each instrument depends on the correlation between base-period industrial composition and the error term, Δu_{jct}^G . If the instruments are not valid, each will weight this correlation differently and each instrument will produce different estimates (Beaudry et al., 2012, 2018).

³¹The traditional Bartik is constructed as a local weighted average of national-level employment growth across industries, $Bartik_{ct} = \sum_j \hat{\eta}_{jct} \cdot g_{jt}$. The $\hat{\eta}_{ic}$ are constructed as in section 3.2 and the national-level employment growth rates come from the g_{it} in equation (26). We interpret this variable as a proxy for city income and proportional to local expenditure which is part of the local demand shifter. We interact this variable with industry indicators to allow industry specific effects.

specifications in columns (3)-(7). In the bottom panel, we again present the Hansen's- J over-identification test which easily fails to reject in every specification.

[TABLE 2 ABOUT HERE]

An estimate of σ of 1.75 suggests that substitutability among varieties in demand is low, which is not surprising given the relatively high level of industrial aggregation in our data. Our estimates range from 1.75 to 1.78 and are in line with the median estimates reported in the literature. For instance, [Broda & Weinstein \(2006\)](#) report a median elasticity of substitution of 2.2 over the period 1990-2001 for SITC-3 industries. More recently, [Soderbery \(2015\)](#) estimates a median elasticity of substitution of 1.85 across HS8 products. We interpret our estimate of σ in Table 2 as a weighted average of industry specific elasticities of substitution. This is consistent with the fact that, over the period 1996-2010, German manufacturing production was mainly driven by two industries – chemicals (e.g. with an average export share of 13.5) and motor vehicles (e.g. with an export share of 19.1) – that the literature has estimated to have relatively low elasticities of substitution. For instance [Ossa \(2015\)](#) finds an elasticity of 1.71 for road motor vehicles, 1.8 for parts and accessories for tractors, motor cars and other motor vehicles, and 1.75 for miscellaneous chemical products.

Combining the estimate of -8 in the gravity equation and σ , we obtain a trade elasticity of $\kappa = 3.5$ under MC-FE-HET and of 7 under the alternative market structures we consider. Thus, our trade elasticity falls comfortably in the range of estimates documented in the literature (see Table 3.5 of [Head et al. \(2014\)](#)). In the next section, we use our estimates of these structural parameters, along with the Welfare equation from section 2.4, to estimate the relevance of the impact of trade on the employment rate as an additional margin of adjustment when calculating the welfare gains from trade.

6 Application: The Rise of the East and the Far East

Our relatively low estimate of the elasticity of substitution in consumption suggests that omitting unemployment and firm heterogeneity might lead to an underestimation of the welfare gains from trade. We examine this possibility in this section and exploit Germany's rapid trade integration with China and Eastern Europe between 1988 and 2008 to study the welfare consequences of increased market access across cities in West Germany.

In particular, we take the trade elasticity, changes in local employment rates, domestic trade shares and industry composition as given by the data and ask: how do the welfare gains from trade with the East over two decades differ relative to those predicted by ACR's welfare formula when changes in unemployment are accounted for? From Proposition 1,

the answer to this question depends on the market structure and on the existence of firm heterogeneity. Table 3 shows this.

[TABLE 3 ABOUT HERE]

The relative gains from trade under MC-FE-HET, given in column 1 of Table 3, depend on the elasticity of substitution in consumption. We set $\hat{\sigma} = 1.78$ from Table 2. To be clear, this counterfactual exercise is in the spirit of ACR; that is, the relative gains formula $\hat{e}_c^{1+\frac{1}{\sigma-1}}$ assumes that two MC-FE-HET models, one featuring search frictions and unemployment (our model) and the other featuring frictionless labor markets (ACR), are calibrated to deliver the same trade elasticity and changes in local employment rates, domestic trade shares and industry composition. Note that the relative gains from trade formula is still valid when the underlying policy experiment involves changes in the local labor endowments. This follows from (18), provided that the two models are also calibrated to match the observed changes in local labor endowments. In this case, $\hat{e}_c^{1+\frac{1}{\sigma-1}}$ should be interpreted as measuring relative changes in the per-capita equivalent variation.

The same principles apply when comparing the relative gains from trade under alternative market structures. In column 2 of Table 3, the relative gains from trade under MC-FE-HOM are a function of the trade elasticity. Following the usual practice in the literature, we recover it from the gravity equation. Under MC-FE-HOM, the trade elasticity is equal to the wage elasticity minus one. Based on our estimates from Table 1, we set $\hat{\varepsilon} = 7$. Finally, the last column of the table shows that, under PC or MC-RE, the relative gains from trade solely depend on how market access affects the unemployment rate across local labor markets.

In order to implement the formulas in Table 3 empirically, we need to estimate the impact of increased trade with China and Eastern Europe on the employment rate growth of cities of West Germany. We follow the methodology developed by [Dauth et al. \(2014\)](#) (and [Autor et al. \(2013\)](#) for the US) to study the impact of increased trade with the East on the labor market between 1988-2008.³² Specifically, using data for two time periods (1988-1998 and 1998-2008) we regress:

$$\frac{e_{c(t+10)}}{e_{ct}} = \beta_{IPW} \cdot IPW_{ct} + \beta_{EPW} \cdot EPW_{ct} + X'_{ct} \alpha + d_{rt} + u_{ct}, \quad (28)$$

³²The authors thank [Dauth et al. \(2014\)](#) for sharing the public version of their data which is available for 1988, 1998 and 2008, and 326 cities in Germany. For their analysis at the local level, [Dauth et al. \(2014\)](#) use the IAB-Establishment History Panel (BHP), a confidential database which contains the universe of all German establishments. For this reason, the time frame and the level of disaggregation of industries and cities we use in Section 5 differs from [Dauth et al. \(2014\)](#). In addition the BHP does not provide information on exports and establishment revenues.

where e_{ct} is computed by dividing total employment by the size of working age population in city c and time t , X'_{ct} are city-specific controls (the share of employment in tradable goods industries, the share of high-skilled, foreign and female workers, as well as the percentage of routine/intensive occupations), d_{rt} is a set of region-time fixed effects, and IPW_{ct} and EPW_{ct} are observed decadal changes in import and export exposure, respectively. Both measures are defined and instrumented as in [Dauth et al. \(2014\)](#), and we refer to the latter paper for further details.³³ We then use the estimates to calculate the predicted impact on the employment rate:

$$\dot{e}_{ct} = \hat{\beta}_{IPW} \cdot IPW_{ct} + \hat{\beta}_{EPW} \cdot EPW_{ct} + 1. \quad (29)$$

Results from this exercise are presented in Table 4. Panel I shows the IV estimates obtained from estimating equation (28). Columns 1-3 shows results obtained when using trade with both Eastern Europe and China to compute IPW_{ct} and EPW_{ct} . Column 4 uses trade exposure with Eastern Europe only and the last column is based on trade with China. The first two columns use data for each decade separately.

[TABLE 4 ABOUT HERE]

Column 3 suggests that, as expected, import exposure has a negative and statistically significant impact on local employment rate growth while export exposure tends to boost employment rates. Columns 4 and 5 indicate that these results are driven by trade with Eastern Europe. Trade with China has a minimal impact on local employment growth and appears to affect German cities via imports only.

Panel II of Table 4 shows the implied local employment rate growth (from the combined import and export exposure). Focusing on column 3, we find that increased trade with

³³Both measures are directly taken from [Dauth et al. \(2014\)](#). $IPW_{ct} = \sum_i \frac{E_{ict}}{E_{it}} \frac{\Delta M_{i(t+10)}^{G \leftarrow East}}{E_{ct}}$, where Δ denotes a decadal time difference (i.e. 1988-1998 and 1998-2008), $\frac{E_{ict}}{E_{it}}$ is city c 's share of industrial employment and E_{ct} is city c manufacturing employment. $\Delta M_{i(t+10)}^{G \leftarrow East}$ denotes the change in imports from the East (China and/or Eastern Europe) between t and $t+10$. Therefore, the measure of local import exposure is a weighted average of imports from the East to Germany, where the weights are local industrial employment as a share of aggregate national employment, and captures the extent to which a city was exposed to imports from the East. The instruments for IPW_{ct} is given by $IVIPW_{ct} = \sum_i \frac{E_{ic(t-10)}}{E_{(it-10)}} \frac{\Delta M_{i(t+10)}^{Others \leftarrow East}}{E_{c(t-10)}}$, where $\Delta M_{i(t+10)}^{Others \leftarrow East}$ denotes changes in imports from the East to other high income countries (Australia, Canada, Japan, Norway, New Zealand, Sweden, Singapore, and the United Kingdom). EPW_{ct} and the corresponding instruments are constructed in similar ways but are based on exports. Standard errors are clustered at the level of 50 larger labor markets areas, defined as in [Kropp & Schwengler \(2011\)](#). Finally, note that unlike [Dauth et al. \(2014\)](#), we follow [Autor et al. \(2013\)](#) and weigh our regression by the share of the population in year 1978. This means we restrict the data to West Germany, since this information is only available for the West, and that we work with a balanced panel.

Eastern Europe and China led to a 3% rise in the growth of the employment rate for the median local labor market in West Germany. The estimated employment growth rates from Panel II are used as inputs to compute the relative gains from trade, according to Table 3.

Next, we compute the relative gains from trade according to Table 3, using the estimated employment rate growth from Panel II as an input for \dot{e}_c . Panel III of Table 4 reports the results. In column 3, we find that for the median local labor market in West Germany our formula under MC-FE-HET yields welfare gains that are 6% larger than those predicted by ACR's formula. In contrast, accounting for changes in the employment rate in frameworks with homogeneous firms, monopolistic competition with restricted entry or perfect competition yield relative welfare gains that are 3% larger for the median labor market. Disaggregated results corresponding to the MC-FE-HET case are mapped in Figure 1.

[FIGURE 1 ABOUT HERE]

The figure exhibits substantial variation in the relative welfare gains from trade across local labor markets; e.g. ranging from 0.7 to 1.52 when looking at trade with both China and Eastern Europe. Interestingly, the figure suggests that in a framework with heterogeneous firms, omitting labor market frictions might lead to underestimate the welfare gains from market access to up to 52%, with the bias being larger for cities close to the border in the South-West region. The map also suggests that ACR's welfare formula may overestimate the gains in a few cities which were, presumably, hit more heavily by import competition.

Finally, in Table 5, we evaluate the impact of trade exposure on population (column 1), wages (column 2) and employment (column 3).³⁴ The last column corresponds to column 3 of Table 4. Estimates indicate that most of the trade effects on the employment rate are driven by changes in local employment, while population and wages do not seem to respond to imports or exports in a statistically significant way. Therefore, this set of results suggest that greater trade integration with the East and the far East was mostly absorbed by shifts in labor demand. In addition, these results are also evidence of a rather inelastic labor supply and support our modeling assumption of no migration or population growth across local labor markets.

[TABLE 5 ABOUT HERE]

7 Conclusion

We develop a model and an empirical strategy to estimate the gains from trade in the presence of frictions in the labor market. Our model delivers a welfare formula showing

³⁴Table D.3 of the Online Appendix shows the results for Eastern Europe and China separately.

that trade liberalization affects welfare through two channels: (i) the traditional adjustment margin studied in ACR, which depends on the trade elasticity and on changes in the share of domestic expenditure; and (ii) a new adjustment margin operating through shifts in the employment rate. A key takeaway from the theory is that the micro details of the model matter when evaluating the gains from trade in economies with equilibrium unemployment. In particular, conditional on the share of domestic expenditure and the trade elasticity, the welfare implications of trade-induced changes in unemployment depend on the goods market structure and on the degree of firm heterogeneity.

The paper proposes a novel identification strategy to uncover the two key structural parameters needed to analyze welfare changes in a broad range of market structures, the trade elasticity and the elasticity of substitution in consumption. Our identification strategy follows naturally from our model, based on Bartik-style instruments that exploit exogenous differences in industrial employment composition across local labor markets. Applying this methodology to study the rise of trade with the East, we find that omitting trade-induced changes in the employment rate typically leads to an underestimation of the gains from trade in West German local labor markets. This bias is particularly important when the underlying market structure is monopolistic competition with free entry and heterogeneous firms.

References

- Acemoglu, D., Autor, D., Dorn, D., Hanson, G. H., & Price, B. (2016). Import Competition and the Great US Employment Sag of the 2000s. *Journal of Labor Economics*, 34(S1), S141–S198.
- Arkolakis, C., Costinot, A., & Rodríguez-Clare, A. (2012). New Trade Models, Same Old Gains? *American Economic Review*, 102(1), 94–130.
- Armington, P. S. (1969). A Theory of Demand for Products Distinguished by Place of Production. *IMF Staff Papers*, 16(1), 159.
- Autor, D., Dorn, D., & Hanson, G. H. (2013). The China Syndrome: Local Labor Market Effects of Import Competition in the United States. *American Economic Review*, 103(6), 2121–68.
- Bartik, T. J. (1991). *Who Benefits from State and Local Economic Development Policies?* Kalamazoo, MI: Upjohn Press, W.E. Upjohn Institute for Employment Research.
- Beaudry, P., Green, D. A., & Sand, B. M. (2012). Does Industrial Composition Matter for Wages? A Test of Search and Bargaining Theory. *Econometrica*, 80(3), 1063–1104.
- Beaudry, P., Green, D. A., & Sand, B. M. (2018). In Search of Labor Demand. *American Economic Review*, 108 (9), 2714–57.
- Blanchard, O. J. & Katz, L. F. (1992). Regional Evolutions. *Brookings Papers and Economic Activity*, (1), 1–75.
- Borusyak, K., Hull, P., & Jaravel, X. (2018). Quasi-Experimental Shift-Share Research Designs. *NBER Working Paper 24997*.
- Broda, C. & Weinstein, D. (2006). Globalization and the Gains from Variety. *Quarterly Journal of Economics*, 121(2), 541–585.
- Card, D., Heining, J., & Kline, P. (2013). Workplace Heterogeneity and the Rise of West German Wage Inequality. *Quarterly Journal of Economics*, 128(3), 967–1015.
- Chaney, T. (2008). Distorted Gravity: The Intensive and Extensive Margins of International Trade. *American Economic Review*, 98(4), 1707–21.
- Dauth, W., Findeisen, S., & Suedekum, J. (2014). The Rise of the East and the Far East: German Labor Markets and Trade Integration. *Journal of the European Economic Association*, 12(6), 1643–1675.

- Feenstra, R., Ma, H., & Xu, Y. (2017). US Exports and Employment. *NBER Working Paper 24056*.
- Feenstra, R. C. (1994). New Product Varieties and the Measurement of International Prices. *American Economic Review*, (pp. 157–177).
- Felbermayr, G., Prat, J., & Schmerer, H.-J. (2011). Globalization and Labor Market Outcomes: Wage Bargaining, Search Frictions, and Firm Heterogeneity. *Journal of Economic Theory*, 146(1), 39–73.
- Fischer, G., Janik, F., Mueller, D., & Schmucker, A. (2009). *The IAB Establishment Panel – Things Users Should Know*. In: Schmollers Jahrbuch. Zeitschrift für Wirtschafts- und Sozialwissenschaften, Jg. 129, H. 1, S. 133-148.
- Goldsmith-Pinkham, P., Sorkin, I., & Swift, H. (2017). Bartik Instruments: What, When, Why, and How. *NBER Working Paper 24408*.
- Greenstone, M., Mas, A., & Nguyen, H.-L. (2015). Do Credit Market Shocks Affect the Real Economy? Quasi-Experimental Evidence from the Great Recession and ‘Normal’ Economic Times. *NBER Working Paper 20704*.
- Head, K., Mayer, T., et al. (2014). Gravity Equations: Toolkit, Cookbook, Workhorse. *Handbook of International Economics*, 4, 131–195.
- Heid, B. & Larch, M. (2016). Gravity with Unemployment. *Journal of International Economics*, 101, 70–85.
- Heining, J., Klosterhuber, W., & Seth, S. (2014). *An overview on the Linked Employer-Employee Data of the Institute for Employment Research (IAB)*. In: Schmollers Jahrbuch. Zeitschrift für Wirtschafts- und Sozialwissenschaften, Jg. 134, H. 1, S. 141-148.
- Heining, J., Scholz, T., & Seth, S. (2013). *Linked-Employer-Employee Data from the IAB: LIAB Cross-Sectional Model 2 1993-2010 (LIAB QM2 9310)*. Fdz-datenreport 02/2013 (en).
- Helpman, E. & Itskhoki, O. (2010). Labour Market Rigidities, Trade and Unemployment. *Review of Economic Studies*, 77(3), 1100–1137.
- Helpman, E., Itskhoki, O., Muendler, M., & Redding, S. (2017). Trade and Inequality: From Theory to Estimation. *Review of Economic Studies*, 84(1), 357–405.

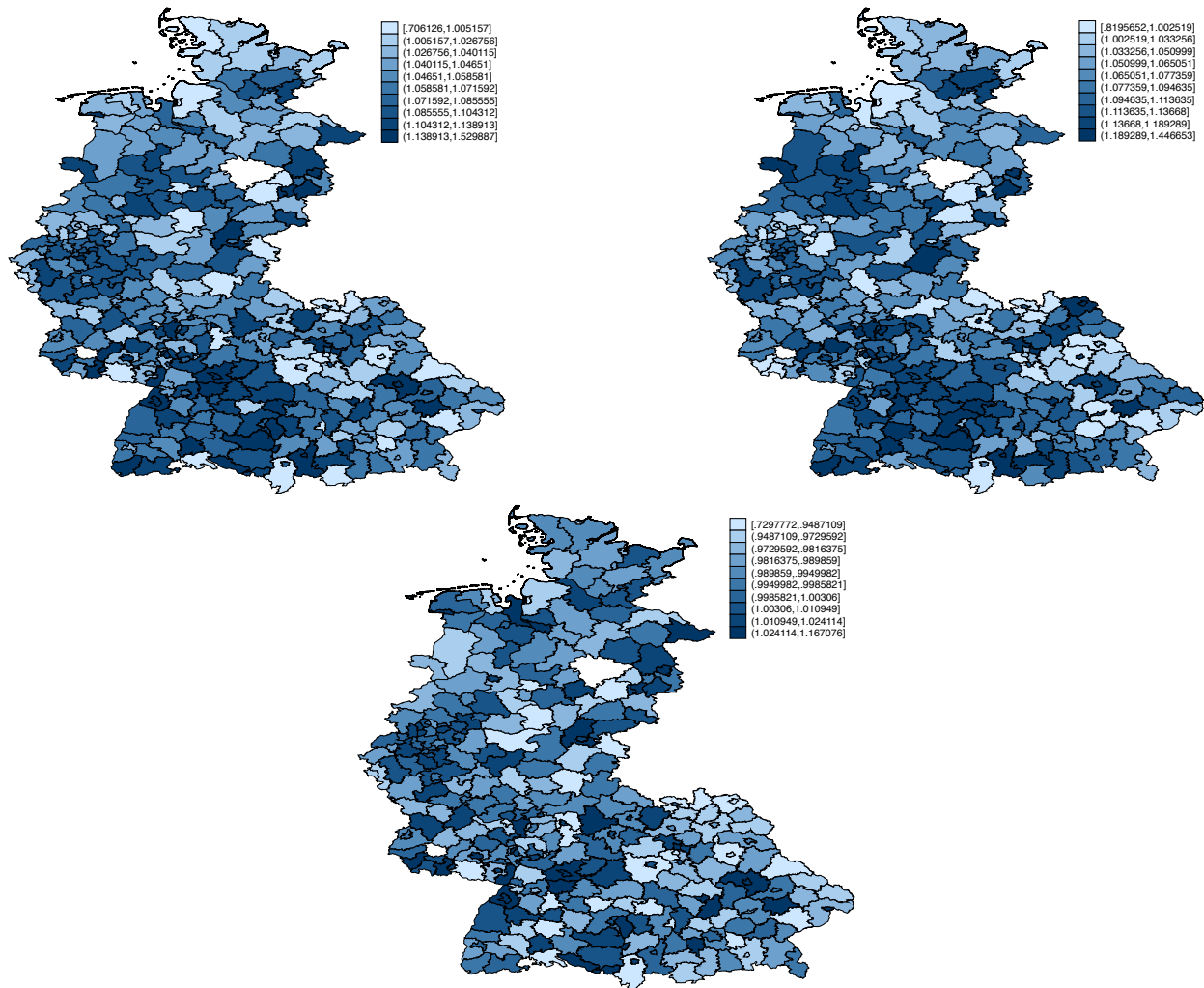
- Helpman, E., Itskhoki, O., & Redding, S. (2010). Inequality and Unemployment in a Global Economy. *Econometrica*, 78(4), 1239–1283.
- Hopenhayn, H. A. (1992). Entry, Exit, and Firm Dynamics in Long Run Equilibrium. *Econometrica*, 60(5), 1127–1150.
- Kropp, P. & Schwengler, B. (2011). Abgrenzung von Arbeitsmarktregionen: ein Methodenvorschlag. *Raumforschung und Raumordnung*, 69(1), 45–62.
- Krugman, P. (1980). Scale Economies, Product Differentiation, and the Pattern of Trade. *American Economic Review*, 70(5), 950–959.
- Melitz, M. J. (2003). The Impact of Trade on Intra-Industry Reallocations and Aggregate Industry Productivity. *Econometrica*, 71(6), 1695–1725.
- Melitz, M. J. & Redding, S. J. (2014). Heterogeneous Firms and Trade. *Handbook of International Economics*, 4, 1–54.
- Mühlemann, S. & Leiser, M. S. (2015). Ten Facts You Need To Know About Hiring.
- Ossa, R. (2015). Why Trade Matters after All? *Journal of International Economics*, 97, 266–277.
- Pierce, J. R. & Schott, P. K. (2016). The Surprisingly Swift Decline of US Manufacturing Employment. *American Economic Review*, 106(7), 1632–62.
- Pissarides, C. A. (2000). *Equilibrium Unemployment Theory*. MIT press.
- Redding, S. J. & Rossi-Hansberg, E. (2017). Quantitative Spatial Economics. *Annual Review of Economics*, 9, 21–58.
- Soderbery, A. (2015). Estimating Import Supply and Demand Elasticities: Analysis and Implications. *Journal of International Economics*, 96(1), 1–17.
- Song, J., Price, D. J., Guvenen, F., Bloom, N., & von Wachter, T. (2018). Firming Up Inequality. *The Quarterly Journal of Economics*, 134(1), 1–50.
- Stole, L. A. & Zwiebel, J. (1996). Intra-Firm Bargaining under Non-Binding Contracts. *Review of Economic Studies*, 63(3), 375–410.
- Świącki, T. (2017). Intersectoral Distortions and the Welfare Gains from Trade. *Journal of International Economics*, 104, 138–156.

Tschopp, J. (2015). The Wage Response to Shocks: The Role of Inter-Occupational Labor Adjustment. *Labour Economics*, 37, 28–37.

Tschopp, J. (2017). Wage Formation: Towards Isolating Search and Bargaining Effects from the Marginal Product. *Economic Journal*, 127, 1693–1729.

Figures

Figure 1: The Rise of the East and the Far East: welfare gains from trade accounting for unemployment changes relative to ACR, under MC-FE-HET (West Germany).



Notes: Each figure uses $\hat{\sigma} = 1.78$ and the estimates from Table 4 for the period 1988-2008. The first figure is based on trade with China and Eastern Europe (column 3 of Table 4). The second figure focuses on trade with Eastern Europe (column 4 of Table 4) and the last one is based on China only (column 5 of Table 4).

Tables

Table 1: Gravity Estimation

I. OLS/2nd Stage	OLS	2SLS					
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Coefficient (Δw_{ic})	-1.98*	-7.98***	-7.80***	-8.01***	-7.82***	-7.93***	-7.96***
city-year	(1.03)	(2.77)	(2.71)	(2.69)	(2.73)	(2.70)	(2.68)
2-way	(1.03)	(3.07)	(2.96)	(2.95)	(2.98)	(2.94)	(2.97)
Controls:							
Industry FE \times Δ City Empl. Rate	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry \times Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
City FE	No	No	Yes	Yes	Yes	Yes	Yes
City Trends	No	No	No	Yes	No	No	No
Lag City Manuf. Share	No	No	No	No	Yes	No	No
Manuf. \times Trend	No	No	No	No	No	Yes	Yes
Demog. \times Trend	No	No	No	No	No	No	Yes
II. First-stage							
IV_{ct}^B		2.42*	3.90**	3.91**	3.88**	3.84**	3.91**
city-year		(1.42)	(1.59)	(1.64)	(1.60)	(1.60)	(1.62)
2-way		(1.43)	(1.68)	(1.74)	(1.69)	(1.69)	(1.71)
IV_{ct}^W		4.57***	4.22***	4.20***	4.22***	4.23***	4.19***
city-year		(0.48)	(0.45)	(0.44)	(0.45)	(0.46)	(0.44)
2-way		(0.51)	(0.52)	(0.51)	(0.51)	(0.52)	(0.51)
<i>F</i> -Stat.:							
city-year		80.45	97.18	100.28	97.82	98.56	100.02
2-way		58.92	64.26	65.08	64.46	64.81	65.12
Over-id. <i>p</i> value:							
city-year		0.56	0.91	0.82	0.90	0.85	0.89
2-way		0.58	0.92	0.85	0.91	0.87	0.91
Observations	3940	3713	3713	3713	3713	3713	3713

Notes. Standard errors, in parentheses, are clustered at the city-year (first line) and two-way clustered at the city-year and industry-city (second line) level. (***), (**), and (*) denote significance at the 1%, 5% and 10% level, respectively, and refer to city-year clustering. All models are estimated using 24 city by 29 manufacturing industry cells in first differences from 1996-2010. The dependent variable is the change in $\ln \frac{X_{icFt}}{R_{ict}}$, the city-industry ratio of exports to revenues. $\Delta \ln w_{ict}$ is the regression adjusted city-industry wage. Column 1 is estimated via Ordinary Least Squares and columns 2-6 are estimated via Two Stage Least Squares. All regressions are weighted by the $t-1$ number of establishments in the city-industry cell. The control Manuf. \times Trend is the average 1992/93 city share of manufacturing employment, interacted with linear trends. The control set Demog. \times Trend includes the average 1992/93 city share of college graduates, female workers, native Germans, log employment rate, and log size of the labour force – all interacted with linear trends. Panel II shows the the first-stage estimates and the associated tests of instrument relevance. The second last row shows the *p*-value for the Hansen *J* overidentification test, and the last row shows the number of city-industry cells used in the estimations.

Table 2: Revenue Estimation

I. OLS/2nd Stage	OLS		2SLS				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Coefficient (Δw_{ic})	-0.54*	-0.75*	-0.76*	-0.78*	-0.77*	-0.76*	-0.75*
city-year	(0.28)	(0.45)	(0.45)	(0.42)	(0.44)	(0.43)	(0.43)
2-way	(0.28)	(0.57)	(0.57)	(0.56)	(0.57)	(0.57)	(0.56)
σ	1.54***	1.75***	1.76***	1.78***	1.77***	1.76***	1.75***
city-year	(0.28)	(0.45)	(0.45)	(0.42)	(0.44)	(0.43)	(0.43)
2-way	(0.28)	(0.57)	(0.57)	(0.56)	(0.57)	(0.57)	(0.56)
Controls:							
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE \times Δ City Empl. Rate	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE \times Bartik	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry \times Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
City FE	No	No	Yes	Yes	Yes	Yes	Yes
City Trends	No	No	No	Yes	No	No	No
Lag Manuf. Share	No	No	No	No	Yes	No	No
Manuf. \times Trend	No	No	No	No	No	Yes	Yes
Demog. \times Trend	No	No	No	No	No	No	Yes
II. First-stage							
IV_{ct}^B		3.74**	3.74**	3.83**	3.82**	3.74**	3.80**
city-year		(1.58)	(1.58)	(1.64)	(1.59)	(1.62)	(1.63)
2-way		(1.99)	(1.99)	(2.04)	(2.00)	(2.02)	(2.02)
IV_{ct}^W		3.87***	3.87***	3.86***	3.84***	3.87***	3.86***
city-year		(0.58)	(0.58)	(0.60)	(0.59)	(0.60)	(0.60)
2-way		(0.72)	(0.72)	(0.74)	(0.73)	(0.74)	(0.74)
F-Stats:							
city-year		36.98	36.97	36.82	37.24	36.66	36.97
2-way		27.68	27.68	27.67	28.05	27.56	27.73
Hansen p -vals:							
city-year		0.15	0.14	0.16	0.14	0.12	0.15
2-way		0.23	0.22	0.23	0.21	0.19	0.22
Observations	46503	46503	46503	46503	46503	46503	46503

Notes. Standard errors, in parentheses, are clustered at the city-year (first line) and two-way clustered at the city-year and industry-city (second line) level. (***), (**), and (*) denote significance at the 1%, 5% and 10% level, respectively, and refer to city-year clustering. All models are estimated using 24 city by 29 manufacturing industry cells in first differences from 1996-2010. The dependent variable is the change in $\ln r(\varphi)_{ic}$, firm-level city-industry domestic revenues. $\Delta \ln w_{ict}$ is the regression adjusted city-industry wage. Column 1 is estimated via Ordinary Least Squares and columns 2-6 are estimated via Two Stage Least Squares. All regressions are weighted by establishment survey weights. The control $\text{Manuf.} \times \text{Trend}$ is the average 1992/93 city share of manufacturing employment, interacted with linear trends. The control set $\text{Demog.} \times \text{Trend}$ includes the average 1992/93 city share of college graduates, female workers, native Germans, log employment rate, and log size of the labour force – all interacted with linear trends. Panel II shows the the first-stage estimates and the associated tests of instrument relevance. The second last row shows the p -value for the Hansen J overidentification test, and the last row shows the number of city-industry cells used in the estimations.

Table 3: Gains from trade in frictional settings relative to those predicted by ACR's welfare formula

MC-FE-HET (Melitz (2003) and Chaney (2008))	MC-FE-HOM (Krugman (1980))	PC or MC-RE (Armington (1969))
$\dot{e}_c^{1+\frac{1}{\sigma-1}}$ $\hat{\sigma} = 1.78$	$\dot{e}_c^{1+\frac{1}{\hat{\varepsilon}}}$ $\hat{\varepsilon} = 7$	\dot{e}_c

Table 4: Trade Exposure, Employment Rate Growth and the Relative Gains from Trade

I. 2nd Stage	Eastern Europe + China			Eastern Europe	China
	(1)	(2)	(3)	(4)	(5)
	1988-98	1998-08	1988-2008	1988-2008	1988-2008
Δ Import Exposure	-0.0099 (0.0072)	-0.0085** (0.0035)	-0.0096** (0.0039)	-0.029** (0.011)	-0.0086** (0.0041)
Δ Export Exposure	0.017** (0.0078)	0.012** (0.0053)	0.012** (0.0043)	0.024** (0.0085)	0.013 (0.014)
Observations	326	326	652	652	652
R^2	0.328	0.109	0.420	0.353	0.417
II. Employment rate growth					
Predicted \dot{e}_c					
Mean	101.58	102.91	102.78	103.53	99.60
Med	101.38	102.55	102.54	103.03	99.90
10th pct.	100.31	101.05	100.61	100.56	98.27
90th pct.	103.02	105.09	105.14	107.12	100.76
III. Relative Welfare Gains					
MC-FE-HET: $(\dot{e}_c)^{1+\frac{1}{\sigma-1}}$					
Mean	103.64	106.76	106.46	108.25	99.10
Med	103.19	105.92	105.88	107.05	99.77
10th pct.	100.71	102.41	101.40	101.29	96.09
90th pct.	107.02	112.01	112.12	117.00	101.73
MC-FE-HOM: $(\dot{e}_c)^{1+\frac{1}{\xi}}$					
Mean	101.81	103.33	103.18	104.05	99.55
Med	101.58	102.92	102.90	103.47	99.89
10th pct.	100.35	101.20	100.70	100.64	98.02
90th pct.	103.46	105.84	105.90	108.18	100.87

Notes. Panel I presents the regression results of equation (28), estimated over 326 cities of West Germany. Standard errors, in parentheses, are clustered at the level of 50 larger labor markets areas. (***) (**), and (*) denote significance at the 1%, 5% and 10% level, respectively. The dependent variable is the employment rate growth in city c . e_{ct} is computed by dividing total employment by the size of working age population in city c and time t . Δ Import Exposure (IPW_{ct}) and Δ Export Exposure (EPW_{ct}) are observed decadal changes in import and export exposure, respectively. Specifically, $IPW_{ct} = \sum_i \frac{E_{ict}}{E_{it}} \frac{\Delta M_{i(t+10)}^{G \leftarrow East}}{E_{ct}}$, where Δ denotes a decadal time difference, $\frac{E_{ict}}{E_{it}}$ is city c 's share of industrial employment and E_{ct} is city c manufacturing employment. $\Delta M_{i(t+10)}^{G \leftarrow East}$ denotes the change in imports from the East between t and $t+10$. Δ Export Exposure (EPW_{ct}) is computed similarly using exports. Each specification includes a set of region-time fixed effects and city-specific controls (the share of employment in tradable goods industries, the share of high-skilled, foreign and female workers, as well as the percentage of routine/intensive occupations). In each column, we instrument import exposure using $IVIPW_{ct} = \sum_i \frac{E_{ic(t-10)}}{E_{(it-10)}} \frac{\Delta M_{i(t+10)}^{Others \leftarrow East}}{E_{c(t-10)}}$, where $\Delta M_{i(t+10)}^{Others \leftarrow East}$ denotes changes in imports from the East to other high income countries. We instrument export exposure in a similar way using exports. In columns 1-3, IPW_{ct} and EPW_{ct} are computed using imports from and exports to both China and Eastern Europe. Column 4 focuses on trade with Eastern Europe and column 5 only uses trade with China. Columns 1, 2 and 3-5 use decadal difference over the period 1988-1998, 1998-2008 and 1988-2008, respectively. We weigh our regressions by the share of the population in year 1978. In Panel II, the Relative Gains from Trade under PC or MC-RE equal \dot{e} , the predicted employment growth, calculated using equation (29). Panel III presents the estimated relative gains from trade. Both employment rate growth in panel II and relative welfare gains in panel III are expressed in percentage.

Table 5: Trade Exposure and Other Outcomes

	Population	Wages	Employment	Emp. Rate
	(1)	(2)	(3)	(4)
Δ Import Exposure	-0.0028 (0.0021)	-0.000060 (0.00026)	-0.012** (0.0052)	-0.0096** (0.0039)
Δ Export Exposure	-0.00078 (0.0012)	0.00050 (0.00033)	0.0100** (0.0045)	0.012** (0.0043)
Constant	0.18** (0.047)	0.028** (0.0049)	0.38** (0.079)	0.16** (0.053)
Observations	652	652	652	652
R^2	0.446	0.952	0.237	0.420

Notes. Standard errors, in parentheses, are clustered at the level of 50 larger labor markets areas. (***), (**), and (*) denote significance at the 1%, 5% and 10% level, respectively. The Table presents regression results of (28), estimated on different city outcome variables over 326 cities of West Germany. The dependent variables are population growth (column 1), the growth of wages (column 2), employment growth (column 3) and the employment rate growth (column 4) at the city level. The specification in column 4 corresponds to the specification in column 3 of Table 4. Δ Import Exposure (IPW_{ct}) and Δ Export Exposure (EPW_{ct}) are observed decadal changes (1988-1998 and 1998-2008) in import and export exposure, respectively. IPW_{ct} and EPW_{ct} are computed using imports from and exports to both China and Easter Europe. Specifically, $IPW_{ct} = \sum_i \frac{E_{ict}}{E_{it}} \frac{\Delta M_{i(t+10)}^{G \leftarrow East}}{E_{ct}}$, where Δ denotes a decadal time difference, $\frac{E_{ict}}{E_{it}}$ is city c 's share of industrial employment and E_{ct} is city c manufacturing employment. $\Delta M_{i(t+10)}^{G \leftarrow East}$ denotes the change in imports from the East between t and $t + 10$. Δ Export Exposure (EPW_{ct}) is computed similarly using exports. Each specification includes a set of region-time fixed effects and city-specific controls (the share of employment in tradable goods industries, the share of high-skilled, foreign and female workers, as well as the percentage of routine/intensive occupations). In each column, we instrument import exposure using $IVIPW_{ct} = \sum_i \frac{E_{ic(t-10)}}{E_{(it-10)}} \frac{\Delta M_{i(t+10)}^{Others \leftarrow East}}{E_{c(t-10)}}$, where $\Delta M_{i(t+10)}^{Others \leftarrow East}$ denotes changes in imports from the East to other high income countries. We instrument export exposure in a similar way using exports. We weigh our regressions by the share of the population in year 1978.