ESTIMATING THE GAINS FROM TRADE IN FRICTIONAL LOCAL LABOR MARKETS

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Abstract
We develop a theory and an empirical strategy to estimate the welfare gains from trade in economies with frictional local labor markets. We obtain a welfare formula that nests several standard market structures and features an additional adjustment margin, via the employment rate. To obtain causal estimates of the two key parameters for counterfactual analysis, the trade elasticity and the elasticity of substitution in consumption, we propose a theoretically-consistent identification strategy that exploits variation in industrial composition across local labor markets. We examine Germany's recent trade integration with China and Eastern Europe. Under monopolistic competition with free entry and firm heterogeneity, the welfare gains are 5.5% larger than in the corresponding frictionless setting. The relative welfare gains are more modest under alternative market structures. (JEL: F12, F16, J31, J60)

Keywords: Welfare gains from trade, trade elasticity, local labor markets, unemployment, wages, search and bargaining.

Acknowledgments: 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, Andrei Levchenko, Marc Muendler, Tomasz Święcki 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, Ryerson University, and the University of Michigan for helpful comments and suggestions. Busra Ariduru provided outstanding research assistance.

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Journal of the European Economic Association
Preprint prepared on November 1st, 2021 using jeea.cls *v1.0.*

1. Introduction

Recent global developments, including a trade war, Brexit and the pandemic, have 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 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. Moreover, we remain largely ignorant of the sensitivity of quantitative results to the underlying microstructure needed to map labor market outcomes into welfare. 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 multiple industries and locations – local labor markets – where consumption goods are traded under alternative microeconomic assumptions. Our first contribution is to derive a welfare formula that enables a comparison of the gains from trade across models with different market structures (perfect competition and monopolistic competition with free or restricted entry) featuring either homogeneous or heterogeneous firms. 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 – showed 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. ACR then pondered the importance of the microstructure of trade models when quantifying the gains from trade, memorably concluding: "So far, not much". 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 due to 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, conditional 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 formulation 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 to 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., 2020). 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.

Finally, we exploit the rise of trade with China and Eastern Europe between 1988 and 2008 to assess the quantitative importance of alternative assumptions about the micro structure of the model when computing the gains from trade in frictional local labor markets in West Germany. To compare the welfare implications of different micro assumptions, we follow the ex-post approach advocated by Costinot & Rodríguez-Clare (2014), implicitly calibrating different versions of our model to match the same set of empirical moments. Our ex-post welfare evaluations take the trade elasticity and trade-induced 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 5.5% 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 2.5% 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. Święcki (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.

Closer to our approach, a recent literature studies the effects of trade shocks in quantitative models featuring equilibrium unemployment or non-employment, such as Coşar et al. (2016), Caliendo et al. (2019), Carrère et al. (2020), Kim & Vogel (2020), Rodríguez-Clare et al. (2020) and Dix-Carneiro et al. (2021). Relative to these studies, our analysis nests multiple market structures to gauge the relative importance of these micro-level assumptions when estimating the gains from trade with equilibrium unemployment in various workhorse trade models.[1] We thus shed light on the sensitivity of quantitative results to alternative microeconomic assumptions on which different strands of the literature rely on to map labor market outcomes into welfare.

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

1. Rodríguez-Clare et al. (2020) investigate the welfare effects of the China Shock on US local labor markets in a model with perfectly competitive product markets but nominal wage rigidity, a friction we do not consider here.

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.

Outline. The remainder of the paper is organized as follows. Section 2 presents the theoretical framework and focuses on the welfare analysis of trade shocks. 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, describes how to close the model and compute equilibrium, provides details on the linear approximation and reports 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 $c \in \{1, ..., C\}$. 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 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

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

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 simplify the notation.[2] For good i in market n, the aggregate demand for variety ω with price $p_{in}(\omega)$ is

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

2. At 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.

where $A_{in} \equiv X_{in} P_{in}^{\sigma_i - 1}$ 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.

Market Structure and Technology. Our welfare analysis spans alternative market structures for consumption goods. For ease of exposition, however, 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 Appendix. The latter also contains a complete treatment of perfect competition in the goods market.

At any time, a competitive fringe of risk-neutral firms can start production of unique varieties of good i in city c. Production requires labor (production workers) and two types of intermediate services: recruitment and marketing. In all specifications of our theory, both intermediates are homogeneous services, specific to industry i, produced with labor (recruitment or marketing workers) under constant returns and traded domestically in competitive markets (non-tradable across cities). The next section describes the occupational choices of workers. Prior to the beginning of every period, firms and intermediate service suppliers are hit with an i.i.d. shock that forces them to exit and their workers to become unemployed with probability δ_c.

Recruitment services supply the vacancies that firms and marketing agencies need to match with production and marketing workers, respectively. In turn, marketing agencies supply services that operate as start-up and fixed costs for firms in the industry. In particular, firms commit to a sunk per-period investment f_{ic}^{E}, first incurred in the period that immediately follows entry. This allows a firm to discover and maintain its time-invariant labor productivity, denoted φ, an independent draw from a known distribution $G_{ic}(\varphi)$ with positive support. To serve any market n, the firm must incur an additional fixed cost f_{icn} per period.[3]

Trade across cities is also subject to iceberg costs, 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.

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. Each individual in city c is endowed with one unit of labor. In addition, we assume that workers are not mobile across cities, hence L_c represents the exogenous labor endowment in c.[4]

The local labor market features search frictions and endogenous occupational choice. In each period, all unemployed workers search. A fraction of them are randomly matched to local industries, as dictated by a linearly homogeneous matching function subject to congestion externalities: $m_c(\theta_c)$ denotes the vacancy filling rate, a decreasing function of the vacancy-unemployment ratio (or labor market tightness) θ_c. The job finding rate is $\theta_c m_c(\theta_c)$ across all industries and $\theta_c m_c(\theta_c)\eta_{ic}$ in any particular industry i, where η_{ic} is the industry's share in city c's total employment.[5] Workers enter production in the period following match creation. Unemployed workers receive a per-capita income transfer b_c, financed by a tax t_c on employed workers that

3. Fixed and entry costs are measured in units of marketing services hired domestically. The present value of the entry cost is derived in section A.3 of the Appendix.

4. This 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.

5. In a stationary equilibrium, all industries replace a constant fraction of their workers in every period.

adjusts endogenously to ensure budget balance in city c (i.e. net transfers within the local labor market sum to zero).

Workers matched to industry i self-select into one of three industry-specific occupations, where they can (i) supply one unit of marketing services; or (ii) supply χ_{ic} units of recruitment services (vacancies); or (iii) work as a production worker in a random firm in the industry.

While marketing and recruitment occupations can supply homogeneous intermediate services to any firm in industry i, production workers produce firm-specific output. Therefore, wages for marketing and recruitment workers are determined competitively while wages for production workers are bargained at the firm level, as described below. All payments are made at the end of each period.

Occupational Choice. The following Bellman equations describe the stationary values of unemployment, denoted U_c, and employment for occupation o in industry i, denoted E^o_{ic},

$$(1+\rho)\,U_c = b_c + \theta_c m_c(\theta_c) \sum_i \eta_{ic} \max_o \{E^o_{ic}\} + [1-\theta_c m_c(\theta_c)]\,U_c, \qquad (2)$$

and

$$(1+\rho)\,E^o_{ic} = w^o_{ic} - t_c + (1-\delta_c)\,E^o_{ic} + \delta_c U_c, \qquad (3)$$

where w^o_{ic} is the (gross) wage for occupation o.[6] In equilibrium, workers matched to industry i must be indifferent between their three occupational choices, hence the value of employment and wages are equalized across occupations. That is, by (3), $E^o_{ic} = E_{ic}$ implies $w^o_{ic} = w_{ic}$ for every o.

6. For production workers, w^o_{ic} and E^o_{ic} should, in general, be interpreted as expectations across firms in industry i. Below we show, however, that equilibrium wages and employment values are equalized across firms in i.

2.2. The Firm's Problem

We analyze the problem of a firm with productivity φ producing good i in city c.[7] As anticipated, we restrict attention to stationary equilibria in which firm productivity distributions and all aggregates remain constant over time. We proceed in three steps. First, taking employment and market entry 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 market entry 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:

$$r_{ic}(l;\varphi) = \left[\sum_n I_{icn}(\varphi) A_{in} \left(\tau_{icn}\right)^{1-\sigma_i}\right]^{\frac{1}{\sigma_i}} (l\varphi)^{\frac{\sigma_i - 1}{\sigma_i}}, \tag{4}$$

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, to maximize the present value of expected profits. Firm φ currently employing l production

7. All firms with the same productivity behave symmetrically in equilibrium, hence we index firms and varieties by φ from now onward.

workers solves:

$$\Pi_{ic}(l;\varphi) = \max_{v} \frac{1}{1+\rho}\Bigg\{ r_{ic}(l;\varphi) - w_{ic}(l;\varphi)l - p_{ic}^{M}\sum_{n} I_{icn}(\varphi) f_{icn} - p_{ic}^{V} v + (1-\delta_c)\,\Pi_{ic}(l';\varphi)\Bigg\},$$

$$s.t. \quad l' = l + m_c(\theta_c)v, \tag{5}$$

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 the firm internalizes the effect of its employment decision on the wage of its production workers. The firm takes as given the prices of marketing and recruitment services, denoted p_{ic}^{M} and p_{ic}^{V}, respectively.

The first-order condition in problem (5),

$$(1-\delta_c)\,\frac{\partial \Pi_{ic}(l';\varphi)}{\partial l'} = \frac{p_{ic}^{V}}{m_c(\theta_c)}, \tag{6}$$

equates the expected marginal profit of hiring an additional worker to the recruitment cost per worker.[8] Equation (6) 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. A firm that starts with no workers thus reaches its optimal long-run employment level in the following period.[9] Second, the marginal profit of hiring an additional

8. Recruitment costs therefore 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 recruitment costs and vary substantially by industry.

9. The 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.

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 production 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 $E_{ic}(l;\varphi)$, satisfies

$$(\rho + \delta_c)\left[E_{ic}(l;\varphi) - U_c\right] = w_{ic}(l;\varphi) - t_c - \rho U_c. \tag{7}$$

The surplus splitting rule that solves the bargaining game can then be written as:

$$(1 - \beta_i)\left[E_{ic}(l;\varphi) - U_c\right] = \beta_i \frac{\partial \Pi_{ic}(l;\varphi)}{\partial l}, \tag{8}$$

where $\beta_i \in (0,1)$ denotes the bargaining power of workers. Combining the revenue function (4), the envelope condition from (5), the first-order condition (6) and the value of employment (7), we can express the surplus-splitting rule (8) as a differential equation for the wage schedule. Its solution is the Wage Curve:

$$w_{ic} = t_c + \rho U_c + \frac{\beta_i}{(1-\beta_i)}\left(\frac{\rho + \delta_c}{1 - \delta_c}\right)\frac{p_{ic}^V}{m_c\left(\theta_c\right)}. \tag{9}$$

Three remarks are in order. First, the equilibrium wage does not vary across firms or occupations within city-industry cells. Intuitively, firms adjust their labor force until the marginal profit of hiring an additional production worker is equalized across firms. By (8), this equalizes the value of employment across firms. Wage equalization across firms then follows from (7). In turn, the indifference condition across occupations implies that equation (9) applies to all workers employed in cell ic, regardless of occupation. Second, inter-industry wage differentials within local labor markets are driven by cross-industry variation in bargaining power (β_i) and costs of posting vacancies (p_{ic}^V). Finally, the city-industry wage w_{ic} depends on the industrial composition of the labor market (i.e. the employment shares η_{ic} for all i) and on the tightness of the labor market, via the worker's outside option U_c. To see this, apply the indifference condition to (2) and (3), then rearrange to obtain

$$\rho U_c = b_c + \frac{\theta_c m_c(\theta_c)}{\rho + \delta_c} \sum_i \eta_{ic} (w_{ic} - t_c - \rho U_c) . \tag{10}$$

By (10), 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.

The Cost of Labor. 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 recruitment cost per worker, $p_{ic}^V/m_c(\theta_c)$, expressed on a per-period basis. We thus define

$$\mu_{ic} \equiv w_{ic} + \left(\frac{\rho + \delta_c}{1 - \delta_c}\right) \frac{p_{ic}^V}{m_c(\theta_c)}, \tag{11}$$

where $p_{ic}^V = w_{ic}/\chi_{ic}$ since vacancies are supplied competitively by recruitment workers.[10] Henceforth, we refer to μ_{ic} as the *cost of labor* in industry i of city c.

As a special case, if the productivity of recuitment workers is inversely related to the vacancy filling rate, $1/\chi_{ic} = k_{ic} m_c(\theta_c)$, the model features a proportional recruitment cost per worker; that is,

$$\frac{p_{ic}^V}{m_c(\theta_c)} = k_{ic} w_{ic}, \tag{12}$$

where $k_{ic} > 0$. In this case, the cost of labor is proportional to the wage. While (11) is sufficient to solve the model, we impose (12) in section 2.5 to enhance the tractability of the welfare analysis.

Firm-level Outcomes. 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. Marketing agencies also incur recruitment costs and supply their services competitively, hence $p_{ic}^M = \mu_{ic}$ pins down fixed costs for firms. These two

10. Section A.2.4 in the Appendix determines the equilibrium prices of recruitment and marketing services.

properties enable closed-form solutions for all firm-level equilibrium outcomes in terms of the cost of labor μ_{ic} and demand shifters A_{in} in all markets n.[11] In particular, the firm's per-period revenue, denoted $r_{ic}(\varphi)$, can be written as

$$r_{ic}(\varphi) = \left(\frac{\sigma_i - 1}{\sigma_i - \beta_i}\right)^{\sigma_i - 1} \left[\sum_n I_{icn}(\varphi) A_{in} \left(\tau_{icn}\right)^{1-\sigma_i}\right] \left(\frac{\varphi}{\mu_{ic}}\right)^{\sigma_i - 1}. \tag{13}$$

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

$$\pi_{ic}(\varphi) = \left(\frac{1 - \beta_i}{\sigma_i - \beta_i}\right) r_{ic}(\varphi) - \mu_{ic} \sum_n I_{icn}(\varphi) f_{icn}. \tag{14}$$

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 (14). 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

$$\left(\frac{1 - \beta_i}{\sigma_i - \beta_i}\right) r_{icn}(\varphi^*_{icn}) = \mu_{ic} f_{icn} \quad \Leftrightarrow \quad \Lambda^0_i A_{in} \left(\tau_{icn}\right)^{1-\sigma_i} \left(\varphi^*_{icn}\right)^{\sigma_i - 1} \left(\mu_{ic}\right)^{-\sigma_i} = f_{icn}, \tag{15}$$

where $r_{icn}(\varphi)$ denotes the sales of firm φ in market n and $\Lambda^0_i > 0$ is a function of parameters σ_i and β_i.[12]

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).[13] By relaxing symmetry across

11. See sections A.2.4 and A.2.5 of the Appendix.

12. More specifically, $\Lambda^0_i = (1 - \beta_i)\,(\sigma_i - 1)^{\sigma_i - 1} / (\sigma_i - \beta_i)^{\sigma_i}$.

13. To see this, assume for a moment that cities are symmetric. In this case, equation (15) pins down the ratio of the export and domestic cutoffs in any industry independently of

cities, we can circumvent this 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. Closing the Model

In a stationary equilibrium, our model aggregates as a standard trade model with heterogeneous firms (Melitz & Redding (2014)). Hence we defer the details to the Appendix. Section A.6 shows how to compute all endogenous variables under trade balance and fiscal balance in every city c.

2.4. 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. The Appendix derives the gravity equation for alternative goods market structures and frictional labor markets: homogeneous firms and restricted entry (special cases of the derivation in this section), and perfect competition.[14] 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} denote the mass of producers in cell ic, we have $X_{icn} = M_{ic} \int_{\varphi^*_{icn}}^{\infty} r_{icn}(\varphi) dG_{ic}(\varphi|\varphi \geq \varphi^*_{icn})$. To eliminate M_{ic} from the gravity equation, we focus on the share of exports in sectoral revenue, X_{icF}/R_{ic},

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).

14. See sections A.10.2, A.11.1 and A.12.4 of the Appendix.

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 $\kappa_i > \sigma_i - 1$.[15] Using equation (13), we obtain

$$\frac{X_{icF}}{R_{ic}} = \frac{\left(\varphi^*_{icF}\right)^{-\kappa_i} f_{icF}}{\sum_n \left(\varphi^*_{icn}\right)^{-\kappa_i} f_{icn}}. \tag{16}$$

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. $\int_0^\infty \pi_{ic}(\varphi) dG_{ic}(\varphi) = \mu_{ic} f^E_{ic}$. Under Pareto productivity, this fixes the denominator of (16).[16] Using the export cutoff condition (15) to eliminate φ^*_{icF} from the numerator of (16), the latter becomes

$$\frac{X_{icF}}{R_{ic}} = \Lambda^1_i \left(f^E_{ic}\right)^{-1} \left(f_{icF}\right)^{1-\frac{\varepsilon_i}{\sigma_i-1}} \left(\frac{\varphi_{\min,ic}}{\tau_{icF}}\right)^{\varepsilon_i} \left(A_{iF}\right)^{\frac{\varepsilon_i}{\sigma_i-1}} \left(\mu_{ic}\right)^{-\frac{\varepsilon_i \sigma_i}{\sigma_i-1}}, \tag{17}$$

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. $\Lambda^1_i > 0$ is a function of parameters β_i, ε_i, σ_i and ρ.[17] 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.[18]

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

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

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

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

18. Note 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^*_{icF} indeed increases, reducing the city's export share of good i. This observation underscores

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. We refer to it as the *wage elasticity* of the gravity equation, denoted ϕ_i^G.

In the empirical section, we rely on causal estimates of the wage elasticity to back out the trade elasticity from the gravity equation, a key step to quantify the welfare gains from trade. The structural mapping between the wage and trade elasticities, however, depends on the underlying market structure for goods. For example, in (17), $\phi_i^G = \varepsilon_i \sigma_i / (\sigma_i - 1)$. More generally, we show[19]

$$\varepsilon_i = \begin{cases} \left(\frac{\sigma_i - 1}{\sigma_i}\right) \phi_i^G, & \text{under MC-FE-HET,} \\ \phi_i^G + 1, & \text{under MC-FE-HOM or MC-RE,} \\ \phi_i^G, & \text{under PC .} \end{cases} \tag{18}$$

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).

Note that under MC-FE-HET, the trade elasticity ε_i is a function of the wage elasticity ϕ_i^G and the elasticity of substitution σ_i. Under the other market structures we consider, the wage elasticity is a sufficient statistic for the trade elasticity.

2.5. The Welfare Gains from Trade

In this section, we study the impact 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

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.

19. See sections A.7, A.10.2, A.11.1 and A.12 in the Appendix.

forms of intranational and international integration. We show that the welfare consequences of economic integration can be approximated by a parsimonious generalization of ACR's welfare formula that features an additional adjustment margin, driven by endogenous changes in 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. Under trade balance, the indirect utility of the representative consumer in city c, denoted V_c, is proportional to the per-period real income in the city:

$$V_c = \rho^{-1}\left(\prod_{i=1}^{I}\left(\alpha_i\right)^{\alpha_i}\right)\frac{W_c}{\prod_{i=1}^{I}\left(P_{ic}\right)^{\alpha_i}}, \tag{19}$$

where $W_c = \sum_{i=1}^{I} L_{ic}w_{ic}$ is the aggregate per-period labor income and L_{ic} is the mass of workers employed in industry i.[20]

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 compute the gains from trade, $\dot{V_c}$ from (19), we use the following implication of the stationary equilibrium under proportional recruitment costs: in every city c, proportional changes in wages and costs of labor are equalized across industries. Formally, for all i and c,

$$\dot{\mu_{ic}} = \dot{w_{ic}} = \dot{g_c}, \tag{20}$$

where $\dot{g_c}$ denotes an endogenous city-specific proportional change in μ_{ic} and w_{ic}. The first equality in (20) follows immediately from (11) and (12). The

20. The derivation of V_c appears in section A.1 of the Appendix. Note that W_c is equal to labor income since aggregate profits are zero (net of entry costs) and net transfers between employed and unemployed workers sum to zero (within cities). Under MC-RE, real income also includes positive aggregate profits (section A.11 in the Appendix).

second from (9) and (12), letting $g_c \equiv t_c + \rho U_c$. Importantly, (20) derives from the properties of the frictional labor market and hence holds for all the goods market structures considered in the paper.

The proportional change in aggregate city income is

$$\dot{W}_c = \dot{g_c}\dot{e_c}\sum_{i=1}^{I} s_{ic}\dot{\eta_{ic}}, \tag{21}$$

where $e_c \equiv \sum_i L_{ic}/L_c$ is the employment rate in city c and $s_{ic} \equiv w_{ic}L_{ic}/W_c$ is industry i's share of income in city c.

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 these external effects on P_{ic}. Section A.9 of the Appendix shows that the proportional change in the price index is

$$\dot{P}_{ic} = (\dot{e_c})^{-\Upsilon_i^e}\left(\sum_{i=1}^{I} s_{ic}\dot{\eta_{ic}}\right)^{-\Upsilon_i^\eta}\left(\frac{\dot{\lambda}_{icc}}{\dot{\eta}_{ic}^{\mathbb{1}}}\right)^{\frac{1}{\varepsilon_i}}\dot{g_c}, \tag{22}$$

where Υ_i^e, Υ_i^η and $\mathbb{1}$ are non-negative reduced-form parameters that depend on the micro details of the model, as defined in Table 1.

[TABLE 1 ABOUT HERE]

Inspecting equations (21) and (22), we immediately recognize the familiar effects of the domestic trade share λ_{icc} and employment share η_{ic} on real income.[21] ACR showed that, with frictionless labor markets, these two variables have no impact on aggregate income but fully capture changes in consumer prices, regardless of market structure.

More importantly, (21) and (22) highlight two new channels through which trade integration impacts both income and consumer prices: (i) changes in the

21. In (22), $\mathbb{1}$ regulates the standard labor supply effect in frictionless multi-sector MC-FE models (ACR, p.114).

employment rate, $\dot{e}_c$, and (ii) the composition of employment share changes, $\sum_{i=1}^{I} s_{ic}\dot{\eta_{ic}}$. Aggregate income changes, absent in the ACR class of models, are independent of market structure. Price changes, however, depend on the goods market structure, as summarized by Υ_i^e and Υ_i^η in Table 1. We explain this key feature in terms of two effects.

First, the labor supply effect: under monopolistic competition and free entry, an increase in the employment rate e_c increases the industry's labor supply and hence the measure of goods produced locally,[22] decreasing P_{ic} with elasticity $1/\varepsilon_i$, ceteris paribus. This effect fully pins down Υ_i^e under MC-FE-HOM. Second, the firm selection effect: with endogenous firm heterogeneity, an increase in the local employment rate increases domestic expenditure, tightening firm selection and decreasing P_{ic} with elasticity $1/(\sigma_i - 1) - 1/\varepsilon_i$.[23]. The sum of the labor supply and selection effects pins down Υ_i^e under MC-FE-HET.

Under PC or MC-RE, however, the measures of consumption goods and producers are fixed, shutting down the labor supply and firm selection effects; hence, $\Upsilon_i^e = 0$ under MC-RE or PC.

The composition of employment share changes, $\sum_{i=1}^{I} s_{ic}\dot{\eta_{ic}}$, is (partly) driven by the covariance between income shares s_{ic} and employment share changes $\dot{\eta_{ic}}$ triggered by the trade shock. When frictions in the labor market are symmetric across industries, this channel is inactive.[24] With asymmetric frictions, however, it contributes to aggregate expenditure, ceteris paribus, and hence impacts $\dot{P}_{ic}$ through the firm selection effect, only under MC-FE-HET. $\Upsilon_i^\eta = 0$ for all other market structures in Table 1.

The main result of this section follows from computing $\dot{V}_c$ from (19) and then substituting income and price changes from (21) and (22).

22. See equations (A.52) and (A.68) for MC-FE-HET and MC-FE-HOM, respectively.

23. See, for example, equation (A.53) in the Appendix.

24. With symmetric frictions, $\chi_{ic} = \chi_c$ and $\beta_i = \beta$. The former implies $p_{ic}^V = p_c^V$ and thus $w_{ic} = w_c$ from (9). Wage equalization implies $s_{ic} = \eta_{ic}$ and thus $\sum_{i=1}^{I} s_{ic}\dot{\eta_{ic}} = 1$.

Proposition 1 *The welfare gains in city c associated with an arbitrary shock to the vector of variable trade costs that leaves intracity trade costs unchanged is*

$$\dot{V}_c = (\dot{e}_c)^{1+\sum_{i=1}^{I}\alpha_i \Upsilon_i^e} \left(\sum_{i=1}^{I} s_{ic}\dot{\eta_{ic}}\right)^{1+\sum_{i=1}^{I}\alpha_i \Upsilon_i^\eta} \prod_{i=1}^{I}\left(\frac{\dot{\lambda}_{icc}}{\dot{\eta}_{ic}^{\mathbb{1}}}\right)^{-\frac{\alpha_i}{\varepsilon_i}}, \tag{23}$$

where parameters Υ_i^e, Υ_i^η and $\mathbb{1}$ depend on the goods market structure, as defined in Table 1.

Expression (23) nests the multi-sector welfare formula derived by ACR for versions of the models considered in this paper that feature a competitive labor market (ACR, p.114). In this case, aggregate employment is constant and inter-industry wage differentials are eliminated, hence $\dot{e}_c = 1 = \sum_{i=1}^{I} s_{ic}\dot{\eta_{ic}}$.[25] In our theory, however, frictions in the labor market generate equilibrium unemployment and thus enable two additional adjustment margins for welfare changes, via the employment rate and the composition of employment share changes, as discussed above.[26] Note 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 (23) 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.[27]

25. To see the latter, note that no inter-industry wage differentials is a special case of symmetric labor market frictions discussed above.

26. A closed-form characterization of this effect is not generally possible. In a symmetric version of our MC-FE-HET 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 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.

27. Note that *within* the class of MC-FE-HET models, Υ_i^e does not vary with the degree of firm heterogeneity. We would expect the latter to determine the endogenous

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 $\dot{V}_c^{PC} \equiv \dot{V}_c/\dot{L}_c$. Proportional changes in per-capita income are still expressed by the right-hand side of (21). The 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. We thus obtain

$$\dot{V}_c^{PC} = (\dot{e}_c)^{1+\sum_{i=1}^{I}\alpha_i\Upsilon_i^e}\left(\dot{L}_c\right)^{\sum_{i=1}^{I}\alpha_i\Upsilon_i^e}\left(\sum_{i=1}^{I}s_{ic}\dot{\eta_{ic}}\right)^{1+\sum_{i=1}^{I}\alpha_i\Upsilon_i^\eta}\prod_{i=1}^{I}\left(\frac{\dot{\lambda}_{icc}}{\dot{\eta}_{ic}^{\mathbb{1}}}\right)^{-\frac{\alpha_i}{\varepsilon_i}}. \tag{24}$$

This extension of (23) 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 (23) depends on two structural parameters (σ_i and ε_i) that determine the welfare gains from trade across market structures, according to Table 1. We propose identifying these parameters from the estimated wage elasticities of the firm-level domestic revenue and local gravity equations, and discuss our empirical strategy in detail below. We then combine our estimates of these parameters with trade-induced changes in local employment rates and the composition of employment share

response of the employment rate across MC-FE-HET models. Melitz & Redding (2015) pursue this alternative approach to comparing welfare changes across frictionless models of firm heterogeneity. Costinot & Rodríguez-Clare (2014) discuss the merits of alternative approaches to model calibration and computation of welfare counterfactuals.

changes estimated from a particular episode of German trade expansion with China and Eastern Europe between 1988 and 2008. For each market structure considered in our theory, this allows us to compute the gains from trade relative to those predicted by the ACR welfare formula and, importantly, to assess the quantitative importance of alternative assumptions about the micro structure of the model when computing the gains from trade.

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).

We start by rewriting the gravity equation (17) as a log-linear function of the observable industry-city specific log wage. Substituting equations (11) and (12) in equation (17), adding time subscripts (since we use data at the city-industry-year level) and first-differencing over time yields:

$$\Delta \ln \left(\frac{X_{icFt}}{R_{ict}} \right) = \Delta d_{it}^{G} + \phi^{G} \Delta \ln w_{ict} + \Delta u_{ict}^{G}, \tag{25}$$

where ϕ^G is the wage elasticity of the local gravity equation, with a structural interpretation that depends on the goods market structure, according to (18); e.g. $\phi^G = -\frac{\kappa\sigma}{(\sigma-1)}$, under MC-FE-HET. The term Δd_{it}^G is a full set of industry-year effects and the error term, Δu_{ict}^G, is a log-linear function of shocks to industry-city-specific *residual* components which are collected in the error term after controlling for Δd_{it}^G. The time differencing operator Δ eliminates time-invariant industry-city effects; e.g. local or industrial fixed comparative advantage stemming from geography, institutions or technology. Note that what is captured by Δd_{it}^G and Δu_{ict}^G depends on the underlying micro structure of the model. For instance, under MC-FE-HET, the inclusion of the industry-year effects, Δd_{it}^G, captures changes in the Foreign demand shifter, A_{iFt}, time-varying industry-specific unobserved variables, such as changes in the industry component of the recruitment cost shifter, fixed costs, trade policy, and non-tariff barriers to trade or (national-level) comparative advantage. Likewise, under MC-FE-HET, the error term, Δu^G_{ict}, includes the industry-city-specific *residual* components in k_{ict}, f^E_{ict}, f_{icFt}, $\varphi_{\min,ict}$ and τ_{icFt}, after partialling out the industry-year fixed effects.

The domestic revenue equation at the firm level can be obtained similarly using equations (11), (12) and (13):

$$\Delta \ln r_{ict}(\varphi) = \Delta d^R_{it} + \phi^R \Delta \ln w_{ict} + T(\varphi) + \Delta \ln \tilde{A_{ict}} + \Delta u^R_{ict}(\varphi), \tag{26}$$

where $\phi^R = 1 - \sigma$. $T(\varphi)$ denotes firm fixed effects that capture firm-specific linear trends in (log) productivity $\ln \varphi_t$. $\tilde{A_{ict}} \equiv \sum_{n \neq F} A_{int} \left(\tau_{icnt}\right)^{1-\sigma}$ 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. $\Delta u^R_{ict}(\varphi)$ is an error term that collects residual variation in the recruitment cost shifter k_{ict}, after accounting for industry-year fixed effects Δd^R_{it}.[28]

Identification of ϕ^G and ϕ^R requires isolating variation in industry-city log wages that is orthogonal to the composite error terms, Δu^G_{ict} and $\Delta u^R_{ict}(\varphi)$, respectively. Under search and bargaining frictions, wages are necessarily endogenous in equations (25) and (26) because wages, domestic revenues and export shares all depend on idiosyncratic changes in the recruitment cost shifter. Thus, estimating (25) and (26) by ordinary least squares would yield inconsistent estimates of ϕ^G and ϕ^R. Next, we show how to exploit the structure of the model to obtain instruments for wages.

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

28. The domestic revenue equation is obtained by setting $I_{icn} = 1$ for $n \neq F$ and zero otherwise in (13) and then inserting (11).

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 the recruitment cost shifter, k_{ic}. Substituting (10) in equation (9), and using the fact that $p^V_{ic}/m_c(\theta_c) = k_{ic}w_{ic}$ and $t_c = \delta b_c/\theta_c m_c(\theta_c)$ (a condition that follows from both the fiscal balance and the Beveridge curve) yields:

$$w_{ic} = \tilde{k}_{ic} \cdot (\tilde{\gamma}_{1c} b_c + \tilde{\gamma}_{2c} \bar{w}_c) \tag{27}$$

where $\bar{w}_c = \sum_j \eta_{jc} w_{jc}$ is the local average wage and $\tilde{k}_{ic} = \left[\frac{(1-\beta)(1-\delta)}{(1-\beta)(1-\delta)-\beta(\rho+\delta)k_{ic}}\right]$ is a function of the cost of recruitment. The coefficients $\tilde{\gamma}_{1c} = (1 - \tilde{\gamma}_{2c})\left[\frac{\delta+\theta_c m_c(\theta_c)}{\theta_c m_c(\theta_c)}\right]$ and $\tilde{\gamma}_{2c} = \left[\frac{\theta_c m_c(\theta_c)}{\rho+\delta+\theta_c m_c(\theta_c)}\right] \in \{0, 1\}$ 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 an industrial composition weighted toward higher paying industries, $\bar{w}_c = \sum_i \eta_{ic} w_{ic}$, due to the strategic complementarity of wages across industries generated by search frictions and bargaining in the labor market (Beaudry et al., 2012).

In our empirical work, we focus on a log-linear approximation of this equation to emphasize the first order effects of industrial composition on wages. To that end, we specify the term $\tilde{k}_{ic}$, without loss, as $\tilde{k}_{ic} = \tilde{k}_i + \tilde{k}_c + \tilde{\xi}_{ic}$, where $\tilde{k}_i$ represents a common (across cities) industry component, $\tilde{k}_c$ represents a city-specific component, and $\tilde{\xi}_{ic}$ is an idiosyncratic component that sums to zero across industries, within cities. Solving for $\bar{w}_c$ in (27) and adding a time subscript, industry-city log wages are related to industrial composition in the following way:

$$\ln w_{ict} = \gamma_0 + \gamma_1 b_{ct} + \frac{\gamma_2}{\gamma_3} K_{ct} + \gamma_3 k_{it} + \gamma_4 k_{ct} + \gamma_5 e_{ct} + \epsilon_{ict}, \tag{28}$$

where γ_0-γ_5 are constant parameters obtained from the linear approximation.[29] Equation (28) shows that, at the national level, inter-industry wage differentials are given by $\gamma_3 k_{it}$, which expresses the average wage in industry i relative to the average wage in an arbitrary omitted industry. The term $K_{ct} = \sum_j \eta_{jct}\nu_{jt}$ is a weighted average of industrial wage premia, where the weights are industry-city-specific employment shares and $\nu_{jt} = \gamma_3 k_{jt}$ denotes the national industry wage premium.

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. Next, we discuss how to exploit variation in K_{ct} to construct model-based instruments for the industry-city wage in equations (25) and (26).

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 product structure of the index K_{ct}, are Bartik-type instruments, as defined by Goldsmith-Pinkham et al. (2020). The first term

29. The steps taken to derive equation (28) are laid out in Appendix C.

captures shifts in national industrial wage premia, 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 local industrial employment shares, η_{ict}, are potentially correlated with the error terms in (25) and (26).

We solve the first issue by exploiting the structure of equation (28). Equation (28) shows that wages vary because of an industry-specific component (ν_{it}), a city-specific component ($\gamma_0 + \gamma_1 b_{ct} + \frac{\gamma_2}{\gamma_3} K_{ct} + \gamma_4 k_{ct} + \gamma_5 e_{ct}$) and an idiosyncratic term (ϵ_{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, which we denote as $\hat{\nu}_{it}$, without directly observing K_{ct}, and the local component of the vacancy posting cost, k_{ct}.[30]

Second, we predict local industrial employment shares from predicted industry-city employment, denoted $\hat{L}_{ict}$ and computed by combining estimates of national-level industrial growth with base-period local industrial composition:

$$\hat{L}_{ict} = L_{ic0} \prod_{s=1}^{t} \left(1 + \hat{\mathcal{G}}_{is}\right), \tag{29}$$

for $t \geq 1$, where L_{ic0} is a base-period level of employment in industry i in the local economy c.[31] National industrial growth rates, denoted, $\hat{\mathcal{G}}_{it}$, are estimated via a generalized leave-one-out method, in a procedure that closely follows Greenstone et al. (2020) and is discussed in more detail in Appendix D.

30. Additional details on implementation are contained in Appendix D.

31. In our empirical implementation, we take the base-period as the average of the years 1992-1993, omit one year, and use 1996-2010 as our estimation sample.

In order to alleviate any concerns that the correlation between our instruments and manufacturing wages is mechanical (since equations 25 and 26 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.

With $\hat{\eta}_{jct}$ and $\hat{\nu}_{jt}$ at hand, we construct instruments:

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

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., 2020; 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 $\hat{\eta}_{ict}$, 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. (2020) and Beaudry et al. (2018). In our framework, the error term contains changes in the residual component of a number of model parameters, and can be generally interpreted as changes in city-industry unobservable comparative advantage. Thus, our instruments are valid if base-period non-manufacturing industrial composition does not predict future *changes* in comparative advantage in manufacturing industries. This condition is formally discussed in Appendix E, as well as an intuitive and theoretically consistent over-identification test that can be performed by leveraging the fact that we have two instruments.

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). The SIAB provide spell-data information on individual demographic characteristics and employment history, including industrial affiliation and daily wage. The LIAB data 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.

The SIAB data are used to construct industry-city wages, national industrial wage premia, predicted and observed local industrial employment shares and employment rates, the instruments, and the Bartik proxy for local demand, following the procedures described in Section 3.2. These variables are then merged to the LIAB data. We use the LIAB data to construct industry-city-specific export shares in revenues and firm-level domestic revenues. We define 24 cities according to Kropp & Schwengler (2011) definition of labor markets; 19 in West Germany and 5 in East Germany. Our industrial classification contains 58 industries ("Abteilungen"), of which 29 belong to the manufacturing sector, grouped according to the 1993 time-consistent 3-digit classification of economic activities. The final data set we use in our estimations below includes the years 1996-2010. In compliance with the FDZ guidelines, each industry-city cell includes at least 20 workers' observations. Additional details are contained in Appendix F.

5. Results

Gravity Equation. Table 2 presents the estimation results for the gravity equation (25) 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, according to (18). Note that all specifications in Table 2 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 2 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 2, 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 2 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.[32] The stars (*) in the table refer to city-year clustering.

[TABLE 2 ABOUT HERE]

Panel II of Table 2 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 week 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.

32. While 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 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).

Panel I of Table 2 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. 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.[33] 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

33. Following Goldsmith-Pinkham et al. (2020), we conduct a more detailed investigation of city initial-characteristics and industrial composition in section G of the Appendix.

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^B_{ct}) and shifts in the national-level industry premia (IV^W_{ct}). 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.[34]

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 ($\hat{\mathcal{G}}_{is}$ from equation (29)) 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

34. As 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 Appendix formally shows this result.

outside options in the same way. In fact, in Panel II of Table 2 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 from 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 2 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.[35]

Revenue Equation. In Table 3 we present our results from the estimation of the domestic revenue equation (26). 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 (26), denoting time-varying firm productivity, that is not present in (25). One complication of estimating the revenue equation, relative to the gravity equation, is that equation (26) 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

35. When we estimate the specifications in Table 2 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 Appendix, we show the conditions under which this would asymptomatically 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).

demand, interacted with a full-set of industry indicators.[36] 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 3 is similar to Table 2 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 2. 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 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 3 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 3 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

36. The traditional Bartik is constructed as a local weighted average of national-level employment growth across industries, $\text{Bartik}_{ct} = \sum_j \hat{\eta}_{jct} \cdot \hat{\mathcal{G}}_{it}$. The $\hat{\eta}_{ic}$ are constructed as in section 3.2 and the national-level employment growth rates come from the $\hat{\mathcal{G}}_{it}$ in equation (D.9) of the Appendix. 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.

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 2.5, to estimate the relevance of the impact of trade on the employment rate and the composition of employment shares as two additional margins of adjustment when calculating the welfare gains from trade under different underlying goods market structures.

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

Proposition 1 suggests that accounting for labor market frictions may be important when calculating the welfare gains from trade – this is particularly true in the presence of heterogeneous firms and a relatively low estimate of the elasticity of substitution in consumption. 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, industry shares of local income, 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 frictions in the labor market are accounted for? From Proposition 1, the answer to this question depends on the goods market structure. Table 4 shows this.

[TABLE 4 ABOUT HERE]

The relative gains from trade under MC-FE-HET, given in column 1 of Table 4, depend on the elasticity of substitution in consumption and on the trade elasticity. We set $\hat{\sigma} = 1.78$ from Table 3 and $\hat{\kappa} = 3.5$ combining estimates from both Tables 2 and 3. To be clear, this counterfactual exercise is in the spirit of ACR; that is, the relative gains formula $(\dot{e_c})^{1+\frac{1}{\sigma-1}} \left(\sum_i s_{ic}\dot{\eta}_{ic}\right)^{1+\frac{1}{\sigma-1}-\frac{1}{\kappa}}$ 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, industry shares of local income 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 (24), provided that the two models are also calibrated to match the observed changes in local labor endowments. In this case, $(\dot{e_c})^{1+\frac{1}{\sigma-1}} \left(\sum_i s_{ic}\dot{\eta}_{ic}\right)^{1+\frac{1}{\sigma-1}-\frac{1}{\kappa}}$ 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 4, the relative gains from trade under MC-FE-HOM are a function of the trade elasticity only. 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 2, 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 local employment rates and the distribution of local industrial employment shares.

In order to stick to ACR's sufficient-statistic approach and implement the formulas in Table 4 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 ($\dot{e}_c$) and the distribution of city-specific industrial employment shares ($\sum_i s_{ic}\dot{\eta}_{ic}$). 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 local labor markets of 326 German cities between 1988-2008.[37]

While employment rate data can be directly taken from Dauth et al. (2014), measuring observed changes in the distribution of city-specific industrial employment shares is more challenging given that industrial employment at the city level (326 cities) is, for confidentiality reasons, not publicly available. However, from equation (21) we can express $\sum_i s_{ic}\dot{\eta}_{ic}$ as follows:

$$\sum_i s_{ic}\dot{\eta}_{ic} = \frac{\dot{W}_c}{\dot{g}_c \dot{e}_c}.$$

W_c can also be taken from Dauth et al. (2014) and g_c can be proxied using the median of industrial wages at a more aggregated local labor market level, as measured in Section 5.

Specifically, using data for two time periods (1988-1998 and 1998-2008) we estimate the following equations simultaneously:

$$\begin{aligned} \frac{e_{c(t+10)}}{e_{ct}} &= \beta_{IPW1} \cdot IPW_{ct} + \beta_{EPW1} \cdot EPW_{ct} + X'_{ct}\alpha_1 + d^1_{rt} + u_{ct1} \\ \frac{W_{c(t+10)}}{W_{ct}} \frac{g_{ct}e_t}{g_{c(t+10)}e_{c(t+10)}} &= \beta_{IPW2} \cdot IPW_{ct} + \beta_{EPW2} \cdot EPW_{ct} + X'_{ct}\alpha_2 + d^2_{rt} + u_{ct2}, \end{aligned} \tag{30}$$

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^1_{rt} and d^2_{rt} are region-time fixed effects, and IPW_{ct} and EPW_{ct} are observed

37. The 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.

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.[38] We then use the estimates to calculate the predicted impact on the employment rate and the distribution of city-specific industrial employment shares:

$$\begin{aligned} \dot{e}_{ct} = & \quad \hat{\beta}_{IPW1} \cdot IPW_{ct} + \hat{\beta}_{EPW1} \cdot EPW_{ct} + 1 \\ \sum_i s_{ic} \dot{\eta}_{ic} = & \quad \hat{\beta}_{IPW2} \cdot IPW_{ct} + \hat{\beta}_{EPW2} \cdot EPW_{ct} + 1. \end{aligned} \tag{31}$$

Results from this exercise are presented in Table 5. Panel A shows the IV estimates obtained from estimating equation (30). 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 5 ABOUT HERE]

38. Both measures are directly taken from Dauth et al. (2014). $IPW_{ct} = \sum_i \frac{E_{ict}}{E_{it}} \frac{\Delta M^{G \leftarrow East}_{i(t+10)}}{E_{ct}}$, 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. $\Delta M^{G \leftarrow East}_{i(t+10)}$ 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 $IVIPW_{ct} = \sum_i \frac{E_{ic(t-10)}}{E_{(it-10)}} \frac{\Delta M^{Others \leftarrow East}_{i(t+10)}}{E_{c(t-10)}}$, where $\Delta M^{Others \leftarrow East}_{i(t+10)}$ 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 similiar 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.

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 B of Table 5 shows the implied local employment rate growth and changes in the distribution of city industrial employment shares (from the combined import and export exposure). Focusing on column 3, we find that increased trade with Eastern Europe and China led to a 2.5% rise in the growth of the employment rate for the median local labor market in West Germany.

Next, we compute the relative gains from trade according to Table 4, using the predicted $\dot{e_c}$ and $\sum_i s_{ic}\dot{\eta}_{ic}$ from Panel B of Table 5 as inputs. Table 6 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 5.5% 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 about 2.5% larger for the median labor market. Disaggregated results corresponding to the MC-FE-HET case are mapped in Figure 1.

[TABLE 6 ABOUT HERE]

The figure exhibits substantial variation in the relative welfare gains from trade across local labor markets; e.g. ranging from 0.92 to 1.27 when looking at trade with both China and Eastern Europe. Interestingly, the figure suggests that in a framework with heterogeneous firms, accounting for trade-induced changes in the employment rate and the composition of employment shares leads to welfare gains from market access to up to 27% than in models that do not include frictional labor markets. In this particular application, these differences are larger for cities close to the border in the South-West region.

[FIGURE 1 ABOUT HERE]

Finally, in Table 7, we evaluate the impact of trade exposure on population (column 1), wages (column 2) and employment (column 3).[39] The last column corresponds to column 3 of Table 5. 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 7 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 that trade liberalization affects welfare through two channels: (i) the traditional adjustment margin studied in ACR, mediated by the trade elasticity and changes in the share of domestic expenditure; and (ii) two new adjustment margins operating through shifts in the employment rate and the composition of industrial employment shares. 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

39. Table H.2 of the Appendix shows the results for Eastern Europe and China separately.

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 once trade-induced changes in the employment rate and the composition of employment shares are accounted for, the welfare gains from trade can be substantially different from those obtained in their frictionless counterpart. Importantly, we find that the underlying market structures matter, a result which is in sharp contrast with ACR.

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Tables

TABLE 1. $\dot{P}_{ic}$ Elasticities and Market Structure

	Υ_i^e	Υ_i^η	$\mathbb{1}$
MC-FE-HET	$\frac{1}{\sigma_i - 1}$	$\frac{1}{\sigma_i - 1} - \frac{1}{\varepsilon_i}$	1
MC-FE-HOM	$\frac{1}{\varepsilon_i}$	0	1
MC-RE or PC	0	0	0

Table 2. 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
Manuf. Share$_{t-1}$	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
Observations	3940	3713	3713	3713	3713	3713	3713
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)
III. Relevance and Over-identification							
F-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. p 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

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. Column 1 is estimated via OLS and columns 2-6 are estimated via 2SLS. 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. Panel III shows the F-statistic for the test of instrument relevance and the p-value for the Hansen J over-identification test.

TABLE 3. 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×							
Δ City Empl. Rate	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE×							
Bartik	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry×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
Manuf. Share$_{t-1}$	No	No	No	No	Yes	No	No
Manuf.×Trend	No	No	No	No	No	Yes	Yes
Demog.×Trend	No	No	No	No	No	No	Yes
Observations	46503	46503	46503	46503	46503	46503	46503
II. First-stage							
IV^B_{ct}		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^W_{ct}		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)
III. Relevance and Over-identification							
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

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. Column 1 is estimated via OLS and columns 2-6 are estimated via 2SLS. All regressions are weighted by establishment survey weights. The control Manuf.×Trend is the average 1992/93 city share of manufacturing employment, interacted with linear trends. The control set Demog.×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. Panel III shows the F-statistic for the test of instrument relevance and the p-value for the Hansen J over-identification test.

TABLE 4. 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))
$(\dot{e_c})^{1+\frac{1}{\sigma-1}} \left(\sum_i s_{ic}\dot{\eta}_{ic}\right)^{1+\frac{1}{\sigma-1}-\frac{1}{\kappa}}$ $\hat{\sigma} = 1.78$, $\hat{\kappa} = 3.5$	$(\dot{e_c})^{1+\frac{1}{\varepsilon}} \left(\sum_i s_{ic}\dot{\eta}_{ic}\right)$ $\hat{\varepsilon} = 7$	$\dot{e}_c \left(\sum_i s_{ic}\dot{\eta}_{ic}\right)$

Table 5. Trade Exposure

	Eastern Europe + China			Eastern Europe	China
	(1) 1988-98	(2) 1998-08	(3) 1988-2008	(4) 1988-2008	(5) 1988-2008
Panel A:					
A.I. 2nd Stage:	Dependent var.: $\hat{e}_c$				
Δ Import Exposure	-0.0099	-0.0085**	-0.0096**	-0.029**	-0.0086*
	(0.016)	(0.0028)	(0.0039)	(0.015)	(0.0045)
Δ Export Exposure	0.017	0.012**	0.012**	0.024**	0.013
	(0.017)	(0.0046)	(0.0040)	(0.0077)	(0.019)
A.II. 2nd Stage:	Dependent var.: $\sum_i s_{ic}\hat{\eta}_{ic} = \frac{\hat{W}_c}{\hat{g}_c \hat{e}_c}$				
Δ Import Exposure	0.025**	0.0037	0.0075**	0.017	0.0078**
	(0.0082)	(0.0036)	(0.0034)	(0.012)	(0.0038)
Δ Export Exposure	-0.027**	-0.0070	-0.0065	-0.011	-0.0091
	(0.0089)	(0.0051)	(0.0040)	(0.0085)	(0.013)
Observations	326	326	652	652	652
Panel B:					
B.I. Predicted:	$\dot{e}$				
Mean	101.58	102.48	102.78	103.53	99.60
Med	101.38	102.12	102.54	103.03	99.90
10th pct.	100.31	100.62	100.61	100.56	98.27
90th pct.	103.02	104.96	105.14	107.12	100.76
B.I. Predicted:	$\sum_i s_{ic}\dot{\eta}_{ic}$				
Mean	99.72	98.08	99.83	99.32	100.73
Med	99.51	98.39	99.62	99.28	100.42
10th pct.	97.41	96.52	98.57	97.89	99.68
90th pct.	101.91	99.35	101.32	100.78	101.97

Notes: Panels A.I and A.II present the second-stage regression results of estimating equations (30) simultaneously, 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. Δ Import Exposure and Δ Export Exposure are observed decadal changes in import and export exposure, respectively, and are computed and instrumented as described in the main text. 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 columns 1-3, Δ Import Exposure and Δ Export Exposure 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. Panel B.I and B.II presents the predicted employment rate growth and changes in the distribution of city-specific industrial employment shares, expressed in percentage and calculated using equation (31).

Table 6. Relative Welfare Gains

	Eastern Europe + China			Eastern Europe	China
	(1) 1988-98	(2) 1998-08	(3) 1988-2008	(4) 1988-2008	(5) 1988-2008
I. MC-FE-HET:	$(\dot{e_c})^{1+\frac{1}{0.78}}\left(\sum_i s_{ic}\dot{\eta}_{ic}\right)^{1+\frac{1}{0.78}-\frac{1}{3.5}}$				
Mean	103.03	102.00	106.03	106.74	100.50
Med	102.50	101.90	105.38	105.82	100.52
10th pct.	100.47	100.14	102.76	102.53	99.72
90th pct.	106.06	104.35	110.07	112.13	101.42
II. MC-FE-HOM:	$(\dot{e_c})^{1+\frac{1}{7}}\left(\sum_i s_{ic}\dot{\eta}_{ic}\right)$				
Mean	101.50	100.99	102.96	103.30	100.25
Med	101.24	100.95	102.66	102.87	100.26
10th pct.	100.23	100.07	101.37	101.26	99.86
90th pct.	102.99	102.15	104.92	105.90	100.71
III. MC-RE and PC:	$\dot{e_c}\left(\sum_i s_{ic}\dot{\eta}_{ic}\right)$				
Mean	101.28	100.58	102.56	102.79	100.31
Med	100.99	100.57	102.33	102.46	100.29
10th pct.	99.96	99.96	101.21	101.25	100.06
90th pct.	102.83	101.41	104.15	104.91	100.64

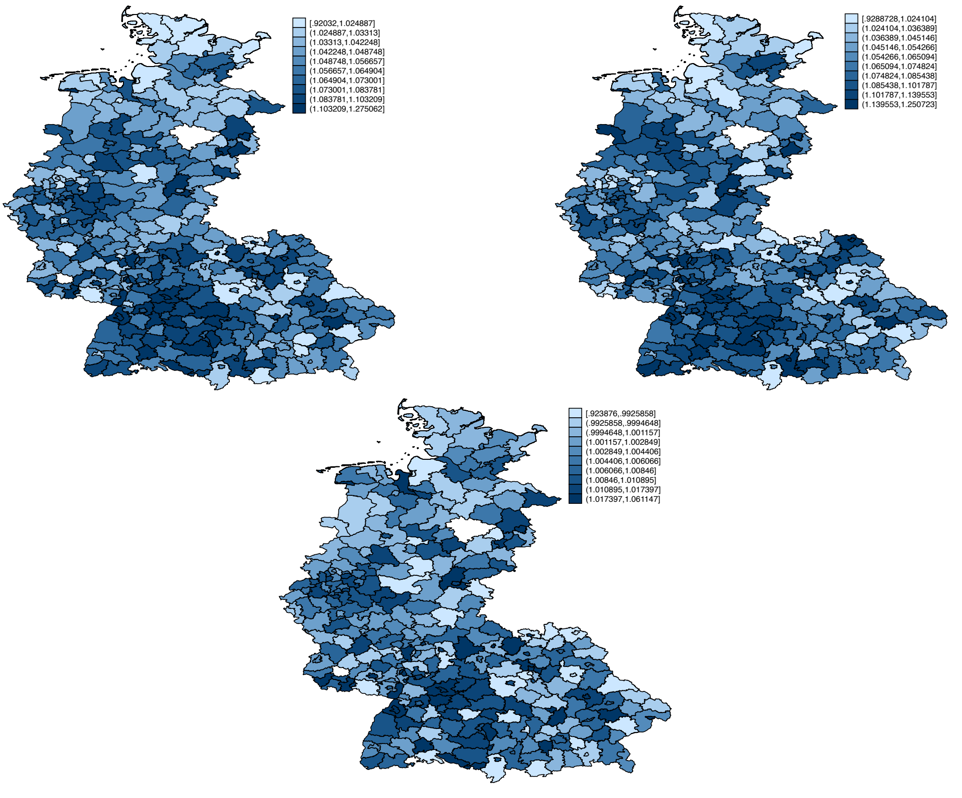
Note: Panel I shows the estimated welfare gains from trade (in percentage) under MC-FE-HET, computed using the predictions of $\dot{e_c}$ and $\left(\sum_i s_{ic}\dot{\eta}_{ic}\right)$, as estimated in Table 5. Panel II presents the relative welfare gains under MC-FE-HOM. The last panel shows relative gains under PC or MC-RE. The structure of the table is similar to that of Table 5: Columns 1-3 reflect results obtained using imports from and exports to both China and Eastern Europe. Column 4 is based on trade with Eastern Europe and column 5 only captures trade with China. Finally, columns 1, 2 and 3-5 are based on decadal difference over the period 1988-1998, 1998-2008 and 1988-2008, respectively.

TABLE 7. Trade Exposure and Other Outcomes

	Population	Wages	Employment	Emp. Rate
	(1)	(2)	(3)	(4)
Δ Import Exposure	-0.0028	-0.000060	-0.012**	-0.0096**
	(0.0021)	(0.00026)	(0.0052)	(0.0039)
Δ Export Exposure	-0.00078	0.00050	0.0100**	0.012**
	(0.0012)	(0.00033)	(0.0045)	(0.0043)
Constant	0.18**	0.028**	0.38**	0.16**
	(0.047)	(0.0049)	(0.079)	(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 (30), 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 5. Δ Import Exposure and Δ Export Exposure are observed decadal changes (1988-1998 and 1998-2008) in import and export exposure, respectively, and are computed and instrumented as described in the main text. 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). We instrument export exposure in a similar way using exports. We weigh our regressions by the share of the population in year 1978.

FIGURE 1. The Rise of the East and the Far East: welfare gains from trade in frictional labor markets relative to their frictionless counterpart, under MC-FE-HET (West Germany).



Notes: Each figure uses $\hat{\sigma} = 1.78$, $\hat{\kappa} = 3.5$ and the estimates from Table 5 for the period 1988-2008. The first figure is based on trade with China and Eastern Europe (column 3 of Table 5). The second figure focuses on trade with Eastern Europe (column 4 of Table 5) and the last one is based on China only (column 5 of Table 5).