

Trade and inequality across local labor markets: The margins of adjustment

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Abstract

Empirical research has documented the importance of non-wage margins of adjustment in the response of local labor markets to trade shocks. To formalize this observation empirically, we decompose the differential impact of a trade shock across U.S. local labor markets (by labor group) on per capita labor income into wage, hours worked per employee, unemployment, and labor force participation margins of adjustment. Our results highlight the importance of heterogeneous treatment effects and quantify the relative importance of non-wage margins of adjustment. To understand the economic mechanisms generating observed effects of trade on regional inequality, we provide a unifying trade framework (featuring frictional unemployment and a labor/leisure tradeoff) and comparative static results across local labor markets by labor group and margin of adjustment. Our theory highlights the importance of heterogeneity in the elasticity of labor supply and the elasticity of matches to vacancies for understanding heterogeneous effects identified in empirical research. We recover these for each labor group by combining our empirical and theoretical results and show that our estimates are broadly in line with vast literatures in labor, public finance, and macroeconomics; where results differ, we suggest a path forward.

1 Introduction

Recent empirical work has identified substantial effects of international trade shocks on inequality across regions and has focused attention on a broad set of margins of adjustment to these shocks. These margins include adjustments in the labor market—including changes in wages, labor force participation, unemployment, and the share of employment in manufacturing—as well as elsewhere in society—including changes in mortality, the marriage market, fertility, and the extent of political polarization.

In order to capture observed impacts of trade on regional inequality, a growing theoretical literature has embedded into otherwise canonical trade models the assumption of limited labor mobility across regions. In line with the canonical trade models on which this literature builds, the theoretical literature has largely emphasized wage responses to trade shocks, with less focus on other labor-market adjustment mechanisms.

In this paper, we study margins of labor-market adjustment to trade shocks both empirically and theoretically. Empirically, we formalize the observation that non-wage margins of adjustment are important for shaping the response of local labor markets to trade shocks. Specifically, we exactly decompose the differential impact of a trade shock on per capita labor income across U.S. local labor markets by labor group into the following margins of adjustment: wages, hours worked per employee, the percentage of the labor force that is employed, and the labor force participation rate. Our results highlight the importance of heterogeneous treatment effects and quantify the relative importance of non-wage margins of adjustment. To understand the economic mechanisms generating observed effects of trade on regional inequality, we provide a unifying trade framework featuring frictional unemployment and a labor/leisure tradeoff with many local labor markets, sectors, and labor groups. The model yields sharp analytic comparative static results across local labor markets by labor group and margin of adjustment that highlight the role of various structural elasticities in shaping both heterogeneity in treatment effects across labor groups and the relative importance of each margin of adjustment. In particular, our theory highlights the importance of heterogeneity in the elasticity of labor supply and the elasticity of matches to vacancies for understanding heterogeneous effects identified in empirical research. Finally, we recover these for each labor group by combining our empirical and theoretical results and show that three of our four estimates are tightly aligned with estimates from vast literatures outside of international trade. We discuss a model extension that might help our fourth elasticity, the labor supply elasticity for low education workers, to better fit micro evidence.

In order to highlight the importance of distinct margins of adjustment, our empirical objective is to provide a simple and exact empirical decomposition of the causal effect of a trade

shock on income per capita across U.S. commuting zones. To achieve this objective in the most transparent way, our empirical strategy follows [Autor et al. \(2013\)](#), henceforth ADH. As in ADH, we leverage a “China shock,” measured as the change in Chinese import exposure per worker in a U.S. commuting zone between the years 1990 and 2007, and instrument with a similar measure constructed using the contemporaneous growth of Chinese exports to other high-income markets.

We study the differential effect across U.S. commuting zones—at the aggregate level and separately across education groups—of this China shock on (i) per capita income. We decompose these effects into four separate margins: (ii) wages, (iii) hours worked per employee, (iv) the percentage of the labor force that is employed (one minus the unemployment rate), and (v) the labor force participation rate. Indexing commuting zones by c , labor groups by g , and years by t , we leverage the following identity:

$$\underbrace{\frac{\text{Income}_{cgt}}{\text{Population}_{cgt}}}_{(i)} = \underbrace{\frac{\text{Income}_{cgt}}{\text{Hours}_{cgt}}}_{(ii)} \times \underbrace{\frac{\text{Hours}_{cgt}}{\text{Employed}_{cgt}}}_{(iii)} \times \underbrace{\frac{\text{Employed}_{cgt}}{\text{Labor force}_{cgt}}}_{(iv)} \times \underbrace{\frac{\text{Labor force}_{cgt}}{\text{Population}_{cgt}}}_{(v)} \quad (1)$$

For workers without a college education, we find that the effect of the China shock on relative per capita income across commuting zones is largely attributed to the combination of (iv) the percentage of the labor force that is employed (30%) and (v) labor force participation (54%). Neither (ii) the average wage nor (iii) the hours worked per employee margins are statistically significant at standard levels. Results for college educated workers are quite different. For this group, the primary margin of adjustment is (ii) the average wage (68%), whereas (iv) the percentage of the labor force that is employed (6%) and (v) labor force participation (8%) play relatively minor roles in the adjustment process.

These results highlight the empirical relevance of heterogeneous treatment effects of trade shocks across labor groups as well as non-wage margins of adjustment, including both frictional unemployment as well as optimal labor-leisure choices (especially for low education workers). Our theoretical framework incorporates these features.

Theoretically, we consider a static assignment model of trade with many regions, sectors, and labor groups, which features search frictions and a labor-leisure decision. While an agent’s region is exogenous, each agent chooses the sector in which to apply for a job and, if the agent is successful in finding a job, how many hours to work.¹ Atomistic firms post vacancies and search is directed: each vacancy is targeted at a specific region, sector, and labor group triple. The model features endogenous wages, unemployment rates, and hours

¹It is straightforward to extend our framework to endogenize location decisions and obtain comparative static results. However, empirical results suggest this margin does not respond significantly to the China shock over our time frame.

worked per employee.²

Allowing the key elasticities—the steady-state elasticity of labor supply, the elasticity of relative labor supply across sectors, and the elasticity of matches to vacancies—to vary freely across labor groups, we consider comparative static exercises comparing outcomes for a given labor group across regions in response to sectoral price changes. Given strong functional form assumptions, we show that changes in the average wage, the share of the labor force that is employed, hours worked per employee, and (therefore) income per capita for a given region and labor group pair are all labor group-specific iso-elastic functions of a region and labor group-specific weighted average of sectoral price changes. For a given labor group, each of these margins falls relatively more in a region in which that labor group has a greater share of its pre-shock income (in the sense of first-order stochastic dominance) in sectors that experience relative price declines.³

In our theory, the elasticity of each of margin of adjustment to the region and group-specific change in sectoral prices is a simple labor group-specific function of the steady-state elasticity of labor supply and the elasticity of matches to vacancies. While these elasticities are the subject of active debate in the labor, macroeconomics, and public finance literatures, amongst others, they have featured less prominently in the trade literature. Given that our theory demonstrates the importance of these elasticities for understanding the vast and growing empirical literature on trade and regional inequality, we take a first stab at recovering these elasticities by education group using the China shock. We combine our empirics and theory and introduce a heroic assumption—the commuting zone and group-specific weighted average of sectoral price changes, which is the relevant shock in our theory, is a linear function of our measured China shock, which is the corresponding independent variable in our empirical exercise—to provide structural estimates of these elasticities by labor group. Our theory shows that the qualitative patterns we identify in the data—common treatment effects across education groups for wages yet larger responses in hours worked and unemployment rates for low education workers—are jointly explained by a higher labor supply elasticity and a higher elasticity of matches to vacancies for unskilled workers than for skilled workers. Our point estimates of three of the four elasticities (two for each education group) are in the middle of the range of canonical estimates from labor, public finance, and macroeconomics. Our labor supply elasticity for low education workers is too high, and we suggest a potential fix for trade models to better fit this elasticity.

²One way to view the labor-leisure tradeoff in the model is that it combines labor force participation and hours worked per employed worker. We therefore also conduct the empirical decomposition featuring three margins—combining two of the margins into $\text{Hours} * \text{Labor force} / (\text{Employed} * \text{Population})$ —rather than our baseline four margins.

³We further provide a simple sufficient condition on model primitives under which this variation in pre-shock income shares is satisfied. Moreover, if we additionally impose common elasticities across labor groups, then we obtain similar comparative static results comparing across region and labor group pairs.

Our paper is related to a large and active literature on trade and inequality. Empirically, our paper builds on the literature studying the impact of international trade shocks on inequality across local labor markets: e.g. [Topalova \(2010\)](#) and [Kovak \(2013\)](#), but especially [Autor et al. \(2013\)](#) and [Dix-Carneiro and Kovak \(2015\)](#), a combination of whose empirical approaches we follow. Specifically, our empirical strategy is identical to [Autor et al. \(2013\)](#) when aggregating across all workers in a commuting zone; when we disaggregate across education groups, we use commuting zone and education specific independent variables, in the spirit of [Dix-Carneiro and Kovak \(2015\)](#), and as suggested by our theoretical framework. Our empirical contribution relative to this literature is minor: we provide an exact empirical decomposition of the impact of a trade shock on income per capita with the goal of motivating our theoretical exercise. While this decomposition itself is novel, our emphasis on the importance of non-wage margins of adjustment is not new to this literature; see e.g. [Autor et al. \(2016\)](#) and [Dix-Carneiro and Kovak \(Forthcoming\)](#). For instance, ADH write that their “results suggest that the predominant focus of the previous literature on wages misses important aspects of labor-market adjustments to trade. We find that local labor markets that are exposed to... China’s rising competitiveness experience increased unemployment, decreased labor-force participation, and increased use of disability and other transfer benefits, as well as lower wages.” Although we are certainly not the first to emphasize the central role of non-wage margins of adjustment, we provide the first decomposition to quantify the relative importance of distinct margins and we quantify the extent of heterogeneity across labor groups.

A growing quantitative trade literature uses assignment models to study the impact of trade on wage inequality either at the national level—see e.g. [Burstein et al. \(Forthcoming\)](#) and [Lee \(2017\)](#)—or across local labor markets—see e.g. [Adão \(2015\)](#) and [Galle et al. \(2017\)](#). Into this environment, [Caliendo et al. \(2018\)](#) and [Adão et al. \(2018a\)](#) introduce a labor-leisure choice. Motivated by our empirical results, we extend these quantitative models to incorporate both a labor-leisure choice and frictional unemployment, in line with the empirical importance of these margins of adjustment; provide analytic comparative static results, to shed light on this literature’s quantitative conclusions; and allow for heterogeneous treatment effects across labor groups, in line with our empirical results.

Our theory builds most directly on [Costinot and Vogel \(2010\)](#) and [Davidson et al. \(1999\)](#). We use the tools and techniques in [Costinot and Vogel \(2010\)](#), which provides analytic comparative static results on factor allocation and wages in high-dimensional environments.⁴ These results apply directly in modern quantitative environments; as reviewed in [Costinot](#)

⁴Unlike [Costinot and Vogel \(2010\)](#), we treat changes in goods prices as exogenous. Leveraging the approach developed in [Costinot and Vogel \(2010\)](#) to extend our results to endogenous goods prices is straightforward in the special case in which there is no within-group heterogeneity, as in [Costinot and Vogel \(2010\)](#).

and Vogel (2015). We extend Stolper-Samuelson insights to additional margins of adjustment as in Davidson et al. (1999), which is the paper closest in spirit to our theoretical contribution. Davidson et al. (1999) introduces frictional unemployment into a two-by-two Heckscher-Ohlin-like model, studies the link between trade and the distribution of income, and obtains an extended Stolper-Samuelson-like theorem.

The remainder of our paper is organized as follows. In Section 2 we empirically decompose the causal impact of the China shock on relative income per capita across U.S. commuting zones, in aggregate and separately by education. In Section 3 we present our model and analytic results. In Section 4 we combine our empirical and theoretical results to take a first stab at parametrizing the key elasticities that shape the importance of each margin of adjustment and ask if existing estimates are capable of generating our empirical results (or equivalently, if our model is missing important elements). We conclude in Section 5.

2 Empirics

In this section, we study the differential impact across U.S. commuting zones of the China shock, following as closely as possible the empirical strategy in ADH; we describe our deviations from their approach in Section 2.2.

We estimate regressions of the form

$$\Delta y_{cgt} = \alpha_{gt} + \beta_g \Delta IPW_{cgt}^{us} + \mathbf{X}'_{cgt} \gamma_g + \varepsilon_{cgt}. \quad (2)$$

Here, ΔIPW_{cgt}^{us} is the change in U.S. import exposure from China per worker in commuting zone c (henceforth, CZ c), in labor group g , and at time t . We describe our independent variable and instrument in detail below. The coefficient β_g is the coefficient of interest for group g . The vector \mathbf{X}'_{cgt} contains a set of controls for group and CZ specific start-of-decade labor force and demographic composition that might be correlated with ΔIPW_{cgt}^{us} and independently affect our dependent variables. The outcome variables of interest, Δy_{cgt} , include natural logarithms of the left-hand side and each of the right-hand side variables in accounting identity (1), expressed in first differences. Also, we consider a version of this identity in which we group together terms (iii) and (v), hours worked per employee and labor force participation, which maps more easily into our theoretical framework below.

We estimate this model separately for distinct labor groups for the interval between 1990 and 2007, stacking the ten-year equivalent first differences for the two periods, 1990 to 2000 and 2000 to 2007, and allowing for the group and period fixed effect α_{gt} .

2.1 Data and measurement

We study labor-market outcomes in 1990, 2000, and 2007. We measure outcomes, y_{cgt} using data from the Integrated Public Use Micro Samples (Ipums; [Ruggles et al. 2018](#)). For 1990 and 2000, we use 5% Census samples. For 2007, we use the combined 2006, 2007, and 2008 1% American Community Survey (ACS) samples. We take a first difference both from 1990 to 2000 and from 2000 to 2007 (adjusting the 2000-2007 difference to obtain a ten-year equivalent first difference). Our sample includes individuals who were between ages 18 and 65 in the year preceding the survey. Residents of institutional and other group quarters are dropped. We define local labor markets as commuting zones, of which there are 722 in the mainland US. Each commuting zone is a cluster of counties characterized by strong commuting ties within and weak commuting ties across zones.

We run regressions using three definitions of labor groups. We consider all workers, college educated workers, and non-college educated workers.

One measurement issue is that respondents report their current unemployment status and labor force participation but report their number of hours worked and income from the previous year. Correspondingly, there are observations for which the respondent reports being unemployed or out of the labor force but also reports positive hours worked and/or earnings. Similarly, there are observations for which the respondent reports being employed but also reports zero hours worked and/or earnings. In our baseline we choose to construct commuting zone and group specific outcome variables without correcting for these timing inconsistencies at the individual level. In the appendix we show that our qualitative results are largely robust (*modulo* an increase in the relevance of the hours worked per employee margin of adjustment) to an alternative approach in which we adjust (past) income and hours worked to be consistent with (current) unemployment and labor force participation variables at the individual level before aggregating to the commuting zone and group level.

We winsorize wages following ADH. We multiply the top-coded total salary income by 1.5 and top code hourly wages to be consistent with top-coded total salary income for full-time full-year workers. We bottom-code hourly wages that are less than the first percentile of the national hourly wage distribution. We multiply these winsorized hourly wages by hours per worker to measure the total salary income variable used in our analysis.

Our measure of the China shock in commuting zone c and group g at time t , denoted by ΔIPW_{cgt}^{us} , is defined as

$$\Delta IPW_{cgt}^{us} = \sum_s \pi_{cgst} \frac{\Delta M_{st}^{us}}{L_{st}},$$

where ΔM_{st}^{us} is the realized change in U.S. real imports from China in sector s at time t , π_{cgst} is the income of employed workers in commuting zone c and group g in industry s at time

t relative to the total income of employed workers in this commuting zone and group at time t , and L_{st} is the number of employed workers in sector s at time t across all groups and commuting zones.⁵ We first difference U.S. real imports from China both from 1991 to 2000 and from 2000 to 2007 to measure ΔM_{st}^{us} . The year 1991 is used instead of 1990 because of data availability for many high-income countries. ΔM_{st}^{us} is measured using the UN Comtrade database at six-digit Harmonized System (HS) codes and is concorded to census industry codes to be compatible with employment information. Employment and income information, which is used to measure π_{cgst} and L_{st} , are from the relevant census sample.

Since the growth in U.S. imports from China in ΔIPW_{cgt}^{us} might be confounded with unobserved domestic demand changes, we utilize the contemporaneous growth in Chinese imports of eight other developed countries to identify Chinese supply-induced changes.⁶ We use the following measure as an instrumental variable,

$$\Delta IPW_{cgt}^{ot} = \sum_s \pi_{cgst-1} \frac{\Delta M_{st}^{ot}}{L_{st-1}},$$

where ΔM_{st}^{ot} is the observed change in Chinese real imports of eight other high-income countries in sector s at time t , π_{cgst-1} is the income of employed workers in group g and commuting zone c in industry s at time $t - 1$ relative to the total income of employed workers in this group and commuting zone at time $t - 1$, and L_{st-1} is the number of employed workers in sector s at time $t - 1$ across all groups and commuting zones. ΔM_{st}^{ot} is first-differenced using both 1991-2000 and 2000-2007, as is ΔM_{st}^{us} . The time $t - 1$ is a ten-year-lagged level compared to the time t . We lag to alleviate potential simultaneity bias. Instrumenting ΔIPW_{cgt}^{us} with ΔIPW_{cgt}^{ot} likely captures the supply-driven variation that arises from the productivity growth in China or decrease in sector-specific trade costs. See ADH for a detailed discussion of this identification strategy.

The commuting zone and group-specific start-of-period controls that we include in the vector \mathbf{X}_{cgt} are the share of income in manufacturing; the share of the population that is college educated and foreign born; the share of employment amongst women; the share of employment in routine occupations; and the average offshorability index of occupations. We drop the share of the college-educated population when focusing separately by education groups. In all regressions, we weight observations by CZ-group-specific initial population and cluster standard errors by state.

⁵We inflate nominal sector-level imports to 2007 USD using the Personal Consumption Expenditure deflator.

⁶The eight other developed countries are Australia, Denmark, Finland, Germany, Japan, New Zealand, Spain, and Switzerland.

2.2 Changes relative to ADH

Our empirical strategy follows ADH except for the following changes. First, we allow for heterogeneous treatment intensity across labor groups within a commuting zone. This requires that our approach deviates from ADH in that we construct CZ and group-specific independent variables, whereas ADH use CZ-specific independent variables. In allowing for heterogeneous treatment intensities within CZs across groups, our approach is similar to [Dix-Carneiro and Kovak \(2015\)](#); although unlike [Dix-Carneiro and Kovak \(2015\)](#), we also allow for heterogeneous treatment effects across labor groups. Because of this difference in approach, we cannot simply use ADH's independent variables. Of course, when aggregating across all education groups, our independent variables are common across all workers in the commuting zone, as in ADH. In this case, our results are qualitatively similar when using their measures of independent variables.

A second, related difference from ADH is that we use the census and ACS to measure our independent variables, whereas ADH use the County Business Patterns (CBP). We cannot use the CBP because it does not report variables separately by labor group.

Third, we use income-share weights in the construction of our China shock, its instrument, and the initial share of manufacturing, whereas ADH use employment-share weights.

2.3 Results

We begin in [Table 1](#) by estimating [equation 2](#) using total per capita income in a CZ as a dependent variable and aggregating across all workers. Our objective here is to show how our result of interest, reported in the first row, varies as we incorporate more commuting zone-specific controls. The first column includes no controls. The second column adds the start-of-period percentage of employment in the manufacturing sector to capture changes in manufacturing outcomes orthogonal to Chinese competition. The third column adds Census division dummies to capture confounding factors across regions. Other columns additionally control for demographic variables to test robustness and eliminate confounds. The result in column (6), which is the most conservative specification, shows that a \$1,000 increase in a CZ's import exposure per worker decreases its per capita income by about 0.75 percent relative to a CZ with no import exposure.

[Table 2](#) presents our baseline empirical results, decomposing the impact of the China shock (for all workers, college educated workers, and non-college educated workers) using the full vector of controls as in column 6 of [Table 1](#). We take the natural logarithm of each variable to exactly decompose changes in income per capita (column 1) into four margins of adjustment: hourly wages (column 2), hours worked per employee (column 3), one minus the unemployment rate (column 4), and labor force participation (column 5). We addition-

Table 1: Imports from China and Change in Per Capita Income
for All Workers in CZs, 1990-2007: 2SLS Estimates
Dependent variable: 10 x annual change in the log of income/working-age population (in %)

	I. 1990-2007 stacked first differences					
	(1)	(2)	(3)	(4)	(5)	(6)
(Δ imports from China to US)/	-1.225*** (0.255)	-1.194*** (0.231)	-1.208*** (0.228)	-0.769*** (0.209)	-0.835*** (0.164)	-0.746*** (0.186)
manufacturing share ₋₁		-0.014 (0.059)	0.086** (0.042)	-0.099 (0.063)	0.123*** (0.046)	0.004 (0.057)
college share ₋₁				-0.592*** (0.166)		-0.443*** (0.145)
foreign born share ₋₁				-0.019 (0.036)		0.116 (0.071)
female share ₋₁				-0.218 (0.137)		0.041 (0.172)
routine occupation share ₋₁					-1.135*** (0.236)	-0.661** (0.311)
average offshorability ₋₁					-0.211*** (0.041)	-0.185*** (0.050)
regional FE	No	No	Yes	Yes	Yes	Yes
	II. 2SLS first stage estimates					
(Δ imports from China to OTH)/	1.042*** (0.137)	1.060*** (0.159)	1.053*** (0.152)	1.005*** (0.137)	1.029*** (0.148)	1.005*** (0.134)
R ²	0.82	0.82	0.84	0.85	0.84	0.85

Notes: N = 1,444 (722 CZs x two time periods). * p<0.10, ** p<0.05, *** p<0.01; standard errors are clustered by state; the regression analyses are weighted by initial CZ share of national population. Regional FE refers to the Census division dummies. All control variables are what are used in ADH.

ally report the term that combines hours worked per employee and labor force participation (column 6), which is consistent with our theoretical analysis. Panel A reports results aggregating across all workers while Panels B and C separately report results exclusively using college and non-college educated workers, respectively. The coefficient in column 1 of Panel A is what is reported in column 6 of Table 1. For each panel, columns 2-6 present regression results using each margin as a dependent variable, so that the coefficients in columns 2-5 add up to the coefficient in column 1 (as do the coefficients in columns 2, 4, and 6).

The results in Panel A (in which we aggregate across all workers) reveal that the effect of China shock on relative per capita income across commuting zones is primarily attributed to the combination of the two extensive margins of employment, labor force participation (50%) and unemployment (29%). Neither the hours worked per employee nor the wage margins are statistically significant at standard levels, although the wage margin is economically significant (22%).

Table 2: Imports from China and the Decomposition of Change in Income per Capita for Each Group in CZ, 1990-2007: 2SLS Estimates
Dependent variable: 10 x annual change in the log of each margin (in %)

	1990-2007 stacked first differences					
	$\Delta \ln \left(\frac{inc}{pop} \right)$ (1)	$\Delta \ln \left(\frac{inc}{hour} \right)$ (2)	$\Delta \ln \left(\frac{hours}{emp} \right)$ (3)	$\Delta \ln \left(\frac{emp}{lf} \right)$ (4)	$\Delta \ln \left(\frac{lf}{pop} \right)$ (5)	$\Delta \ln \left(\frac{hours}{emp} \frac{lf}{pop} \right)$ (6)
<i>Panel A: all workers</i> (Δ imports from China to US)/ worker	-0.746*** (0.186)	-0.174 (0.133)	0.017 (0.061)	-0.213*** (0.034)	-0.376*** (0.127)	-0.359*** (0.092)
<i>Panel B: college educated</i> (Δ imports from China to US)/ worker	-0.424*** (0.151)	-0.290** (0.114)	-0.073* (0.042)	-0.026** (0.010)	-0.035 (0.036)	-0.108** (0.046)
<i>Panel C: non college educated</i> (Δ imports from China to US)/ worker	-1.292*** (0.259)	-0.283 (0.255)	0.065 (0.098)	-0.383*** (0.054)	-0.693*** (0.222)	-0.627*** (0.173)

Notes: N = 1,444 (722 CZs x two time periods). * p<0.10, ** p<0.05, *** p<0.01; standard errors are clustered by state; the regression analyses are weighted by initial CZ share of group-specific national population. *inc* is wage and salary income, *hour* is hours worked, *emp* is employment, and *lf* is the size of the labor force (by CZ and group). Panel A includes all control variables in Table 1 whereas Panels B and C exclude the college-educated population control.

Panels B and C separately identify and decompose the impacts of the China shock across CZs for college and non-college educated workers. Apparently, the decomposition in Panel A largely reflects the results for workers without a college education. According to Panel C, the effect of the China shock on relative per capita income across commuting zones for workers without a college education is primarily attributed to the combination of the two extensive margins of employment, labor force participation (54%) and unemployment (30%). Similarly, neither the hours worked per employee nor the wage margins are statistically significant at standard levels, although the wage margin is economically significant (22%). According to Panel B, the effect of China shock on relative per capita income across commuting zones for college educated workers is largely attributed to the wage margin (approximately 68%). Moreover, hours worked per employee (17%) is the second most important margin of adjustment for these workers. Neither of the two extensive margins of employment—labor force participation (8%) and unemployment (6%)—account for an economically significant share of adjustment, and of these only unemployment is statistically significant at standard levels.

In summary, these results highlight the empirical relevance of heterogeneous treatment effects of trade shocks across labor groups as well as non-wage margins of adjustment, including both frictional unemployment as well as optimal labor-leisure choices (especially

for low education workers). Our theory in the next section is designed specifically to incorporate these features of the data.

3 Theory

We set up our model in Section 3.1, characterize its equilibrium in Section 3.2, provide comparative static results in Section 3.3, and intuition in Section 3.4.

Our objective is to provide the simplest extension possible of a canonical model of international trade. In doing so, we make stark assumptions. Two are worth highlighting. First, we assume that parameters featuring in the search block of the model are common across sectors (we describe the role of these restrictions in footnote 8). Second, we use a static model and ignore transitions (similar to focusing on the steady state of a dynamic model).

3.1 Setup

We consider an economy with many commuting zones (CZs) indexed by $c \in \mathcal{C}$. Agents (may) differ in their observable characteristics. We divide agents into disjoint labor groups, indexed by g , based on these characteristics. The set of agents in group g that lives in CZ c is denoted by Ω_{cg} and has measure $N_{cg} = |\Omega_{cg}|$. There is a finite number of S sectors, indexed by $s \in \mathcal{S}$. Each CZ is a small open economy that treats the real price of each sector s , P_s , as given; these prices are common across CZs.

Each agent chooses the sector in which to search for employment and is either successfully matched or becomes unemployed. An agent who successfully matches (a worker) chooses how many hours to work. An unemployed agent in CZ c and group g receives real unemployment benefits, B_{cg} , which are financed by ad valorem production taxes, τ , which place a wedge between consumption prices, P_s , and production prices, $(1 - \tau)P_s$.

Technology. The sector s production function is the integral of output across workers employed there. Denote by Ω_{cgs}^Y the set of workers in CZ c and group g who are employed in sector s . A worker $\omega \in \Omega_{cgs}^Y$ produces

$$y_{\omega s} = A_{cgs}^Y \varepsilon_{\omega s} H_{\omega s} \text{ if } \omega \in \Omega_{cgs}^Y \quad (3)$$

units of output, where productivity is $A_{cgs}^Y \varepsilon_{\omega s} \geq 0$ per hour and $H_{\omega s} \geq 0$ is the number of hours worked. Output of group g workers in CZ c and sector s is $Y_{cgs} = \int_{\omega \in \Omega_{cgs}^Y} y_{\omega s} d\omega$. Total output of CZ c workers in sector s is then simply $Y_{cs} = \sum_g Y_{cgs}$. We assume that each $\varepsilon_{\omega s}$ is distributed Fréchet with cumulative distribution function $G_g(\varepsilon) = \exp(-\varepsilon^{-\kappa_g})$ with $\kappa_g > 1$.

Labor market frictions. Production requires a worker to be matched with a firm. Search is directed: a firm chooses the CZ, group, and sector in which to post a vacancy; and each worker chooses the sector in which to apply for a job. There is a constant real cost of $F_{cg} > 0$ per vacancy posted in each cgs triplet. There is free entry, so (risk-neutral) firms post vacancies in each cgs triplet until expected profits from a new posting are zero, conditional on any cgs vacancies being posted. Given a number of vacancies directed at cgs , denoted by V_{cgs} , and a number of job applicants, denoted N_{cgs} , the number of successful matches is determined by the matching function

$$M_{cgs}(V_{cgs}, N_{cgs}) = A_{cg}^M V_{cgs}^{\alpha_{cg}} N_{cgs}^{1-\alpha_{cg}}, \quad (4)$$

where $A_{cg}^M > 0$ is the productivity of the matching function. Firms choose how many vacancies to post taking as given market tightness, $\theta_{cgs} \equiv V_{cgs}/N_{cgs}$, and prices, P_s . The probability that any given cgs vacancy is filled is $A_{cg}^M \theta_{cgs}^{\alpha_{cg}-1}$. The probability that an applicant finds a job, which we refer to as the “employment rate” (although this is really one minus the unemployment rate) and which we denote by E_{cgs} , is then simply $E_{cgs} = A_{cg}^M \theta_{cgs}^{\alpha_{cg}}$.

After matching takes place, the firm and worker bargain over the division of the surplus. Outside options at this stage are zero and the vacancy cost is sunk, so the worker gets a fraction, β_{cg} , of revenue.

Utility. The utility of a group g worker who consumes C units of the final good and supplies H hours of labor is

$$u(C, H) = \zeta_g C - \frac{H^{1+v_g}}{1+v_g}, \quad (5)$$

where $\zeta_g, v_g > 0$. Real consumption is simply real income.

Factor market clearing. The measure of agents in Ω_{cg} must equal the measure who apply for positions across all sectors,

$$N_{cg} = \sum_{s \in \mathcal{S}} N_{cgs}. \quad (6)$$

Cross-parameter restrictions. In order for certain integrals to converge, we must impose the following restriction across parameters: $\kappa_g > (1 + v_g)/v_g$.⁷

Taxes and transfers. Unemployment insurance, B_{cg} , is financed by production taxes, τ . Our comparative static results below are independent of the particular determination of these

⁷This restriction holds at standard parameter estimates. Depending on how one views the hours choice as modeled here, the inverse of the parameter v_g is what [Chetty et al. \(2011\)](#) either refer to as the steady-state intensive margin or aggregate elasticity of labor supply; standard estimates fall between 0.33 and 0.6, so its inverse is between 1.7 and 3. A standard estimate of κ_g is around 2; see e.g. [Burstein et al. \(Forthcoming\)](#).

taxes and how they respond to economic shocks. Therefore, we do not take a stand on whether or not the national government's static budget constraint must be balanced.

3.2 Characterization

First, we solve for vacancy choices. Second, we solve for worker hours conditional on employment in sector s . Third, focusing on an equilibrium in which market tightness is common across sectors, $\theta_{cg} = \theta_{cgs}$ for all s , we solve for worker allocations across sectors; we show that given these worker choices, firm choices are consistent with market tightness being common across sectors. Finally, we solve for the endogenous variables of interest.

Firm choices. Here we assume that firms post vacancies for all cgs triplets, a condition that is satisfied in equilibrium if $A_{cgs}^Y > 0$ for all cgs .

Equating total profits for cgs vacancies to zero, we obtain

$$(1 - \beta_{cg})(1 - \tau)P_s Y_{cgs} = F_{cg} V_{cgs},$$

where $F_{cg} V_{cgs}$ is the total cost of vacancy posting, $(1 - \tau)P_s Y_{cgs}$ is total revenue net of taxes, and $(1 - \beta_{cg})$ is the firm's share of this revenue. The zero profit condition above together with equation (4) and the definition of market tightness yield a solution for market tightness as a function of output per match,

$$(1 - \tau)P_s \theta_{cgs}^{\alpha_{cg}-1} A_{cg}^M \frac{Y_{cgs}}{M_{cgs}} = \frac{F_{cg}}{1 - \beta_{cg}}. \quad (7)$$

Worker choices (I): labor-leisure choice. Conditional on employment in sector s , a worker $\omega \in \Omega_{cgs}^Y$ faces a real hourly wage of $\beta_{cg} A_{cgs}^Y \varepsilon_{\omega s} (1 - \tau) P_s$. Each worker $\omega \in \Omega_{cgs}^Y$ chooses the number of hours to work to maximize utility, equation (5), taking as given prices, P_s and, therefore, the real wage. Optimal hours worked for one such employee is

$$H_{\omega s} = (\beta_{cg} \zeta_g A_{cgs}^Y \varepsilon_{\omega s} (1 - \tau) P_s)^{\frac{1}{v_g}} \text{ for each } \omega \in \Omega_{cgs}^Y. \quad (8)$$

Worker choices (II): sector choice. Equations (5) and (8) imply that a worker $\omega \in \Omega_{cgs}^Y$ obtains utility

$$u_{\omega s}^E = \frac{v_g}{1 + v_g} \left(\beta_{cg} \zeta_g A_{cgs}^Y \varepsilon_{\omega s} (1 - \tau) P_s \right)^{\frac{1+v_g}{v_g}},$$

whereas an unemployed agent $\omega \in \Omega_{cg}$ obtains utility

$$u_{cg}^U = \zeta_g B_{cg}.$$

An agent's expected utility if applying for employment in s is given by

$$\mathbb{E}[u_{\omega s}] = E_{cgs} u_{\omega s}^E + (1 - E_{cgs}) u_{cg}^U.$$

An agent $\omega \in \Omega_{cg}$ chooses s to maximize her expected utility, so that $\omega \in \Omega_{cg}$ applies to s if and only if $\mathbb{E}[u_{\omega s}] > \max_{s' \neq s} \mathbb{E}[u_{\omega s'}]$.

Under the assumption that $\theta_{cg} = \theta_{cgs}$ for all cgs , we have $E_{cgs} = E_{cgs'}$. Together with our assumption that ε is distributed Fréchet, this implies that the probability that an agent in cg applies to s , which we denote by $\pi_{cgs} = N_{cgs}/N_{cg}$, is simply

$$\pi_{cgs} = \frac{1}{\Phi_{cg}} \left(A_{cgs}^Y P_s \right)^{\kappa_g}, \quad (9)$$

where

$$\Phi_{cg} = \sum_{s' \in \mathcal{S}} \left(A_{cgs'}^Y P_{s'} \right)^{\kappa_g}. \quad (10)$$

Equilibrium. Equation (3), equation (8), and our assumption that $\varepsilon_{\omega s}$ is distributed Fréchet yield a solution for output per worker in terms of the share of workers who apply to sector s ,

$$\frac{Y_{cgs}}{M_{cgs}} = A_{cgs}^Y \left(\beta_{cg} \zeta_g A_{cgs}^Y (1 - \tau) P_s \right)^{\frac{1}{v_g}} \gamma_{g1} \pi_{cgs}^{\frac{-(1+v_g)}{\kappa_g v_g}}, \quad (11)$$

where $\gamma_{g1} = \Gamma \left(1 - \frac{1+v_g}{\kappa_g v_g} \right)$ and $\Gamma(\cdot)$ is the gamma function. The previous expression and equation (9), which was derived under the assumption that $\theta_{cg} = \theta_{cgs}$, yield a solution for the value of output per worker that does not vary across s ,

$$\frac{Y_{cgs}}{M_{cgs}} P_s = \left(\beta_{cg} \zeta_g (1 - \tau) \right)^{\frac{1}{v_g}} \gamma_{g1} \Phi_{cg}^{\frac{1+v_g}{\kappa_g v_g}}.$$

The previous expression and equation (7)—the zero profit condition for posting vacancies—yield a solution for market tightness,

$$\theta_{cgs}^{1-\alpha_{cg}} = (1 - \tau)^{\frac{1+v_g}{v_g}} A_{cg}^M \frac{1 - \beta_{cg}}{F_{cg}} \left(\beta_{cg} \zeta_g \right)^{\frac{1}{v_g}} \gamma_{g1} \Phi_{cg}^{\frac{1+v_g}{\kappa_g v_g}}$$

that is common across sectors, i.e. that satisfies $\theta_{cgs} = \theta_{cg}$.⁸

In equilibrium, the probability that a job seeker in cgs is matched as well as the average wage per hour worked and hours worked per employee in cgs are all common across sectors s . Denote these by E_{cg} , W_{cg} , and H_{cg} , respectively. We obtain the following proposition,

⁸This condition highlights the role of the assumptions that A_{cg}^M , β_{cg} , F_{cg} , and α_{cg} do not vary across sectors.

which is proven in the appendix.

Proposition 1. *The average wage per hour worked ($K = W$), hours worked per employee ($K = H$), and the employment rate ($K = E$) in cg are given by*

$$K_{cg} = v_{cg}^K \Phi_{cg}^{\frac{1}{\kappa_g} \beta_g^K} \quad \text{for } K = W, H, E, \quad (12)$$

where the v_{cg}^K terms are positive constants, $\beta_g^W \equiv 1$, $\beta_g^H \equiv \frac{1}{v_g}$, and $\beta_g^E \equiv \frac{1+v_g}{v_g} \frac{\alpha_{cg}}{1-\alpha_{cg}}$.

Of course, Proposition 1 immediately implies that income per capita for labor group g in CZ c , $I_{cg} \equiv W_{cg}H_{cg}E_{cg}$, is given by

$$I_{cg} = v_{cg}^I \Phi_{cg}^{\beta_{cg}^I},$$

where $v_{cg}^I \equiv v_{cg}^W v_{cg}^H v_{cg}^E > 0$ and $\beta_{cg}^I \equiv \frac{1}{\kappa_g} (\beta_g^W + \beta_g^H + \beta_{cg}^E)$. In all that follows, we assume that $\alpha_g \equiv \alpha_{cg}$ for all c . In this case, $\beta_g^E \equiv \beta_{cg}^E$ and $\beta_g^I \equiv \beta_{cg}^I$ for all c .

3.3 Comparative static results

Consider a shock to the vector of sectoral real prices and denote by $x = d \ln X$ the change in the natural logarithm of any variable X in response to this shock. Average wages and hours worked conditional on employment of cg workers as well as the employment rate of cg agents change both because of changes in Φ_{cg} but also because the tax rate, τ , may also change (for instance if the government budget must remain balanced). However, since tax rates are common across goods and space, only changes in Φ_{cg} affect relative wages, hours worked, or employment rates.

Changes in Φ_{cg} , denoted ϕ_{cg} , are simply a group-specific multiple of the weighted average of price changes, where weights are given by the share of cg labor income earned across sectors,

$$\phi_{cg} = \kappa_g \sum_s \pi_{cgs} p_s.$$

Hence, changes in wages, hours worked conditional on employment, the employment rate, and income per capita of group g agents in commuting zone c' relative to commuting zone c are given by

$$k_{c'g} - k_{cg} = \beta_g^K \sum_s (\pi_{c'gs} - \pi_{cgs}) p_s \quad \text{for } K = W, H, E, I. \quad (13)$$

This directly implies that if $d \ln P_s = p_s$ is increasing in s and $\pi_{c'gs}$ first-order stochastically dominates π_{cgs} (π_{cgs} is the distribution of cg labor income across sectors s), then $k_{c'g} > k_{cg}$ for $K = W, H, E, I$. That is, if group g is disproportionately employed in high s sectors

within c' compared to c (in the sense of first-order stochastic dominance), then a shock that increases the relative prices of high s sectors must increase the average wage, average hours worked per employee, the employment rate, and income per capita of group g within c' relative to c . Finally, according to equation (9), a sufficient condition for $\pi_{c'gs}$ to first-order stochastically dominate π_{cgs} is that $A_{c'gs}^Y$ dominates A_{cgs}^Y in terms of the maximum-likelihood ratio property. We summarize these results in the following proposition.

Proposition 2. *Changes in wages, hours worked conditional on employment, the employment rate, and income per capita of group g agents in c' relative to in c are given by equation (13). If $\pi_{c'gs}$ first-order stochastically dominates π_{cgs} and $p_{s'} \geq p_s$ for all $s' \geq s$, then $k_{c'g} \geq k_{cg}$ for $K = W, H, E, I$. Finally, if $A_{c'gs'}^Y A_{cgs}^Y \geq A_{c'gs}^Y A_{cgs'}^Y$ for all $s' \geq s$, then $\pi_{c'gs}$ first-order stochastically dominates π_{cgs} .*

3.4 Intuition

Here we provide intuition for our results. The wage comparative static result follows from the envelope condition. In response to a small change in sector prices, the average cg wage may change for two reasons. First, each infra-marginal worker who does not switch sectors will experience a change in wage exactly equal to the change in her sector's price. Second, workers switch across sectors. However, since a switcher is indifferent between sectors and there are no compensating differentials or switching costs, a switcher's wage will not change in response to switching. Hence, the change in each worker's wage equals the change the price of the worker's original sector. Averaging wages across workers within cg yields the weighted average of sector price changes, weighted by cg income shares across sectors in the original equilibrium. This explains both the structure of the relative wage result as well as the fact that the elasticity, β_g^W , is exactly equal to one.

Taking these wage effects as given, if the labor supply elasticity is $1/v_g$ (as implied by our GHH preferences) then the response of average hours worked across cg workers is simply $\beta_g^H = 1/v_g$ times the response of average wages.⁹

Finally, consider the response of the frictional unemployment margin. While changes in prices may induce agents to switch sectors, to a first order these switches will not affect a labor group's employment rate—at given vacancies—since the likelihood of successfully finding employment is equalized across sectors in the initial equilibrium. Hence, changes in employment rates are induced by changes in firm vacancy choices, and all else equal firms post more vacancies when a sector's price rises. This explains why β_g^E is increasing in the elasticity of matches to vacancies, α_g . The incentive for firms to post vacancies in a given cgs rises with the price of the sector for two reasons. First, a higher price generates

⁹Selection into unemployment does not affect the wage or hours margins, since unemployed workers are randomly selected within each cg pair.

more revenue at fixed hours worked. Second, a higher price increases hours worked of each individual worker, which raises revenue further. This explains why β_g^E is also increasing in the labor supply elasticity, $1/v_g$.

4 Connecting empirics and theory

Our theory provides explicit solutions linking the elasticity of each margin of adjustment to primitive structural elasticities. This serves two useful purposes. First, it highlights the importance of heterogeneity in the elasticity of labor supply, $1/v_g$, and the elasticity of matches to vacancies, α_g , for understanding heterogeneous treatments effects identified in empirical research. Second, it provides a clear mapping from the relative importance of each margin of adjustment to the strength of particular economic mechanisms. In this section we recover the elasticity of labor supply and the elasticity of matches to vacancies for each labor group by combining our empirical and theoretical results. We show that heterogeneity in treatment effects in the data are consistent with a higher elasticity of labor supply and a higher elasticity matches to vacancies for low education workers. Our point estimates of three of the four elasticities (two for each education group) are in the middle of the range of canonical estimates from labor, public finance, and macroeconomics. Our labor supply elasticity for low education workers is too high, and we suggest a potential fix for trade models to better fit this elasticity.

To link our theory to the data, we must make two heroic assumptions. First, we must assume that unemployment and labor force participation reported in the data reflect frictional unemployment and optimal labor-leisure choices in the model. In practice, observed hours worked in the data may not reflect optimal labor supply choices because workers may not be on their labor supply curves; see e.g. [Michaillat \(2012\)](#) for a search-and-matching model of unemployment in which jobs are rationed. Hence, we both report the labor supply elasticities consistent with our model and empirics as well as take existing estimates of labor supply elasticities and report what share of our observed empirical variation in hours induced by the China shock is accounted for by optimal labor supply choices (versus forces such as job rationing).

Second, in order to obtain structural parameters using equation (13), we need to measure ϕ_{cgt} , the commuting zone and group-specific weighted average of sectoral price changes (starting from time t). Here, we assume that changes in sectoral prices, p_{st} are a scalar, μ , times $\frac{\Delta M_{st}^{us}}{L_{st}}$. In this case, we have a simple relationship between the forcing variable in our model and the independent variable in our empirics,

$$\mu\phi_{cgt} = \Delta IPW_{cgt}^{us}$$

and the coefficients reported in Table 2 provide structural estimates of $\mu\beta_g^K$.

Our theory predicts that $\beta_g^W = 1$ for all g . Hence, the coefficient on the impact of the China shock on wages in column 2 of Table 2 yields a value of $\mu = -0.283$ for non-college educated workers and of $\mu = -0.290$ for college educated workers. We choose $\mu = -0.29$. Given this value of μ , we can recover each β_g^K from our empirical estimates in Table 2 by simply dividing the estimated coefficient by -0.29 . We obtain $\beta_g^H = 1/v_g = 2.16$ for non-college and $\beta_g^H = 1/v_g = 0.37$ for college educated workers. For college educated workers this estimate is squarely in line with empirical estimates of the aggregate labor supply elasticity, but for non-college educated workers this estimate is substantially above standard estimates; see e.g. Chetty et al. (2011). As discussed above, this suggests that non-college educated workers may not be on their labor supply curves, perhaps because of job rationing. Using an elasticity of 0.59 from Chetty et al. (2011), this suggests that worker optimization over hours explains only about one quarter of the variation across commuting zones in non-college hours in response to the China shock.

Finally, we use column 4 of Table 2 to recover the elasticity of matches with respect to vacancies, α_g , for both education groups. The coefficients of -0.383 and -0.026 for non-college and college educated workers, respectively, and our estimates of μ and $1/v_g$ yield estimates of the elasticity of matches with respect to vacancies of $\alpha_g = 0.41$ and $\alpha_g = 0.21$ for non-college and college educated workers, respectively. These estimates are broadly consistent with the large macroeconomics literature estimating a single elasticity for all workers—see e.g. Petrongolo and Pissarides (2001) for a review of estimates—as well as the heterogeneous values across education groups estimated in Fahr and Sunde (2004), which estimates $\alpha_g = 0.37$ and $\alpha_g = 0.28$ for low education and high education workers, respectively.

5 Conclusions

In this paper we study margins of labor-market adjustment to trade shocks. Empirically, we decompose the differential impact on per capita income across U.S. commuting zones of the China shock. While our empirical exercise follows Autor et al. (2013) as closely as possible and, therefore, does not contribute methodologically to identification of trade shocks on local labor markets (see Goldsmith-Pinkham et al. (2018) and Borusyak et al. (2018)) or inference in such settings (see Adão et al. (2018b)), our decomposition—into wages, hours worked per employee, the unemployment rate, and the labor force participation rate—is novel and motivates our theoretical contribution. Our results highlight the empirical relevance of heterogeneous treatment effects of trade shocks across labor groups, non-wage margins of adjustment, and frictional unemployment in addition to optimal labor-leisure choices.

Theoretically, we show that an assignment model of international trade extended to incorporate frictional unemployment and optimal labor-leisure decisions yields simple analytic comparative static results across local labor markets, by labor group, and for each margin of adjustment. Since our model extends the most-common frameworks in the quantitative literature on trade and inequality, our analytic results help broaden the literature—by incorporating both leisure and frictional unemployment—and open the black box of quantitative work.

In our theory, the elasticity of each of margin of adjustment to a trade shock is a simple function of the steady-state elasticity of labor supply and the elasticity of matches to vacancies. Given that our theory demonstrates the importance of these elasticities for understanding the vast and growing empirical literature on trade and regional inequality, we take a first stab at recovering these elasticities by education group using the China shock. We find elasticities that are broadly consistent with those in the literature with one exception: our estimate of the labor supply elasticity for non-college workers is substantially larger than standard estimates. This suggests that future theoretical work on the impact of trade across local labor markets may benefit from incorporating job rationing.

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Online Appendix

Trade and inequality across local labor markets:

The margins of adjustment

Ryan Kim and Jonathan Vogel

A Proof of Proposition 1

Under the assumption that $E_{cgs} = E_{cg}$, we have

$$\mathbb{E}[u_{\omega s}] > \max_{s' \neq s} \mathbb{E}[u_{\omega s'}] \iff u_{\omega s}^E > \max_{s' \neq s} \left\{ u_{\omega s'}^E \right\}$$

As we show above, we have

$$u_{\omega s}^E = \frac{v_g}{1 + v_g} \left(\beta_{cg} \zeta_g A_{cgs}^Y \varepsilon_{\omega s} (1 - \tau) P_s \right)^{\frac{1+v_g}{v_g}}$$

so that

$$\mathbb{E}[u_{\omega s}] > \max_{s' \neq s} \mathbb{E}[u_{\omega s'}] \iff \left(A_{cgs}^Y \varepsilon_{\omega s} P_s \right)^{\frac{1+v_g}{v_g}} > \max_{s' \neq s} \left\{ \left(A_{cgs'}^Y \varepsilon_{\omega s'} P_{s'} \right)^{\frac{1+v_g}{v_g}} \right\}$$

Hence, we have

$$\mathbb{E}[u_{\omega s}] > \max_{s' \neq s} \mathbb{E}[u_{\omega s'}] \iff A_{cgs}^Y \varepsilon_{\omega s} P_s > \max_{s' \neq s} \left\{ A_{cgs'}^Y \varepsilon_{\omega s'} P_{s'} \right\}$$

Hence, we obtain equations (9) and (10).

Recall that the real wage of a worker $\omega \in \Omega_{cg}$ who is employed in sector s is

$$W_{\omega s} = \beta_{cg} (1 - \tau) A_{cgs}^Y P_s \varepsilon_{\omega s}$$

Given the assumption that $\varepsilon_{\omega s}$ is distributed Fréchet, we have

$$W_{cg} = \beta_{cg} (1 - \tau) \gamma_{g2} \Phi_{cg}^{\frac{1}{\kappa_g}}$$

where

$$\gamma_{g2} \equiv \Gamma \left(1 - \frac{1}{\kappa_g} \right)$$

Recall that hours worked of a worker $\omega \in \Omega_{cg}$ who is employed in sector s are

$$H_{\omega s} = (\beta_{cg} \zeta_g A_{cgs}^Y \varepsilon_{\omega s} (1 - \tau) P_s)^{\frac{1}{v_g}}$$

Given the assumption that $\varepsilon_{\omega s}$ is distributed Fréchet, we have

$$H_{cgs} = (\beta_{cg} (1 - \tau) \zeta_g A_{cgs}^Y P_s)^{\frac{1}{v_g}} \gamma_{g3} \pi_{cgs}^{-\frac{1}{\kappa_g v_g}}$$

where

$$\gamma_{g3} \equiv \Gamma \left(1 - \frac{1}{v_g \kappa_g} \right)$$

Substituting in for π_{cgs} yields

$$H_{cg} = (\beta_{cg} (1 - \tau) \zeta_g)^{\frac{1}{v_g}} \gamma_{g3} \Phi_{cg}^{\frac{1}{\kappa_g v_g}}$$

Recall that the probability of a worker $\omega \in \Omega_{cg}$ finding a job in sector s is

$$E_{cgs} = A_{cg}^M \theta_{cgs}^{\alpha_{cg}}$$

and that

$$\theta_{cg}^{1 - \alpha_{cg}} = (1 - \tau)^{\frac{1 + v_g}{v_g}} A_{cg}^M \frac{1 - \beta_{cg}}{F_{cg}} (\beta_{cg} \zeta_g)^{\frac{1}{v_g}} \gamma_{g1} \Phi_{cg}^{\frac{1 + v_g}{\kappa_g v_g}}$$

Combining these, we obtain

$$E_{cgs} = A_{cg}^M \left[(1 - \tau)^{\frac{1 + v_g}{v_g}} A_{cg}^M \frac{1 - \beta_{cg}}{F_{cg}} (\beta_{cg} \zeta_g)^{\frac{1}{v_g}} \gamma_{g1} \right]^{\frac{\alpha_{cg}}{1 - \alpha_{cg}}} \Phi_{cg}^{\frac{1 + v_g}{\kappa_g v_g} \frac{\alpha_{cg}}{1 - \alpha_{cg}}}$$

In summary, we obtain Proposition 1, with constants given by

$$\begin{aligned} \nu_{cg}^W &\equiv \beta_{cg} (1 - \tau) \gamma_{g2} \\ \nu_{cg}^H &\equiv (\beta_{cg} (1 - \tau) \zeta_g)^{\frac{1}{v_g}} \gamma_{g3} \\ \nu_{cg}^E &\equiv A_{cg}^M \left[(1 - \tau)^{\frac{1 + v_g}{v_g}} A_{cg}^M \frac{1 - \beta_{cg}}{F_{cg}} (\beta_{cg} \zeta_g)^{\frac{1}{v_g}} \gamma_{g1} \right]^{\frac{\alpha_{cg}}{1 - \alpha_{cg}}} \end{aligned}$$

Finally, in order for γ_{g1} , γ_{g2} , and γ_{g3} to converge, we require that $\kappa_g > \frac{1 + v_g}{v_g}$, $\kappa_g > 1$, and $\kappa_g > \frac{1}{v_g}$, respectively. A sufficient condition for the first and third conditions to hold—given that we imposed the second upon introducing the parameter κ_g —is that we have $\kappa_g > \frac{1 + v_g}{v_g}$, which is the cross-parameter restriction we impose.

B Empirical robustness

One issue regarding our decomposition exercise, as described in Section 2.1, is that respondents report their current unemployment status and labor force participation but report their number of hours worked and income from the previous year. Correspondingly, there are observations for which the respondent reports being unemployed or out of the labor force yet also reports positive hours worked and/or earnings. Similarly, there are observations for which the respondent reports being employed but also reports zero hours worked and/or earnings. In our baseline we constructed commuting zone and group specific outcome variables without first correcting for these timing inconsistencies at the individual level. Here, we take an alternative approach. We adjust (past) income and hours worked to be consistent with (current) unemployment and labor force participation variables by replacing hours worked and income to be zero if respondents report that they are unemployed or not in labor force. We also drop those respondents who report that they are currently employed but have zero hours worked or income last year. After these adjustments, we then construct commuting zone and group specific outcome variables. We show that our qualitative results are largely robust to these adjustments.

Table 3: Imports from China and the Decomposition of Change in Income per Population for Each Group in CZs, 1990-2007: 2SLS Estimates
Dependent variable: 10 x annual change in the log of each margin (in %)

	1990-2007 stacked first differences					$\Delta \ln \left(\frac{\text{hours}}{\text{emp}} \frac{\text{lf}}{\text{pop}} \right)$ (6)
	$\Delta \ln \left(\frac{\text{inc}}{\text{pop}} \right)$ (1)	$\Delta \ln \left(\frac{\text{inc}}{\text{hour}} \right)$ (2)	$\Delta \ln \left(\frac{\text{hours}}{\text{emp}} \right)$ (3)	$\Delta \ln \left(\frac{\text{emp}}{\text{lf}} \right)$ (4)	$\Delta \ln \left(\frac{\text{lf}}{\text{pop}} \right)$ (5)	
<i>Panel A: all workers</i> (Δ imports from China to US)/ worker	-0.955*** (0.214)	-0.131 (0.139)	-0.171*** (0.044)	-0.235*** (0.036)	-0.419*** (0.136)	-0.590*** (0.155)
<i>Panel B: college educated</i> (Δ imports from China to US)/ worker	-0.448*** (0.148)	-0.282*** (0.100)	-0.097*** (0.034)	-0.028** (0.011)	-0.040 (0.040)	-0.137** (0.055)
<i>Panel C: non college educated</i> (Δ imports from China to US)/ worker	-1.712*** (0.277)	-0.238 (0.252)	-0.284*** (0.067)	-0.422*** (0.057)	-0.768*** (0.235)	-1.052*** (0.265)

Notes: N = 1,444 (722 CZs x two time periods). * p<0.10, ** p<0.05, *** p<0.01; standard errors are clustered by state; the regression analyses are weighted by initial CZ share of group-specific national population. *inc* is wage and salary income, *hour* is hours worked, *emp* is employment, and *lf* is the size of the labor force (by CZ and group). Panel A includes all control variables in Table 1 whereas Panels B and C exclude the college-educated population control.

Table 3 shows that adjusting (past) income and hours worked to be consistent with (cur-

rent) unemployment and labor force participation variables yields similar results as in our baseline. The primary difference from our baseline approach to measurement is that the hours worked per employee margin becomes substantially more important.

Panel A (in which we aggregate across all workers) shows that the effect of China shock on relative per capita income across commuting zone is still primarily attributed to the combination of labor force participation and unemployment (68% here relative to 79% in Table 2). Now, however, the contribution of the hours worked per employee margin is economically (21%) and statistically significant. The greater importance of this margin of adjustment in Table 3 compared to Table 2 is robust across labor groups. However, the other conclusions of Table 2 remain robust. Panel C shows that results aggregating across all workers still largely reflect results for non-college-educated workers, where the effect on per capita income remains dominated by the combination of labor force participation and unemployment (70% here relative to 83% in Table 2). Finally, Panel B shows that the hourly wage margin continues to dominate for college educated workers (63% here relative to 68% in Table 2).

These results are broadly consistent with the main empirical results in Table 2, *modulo* the increase in the relevance of the hours worked per employee margin. They highlight the empirical relevance of heterogeneous treatment effects of trade shocks across labor groups as well as non-wage margins of adjustment, including both frictional unemployment as well as optimal labor-leisure choices (especially for low education workers).