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TRADE AND WELFARE (ACROSS LOCAL LABOR MARKETS)

Ryan Kim
Jonathan Vogel

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ABSTRACT

What are the welfare implications of trade shocks? We provide a sufficient statistic that measures changes in welfare, to a first-order approximation, taking into account adjustment in labor supply, in frictional unemployment, and in the sectors to which workers apply while allowing for arbitrary heterogeneity in worker productivity and nonpecuniary returns across sectors. We apply these insights to measure changes in welfare across commuting zones (CZs) in the U.S. between 2000-2007. We find that granting China permanent normal trade relations lowers the welfare of a CZ at the 90th percentile of exposure by 3.1 percentage points relative to a CZ at the 10th percentile; of this, approximately 65 percent is due to changes in unemployment and much of this is driven by the non-pecuniary costs of unemployment.

Ryan Kim
School of Advanced International Studies
Johns Hopkins University
1717 Massachusetts Ave NW
Washington, DC 20036
rkim59@jhu.edu

Jonathan Vogel
Department of Economics
University of California at Los Angeles
8283 Bunche Hall
Mail Code 147703
Los Angeles, CA 90095
and NBER
jonathan.e.vogel@gmail.com

1 Introduction

Recent empirical work has identified substantial effects of international trade shocks on a broad set of labor-market adjustment margins across regions, including adjustment in wages, labor force participation, and unemployment. In order to understand the welfare implications of these shocks, a growing quantitative literature has embedded the assumption of limited labor mobility across regions into otherwise canonical quantitative trade models. However, this quantitative literature has only incorporated a small subset of the adjustment margins that have featured prominently in the empirics. In particular, this analysis has largely been restricted to wage responses, abstracting from unemployment and, often, labor supply. Moreover, the quantitative literature has imposed strong functional form restrictions.

The goal of this paper is to identify empirically the relative welfare implications of trade (or other) shocks across regions. First, we use theory to provide a sufficient statistic that measures changes in welfare at the individual level, to a first-order approximation, taking into account labor-market adjustment along multiple margins (including frictional unemployment) while imposing minimal functional form assumptions (including allowing agents to differ arbitrarily both in their productivities if working in each sector and also in the non-pecuniary benefits they derive from working in each sector). We then aggregate this measure up across individuals within an arbitrarily defined group. Second, we measure this sufficient statistic over the period 2000 and 2007, linking groups in the theory to U.S. commuting zones in the data. These measured changes in welfare are unconditional, in the sense that they depend on all changes in the economic environment. Third, we identify the impact of a particular trade shock—granting China permanent normal trade relations (PNTR)—on changes in welfare across U.S. commuting zones (CZs) using the same research design as in the reduced-form empirical literature, but replacing the change in a particular margin of adjustment with the change in welfare.[1] In our baseline specification, we find that granting China PNTR lowers the welfare of a CZ at the 90th percentile of exposure by 3.1 percentage points relative to a CZ at the 10th percentile between 2000 and 2007. Approximately 65 percent of this causal effect is accounted for by changes in unemployment and much of this is accounted for by the non-pecuniary costs of unemployment.

Our starting point, in Section 2, is to derive theoretically a measure of the change in welfare, to a first-order approximation, at the individual and group level. In our framework,

[1]Throughout the paper we use changes in welfare to describe the negative of the compensating variation relative to initial income: the negative of the transfer received in the terminal equilibrium under the new parameter values at which the set of agents can be made indifferent, in expectation, between the initial and the terminal equilibria relative to the initial income of the set of agents, where expectations are taken over the probability of unemployment.

each agent chooses the job to apply to—across all sectors in the labor force as well as home production (i.e. non-participation)—to maximize expected utility. Each agent is characterized by a vector of productivities (one for each job) that shapes the agent's pecuniary return, a vector of amenity values (one for each job) that shapes the agent's non-pecuniary return, and a vector of employment probabilities (one for each job) that determines the probability that the agent will successfully obtain employment in the job to which she applies.[2] If an agent does not successfully obtain employment, she becomes unemployed. Our framework thus features endogenous labor supply, a choice of which sector to apply for work conditional on labor force participation, and frictional unemployment. Relative to the large quantitative trade literature, our framework dispenses with functional form restrictions on production functions and on the distributions both of an agent's productivities and non-pecuniary returns across each sector, non-participation, and unemployment.

Our approach, which leverages envelope conditions, highlights that changes in labor allocations across sectors and in the labor force participation rate—both of which are emphasized in the empirical literature—have no first-order effects on welfare, whereas changes in unemployment—emphasized in the empirical literature but largely ignored in the quantitative literature—and in wages per efficiency unit are welfare relevant.[3] In addition, our methodology provides a theory-consistent sufficient statistic for combining the responses of each of these adjustments into a single welfare-change metric.

The specific form of our welfare-change sufficient statistic is intuitive. The elasticity of welfare to the price index for final consumption (which we allow to vary across workers in the theory, but not the empirics) is negative one, as expected. On the other hand, the elasticity of welfare to wages per efficiency unit is less than one and equals the share of the agent's expected income arising from successful employment (wage changes in the sector to which an agent applies for work only affect the agent's utility if the agent becomes successfully employed). This nests models that abstract from unemployment, which find that this elasticity is one. The elasticity of welfare to the probability of unemployment has two components: a pecuniary component arising from the agent-specific loss in income associated with unemployment and a non-pecuniary component arising from the agent-specific gap between the amenity value of employment in the sector to which the agent applies and of unemployment. The fact that the welfare elasticity of unemployment alone contains a non-pecuniary component—even though agents have (potentially) heterogeneous amenity

[2] Heterogeneity in worker productivity across jobs is at the heart of a substantial literature in labor and international trade; see e.g. Roy (1951) and Ricardo's theory of comparative advantage. Heterogeneity in worker preferences across jobs is crucially important for explaining the wage distribution; see e.g. Heckman and Sedlacek (1985) in labor and Dix-Carneiro (2014) in international trade.

[3] If in practice an agent who is not participating in the labor force is not choosing non-participation—that is, if she is off her labor supply curve—then such an agent should be considered unemployed within our model. In empirical robustness we consider this alternative mapping between model and data.

values across sectors and non-participation too—arises because these other margins of adjustment are subject to an envelope condition, whereas unemployment is not (agents do not choose to be unemployed).

As an intermediate step between theory and identifying the impact of a trade shock on welfare, we show how to measure theory-consistent relative welfare changes over time. In particular, we apply our general results to measure changes in relative welfare across U.S. commuting zones between 2000 and 2007 in Section 3. We make two contributions in this section.

First, we show how to measure the change in the wage per efficiency unit in a given sector. Theory dictates that the change in wage per efficiency unit in a given sector be measured as a sector fixed effect in a Mincer-style wage regression of wage changes at the individual worker level that is estimated only on the subset of workers who are employed in the same sector across time periods. We must focus on wage changes *within a fixed set of workers who start in a given sector*, rather than average wage changes within the sector across time, to address issues of selection: changes in average wages of workers employed in a sector depend on changes in wages per efficiency unit but also reflect changes in the composition of the workers in the sector, which have first-order effects on income in the presence of productivity differences across workers. For instance, suppose that the wage per efficiency unit rises in a sector. If the workers who enter this sector in response are less (or more) productive than those initially employed in the sector—conditional on observable characteristics—then the measured change in the average wage will rise by less (more) than the increase in the wage per efficiency unit. We also must focus on the *subset of those who stay employed in the sector over time*, rather than the full set who start employed in the sector, to address a distinct selection issue: changes in average wages within the set of workers initially employed in a given sector depend on changes in the sector's wage per efficiency unit but also reflect changes in worker income arising from workers moving out of their initial sector (including moving to another sector, out of the labor force, or into unemployment), which have first-order effects on income (only) in the presence of non-pecuniary components of utility. For instance, suppose that the wage per efficiency unit falls in a sector. If the workers who leave this sector in response move into sectors that offer higher (or lower) non-pecuniary returns on average, then the change in the average wage for the set of workers initially employed in the sector will fall by more (less) than the decrease in the wage per efficiency unit.

Second, we show how to use the pecuniary impact of changes in the unemployment rate to measure its non-pecuniary impact. A substantial life satisfaction literature—see e.g. Frey and Stutzer (2002)—uses subjective well being measures to identify the compensating variation associated with unemployment and to relate the total effect of unemployment to its purely pecuniary effect; it is a well-established fact that the non-pecuniary component is substantially larger than the pecuniary component. Since we are able to measure the pecuniary impact on welfare of changes in the unemployment rate, and the life satisfaction literature identifies the relative importance of pecuniary and non-pecuniary effects, we can construct the model-consistent non-pecuniary welfare costs of changes in the unemployment rate.

We find large changes in relative welfare across commuting zones (CZs) in the U.S. between 2000 and 2007. For example, ranking commuting zones from those experiencing the smallest to the largest increase in welfare, the commuting zone at the 90th percentile experiences an increase in welfare of approximately 7.9 percentage points relative to the commuting zone at the 10th percentile. Decomposing the variance of welfare changes across CZs, we find that the component associated with changes in unemployment accounts for approximately 50 percent, the component associated with changes in wages per efficiency unit approximately 20 percent, and the covariance between these components the remainder.

We conclude our baseline analysis by revisiting the substantial empirical literature on local effects of trade shocks, replacing the literature's various dependent variables (changes in separate margins of adjustment) with our measured sufficient statistic for welfare changes. We apply our general results to one particular change in U.S. trade policy that eliminated potential tariff increases on Chinese imports: the granting of Permanent Normal Trade Relations (PNTR) to China, which passed Congress in 2000 and became effective upon China's accession to the World Trade Organization in 2001, as studied in Pierce and Schott (2016) and Handley and Limão (2017). As shown in Pierce and Schott (2016), this policy—which eliminated the possibility of sudden tariff spikes on Chinese imports—lead to a relative decline in employment (and increase in imports from China) in relatively exposed industries (those with a larger reduction in trade policy uncertainty).

Before studying relative welfare effects across regions of granting China PNTR, we first show that this policy also strongly lowered wages per efficiency unit in more- relative to less-exposed industries. In particular, the wage per efficiency unit in a sector at the 90th percentile of exposure fell by approximately 11 percent relative to in a sector at the 10th percentile between 2000 and 2007. Consistent with evidence in Pierce and Schott (2016) on employment effects, we find no evidence of differential pre-trends in wages per efficiency unit.

To identify the impact of CZ-specific exposure to granting China PNTR, we aggregate Pierce and Schott's sector-level measure of exposure up to the CZ level, with weights given by the share of CZ labor income earned in each sector. We find that granting China PNTR lowers the welfare of a CZ at the 90th percentile of exposure by 3.1 percentage points relative to a CZ at the 10th percentile between 2000 and 2007. Of this relative welfare effect, approximately 65 percent arises from changes in the probability of unemployment, with the remainder arising from changes in wages per efficiency unit. We show that there is no evidence of these results being the continuation of pre-existing trends.

Finally, we conduct a range of robustness in Section 5. In our baseline analysis we assume that workers choose optimally between participating in the labor force and home production. Hence, we measure the probability of successfully finding a job using our own construction of an appropriately disaggregated U-3 unemployment rate, which is the official unemployment rate reported by the U.S. Bureau of Labor Statistics. However, alternative assumptions are equally reasonable. In Section 5.1 we consider an alternative mapping between the theory and the data in which we assume that all agents who are out of the labor force are not on their labor supply curves. Moreover, in our baseline analysis we also abstract from an intensive margin of labor supply (given our own evidence that this margin does not respond strongly to granting China PNTR). In Section 5.2 we extend our theoretical model to incorporate this additional margin of adjustment and revisit our baseline empirical results. Finally, in our baseline analysis we control for each CZ's lagged manufacturing share using measures from Autor et al. (2013). In Section 5.3 we consider various alternative measures for this control, given its importance for empirical results.

Literature. Our paper is motivated by and builds on a large and growing empirical literature studying the impact of international trade (and other) shocks on local labor market inequality across a range of margins of adjustment; see e.g., Topalova (2010), Kovak (2013), Autor et al. (2013), Autor et al. (2015), Dix-Carneiro and Kovak (2017), McCaig and Pavcnik (2018), and Dix-Carneiro and Kovak (2019). Our objective is to replicate the research design developed in this literature, but use it to identify the relative *welfare* implications of a particular trade shock.

Our approach is most related to a trade literature inspired by Porto (2006)—see e.g. Atkin et al. (2018)—that similarly calculates the group-specific compensating variation of a trade shock under minimal functional form restrictions using a first-order approximation.[4] This literature emphasizes distributional changes in welfare induced by differential changes in consumer price indices. While our theory incorporates this channel, our empirical investigation abstracts from heterogeneous changes in consumer price indices across groups. Instead, we focus on the distribution of gains arising from the labor market. We incorporate frictional unemployment, endogenous labor supply, and heterogeneous productivities and non-pecuniary benefits. In practice, incorporating endogenous labor supply does not affect results under our baseline assumption that workers who are not unemployed are on their labor supply curves. However, incorporating heterogeneous productivities and non-

[4]Our sufficient statistic approach also builds on the literature in public finance trying to isolate robust insights for welfare analysis across models—see, e.g., Chetty (2009)—which has been popularized in the trade literature by Arkolakis et al. (2012).

pecuniary benefits affects measurement of the wage effects of a trade (or any other) shock as described above. And, at least in our application, incorporating unemployment—and the non-pecuniary costs associated with unemployment—appears to be of first-order importance both for measuring unconditional welfare changes and for identifying the impact on welfare of granting China PNTR.

The particular trade shock on which we focus in our application builds on the industry-level shock introduced and studied in Pierce and Schott (2016) and Handley and Limão (2017). In the process of studying welfare changes across U.S. commuting zones, we also study changes across sectors in wages per efficiency unit, addressing issues of selection across workers by tracking individuals over time, in the spirit of Autor et al. (2014), but also addressing issues of selection across jobs within the set of workers. This approach to measuring changes in wages per efficiency unit may be useful more broadly to any papers studying Roy-style models of the labor market or concerned with heterogeneity across workers more generally.

A growing theoretical and quantitative trade literature uses Roy-style assignment models to study the impact of trade on wage inequality either at the national level—see e.g. Burstein et al. (2019) and Lee (2019)—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. (2018) introduce a labor-leisure choice and Kim and Vogel (2020) additionally introduce frictional unemployment.[5] Our approach dispenses with functional form restrictions imposed in the literature. To do so, we use a first-order approximation that leverages a number of envelope conditions. We find that incorporating frictional unemployment and including both pecuniary and non-pecuniary welfare effects of changes in the unemployment rate are central to understanding the implications of granting China PNTR; given the estimated impacts of other trade shocks on unemployment, see e.g. Autor et al. (2013), this finding likely generalizes to other empirical contexts.

Our paper's objective is related to a macroeconomics literature providing better measures of economic welfare than GDP. Relative to this literature, we focus on changes in welfare (rather than levels), which allows us to generalize the underlying frameworks to incorporate arbitrary heterogeneity across agents, multiple sectors, and frictional unemployment (amongst others). At the same time, we abstract from changes in life expectancy, which play an important role in cross-country comparisons of welfare levels; see e.g. Jones and Klenow (2016).

[5] In Kim and Vogel (2020), we provide a static search and matching model featuring a labor-supply choice—nested by the framework in this paper—in which we solve analytically for counterfactual implications of world price shocks for each margin of adjustment and for welfare. The present paper imposes many fewer restrictions and, therefore, is better suited to identifying empirically the impact of observed trade shocks. Lyon and Waugh (2019) also introduce frictional unemployment, but into a quantitative model less similar to those cited above.

Up to this point, we have emphasized the benefits of our approach. Our theoretical approach also has four important limitations. The first is that we use a first-order approximation. While this allows for substantial generality in the underlying model, in practice shocks are never arbitrarily small and the approximation may suffer. The second is that our methodology identifies the relative welfare effects of observed shocks but neither their absolute welfare effects nor the effects of counterfactual shocks. Third, while our framework is well-suited to comparisons across (stochastic) steady states, by abstracting from savings/borrowing it is less well-suited to studying transitions. Fourth, to leverage envelope conditions, we abstract from fixed costs of switching sectors.[6]

2 Theory

2.1 Model

There is a continuum of agents, denoted by $\omega \in \Omega$, who are separated into disjoint groups indexed by g, with the set of agents in group g denoted by $\Omega_g \subseteq \Omega$. Agents can either be employed in one of S sectors, in the labor force but unemployed, or out of the labor force. We index each possibility by s, with $s \in \{1, ..., S\}$ indicating one of the S sectors in which an agent can be employed, $s = 0$ indicating non-participation, and $s = u$ indicating unemployment.

An agent ω is characterized by her group, a vector of productivities that shape her pecuniary reward to being in each s, a vector of amenity values (compensating differentials) that shape her non-pecuniary reward to being in each s, and a vector of employment probabilities that shape the likelihood of successfully finding employment in each $s \in \{1, ..., S\}$. We denote by $\varepsilon_{\omega s} \geq 0$ the productivity (or efficiency units) of agent ω if in s and by $\eta_{\omega s}$ the amenity value experienced by agent ω if in s.

Each agent chooses to apply to the $s \in \{0, 1, ..., S\}$ that maximizes her expected utility. Agents do not apply to be unemployed; however, an agent ω who applies to $s \in \{0, 1, ..., S\}$ may become employed in s or unemployed. We denote by $E_{\omega s} \in [0, 1]$ the probability of successful employment for an agent ω who applies to s, which each agent treats as exogenous. Of course, agents who choose not to participate in the labor force cannot become unemployed, so $E_{\omega 0} = 1$ for all ω. We say that an agent "works" in s even if $s = u$, in which case the agent is unemployed.

If agent ω works in s, her nominal income is given by $\varepsilon_{\omega s} w_{gs}$, where $\varepsilon_{\omega s}$ denotes ω's productivity in s, as described above, and w_{gs} denotes the wage per efficiency unit for all

[6] For papers addressing the first two limitations, see the large quantitative literature cited above; for the third, see e.g. Waugh (2019); for the fourth, see e.g. Artuç et al. (2010).

agents in group g working in s. The agent treats both $\varepsilon_{\omega s}$ and w_{gs} as exogenous. We assume that this structure describes employment within sectors, non-participation (in which case we are assuming agents operate a home-production technology), and unemployment (again, we assume that agents operate a home production technology when unemployed, although perhaps with a lower return than when out of the labor force). Agents have homothetic preferences across goods within each group g, although these preferences may vary across groups. Hence, given nominal income, the agent obtains $C_{\omega s} = \varepsilon_{\omega s} w_{gs} / P_g$ units of real consumption, where P_g is the price index facing agents in group g.[7]

We assume that non-pecuniary benefits of working in s are separable from real consumption: the utility of an agent $\omega \in \Omega_g$ who consumes $C_{\omega s}$ units of the final good and works in s is given by

$$U_{\omega s} = \zeta_g (C_{\omega s} + \eta_{\omega s}) \tag{1}$$

where $\zeta_g > 0$ and where $\eta_{\omega s}$ is the amenity value agent ω associates with working in s, as described above.

Timing. Each agent in group g knows all parameters—including the $\omega \times s$-specific productivity, amenity, and employment probability vectors—and applies to the $s \in \{0, 1, ..., S\}$ that maximizes her expected utility. Subsequently, she either successfully obtains employment in the s to which she applied or becomes unemployed.

2.2 Welfare changes

We consider the welfare implications of local changes in wages per efficiency unit, $\{w_{gs}\}$, in probabilities of successfully finding employment, $\{E_{\omega s}\}$, and in price indices, $\{P_g\}$, each of which our agents treat as exogenous; we hold the wage per efficiency unit within non-participation, w_{g0}, and unemployment, w_{gu}, fixed. We calculate the compensating variation for each agent given these shocks. Specifically, we solve for the transfer, Y_ω, received in the terminal equilibrium under the new parameter values at which the agent is indifferent, in expectation, between the initial and the terminal equilibria. We first characterize an agent's equilibrium choices and then use these to solve for her compensating variation. Finally, we construct our measure of the change in welfare for group g, which is a particular aggregation of individual-level compensating variations.

Characterizing equilibrium choices. Given that ω works in $s \in \{u, 0, ..., S\}$, her indirect utility can be expressed as $V_{\omega s}$. Expected indirect utility if applying to $s \in \{0, ..., S\}$ can then be expressed as

$$\mathbb{E}[V_\omega | s] = E_{\omega s} V_{\omega s} + (1 - E_{\omega s}) V_{\omega u}$$

[7] We assume that any taxes supporting, for example, unemployment insurance, are levied on consumption of the goods that enter into the price index.

Agent ω chooses an s that maximizes $\mathbb{E}[V_\omega|s]$. Denote by S_ω the set of expected utility maximizing choices and by

$$\mathbb{E}[V_\omega] \equiv \mathbb{E}[V_\omega|s \in S_\omega] = \max_s\{\mathbb{E}[V_\omega|s]\}$$

her expected utility if applying to any sector $s \in S_\omega$.

Compensating variation at the agent level. Agents optimize over their initial choices of labor force participation and the specific sector to which to apply conditional on labor force participation. Hence, when calculating the welfare implications of small shocks, envelope conditions apply to each of these margins of adjustment.

For any agent ω for whom the optimal s was unique in the initial equilibrium, $|S_\omega| = 1$, this implies that the total derivative of expected utility, $d\mathbb{E}[V_\omega]$, equals its partial derivative holding fixed the initial choice of s to which to apply, $\partial\mathbb{E}[V_\omega]$. On the other hand, if an agent initially is indifferent between two or more s, i.e. $|S_\omega| \geq 2$, expected utility is not generically differentiable. Nevertheless, following Milgrom and Segal (2002), an envelope condition continues to apply even to these agents. Specifically, amongst the set of optimal choices between which the agent is initially indifferent, S_ω, the directional derivative of expected utility equals the partial derivative holding s fixed at s^*_ω, where $s^*_\omega \in S_\omega$ is the element of the initially optimal set S_ω that maximizes the directional derivative of expected utility. In general, s^*_ω coincides with the agent's choice in the terminal equilibrium; for those agents for which the agent's initial optimum was unique, $|S_\omega| = 1$, the initial and terminal choices are identical.

Denote by $RI_{\omega s}$ agent ω's real income in the initial equilibrium if ω were to work in $s \in \{s^*_\omega, u\}$ and let $\mathbb{E}[RI_\omega] \equiv E_{\omega s^*_\omega} RI_{\omega s^*_\omega} + (1 - E_{\omega s^*_\omega}) RI_{\omega u}$ denote agent ω's expected real income if ω were to apply to s^*_ω in the initial equilibrium. Leveraging the envelope condition, we solve for agent ω's compensating variation by solving $d\mathbb{E}[V_\omega]\Big|_{Y_\omega=0} = 0$, yielding the solution[8]

$$\frac{dY_\omega}{P_g \mathbb{E}[RI_\omega]} = d\ln P_g - \frac{E_{\omega s^*_\omega} RI_{\omega s^*_\omega}}{\mathbb{E}[RI_\omega]} d\ln w_{g s^*_\omega} - E_{\omega s^*_\omega}\left[\frac{\eta_{\omega s^*_\omega} - \eta_{\omega u}}{\mathbb{E}[RI_\omega]} + \frac{RI_{\omega s^*_\omega} - RI_{\omega u}}{\mathbb{E}[RI_\omega]}\right] d\ln E_{\omega s^*_\omega} \quad (2)$$

Intuition. To understand the structure and intuition for (2), it is useful to start from simpler frameworks that abstract from all margins of adjustment and any heterogeneity, and then build back up to our baseline framework and (2) step by step. First, consider a framework

[8]Here we are avoiding the burdensome notation of directional derivatives, but for agents satisfying $|S_\omega| > 1$, this is a directional derivative.

featuring no choice of sector or extensive margin of labor supply (and so no non-pecuniary components of utility), no unemployment, and no heterogeneity. In this case, we obtain the well-known result that the agent's real compensating variation relative to initial expected real income simply equals the negative of the log change in ω's real wage:

$$\frac{dY_\omega}{P_g}\frac{1}{\mathbb{E}[RI_\omega]} = d\ln P_g - d\ln w_g$$

Incorporating many sectors, an extensive margin of labor supply (i.e. non-participation), and heterogeneity across workers in sector-level productivities, the change in the real wage for agent ω must be evaluated from $s = s^*_\omega$, which is the s in which ω works in the initial equilibrium for all ω for which the initially optimal choice was unique:

$$\frac{dY_\omega}{P_g}\frac{1}{\mathbb{E}[RI_\omega]} = d\ln P_g - d\ln w_{gs^*_\omega}$$

Additionally incorporating unemployment introduces two changes. First, wage changes only impact utility if the agent is successfully employed, which reduces the importance of changes in the wage relative to changes in the price index. In particular, the coefficient on wage changes equals the share of expected real income arising from employment. Second, because agents do not choose to be unemployed, there is no envelope condition that applies to this margin of adjustment. Hence, a change in the probability of unemployment has a first-order impact on expected welfare and this impact is increasing in the gap between the utility level achieved within employment and unemployment. In the absence of non-pecuniary components of utility this gap in utility depends exclusively on the gap in real income:

$$\frac{dY_\omega}{P_g}\frac{1}{\mathbb{E}[RI_\omega]} = d\ln P_g - \frac{E_{\omega s^*_\omega} RI_{\omega s^*_\omega}}{\mathbb{E}[RI_\omega]} d\ln w_{gs^*_\omega} - E_{\omega s^*_\omega}\frac{RI_{\omega s^*_\omega} - RI_{\omega u}}{\mathbb{E}[RI_\omega]} d\ln E_{\omega s^*_\omega}$$

Additionally incorporating the non-pecuniary component of utility, the utility gap between employment and unemployment now depends as well on the gap between the amenity value that ω experiences in $s = s^*_\omega$ and in $s = u$, yielding (2). Of course, in the presence of a non-pecuniary component of utility, envelope conditions continue to apply, so that the non-pecuniary component of utility only matters for utility changes arising from unemployment (rather than utility changes associated with switching across sectors or between participation and non-participation).[9]

[9] In robustness, we take an alternative view in which each person who is not employed in the data is assumed to off her labor supply curve, like the unemployed in our baseline model. According to this alternative view, no envelope condition applies to the extensive margin of labor supply.

Aggregation. In practice, we are interested in constructing changes in welfare at the level of the group, g. Specifically, we define

$$\Delta Welfare_g \equiv -\frac{1}{P_g}\frac{1}{RI_g}\int_{\Omega_g} dY_\omega = -\frac{1}{I_g}\int_{\Omega_g} dY_\omega$$

which is the *negative* of the nominal transfer received in the terminal equilibrium under the new parameter values at which all agents within group g can be made indifferent, in expectation, between the initial and the terminal equilibria (relative to the group's initial nominal income, I_g). In practice, changes in utility are positive when the compensating variation is negative (and vice versa); hence, we measure changes in welfare using the negative of the sum of compensating variation across agents divided by the sum of their initial incomes.

3 From theory to data: measurement

In this section, we measure the group-level welfare change constructed theoretically in Section 2. In our application, we study changes in labor-market outcomes between 2000 and 2007. Our concept of a group in the theory, g, is a commuting zone (CZ), as developed by Tolbert and Sizer (1996). Each CZ is a cluster of counties characterized by strong commuting ties within and weak commuting ties across zones. We use the 722 CZs in the mainland U.S. as defined in 1990. Our concept of a sector in the theory, s, is a two-digit aggregation of the 2000 census industrial classification, of which there are 90.

In Section 3.1 we make additional assumptions that facilitate bringing the theory to our particular data environment. In Section 3.2 we describe how we measure group-level welfare changes for each of our 722 CZs between 2000 and 2007. Finally, in Section 3.3 we provide results on the unconditional distribution of welfare changes across U.S. commuting zones over this time period.

3.1 Restrictions

In this subsection we impose three sets of restrictions that prove useful in the measurement of group-level welfare changes, $\Delta Welfare_g$.

First, we assume that the set of workers for whom the initially optimal choice of s is not unique, i.e. the ω for whom $|S_\omega| > 1$, is of zero mass (in terms of income). Under this restriction, welfare changes can be calculated allocating almost all agents to the *initial* choice of s. This condition is satisfied for almost all vectors of initial wages per efficiency unit if either the underlying distribution of productivities, ε, or amenities, η, has no mass points and if no agent is infinitely productive. On the other hand, this condition is violated, for instance, if all agents within g are homogeneous and these agents choose to apply to more than one s in the initial equilibrium.[10]

Second, we assume that changes in wages per efficiency unit within a sector s are common across g: $d \ln w_{gs} = d \ln w_s$. This is a strong restriction that we impose because the dataset we use to measure changes in wages per efficiency unit is relatively small, making it difficult to measure with any precision changes in wages across all approximately 65,000 gs pairs ($\approx$ 90 sectors $\times$ 722 CZs). In practice, with a larger dataset it is straightforward to dispense with or relax this restriction given our approach to measuring changes in wages per efficiency unit described below.

Third, we assume that agent-and-sector-specific unemployment rates are common across sectors and across agents with common observable characteristics living within a given CZ. That is, we assume that $E_{\omega s} = E_{g\gamma}$ for any sector, $s \in \{1, ..., S\}$, and for any $\omega \in \Omega_{g\gamma} \subset \Omega_g$, where $\Omega_{g\gamma}$ denotes the particular subset of workers (out of 80 subsets) in CZ g who have common observable characteristics defined by age, gender, race, and education.[11] We assume that the probability of successful employment is common across sectors because there is no dataset with an unemployment rate that is specific to the sector to which an agent applies; similarly, given an agent's CZ and observable characteristic, there is no dataset that contains an agent-specific probability of successful employment. In practice, $E_{g\gamma}$ is a non-parametric predictor of the probability that $\omega \in \Omega_{g\gamma}$ successfully obtains employment if applying to any sector $s \in \{1, ..., S\}$.

These restrictions simplify the measurement of group-specific welfare changes. In particular, we obtain

$$\begin{aligned}\Delta Welfare_g = & -d \ln P_g + \sum_{s=1}^{S} \frac{I_{gs}}{I_g} d \ln w_s \\ & + \sum_{\gamma} \left(\frac{I^E_{g\gamma}}{I_g} - \frac{E_{g\gamma}}{1 - E_{g\gamma}} \frac{I^U_{g\gamma}}{I_g} \right) d \ln E_{g\gamma} + \frac{1}{RI_g} \sum_{\gamma} \left(\sum_{s=1}^{S} N^E_{g\gamma s} (\bar{\eta}^E_{g\gamma s} - \bar{\eta}^U_{g\gamma s}) \right) d \ln E_{g\gamma} \end{aligned} \tag{3}$$

where I_{gs} denotes the total income of agents in CZ g who are successfully employed within sector s, where $I^E_{g\gamma}$ and $I^U_{g\gamma}$ denote total income of the employed in the labor force and of the unemployed summed across all agents in $\Omega_{g\gamma}$, where $N^E_{g\gamma s}$ denotes the number of agents

[10] It is straightforward to conduct our empirical analysis without imposing this restriction (by using terminal rather than initial allocations and instrumenting for these terminal allocations using initial allocations). At the same time, this is a mild restriction; it is equivalent to assuming that the income share of agents applying to each s is continuous in the shocked parameters.

[11] We group ages into four bins: 18-29, 30-41, 42-53, and 54-65. We group gender and race each into two bins. And we group education into five bins: less than a high school diploma, a high school diploma, some college, college complete, and graduate training. Each γ is the intersection of each of these characteristics, yielding 80 γ within each CZ.

with observable characteristics γ within CZ g who are successfully employed in s, and where $\bar{\eta}^E_{g\gamma s}$ and $\bar{\eta}^U_{g\gamma s}$ denote the average amenity values across all agents with observable characteristics γ within CZ g who apply for employment in s if employed, $\bar{\eta}^E_{g\gamma s}$, and if unemployed, $\bar{\eta}^U_{g\gamma s}$. Each of these terms is measured in the initial equilibrium.

The group-level welfare change in (3) represents a natural aggregation of the individual-level compensating variation in (2). The first two terms on the right-hand of (3) represent the components of welfare associated with changes in the price index and wages per efficiency unit. Here, the weight on a particular sector's change in the wage per efficiency unit is the share of total group-level income that is earned within successful employment in that sector in the initial equilibrium whereas in (2) it was the share of an individual's expected income that is earned within employment in the relevant sector. The third and fourth terms on the right-hand of (3) represent the pecuniary and non-pecuniary components of changes in welfare associated with changes in the probability of successful employment, respectively. These are again quite similar to the respective components from the individual-level compensating variation in (2).[12]

3.2 Measuring CZ-level relative welfare changes

Our objective is to measure (3) for all 722 commuting zones between 2000 and 2007. Doing so requires that we construct each of the four components on the right-hand-side of (3) for each CZ.

We measure the change in the price index using the Consumer Price Index research series for all Urban Consumers using current methods (CPI-U-RS) from the BLS. Here, we assume that $d \ln P_g$ is common across space.[13]

We use the 2000 census to measure the total income of agents in Ω_g who are successfully employed within sector s, I_{gs}. We also use the 2000 census to measure the number of agents in $\Omega_{g\gamma}$ who are successfully employed in s, $N^E_{g\gamma s}$, and the total income of the employed in the labor force, $I^E_{g\gamma}$, and of the unemployed, $I^U_{g\gamma}$, summed across all agents in $\Omega_{g\gamma}$. In our baseline, we use all non-labor income in constructing $I^U_{g\gamma}$; however, our results are quantitatively very similar if we additionally exclude other sources of income, such as interest, dividends, and rental income. Total group income is then the sum of $I^E_{g\gamma}$, $I^U_{g\gamma}$, and a measure of the income of those out of the labor force all summed across γ. We measure the income of those out of the labor force as non-wage income, although our quantitative results are very similar

[12]The coefficient $E_{g\gamma}/(1 - E_{g\gamma})$ that multiplies the income of the unemployed, $I^U_{g\gamma}$, scales up the total income of the unemployed to the level that would exist if the same number of agents were unemployed as are employed.

[13]In unpublished work, we have also corrected price indices for CZ-specific local house price appreciation. However, since agents consume and potentially own housing, we prefer our baseline approach.

if we include wage income as well.[14] We also use the 2000 census to measure the probability that an agent in the labor force in CZ g and with observable characteristics γ is employed, setting $E_{g\gamma}$ to equal the number of employed relative to the labor force (employed and looking for work) within $\Omega_{g\gamma}$ (i.e. one minus the unemployment rate for subgroup γ within CZ g). To measure $d \ln E_{g\gamma}$, we also require the value of $E_{g\gamma}$ in 2007; we use the combined 2006, 2007, and 2008 1% American Community Survey samples.[15]

To measure the non-pecuniary component of welfare changes, we require the average gap across all agents in the labor force between the non-pecuniary component in utility if employed in the sector to which the agent applies and if unemployed. And this gap must be measured in the same units as the three pecuniary components of utility. Using subjective measures of well being, a substantial life satisfaction literature cutting across economics, psychology, and marketing (amongst others) aims to measure the compensating variation associated with unemployment: the impact of unemployment is quantified by calculating the amount of income necessary to compensate an individual for the change in well-being associated with the loss of her job.[16] Comparing this compensating variation to the actual income loss of unemployment, the literature provides a metric by which to construct the non-pecuniary component of utility changes arising from changes in unemployment given our ability to measure the pecuniary component of utility changes arising from changes in unemployment. Knabe and Ratzel (2011) find that the non-pecuniary component of the compensating variation is about twice the pecuniary component; that is, the transfer required to maintain well being after entering unemployment is approximately three times the income loss associated with unemployment. Relative to the literature, their estimate is a lower bound on the relative importance of the non-pecuniary component, since they incorporate into the pecuniary component not only the current income loss associated with unemployment, but also future losses.[17] We use this lower bound because it provides the most conservative (lowest) measure of the welfare implications of the trade shock in our empirical section. Hence, we measure the non-pecuniary component as equalling two times the pecuniary component, the measurement of which was described above.

The final component we must measure is the change in the wage per efficiency unit in each sector, $d \ln w_s$. We obviously cannot measure $d \ln w_s$ using changes in average wages within a sector. In the presence of productivity heterogeneity across workers, measured

[14] In the census, respondents report their current unemployment status and labor force participation but report their number of hours worked and income from the previous year.

[15] All Census and American Community Survey data come from the Integrated Public Use Micro Samples (Ipums; Ruggles et al., 2020)

[16] In economics, this literature includes, amongst many others, Frey and Stutzer (2002) and Blanchflower and Oswald (2004).

[17] For a higher relative importance of the non-pecuniary component, see e.g. Winkelmann and Winkelmann (1998).

changes in average wages within a sector reflect changes in wages per efficiency unit and changes in worker composition (i.e., the set of workers in a sector is selected and changes over time). We also cannot use changes in income for the set of agents initially employed in a given sector. In the presence of non-pecuniary components of utility, while changing sectors or moving out of the labor force—compositional changes across s for a fixed worker—has no first-order effect on an agent's *utility*—by the envelope condition—it does have a first-order effect on an agent's *income*. Similarly, in the presence of frictional unemployment, movements into unemployment have first-order effects on income (even in the absence of non-pecuniary components of utility), which also implies that we cannot measure $d \ln w_s$ using changes in income for the set of agents initially employed in a given sector.

To account for selection across workers, we leverage panel data on individual earnings. To account for selection across sectors (and non-employment and unemployment) within a fixed set of workers, we focus on the sample of workers who stay in the same sector over time. Specifically, indexing time by t, suppose that the non-pecuniary component of utility varies arbitrarily over time, $\eta_{\omega st}$, and that wages per efficiency unit vary arbitrarily over time, w_{st}. We express worker productivity in the initially optimal choice over time as $\varepsilon_{\omega s^*_\omega t} = \varepsilon_{\omega s^*_\omega} \varepsilon_{\omega t}$, where $\varepsilon_{\omega s^*_\omega}$ is a time-invariant component of productivity that shapes productive comparative advantage and where $\varepsilon_{\omega t}$ is a time-varying component that affects ω's productivity in a common manner across s. In this case, for any agent employed in sector s both in period t and $t+1$ (we refer to such an agent as a sector s *stayer*), we have

$$d \ln wage_{\omega t} = d \ln w_{st} + d \ln \varepsilon_{\omega t}$$

where $wage_{\omega t}$ is the worker's wage in period t and $dx_t = x_{t+1} - x_t$ for any variable x. If the change in each worker's productivity, $d \ln \varepsilon_{\omega t}$, is uncorrelated with the sector of employment, this implies that we can estimate the change in the wage per efficiency unit of each sector as a sector fixed effect when estimating the previous regression using OLS in the sample of stayers. In practice, this identification assumption is strong. It requires, for instance, that if sectors differ in the characteristics of the workers they employ, then there be no change in the returns to those worker characteristics (e.g. if one sector hires a relatively educated workforce, then there must be no skill-biased technical change). Hence, instead we incorporate a vector of initial observable worker characteristics, the vector $X_{\omega t}$, and estimate a Mincer-style wage regression on wage changes using OLS on the sample of stayers, where a sector fixed effect identifies the annual growth rate of the wage per efficiency unit in each sector. Specifically, using data from 2000-2007 in which each stayer ω is in the data in exactly

Industry name	dlnw_s	NTR gap
Crop and animal production; forestry except logging	-0.13	0.00
Fishing, hunting, and logging	0.80	0.00
Oil and gas, coal, and metal ore mining	0.80	0.07
Nonmetallic mining and supporting activities for mining	0.29	0.13
Electric and gas generation and distribution	0.09	0.00
Water, steam, air conditioning, and irrigation system; sewage treatment facilities	-0.36	0.00
Construction	0.02	0.00
Animal food, sugar, fruit and vegetable preserving foods	-0.17	0.12
Dairy, animal slaughtering and process, retail bakeries	-0.30	0.14
Bakeries (except retail), seafood, and other foods	0.06	0.14
Tobacco and beverage	0.15	0.21
Fabric, textile, fiber, and other mills (except knitting)	-0.30	0.46
Textile product	-0.16	0.47
Knitting mills and apparel	0.01	0.50
Leather tanning and products	-0.67	0.28
Pulp, paper, and paperboard mills	-0.24	0.31
Printing and related support activities	-0.10	0.26
Petroleum refining and products	0.14	0.14
Resin and rubber; agricultural chemicals; pharmaceuticals and medicines	-0.22	0.16
Cleaning compound and cosmetics; industrial chemicals; paint and coating	-0.16	0.18
Rubber and plastics products	-0.19	0.35
Glass, clay, pottery, and ceramics products	-0.22	0.34
Cement, concrete, lime, and gypsum products	0.02	0.21
Nonferrous metal production and processing; steel products	-0.30	0.20
Metal forgings and stampings; cutlery; foundries	0.25	0.30
structural metals, containers, machine shops; coating, engraving, heat training	-0.17	0.33
Other metal products; ordnance	-0.23	0.35
Agriculture, construction, mining, oil, and commercial industry machinery	-0.21	0.28
Machinery; engines, turbines, and power transmission equipment	-0.07	0.30
Communications and computer equipment, electronic components and products	0.00	0.34
Electrical machinery, equipment, and supplies; household appliances	-0.02	0.33
Aerospace, aircrafts, motor vehicles equipment and parts	-0.14	0.26
Shipbuilding, railroad rolling stock, other transportation equipment	-0.27	0.22
Wood products and preservation	-0.47	0.26
Furniture, fixtures, and miscellaneous wood products	-0.17	0.33
Medical equipment and supplies; toys, sporting goods, and other manufacturing	-0.20	0.39
Motor vehicles, parts and supplies; furniture and home furnishing; construction materials	0.46	0.00
Commercial equipment and supplies; metals and minerals; electrical goods	-0.14	0.00
Machinery equipment, and supplies; recyclable material	0.01	0.00
Paper, drugs, and chemical products; apparel, fabrics, and notions	0.24	0.00
Groceries, farm, and petroleum products	-0.02	0.00
Alcoholic beverages, farm supplies; miscellaneous nondurable goods	-0.26	0.05
Motor vehicle dealers, auto parts and accessories stores	0.08	0.00
Radio, tv, computer, household appliance, furniture, and home furnishings stores	-0.21	0.54
Hardware stores	0.09	0.00
Grocery stores	-0.13	0.28
Pharmacies and personal care stores; gasoline stations	0.03	0.00
Clothing, accessories, jewelry, luggage, and leather stores	0.12	0.00
Sporting goods, hobby, sewing, and music stores	-0.37	0.00
Book stores and news dealers; department stores	0.10	0.00
Florists; office supplies and stationery stores	0.06	0.00
Gift shops; electronic shopping	0.23	0.00
Vending machine operators; fuel dealers	-0.02	0.00
Not specified trade	-0.14	0.00
Air, rail, water transportation	0.04	0.00
Truck transportation; bus, taxi, and limousine service	-0.30	0.00
Pipeline, scenic and sightseeing transportation	-0.14	0.00
Postal service and messengers; storage	-0.07	0.00
Publishing	-0.12	0.12
Sound recording, motion pictures, and video industries	0.06	0.15
Telecommunication services	0.20	0.00
Information and data processing services	-0.06	0.00
Banking and related activities	0.10	0.18
Financial investments, insurance carriers, and related activities	0.04	0.00
Real estate; automotive equipment rental	-0.00	0.00
Commercial, industrial, and other intangible assets rental and leasing	-0.00	0.32
Architectural, engineering, accounting, legal, and related services	0.11	0.18
Computer systems design, management, technical consulting and related services	0.05	0.23
Veterinary, scientific R&D, advertising, and other services	0.26	0.08
Employment and business support services	-0.21	0.18
Security and travel arrangements services; services to dwellings	-0.12	0.18
Landscaping, waste management, and other services	-0.09	0.18
Educational services	-0.03	0.32
Offices of physicians, dentists, and chiropractors	0.05	0.00
Offices of optometrists and other health practitioners; ambulatory care	0.07	0.00
Hospitals; home and other health care services	0.04	0.00
Residential care facilities	-0.07	0.00
Individual, family, community, and emergency services	-0.13	0.00
Child daycare services	0.10	0.00
Recreation services; bowling centers, museums, arts, sports, and related industries	-0.01	0.32
Restaurants, traveler accommodation, recreational vehicle parks, and camps	-0.24	0.28
Automotive and electronic equipment repair and maintenance; car washes	-0.19	0.00
Commercial equipment and household goods repair and maintenance	-0.08	0.00
Personal care services, nail and beauty salons	0.01	0.32
Laundry services; funeral homes, cemeteries and crematories	-0.15	0.00
Religious, civic, social, and professional organizations; labor union	0.05	0.00
Private households	-0.37	0.00
General government and support; public finance activities	-0.25	0.00
Administration of human resources, environmental quality, and housing programs	-0.14	0.00
Administration of economic programs; national security	0.04	0.00

Log changes in wages per efficiency unit (relative to the median) and the level of the NTR gap (as defined using 1990 data) for the 90 2-digit Census industries. Unmeasured NTR gaps are set to zero.

Table 1: The 2000-2007 growth rate in wage per efficiency unit and the sector-level NTR gap

two consecutive years (t and $t+1$ for some t in 2000-2006), we estimate

$$d \ln wage_{\omega t} = \mathbb{FE}_s + \beta X_{\omega t} + d \ln \varepsilon_{\omega t} \tag{4}$$

where the sector fixed effect identifies sector s's annual growth rate of the wage per efficiency unit between 2000 and 2007.[18] The identification assumption is that conditional on observable characteristics, productivity changes in the initially optimal choice are uncorrelated with that choice. We then multiply the sector fixed effect by seven to obtain the seven-year log change in the sector wage per efficiency unit.

We implement (4) empirically using the Merged Outgoing Rotation Group (MORG) of the Current Population Survey (CPS). The MORG CPS links respondents across their fourth and eighth interviews, one year apart. In each such interview, we observe the worker's wage, $wage_{\omega t}$, and sector of employment, $s_{\omega t}$. We define a stayer as a respondent who is employed in the same 2-digit aggregation of the 2000 census industrial classification.[19]

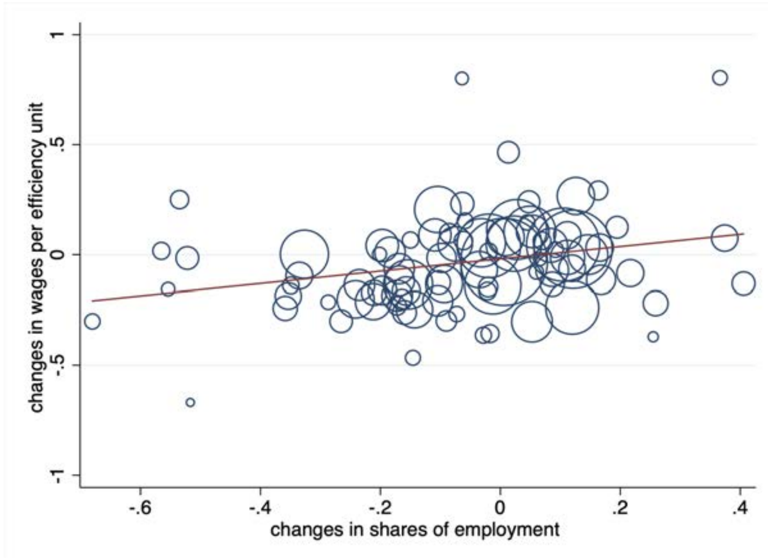
Table 1 lists the 90 sectors in our analysis and our measure of the seven-year log change in the wage per efficiency unit (relative to the median across sectors) in each. The sector with the greatest increase in the nominal wage per efficiency unit over this period is the Oil and gas, coal and metal ore mining industry; this is not surprising given the large increase in oil prices and the resulting growth of employment in the industry (the industry's share of national employment rose by approximately 35 percent) over the time period. The sector with the greatest decrease is Leather tanning and products; this is not surprising given the approximately 50 percent decline in the industry's share of national employment between 2000 and 2007.

More generally, there is a strong correlation between the log change in a sector's wage per efficiency unit and the percent change in the sector's share of national employment between 2000 and 2007 (a piece of data that is not used in our measurement of changes in wages per efficiency unit). Figure 1 displays this relationship. Regressing the change in each sector's wage per efficiency unit on the percent change in each sector's employment between 2000 and 2007—weighing observations by labor income in 2000—yields a coefficient of 0.256 that is significant at the 1% level.[20] The unconditional variation in a sector's wage per efficiency unit is, of course, a function of all shocks. We will identify the causal impact of granting China PNTR in Section 4.2.

[18] We group workers into 5 education categories (less than high school, high school graduates, some college, college graduates, graduate school) and 16 experience categories (by three-year experience bins). We interact the 5 education categories and 16 experience categories to create eighty groups. Our vector of observable characteristics includes the 80 education×experience dummy variables as well as a gender dummy variable.

[19] We match respondents across the MORG CPS following the approach in Colas (2018).

[20] Results are similar when the regression is unweighted and when we restrict the sample to the 50 sectors for which the NTR gap is defined.



Scatterplot of log changes in wages per efficiency unit (relative the median change across sectors) and in the share of national employment between 2000 and 2007 for the 90 sectors. Weights are the year 2000 income of each sector.

Figure 1: Changes in wages per efficiency unit and changes in employment shares

3.3 Unconditional relative welfare changes across CZs

Figure 2 displays the change in welfare across all 722 CZs between 2000 and 2007, minus the median value of this change across CZs. There have been large changes in relative welfare

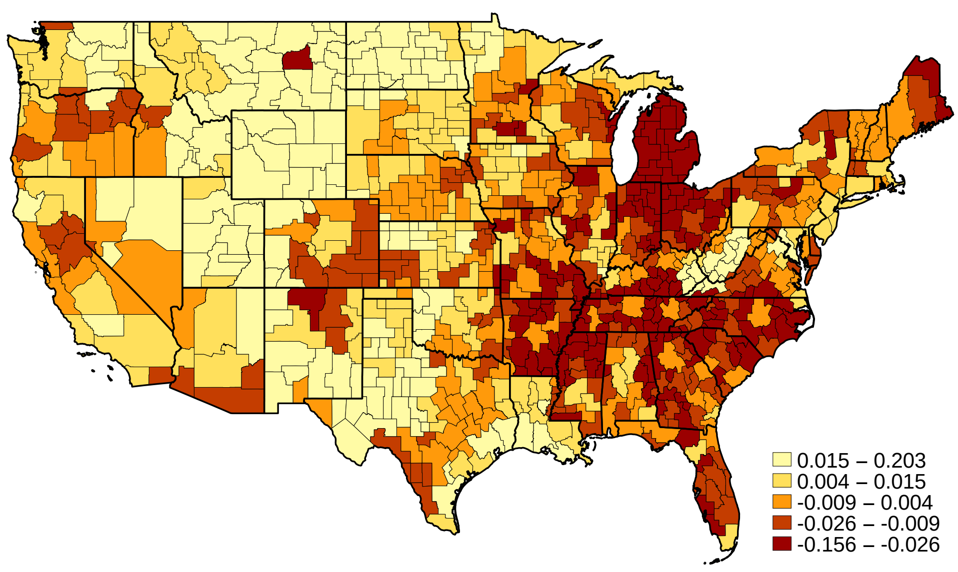


Figure 2: $\Delta Welfare_g$ across U.S. CZs minus the median value across CZs: 2000-2007

across commuting zones in the U.S. between 2000 and 2007. For example, ranking commuting zones from the smallest increase in welfare to the largest, the commuting zone at the 80th percentile experiences an increase in welfare of approximately 4.1 percentage points relative to a commuting zone at the 20th percentile ($0.015 - (-0.026)$), with substantially larger gaps between CZs in the extremes of the distribution.

To what extent is the variation in welfare changes across U.S. commuting zones accounted for by variation in each of the CZ-specific components of welfare? Table 2 decomposes the variance of $\Delta Welfare_g$ into the wage per efficiency unit component, the combination of the pecuniary and non-pecuniary unemployment components, and their covariance. Changes in unemployment account for approximately 50% of the variance, changes in wages per efficiency unit approximately 20%, and the covariance between these components the remainder. We conclude that changes in unemployment rates are first-order drivers of changes in welfare across U.S. commuting zones over this time horizon, at least unconditionally.

Var($\Delta Welfare_g$)	**Var(d ln w_g)**	**Var(d ln E_g)**	**2Cov(d ln w_g,d ln E_g)**
0.0028	0.0006	0.0014	0.0007

First column displays the variance of welfare changes across CZs. Second, third, and fourth columns report the variance of each component and 2 times their covariance.

Table 2: Decomposing the variance of welfare changes across U.S. CZs btw 2000-2007

The unconditional variation in welfare across space is, of course, a function of all shocks (and measurement error). It remains to identify the impact of the trade shock in our particular application—granting China PNTR—on welfare. It also remains to identify the extent to which the welfare effects of granting China PNTR are transmitted through each of the welfare components. We next turn to these issues.

4 Empirics

In this section, we identify the causal impact on welfare across U.S. commuting zones of granting Permanent Normal Trade Relations (PNTR) to China. In particular, we estimate

$$\Delta Welfare_g = \alpha_0 + \beta_0 \mathrm{NTRG}_g + \mathbf{X}_g' \gamma + \epsilon_g \tag{5}$$

where NTRG_g is our measure of the CZ-specific shock induced by granting PNTR to China and $\mathbf{X}_g'$ is a vector of CZ controls that we describe below. We will also run versions of (5) in which we decompose welfare changes into their components: wage changes and the combination of the pecuniary and non-pecuniary components of unemployment changes. The price index is common across CZs and therefore absorbed into the constant, α_0. Our empirical analysis identifies *relative* welfare effects.

In Section 4.1 we first describe the sector-level trade shock on which we focus, NTR gap_s, and how we construct the CZ-level shock, NTRG_g, from this sector-level trade shock. In Section 4.2 we investigate an intermediate question, which is the impact of the sector-level trade shock on sector-level wages per efficiency unit. Specifically, we estimate

$$d \ln w_s = \alpha_1 + \beta_1 \text{NTR gap}_s + \epsilon_s \tag{6}$$

Finally, in Section 4.3 we describe our main results estimating (5). We defer robustness exercises to Section 5.

4.1 The NTR Gap

Following Pierce and Schott (2016) and Handley and Limão (2017) (henceforth PS and HL), we study the impact of granting Permanent Normal Trade Relations (PNTR) to China. As argued in PS and HL, China's ascension into the WTO was not accompanied by marked reductions in U.S. tariffs. In practice, China's exports to the U.S. both before (since 1980) and after its ascension to the WTO were subject to Normal Trade Relation (NTR) tariff rates reserved for WTO members.

However, whether or not these NTR rates would continue to apply to imports from China was subject to annual renewal, which implied substantial uncertainty on sector-level tariffs. If these rates were not renewed, then tariffs on Chinese imports would have risen to non-NTR rates, from an average of 4 percent to an average of 37 percent in 1999. Pierce and Schott (2016) refer to the gap between the NTR and the non-NTR rates as the 'NTR gap.' This gap varies widely across sectors and provides a sector-specific measure of trade policy uncertainty. The U.S. Congress voted to grant China PNTR in October 2000 and this change in policy became effective at the end of 2001. The elimination of this uncertainty then provides a heterogeneous reduction in trade policy uncertainty across sectors, measured by the initial gap as defined in 1990, which we denote by NTR gap_s.[21] Table 1 lists the set of 50 sectors for which the NTR gap_s is defined and the associated NTR gap_s of each sector; we set the NTR gap to zero in the remaining 40 sectors.[22]

PS study the impact of granting China PNTR on sectoral employment. They show that sectors with a larger NTR gap_s experience a relative decline in employment after China joins the WTO. HL study the impact of granting China PNTR on trade growth and U.S. prices. We study the impact of granting China PNTR on sectoral wages per efficiency unit as in (6) and—aggregating the sectoral shock up to a CZ-level shock—we study its impact on relative welfare across space, as in (5).

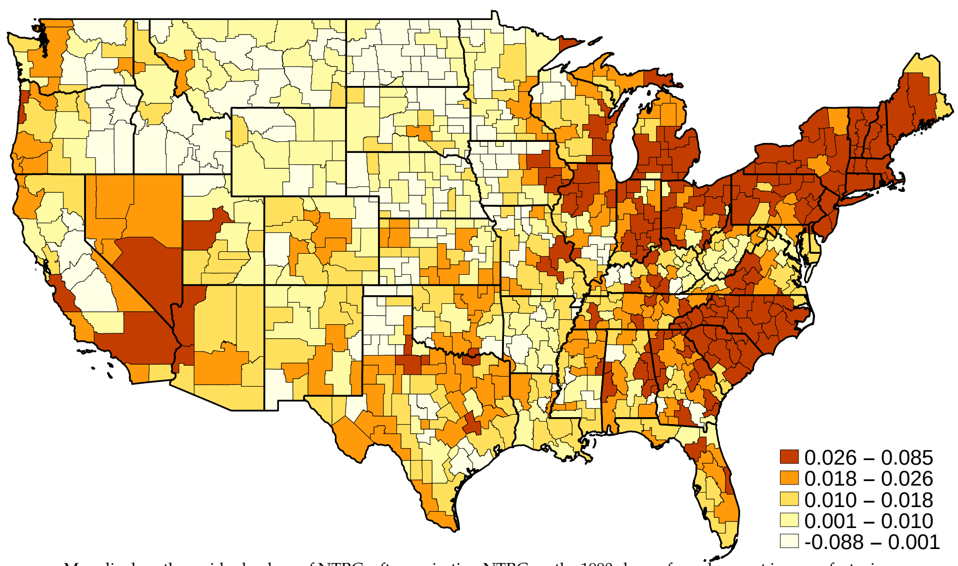
[21] We map PS's NTR gap_s, which is defined using 6-digit 1997 NAICS industry codes, to a given ind2000 code in IPUMS using our own concordance based on one available on IPUMS. We then aggregate up to two-digit ind2000 codes taking a simple average across the more disaggregated ind2000 codes for which NTR gap_s is defined.

[22] With the exception of one agricultural sector, these are all non-goods-producing sectors.

We construct our CZ-level shock, NTRG_g, as

$$\text{NTRG}_g \equiv \sum_s \frac{I_{gs,1980}}{\sum_{s'=1}^{S} I_{gs',1980}} \text{NTR gap}_s$$

where $I_{gs,1980}$ denotes the total income of agents in Ω_g who are successfully employed within sector s in 1980. That is, NTRG_g is the weighted average across sectors of the sector-level NTR gap, where the weight on sector s in CZ g is the labor income earned by the employed within s in CZ g relative to total labor income earned by the employed across all sectors in CZ g; in constructing NTRG_g, we set to zero the sector-level NTR gap_s in any sector in which it is not defined. Figure 3 displays the resulting NTRG_g—residualized after projecting on the 1990 share of employment in manufacturing as measured in Autor et al. (2013)—across all 722 CZs. There is substantial geographic variation in the exposure of regions to the elimination of trade policy uncertainty, even after controlling for the 1990 share of employment in manufacturing.



Map displays the residual values of NTRG, after projecting NTRG on the 1990 share of employment in manufacturing.

Figure 3: The residualized NTRG

4.2 Granting China PNTR and sectoral wages per efficiency unit

To what extent does a greater reduction U.S. trade policy uncertainty (measured by NTR gap_s) cause a greater reduction in wages per efficiency unit (measured by $d \ln w_s$) across U.S. sectors? Table 3 reports the results of estimating (6) using OLS. In Column 1 we weight observations by occupation income and in Column 2 we weight by occupation employment in the year 2000. In Column 3 we include only goods-producing industries and in column

4 instead include a fixed effect for identifying the goods-producing industries. In Column 5 we control for the share of U.S. workers in 2000 who have a college degree, measured using the 2000 Census, and in Column 6 we include both a goods-producing fixed effect and a control for the share of U.S. workers in 2000 who have a college degree.

Results are qualitatively and quantitatively consistent across columns; sectors with larger NTR gaps experience economically and statistically significant relative declines in wages per efficiency unit. We find that granting China permanent normal trade relations lowers the wage per efficiency unit in a sector at the 90th percentile of exposure by 11 percent (in Column 6) relative to in a sector at the 10th percentile.

	$d\ln w_s$					
	(1)	(2)	(3)	(4)	(5)	(6)
NTR gap_s	-0.655***	-0.611**	-0.624	-0.606***	-0.576***	-0.581***
	(0.205)	(0.230)	(0.443)	(0.204)	(0.176)	(0.183)
goods_s				-0.054		0.007
				(0.043)		(0.040)
college share_s					0.097***	0.099***
					(0.020)	(0.024)
Observations	50	50	32	50	50	50
$E[d\ln w_s : \text{NTR}_{p90}\text{-NTR}_{p10}]$	-.13	-.12	-.15	-.12	-.11	-.11
sample	all	all	goods	all	all	all
weight	inc	emp	inc	inc	inc	inc

The estimating equation is (6). Sample denotes the sectors used in the regression, where "all" indicates that all sectors with an NTR gap are included and "goods" indicates that only the subset of goods-producing sectors are included. Weight refers to the regression weight, where "inc" or "emp" indicate that initial income or employment shares are used.

Table 3: The impact of granting China PNTR on changes in wages per efficiency unit across sectors, 2000-2007.

Do the effects identified in Table 3 represent the causal effects of granting China PNTR on wages per efficiency unit or the continuation of pre-existing trends? Pierce and Schott (2016) provide evidence of a lack of pre-existing employment trends across sectors that are correlated with the NTR gap_s. To verify that our results capture the effects of exposure to granting China permanent normal trade relations rather than the continuation of pre-existing trends, we conduct a similar falsification exercise for changes in wages per efficiency unit. We regress past changes in wages per efficiency unit between 1990 and 2000 on future exposure to granting China PNTR.[23] Table 4 reports the results of this falsification exercise.[24] The point estimate of the coefficient on NTR gap_s provides little evidence consistent with differential pre-trends across more and less exposed sectors. Together with the previous evidence in PS, we take this as evidence in favor of our causal interpretation of the results in Table 3 (and our baseline results on welfare).

[23] In order to be consistent with our baseline analysis, which is conducted over the years 2000-2007, we multiply the yearly change in the wage per efficiency unit of each sector in the pre-period by 7.

[24] The panel structure of the MORG CPS has a break between June to December 1994 and 1995 and between January to August 1995 and 1996. We use changes between 1990-1994 and 1996-2000 to construct the pre-shock

	$d \ln w_s$					
	(1)	(2)	(3)	(4)	(5)	(6)
NTR gap$_s$	0.199	0.147	0.135	0.248	0.239	0.258
	(0.231)	(0.234)	(0.251)	(0.234)	(0.237)	(0.241)
goods$_s$				-0.049		-0.025
				(0.037)		(0.035)
college share$_s$					0.045	0.037
					(0.030)	(0.029)
Observations	50	50	32	50	50	50
sample	all	all	goods	all	all	all
weight	inc	emp	inc	inc	inc	inc

Each regression corresponds to the same column in our baseline regressions in Table 3, but with the dependent variable replaced by the 7-year equivalent change in the wage per efficiency unit between 1990-2000.

Table 4: Falsification: Changes in wages per efficiency unit across sectors, 1990-2000.

4.3 Granting China PNTR and local welfare

We finally proceed to our baseline empirical analysis: identifying the causal effect of exposure to granting China PNTR on relative welfare across U.S. commuting zones between 2000 and 2007. A necessary condition to obtain a consistent estimate of the causal effect of interest, β_0, using OLS to estimate estimate (5) is that $\mathbb{E}[\epsilon_g \text{ntrg}_g] = 0$, where ntrg_g is the residualized value of NTRG_g after projecting on a constant and $\mathbf{X}_g$. The vector $\mathbf{X}_g$ in (5) contains CZ-specific 1990 labor force and demographic composition that might be correlated with NTRG_g and independently affect our dependent variables. Following Autor et al. (2013), this vector includes the manufacturing share; the share of the population that are college educated and the share that is foreign born; the share of employment among women; regional fixed effects for the nine Census divisions, which absorb trends that are common across CZs within broad geographic regions; the share of employment in routine occupations; and the average offshorability index of occupations.[25] We take the values of these control variables directly from Autor et al. (2013). In all regressions, we weight observations by each CZ's initial income and cluster standard errors by state.

Table 5 reports our baseline results on the impact of granting China PNTR on relative welfare across U.S. CZs between 2000 and 2007. The first column includes no controls. The second column controls for the 1990 manufacturing share. This manufacturing share is correlated with the commuting zone's NTRG_g, since the sectoral NTR gap$_s$ is positive for all manufacturing sectors but is zero for many non-manufacturing sectors, so that a CZ with more employment within manufacturing mechanically will have a higher NTRG_g. More-

changes in wages per efficiency unit.

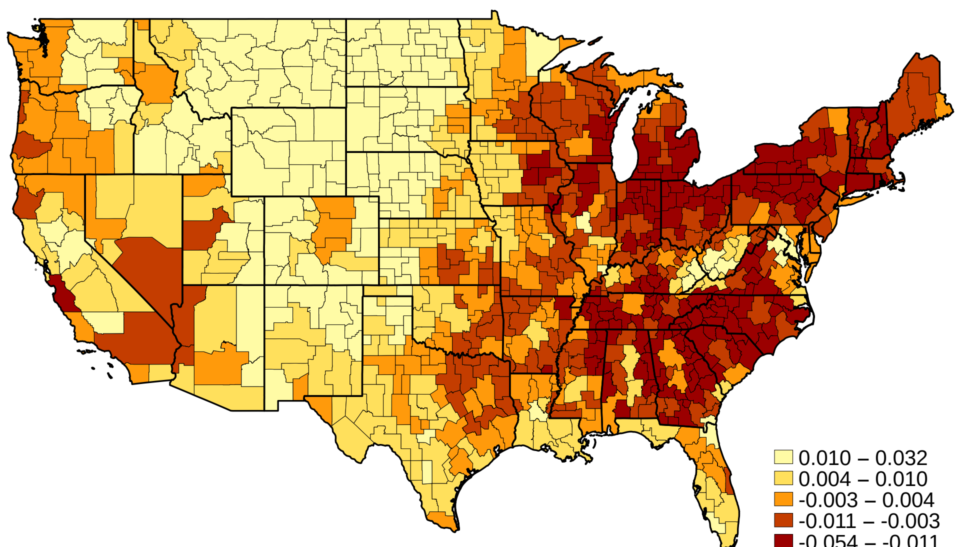
[25] Routineness and offshorability are based on occupation-level data that are aggregated up to the CZ level. Routine occupations are intensive in tasks that follow a set of precise rules and procedures and are more easily substitutable with computers. Offshorable occupations are intensive in tasks that make little use of face-to-face interaction and are more easily executed from a distance.

	$\Delta Welfare_g$				
	(1)	(2)	(3)	(4)	(5)
NTRG_g	-0.819***	-0.453**	-0.523***	-0.544***	-0.507***
	(0.162)	(0.189)	(0.178)	(0.149)	(0.141)
manufacturing share$_{-1}$		✓	✓	✓	✓
college share$_{-1}$				✓	✓
foreign born share$_{-1}$				✓	✓
female share$_{-1}$				✓	✓
routine occupation share$_{-1}$					✓
average offshorability$_{-1}$					✓
regional FE			✓	✓	✓
$E[\Delta Welfare_g : \text{NTRG}_{p90}\text{-NTRG}_{p10}]$	-.051	-.028	-.032	-.034	-.031

Regressions are weighted by each CZ's population in 2000 and standard errors are clustered by state. The control manufacturing share$_{-1}$ refers to the share of employed income earned within manufacturing; college share$_{-1}$ and foreign born share$_{-1}$ refer to the relevant shares of the population; female share$_{-1}$ refers to the female share of employment; routine occupation share$_{-1}$ and average offshorability$_{-1}$ refer to the share of employment in the most routine and the most offshorable occupations. All controls are defined in 1990.

Table 5: The welfare effect of granting China PNTR.

over, given the secular decline in manufacturing, CZs with a higher share of employment in manufacturing in 1990 experience relative declines in welfare between 2000 and 2007. Once we control for the manufacturing share, the impact of the NTRG_g on welfare becomes stable as we include additional controls. The column 5 point estimate implies that granting China permanent normal trade relations lowers the welfare of a CZ at the 90th percentile of exposure by 3.1 percentage points relative to a CZ at the 10th percentile.



Map displays the point estimate on NTRG_g in column 5 in Table 5 multiplied by the value of NTRG_g, minus the median of this product across all CZs.

Figure 4: The differential effect on welfare of granting China PNTR (relative to the median)

Figure 4 displays the spatial distribution of differential welfare changes caused by granting China PNTR. Here, only the differences in the mapped values are informative; hence, we normalize the median value across CZs to zero. Each mapped value is set by multiplying the point estimate on NTRG_g in column 5 in Table 5 by the value of NTRG_g and subtracting from this the median value of this product across CZs. The figure's legend allows one to construct the difference in welfare changes between any two quintiles in the distribution. For instance, the difference between the most and least exposed CZs is 8.6 percentage points (0.032 - (-0.054)), and the difference between the 80th percentile and the 20th percentile is 2.1 percentage points (0.010 - (-0.011)).

	$\Delta Welfare_g$	$d \ln w_g$	$d \ln E_g$
	(1)	(2)	(3)
NTRG_g	-0.507***	-0.179**	-0.329***
	(0.141)	(0.070)	(0.096)
$E[\Delta Welfare_g : \text{NTRG}_{p90}\text{-NTRG}_{p10}]$	-.031	-.011	-.02

The first column replicates Column 5 in Table 5. The second and third columns replicate this empirical strategy, but replacing welfare changes with each component.

Table 6: Decomposing the welfare effect of granting China PNTR.

Table 6 decomposes the causal effect of granting China PNTR on relative welfare into its impact through changes in wages per efficiency unit and its impact through changes in unemployment rates (which combines the pecuniary and non-pecuniary components). Regressions build on the more detailed specification in column 5 of Table 5. Approximately 65 percent (= 0.329/0.507) of the welfare effects of the trade shock are transmitted through changes in the unemployment rate.

Falsification. To verify that our results capture the effects of exposure to granting China permanent normal trade relations rather than the continuation of pre-existing trends, we conduct a falsification exercise. We regress past changes in welfare and both of its components between 1990 and 2000 on future exposure to granting China PNTR.[26] Table 7 reports results corresponding to our baseline specification, column 5 in Table 5. The point estimates for the coefficient of NTRG_g and both of its components provide little evidence consistent with differential pre-trends across more and less exposed CZs for welfare or for either of its components.

	$\Delta Welfare_g$	$d \ln w_g$	$d \ln E_g$
	(1)	(2)	(3)
NTRG_g	-0.030	-0.083	0.053
	(0.085)	(0.061)	(0.053)

Each regression replicates those reported in Table 6, but with the dependent variable replaced by the 7-year equivalent change in the relevant term between 1990-2000.

Table 7: Falsification: Changes in welfare and its components between 1990 and 2000.

5 Robustness

In this section we consider three robustness exercises.

[26] In order to be consistent with our baseline analysis, which is conducted over the years 2000-2007, we construct a seven-year equivalent $\Delta Welfare_g$.

	$\Delta Welfare_g$	$d \ln w_g$	$d \ln E_g$
	(1)	(2)	(3)
NTRG_g	-0.453***	-0.179**	-0.275**
	(0.148)	(0.070)	(0.122)
$E[\Delta Welfare_g : \text{NTRG}_{p90}\text{-}\text{NTRG}_{p10}]$	-0.028	-0.011	-0.017

Each regression replicates those reported in Table 6, but under the assumption that agents who report being out of the labor force are actually unemployed.

Table 8: Changes in welfare assuming non-employed are not on their labor supply curves.

5.1 Is non-participation a choice?

In our baseline, we have assumed that workers choose optimally between participating in the labor force and home production (non-participation). Hence, we measure the probability of successfully finding a job using our own constructed version of the U-3 unemployment rate, which is the official unemployment rate reported by the U.S. Bureau of Labor Statistics, disaggregated to the commuting zone, g, and subgroup, γ, level. However, alternative assumptions are equally reasonable.[27]

To check the sensitivity of our empirical results to the assumption that those not participating in the labor force are on their labor supply curves, we make an extreme alternative assumption. We assume that agents who report being out of the labor force are actually unemployed. Specifically, we drop $s = 0$ from the model and in the data we group all unemployed and out of the labor force into $s = u$. In this case, we are assuming that respondents who report being out of the labor force are not on their labor supply curves, just as we assume for respondents who report being non-employed and actively looking for a job.

Table 8 reports our results under this alternative set of assumptions. Regressions build on the more detailed specification in column 5 of Table 5. Our results are very similar to our baseline in all respects. First, our column 1 estimate implies that granting China permanent normal trade relations lowers the welfare of a CZ at the 90th percentile of exposure by 2.8 percentage points relative to a CZ at the 10th percentile (compared to 3.1 percentage points in our baseline). Second, our column 2 and 3 estimates imply that approximately 61 percent of the welfare effects of the trade shock are transmitted through changes in the unemployment rate (compared to 65 percent in our baseline).

5.2 Intensive margin of labor supply

In our baseline, we have assumed that labor supply is endogenous only through variation in the extensive margin of participation. In this section, we incorporate an endogenous

[27] U3 is total unemployed (defined as those actively seeking employment), as a percent of the civilian labor force (employed plus unemployed). A frequently used alternative is U6, which is total unemployed, plus all persons marginally attached to the labor force, plus total employed part time for economic reasons, as a percent of the civilian labor force plus all persons marginally attached to the labor force. We instead use an extreme assumption of unemployment in our robustness.

intensive margin of labor supply. Specifically, if agent ω works in s and chooses to work $H_{\omega s}$ hours, her nominal income is given by $\varepsilon_{\omega s} H_{\omega s} w_{gs}$. The utility of an agent $\omega \in \Omega_g$ who consumes $C_{\omega s}$ units of the final good, supplies $H_{\omega s}$ hours of labor, and works in s is given by

$$U_{\omega s} = \zeta_g C_{\omega s} - \frac{H_{\omega s}^{1+v_g}}{1+v_g} + \zeta_g \eta_{\omega s} \tag{7}$$

where $\zeta_g, v_g > 0$ are parameters that may differ across groups.[28]

Regarding timing, we assume that each agent in group g knows all parameters and applies to the $s \in \{0, 1, ..., S\}$ that maximizes her expected utility. Subsequently, she either successfully obtains employment in the s to which she applied or becomes unemployed. After the realization of her employment probability, she chooses her work hours.

We solve for an agent's choices using backwards induction. Given that ω works in $s \in \{u, 0, ..., S\}$, her indirect utility can be expressed as a function of hours worked as $V_{\omega s}(H)$. Denote by $H_{\omega s}$ her equilibrium choice and by

$$V_{\omega s} \equiv V_{\omega s}(H_{\omega s}) = \max_{H \geq 0} \{V_{\omega s}(H)\}$$

her indirect utility, which is itself a function of only parameters and the s in which she works. From this point, we follow the approach of our baseline case. In place of (2), we obtain

$$\begin{aligned} \frac{dY_\omega}{P_g \mathbb{E}[RI_\omega]} = d \ln P_g - \frac{E_{\omega s_\omega^*} RI_{\omega s_\omega^*}}{\mathbb{E}[RI_\omega]} d \ln w_{g s_\omega^*} \\ - E_{\omega s_\omega^*} \left[\frac{\eta_{\omega s_\omega^*} - \eta_{\omega u}}{\mathbb{E}[RI_\omega]} + \frac{v_g}{1+v_g} \frac{RI_{\omega s_\omega^*} - RI_{\omega u}}{\mathbb{E}[RI_\omega]} \right] d \ln E_{\omega s_\omega^*} \end{aligned} \tag{8}$$

which differs in only one dimension: the pecuniary component of welfare changes associated with changes in the probability of employment is multiplied by $v_g/(1+v_g)$.

In bringing this extension to the data, we calibrate $v_g = 1/0.33$ to match the (inverse of) the uncompensated intensive-margin labor supply elasticity; see e.g. Chetty et al. (2011). With preferences of the form in (7), there are no income effects so that the uncompensated (Marshallian) labor supply elasticity equals the compensated (Hicksian) one.

Table 9 reports our results incorporating an endogenous intensive margin of labor supply. Regressions build on the more detailed specification in column 5 of Table 5. Our results are similar to those in our baseline. First, our column 1 estimate implies that granting China per-

[28] In unpublished work, we have solved theoretically for welfare changes without imposing linearity (i.e. allowing for risk aversion as in more general GHH preferences) and have measured welfare changes and the impact of the trade shock on welfare under this alternative assumption given an assumed risk aversion parameter. Here the assumption of no borrowing and lending obviously becomes binding.

	$\Delta Welfare_g$	$d \ln w_g$	$d \ln E_g$
	(1)	(2)	(3)
NTRG_g	-0.426***	-0.179**	-0.247***
	(0.120)	(0.070)	(0.072)
$E[\Delta Welfare_g : \text{NTRG}_{p90}\text{-NTRG}_{p10}]$	-.026	-.011	-.015

Each regression replicates those reported in Table 6, but incorporating the extensive margin of participation as in (8).

Table 9: Changes in welfare with the extensive margin of participation.

manent normal trade relations lowers the welfare of a CZ at the 90th percentile of exposure by 2.6 percentage points relative to a CZ at the 10th percentile (compared to 3.1 percentage points in our baseline). Second, our column 2 and 3 estimates imply that approximately 58 percent of the welfare effects of the trade shock are transmitted through changes in the unemployment rate (compared to 65 percent in our baseline).

5.3 Manufacturing share

In our baseline analysis, we control for each CZ's lagged manufacturing share using measures from Autor et al. (2013), which they constructed using the County Business Patterns. As shown in Section 4.3, conditional on this control our results are quantitatively stable as we incorporate additional controls; and as described in Section 4.3, incorporating this control is important for identifying the causal impact of granting China PNTR on CZ-level outcomes. Given its importance, in this section we consider two alternative measures for this control, both defined using the 1990 Census: the share of the working-age population (aged 18-65) employed in manufacturing industries and the share of total wage income earned in manufacturing industries. In both cases, we define manufacturing industries using the ind1990 codes in IPUMS.

Table 10 reports our results using these alternative controls. The top and bottom panels report results building on the more detailed specification in column 5 of Table 5, except replacing our baseline measure of the 1990 manufacturing share using measures constructed from the 1990 Census. The top panel uses the share of the working-age population (aged 18-65) employed in manufacturing industries whereas the bottom panel uses the share of wage income earned in manufacturing industries. Our results are similar to those in our baseline. First, our column 1 estimate implies that granting China permanent normal trade relations lowers the welfare of a CZ at the 90th percentile of exposure by 3.1 percentage points in the top panel and 2.7 percentage points in the bottom panel relative to a CZ at the 10th percentile (compared to 3.1 percentage points in our baseline). Second, our column 2 and 3 estimates imply that approximately 55 percent of the welfare effects of the trade shock are transmitted through changes in the unemployment rate in both the top and bottom panels (compared to 65 percent in our baseline).

	$\Delta Welfare_g$	$d \ln w_g$	$d \ln E_g$
	(1)	(2)	(3)
NTRG_g	-0.493***	-0.222**	-0.271**
	(0.183)	(0.106)	(0.108)
$E[\Delta Welfare_g : \text{NTRG}_{p90}\text{-NTRG}_{p10}]$	-.031	-.014	-.017

Panel A: Manufacturing Share Using Employment

	$\Delta Welfare_g$	$d \ln w_g$	$d \ln E_g$
	(1)	(2)	(3)
NTRG_g	-0.431***	-0.185*	-0.247***
	(0.148)	(0.094)	(0.087)
$E[\Delta Welfare_g : \text{NTRG}_{p90}\text{-NTRG}_{p10}]$	-.027	-.011	-.015

Panel B: Manufacturing Share Using Wage Income

Each regression replicates those reported in Table 6, but replacing our baseline manufacturing share control with alternatives. Manufacturing share using employment is the share of the working-age population employed in manufacturing industries. Manufacturing share using wage income is the share of total wage income earned in manufacturing industries. Both are defined using ind1990 codes in the 1990.

Table 10: The welfare effect of granting China PNTR, controlling for alternative measures of the 1990 manufacturing share.

6 Concluding remarks

What are the welfare effects of trade shocks? This paper starts with the objective of answering this question without imposing strong restrictions and while using a research design identical to that used in the large reduced-form empirical literature interested in the effects of trade shocks on various margins of adjustment.

Motivated by this goal, we derive a sufficient statistic that measures changes in welfare consistent with labor-market adjustment along multiple margins while imposing minimal functional form restrictions. In particular, we allow for an arbitrary and time-varying distribution of non-pecuniary returns across agent-s pairs (where s indexes each sector, non-employment, and unemployment) and arbitrary productivity levels of each agent in each s; and we allow for arbitrary sector-level production functions.

We apply this tool to measure changes in welfare across U.S. commuting zones between 2000 and 2007 (and also between 1990 and 2000). Lastly, we identify the impact of a particular trade shock—granting China permanent normal trade relations—on changes in welfare across U.S. commuting zones. We find that there are substantially negative relative welfare effects of greater CZ-level exposure to this trade policy shock and that the majority of this welfare effect is transmitted through changes in unemployment rates.

Our theoretical approach comes with benefits, but also costs. First, our first-order approximation allows for substantial generality in the underlying model, but our approximation may suffer given the non-negligible size of the trade shock under consideration. Second we identify the relative welfare effects of observed shocks but do not identify the absolute welfare effects of observed shocks or the relative effects of counterfactual shocks.

Our empirical measurement of our theoretical sufficient statistic also suffers from our use of a relatively small panel dataset of worker wages. Because the MORG CPS does not have sufficient observations, we impose a restriction that the change in the wage per efficiency unit in a given sector is common across commuting zones. While this restriction is easily dispensed with in a larger dataset, it is an important open question if such a generalization will dramatically affect welfare calculations; if, for instance, wages per efficiency unit fall by more (less) in more exposed CZs, within sectors, this will tend to magnify (mitigate) the differential effects we have identified.

We hope that our theoretical derivation of a welfare sufficient statistic and empirical approach to measuring its components has impacts beyond our particular empirical application. In particular, we believe that reduced-form empirical analysis can now shed light on the impact of any well-identified shock on a measure of welfare that is consistent with a model that is substantially more general than those currently employed in quantitative work addressing similar issues. In our particular empirical application, it is clear that such generality is important, given that the majority of the effect of granting China PNTR is transmitted through changes in unemployment rates (from which most quantitative trade models abstract) and that two-thirds of the effect of changes in unemployment arise from non-pecuniary returns (from which most quantitative trade models abstract).

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