Are Immigrants a Shot in the Arm for the Local Economy?

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Abstract

Most research on the effects of immigration focuses on the effects of immigrants as adding to the supply of labor. This paper studies the effects of immigrants on local labor *demand*, due to the increase in consumer demand for local services created by immigrants. This effect can attenuate downward pressure from immigrants on non-immigrants' wages, and also benefit non-immigrants by increasing the variety of local services available. For this reason, immigrants can *raise* native workers' real wages, and each immigrant could create more than one job. Using US Census data from 1990 and 2000, we find considerable evidence for these effects: Each immigrant creates 2 local jobs for native-born workers, and 80% of these jobs are in non-traded services. Immigrants appear to raise local non-tradables sector wages and to attract

native-born workers from elsewhere in the country. Overall, it appears that local workers benefit from the arrival of more immigrants.

Most economic research on the effects of immigration focuses on the effects of immigrants as adding to the supply of labor. Prominent examples include Card (1990), Borjas (2003), and Aydemir and Borjas (2011) who look for wage effects of immigration as a rightward shift of the labor supply curve; and Ottaviano and Peri (2012), who argue that immigration adds a new factor of production, labor with a different skill mix. See Friedberg and Hunt (1995) for numerous other examples. This is also the approach to immigration implicit in some objections to immigration in the political arena. For example, Senator Jeff Sessions of Alabama recently objected to currently proposed immigration reform on grounds that it would lead to a rise in the supply of labor and a drop in some native-born workers' wages.[1]

However, in general equilibrium immigrants will affect not only labor *supply*, but also labor *demand*. Many accounts by journalists and other non-economists emphasize the point that immigrants do not serve only as additional workers, but also as additional consumers, and as a result can provide a boost for the local labor market by increasing demand for barbers, retail store workers, auto mechanics, school teachers, and the like.

This paper studies the effects of immigrants on local labor demand, due to the increase in consumer demand for local services created by immigrants. We show how in a simple general equilibrium model this demand effect can provide two benefits to local native-born workers: It can soften the effect of the increase of labor supply on

[1]Dylan Matthews, "No, the CBO report doesnt mean immigration brings down wages," *Washington Post*, June 19, 2013.

wages, by shifting the demand for labor to the right just as the supply is also shifting to the right; and it can lead to an increase in the diversity of local services, conferring an indirect benefit on native-born consumers. Taken together, these effects mean that local real wages can go up as a result of immigration, even in a model where native-born and immigrant labor are perfect substitutes. We take these propositions to US Census data from 1990 and 2000, and show that each immigrant on average generates 2 local jobs for native-born workers, 80% of them in the non-tradables sector. These findings are consistent with a strong effect of local labor demand, generating substantial increases in local services diversity.

Along the way we offer some innovations in empirical technique. We use a new measure of 'non-tradedness' that is easy to implement and has enormous explanatory power. We also employ a new instrument for immigrant inflows based on source-country disasters, alongside a more familiar instrument based on Card (2001).[2]

The effect of local services demand has had much informal discussion, but little scholarly attention. In journalistic accounts of crackdowns on illegal immigrants, for example, local consumer demand effects are sometimes presented as a central part of the story. For example, following more stringent immigration enforcement in Oklahoma City, some residents complained that the moves were 'devastating' to the local economy:[3]

> At Maxpollo, a Hispanic-owned restaurant on S Harvey, Tex-Mex music is

[2]Two previous studies based on a similar type of instrument are Pugatch and Yang (2011), which uses Mexican rainfall data as an instrument for immigration from Mexico, and Kugler and Yuksel (2008), which uses Hurricane Mitch to construct an instrument for immigration from the Caribbean.

[3]Devona Walker, "Immigration crackdown called devastating to economy," *Washington Post*, September 18, 2007.

> played a little above conversation level. The late-afternoon lunch crowd, primarily Hispanic workers, has thinned.
>
> "All of our customers here are Hispanic, said Luiz Hernandez, whose father Max Hernandez owns Maxpollo. "We are going to lose a lot of business. While restaurant employees are not illegal, he assumes many customers are.

Similar stories followed a major federal raid on illegal immigrants in Postville, Iowa in 2008 that incarcerated 10% of the town's population. From one journalist's account:[4]

> Empty storefronts and dusty windows break up a once vibrant downtown. Businesses that catered to the town's Latino population have been hardest hit. Most closed last summer.

A similar story from the *Washington Post*:[5]

> For now, Postville residents – immigrants and native-born – are holding their breath. On Greene Street, where the Hall Roberts' Son Inc. feed store, Kosher Community Grocery and Restaurante Rinconcito Guatemalteco sit side by side, workers fear a chain of empty apartments, falling home prices and business downturns. The main street, punctuated by

[4] Jens Manuel Krogstad, "Postville economy in shambles," *Waterloo/Cedar Falls Courier*, Monday, May 11, 2009.

[5] Spencer S. Hsu, "Immigration Raid Jars a Small Town; Critics Say Employers Should Be Targeted." *Washington Post* Sunday, May 18, 2008, p. A01.

> a single blinking traffic signal, has been quiet; a Guatemalan restaurant temporarily closed; and the storekeeper next door reported a steady trickle of families quietly booking flights to Central America via Chicago.
>
> "Postville will be a ghost town," said Lili, a Ukrainian store clerk who spoke on the condition that her last name be withheld.

As one writer summarized the point in general:

> Population growth creates jobs because people consume as well as produce: they buy things, they go to movies, they send their children to school, they build houses, they fill their cars with gasoline, they go to the dentist, they buy food at stores and restaurants. When the population declines, stores, schools, and hospitals close, and jobs are lost. This pattern has been seen over and over again in the United States: growing communities mean more jobs. (Chomsky (2007), p.8).

We formalize these effects in a simple model of a local economy, or 'town,' with both a tradeables sector and a sector that produces non-tradable services (such as haircuts, food services, and the like). To capture the importance of diversity in local services, that sector is assumed to be monopolistically competitive. The demand for labor in the tradeables sector is exogenous, depending on world markets for the tradable goods, but the demand for labor in the non-tradable services sector is affected by the size of the local population. Adding immigrants to this local economy shifts the labor supply curve to the right but also, by adding to the demand for local services, shifts the labor demand curve to the right (to a smaller degree). The latter shift we term the 'shot in the arm' effect. The net effect is to lower the local equilibrium wage in terms of tradables, but raise the wage in terms of non-tradable services, because of the increased local diversity of those services. The overall real wage could go up or down, depending on how strong the shot-in-the-arm effect is; if it goes up, then in equilibrium $1,000$ immigrants will result in the creation of more than $1,000$ local jobs.

Local demand effects have not been the focus of the majority of immigration research, but there are exceptions. The one study that is closest in spirit to ours is Mazzolari and Neumark (2012), which examines the effect of immigrants on local diversity of services in California. The study finds that more immigrants are associated with fewer small retail stores and more big-box retailers, but that immigrants support a wider range of ethnic restaurants. The focus is quite different from ours, however. That paper focusses on the effect on a higher *share* in immigrants in the local population, controlling for size (p. 1123). The thought experiment under study can be thought of as adding 1,000 immigrants and removing 1,000 native-born workers. In our case, however, the relevant thought experiment is simply adding 1,000 immigrants. Olney (2012) shows that low-skill immigration in the US is correlated with increases in entry of small establishments in the same city, concentrated in low-skill intensive industries. Olney shows that the effect is more plausibly due to the labor-supply effect of immigrants than the effects of immigrants as consumers because the effect is found in mobile low-skill intensive industries but not in non-traded services. However, as with Mazzolari and Neumark (2012), the focus is on changes in the *share* of immigrants in the local population rather than an increase in the local population due to immigration. Another difference between our study and these is that by examining decennial Census data rather than annual data we are looking at more long-run effects.[6]

An important theory paper closely related in spirit to what we do here is Brezis and Krugman (1996), in which manufacturers use labor, capital and local non-traded inputs to produce tradeable output. Non-traded inputs are produced in a monopolistically-competitive industry. Immigration into a town expands the local labor force, initially lowering wages; this encourages entry into the non-traded services sector, expanding the range of inputs for use by local manufacturers, thereby raising labor productivity and encouraging capital to flow into the town. In the new steady state, wages are higher than they were before the immigration. Our approach stresses increased variety of non-traded services purchased by consumers – which we will show has strong support in the data – rather than non-traded inputs produced by firms, but the mechanism that drives the stories is similar. Another related study is Moretti (2010), which measures the effect of one additional tradeable sector job on employment in the local non-traded sector, implicitly through local demand effects such as we emphasize.

We also draw on the literature that investigates whether immigrants to a town displace or attract non-immigrant workers, or in other words, whether the immigrants induce non-immigrants to move away from the town, or attract a net movement of non-immigrant workers to the town. For example, Wozniak and Murray (2012) find no displacement effect with annual data from the American Community Surveys, and a modest attraction effect for low-skill native workers, which they argue could be caused by low-skill workers unable to move away due to liquidity constraints. Wright et al. (1997) find either attraction or at least no displacement effect once city

[6] Altonji and Card (1991) also discuss local-demand effects of immigrants, but without making a distinction between traded and non-traded goods, or raising the issue of local diversity of services.

size has been adequately controlled for. Peri and Sparber (2011) review the evidence on displacement, reviewing the different estimation methods that have been used to test for it, and create simulated data to test the reliability of the different methods. They find that studies that have found a significant displacement effect have used an estimator that is biased in favor of that finding, and that studies that use a more reliable estimator have found either no displacement or a modest attraction effect. We will use findings from these papers in designing our own empirical approach.

In the following section we present the basic theory model we use to clarify these issues, and some refinements. The following sections present our empirical method, the data, and our empirical results, respectively. The final section presents a summary and conclusion.

1 A Basic Model.

We look at a model with a monopolistically competitive local-services sector of the Dixit and Stiglitz (1977) variety, in order to be able to discuss endogenous diversity of such services, and a tradeable-goods sector, which for simplicity we specify as perfectly competitive. The model is similar in spirit to Brezis and Krugman (1996). For the time being we employ three simplifying assumptions: (i) we ignore the effects of immigration on the housing market; (ii) we assume that local labor supply is perfectly inelastic (thus disallowing mobility of native-born workers); and (iii) we treat native-born and immigrant workers as perfect substitutes. Later we will relax these assumptions.

1.1 Preferences

Consider a model of a local economy that we can refer to as a 'town.' Everyone who lives there has the same utility function:

$$U(S,T) = \frac{S^{\theta}T^{1-\theta}}{\theta^{\theta}(1-\theta)^{1-\theta}}, \tag{1}$$

where S is a composite of non-tradable services consumption and T is a composite of tradable goods consumption. Composite services consumption is defined by:

$$\left(S = \int_0^n \left(c^i\right)^{\frac{\sigma-1}{\sigma}} di\right)^{\frac{\sigma}{\sigma-1}}, \tag{2}$$

where c^i is consumption of service i, n is the measure of services available, and $\sigma > 1$ is a constant. The indirect utility function derived from maximizing (2) subject to a given expenditure on services is:

$$S = \frac{E^S}{P^S}, \tag{3}$$

where E^S is total spending on services and P^S is a price index for services given by:

$$P^S = \left(\int_0^n p(j)^{1-\sigma} dj\right)^{\frac{1}{1-\sigma}}, \tag{4}$$

where $p(j)$ is the price of service variety j.

There are n different tradeable goods. Composite tradables consumption is defined by:

$$T = u^T(c^T), \tag{5}$$

where c^T is the n-dimensional vector of consumptions of the different tradable goods and u^T is an increasing, concave, linear homogeneous function. The indirect utility function derived from u^T is:

$$v^T(E^T, q) = \frac{E^T}{\kappa(q)}, \tag{6}$$

where E^T is expenditure on tradeables, q is the price vector for tradeables, and κ is the linear homogeneous price index derived from u^T. The prices for tradeables are fixed and exogenous (the town is not large enough to affect prices for tradeables on its own). Without loss of generality, we choose units so that the aggregate price of tradeables is unity:

$$\kappa(q) = 1. \tag{7}$$

As a result, all prices in the model can be said to be denominated 'in terms of tradeables.'

1.2 Technology.

There is free entry into the services sector. Production of x units of any service requires

$$\alpha + \beta x \tag{8}$$

units of labor, where α and β are positive constants.

Each tradeable good i is produced with labor L^i and sector-specific capital K^i through a linear homogeneous production function f^i. The capital available in each tradeables industry is fixed and exogenous,[7] and each producer takes all prices as given. Each tradeables firm will choose the level of employment to maximize its

[7]Allowing for capital mobility reinforces the main story, a point made forcefully both by Brezis and Krugman (1996) and by Olney (2012).

profits, taking wages and output prices as given. In the aggregate, this generates an allocation of labor within the tradables sector that solves:

$$r(q, w, K) \equiv max_{\{L_i\}} \left\{ \sum_i q^i y^i - wL^i | y^i = f^i(L^i, K^i) \right\} \tag{9}$$

Here $K \equiv (K^1, \ldots, K^n)$ is the vector of industry-specific capital endowments, y^i is the output of tradables sector i, and $r(q, w, K)$ is the income capital-owners receive from tradable-goods production. We can add up the labor demands from the various traded-goods industries to find the total labor demand for the tradeables sector, $L^T \equiv \sum_i L^i$. By the envelope theorem,

$$r_2(q, w, K) = -L^T < 0, \tag{10}$$

where a subscript denotes a partial derivative. If we vary w and trace out the values of L^T that result, we derive a labor-demand curve for the tradables sector. By standard arguments, r is convex with respect to w, and so the value of L^T that maximizes (9) is a decreasing function of w, or:

$$r_{22}(q, w, K) > 0. \tag{11}$$

In other words, the tradeables sector's labor-demand curve slopes downward.

1.3 Equilibrium.

Free entry in the services sector leads to zero profits. This together with profit maximization by each firm lead to a price p^j for each service-providing firm j equal to:

$$p^j = \left(\frac{\sigma}{\sigma - 1}\right)\beta w, \tag{12}$$

a quantity x^j equal to:

$$x^j = \frac{(\sigma - 1)\alpha}{\beta}, \tag{13}$$

and a total number of services equal to:

$$n = \frac{E^S}{\sigma\alpha w}, \tag{14}$$

where E^S is total expenditure on services, all as in Dixit and Stiglitz (1977). Since zero profits imply that total expenditure on services is equal to the wage bill in the service sector, the demand for labor in the service sector must satisfy:

$$L^S = \frac{E^S}{w}. \tag{15}$$

In addition, the price index for services (4) reduces to:

$$P^S = n^{\frac{1}{(1-\sigma)}}\left(\frac{\sigma}{\sigma - 1}\right)\beta w, \tag{16}$$

which is decreasing in the number of varieties n. This is a crucial feature of monopolistic competition. Variety matters to consumers, so if the price of each service is unchanged but the variety of services increases, the utility obtained from one dollar spent on services rises, so the cost of one util falls. Of course, this drop in the real price index for services consumption due to increased variety is not captured by official consumer price statistics.

By the Cobb-Douglas preferences, E^S must be equal to θ times total town income. Total income is equal to labor income plus capital income, and can be written as:

$$I(w, L) = wL + r(q, w, K). \tag{17}$$

Consequently, labor demand in services can be written:

$$\begin{aligned} L^S &= \frac{\theta I(w, L)}{w} \\ &= \theta L + \theta \frac{r(q, w, K)}{w} \\ &= \theta L + \theta r\left(\frac{1}{w}q, 1, \frac{1}{w}K\right). \end{aligned} \tag{18}$$

From (18) it is clear that labor demand in services is decreasing in w but it is also increasing in L for a fixed value of w. This is because an increase in local population increases the local demand for services. In effect, holding w constant, each new arrival to the town will generate θ jobs in the services sector.

The demand for labor in the tradeables sector can be taken from (10) and is also decreasing in w but is independent of L because the tradeables sector does not depend on local demand. The two labor-demand relations (10) and (18) can be represented as downward-sloping curves in a diagram with w on the vertical axis and employment on the horizontal axis, and summed horizontally to produce total labor demand. Now suppose that the total labor supply is composed of L^N native-born workers and L^I immigrants, and is denoted $L^{TOT} \equiv L^N + L^I$. The intersection of the labor-demand curve with the vertical labor-supply curve at L^{TOT} units of labor defines the equilibrium wage.

1.4 The effects of immigration.

Immigration in this simplest version of the model then simply amounts to an increase in L^I, say $\triangle L^I$. From (18), this shifts labor demand to the right by an amount equal to $\theta \triangle L^I$. We will refer to this shift in labor demand as the 'shot-in-the-arm' effect, and is depicted in Figure 1. Since the labor-supply curve shifts to the right by more than labor-demand, the equilibrium wage w must fall. Recall that this is the wage *in terms of tradeables*, not the real utility wage, because it does not reflect any change in the prices or variety of services. In addition, the equilibrium values for L^T and L^S will both rise compared to the case with no immigrants, with their combined increase equal to the rise in L^I.

Note that the shot-in-the-arm effect does not eliminate the drop in the wage in terms of tradables, but it does attenuate it. In Figure 1, the shift in labor supply without this effect would reduce the wage from w^0 to w^1, but the shot-in-the-arm effect pulls it up to w^2. This may help explain why researchers have consistently found modest effects of immigration on local wages.

GDP in both sectors will rise as a result of the new immigrants. To see this, note first that, since w has fallen but tradeables prices have not changed, each tradeable good will increase output and so GDP in the tradeables sector will rise. Now note that in equilibrium the value of tradeables production will be equal to the value of tradeables consumption (otherwise the town's consumers are not spending their whole income).[8] Therefore, the rise in tradeables GDP implies a rise in the value

[8] Formally, if R^T is the total value of tradables output and R^S is the value of nontradable services output, then local income is equal to $R^T + R^S$, which is also therefore the value of local consumption spending. If we write E^T for local consumer spending on tradables and E^S for spending on non-tradables, of course $E^S = R^S$ and consumer budget constraints yield $R^T + R^S = E^T + E^S$. It follows that $E^T = R^T$. Another way of putting this is to observe that trade must be balanced in

of tradeables consumption (E^T). But the value of tradeables consumption is equal to $(1-\theta)$ times total GDP, so total GDP must also have increased. Finally, since the value of services consumption E^S is equal to θ times GDP, the value of services consumption and therefore services-sector GDP has also increased.

Now we can see that although the wage has fallen in terms of tradeables, it has increased in terms of services. To see this, note first that from (12) the price of each service has fallen exactly in proportion with the drop in the wage. Next, note that from (14) the number n of services available has increased, both because the expenditure on services (the numerator) has gone up and because the wage (in the denominator) has fallen. Putting together these two effects, it is clear that the composite price of services (16) has fallen more than the wage.

To sum up, by shifting labor supply to the right, immigration has led to a fall in the wage relative to tradeables (that is, a fall in w). We might call this the 'labor glut' effect. However, immigration has also led to a rise in the number and variety of restaurants, shops, barbers, and the like, by expanding the customer base for those industries, in the process shifting labor demand to the right, which we have referred to as the 'shot in the arm' effect. This results in a drop in P^S that exceeds the drop in w. Given our choice of units that makes tradables the numeraire, the real wage can be written:

$$w^{REAL} = \frac{w}{(P^S)^\theta}. \tag{19}$$

This real wage could go up or down as a result of immigration. If θ is small or labor and capital in tradables sectors are not very substitutable so that tradables labor demand is inelastic, the 'labor glut' effect will dominate and immigration will hurt

equilibrium.

native workers on balance. If θ is sufficiently close to 1 or capital and labor are sufficiently substitutable, so that tradables labor demand is elastic, then the 'shot in the arm to the local economy' effect will dominate and immigration will benefit native workers on balance. Indeed, from (18), if θ is close to 1, there will be no labor glut to speak of because each immigrant will produce close to 1 job and there will be almost no increase in net labor supply. These observations are formalized as follows:

Proposition 1. *Immigration will raise the real wage (19) for native-born workers if and only if:*

$$\theta > \frac{(\sigma - 1)}{\phi_{L,T}\epsilon_{L,T} + \sigma}, \tag{20}$$

where $\phi_{L,T}$ is the share of labor in costs in the tradables sector and $\epsilon_{L,T}$ is the absolute value of the elasticity of labor demand in tradables.

All results are derived in the appendix. Clearly, condition (20) holds if and only if θ is large enough, because that is what makes the 'shot-in-the-arm' effect strong. In addition, holding other parameters constant, (20) will hold if σ is small enough (recalling that it is always greater than 1), since the smaller is σ the more important is the diversity of local services. Holding other parameters constant, the condition will hold if the tradables sector is sufficiently labor-intensive and has sufficiently elastic labor demand, since these properties allow it to absorb additional labor easily. In the limiting case of Ricardian technology, $\epsilon_{L,T}$ will be infinite; in this case, there is no change in the wage in terms of tradables at all, and only the beneficial effect on local services diversity remains.

In this simple model with inelastic labor supply, the increase in total employment must be exactly equal to $\triangle L^I$. We can summarize this observation by saying that each immigrant generates one new job. (Of course, in practice not all immigrants will be workers – some will be dependents, and so in practice with inelastic labor supply each immigrant will generate less than one new job.)

Further, the effect of immigration on employment is not uniform across sectors. The shot-in-the-arm effect increases the demand for labor in the non-tradables sector but not in the tradables sector, and this skews increases in employment toward non-tradables. We can summarize and formalize the point as follows:

Proposition 2. *Immigration will increase the level of employment in both the tradables and non-tradables sectors. An additional immigrant will result in more than θ additional workers employed in non-tradables, and fewer than $(1-\theta)$ additional workers employed in tradeables. Precisely:*

$$\frac{dL^T}{dL^{TOT}} = (1-\theta)\left(\frac{\epsilon_{L,T}}{\epsilon_{L,T} + (1-\theta)\left(\frac{L^{NT}}{L^T}\right)}\right) < (1-\theta). \tag{21}$$

The reason that the increase in employment in the non-tradeables sector is greater than the non-tradables expenditure share θ is that additional immigrants increase the demand for local services, while they have no effect on the demand for tradeables. Note that if the tradeables sector has inelastic labor demand ($\epsilon_{L,T}$ is small), the increase in employment could be almost entirely concentrated in non-tradables. On the other hand, in the limit with the Ricardian case, as $\epsilon_{L,T} \to \infty$, the increase in employment is divided up between the two sectors just in the same proportions as the expenditure shares.[9] This will be worth keeping in mind later in evaluating

[9] In this case, there is no capital income, so GDP is equal to wL^{TOT}, with w fixed by the Ricardian technology in the tradables sector together with world prices. A 10% increase in the local labor force due to immigration will therefore raise GDP by 10%, which will raise spending on both sectors by 10%, and therefore raise employment in both sectors by 10%.

empirical results, because it is a case that will be forcefully rejected by the data.

1.5 Adding a Housing Market.

One unrealistic feature of the basic model presented above is that there is no housing market. This could be important in practice because new immigrants will need somewhere to live, and there is some evidence that immigrants tend to push local housing prices upward (Saiz (2007)). We will find evidence below that these housing effects may help us understand our own empirical results, so it is worth incorporating these effects into the model. Augment the utility function as follows:

$$U(S,T) = \frac{S^{\theta^1} T^{\theta^2} h^{1-\theta^1-\theta^2}}{(\theta^1)^{\theta^1} (\theta^2)^{\theta^2} (1-\theta^1-\theta^2)^{1-\theta^1-\theta^2}}, \tag{22}$$

where h denotes the consumption of housing services. Assume that there is a fixed stock of housing in the town, which can provide a total H units of housing services to the local population. This stock of housing is homogenous and perfectly divisible. The price of housing services is denoted p^H. We assume that the owners of the housing stock live in the town, and therefore spend their income from housing assets on locally-produces services, as well as on tradables and housing. With this specification, the real wage takes the form:

$$\frac{w}{\left(P^S\right)^{\theta^1} \left(p^H\right)^{1-\theta^1-\theta^2}}. \tag{23}$$

We can write the condition for labor-market clearing as follows:

$$\frac{\theta^1}{w}\left[wL^{TOT} + r(q,w,K) + p^H H\right] - r_2(q,w,K) = L^{TOT}. \tag{24}$$

The expression in the square brackets on the left hand side of (24) is the total GDP in the town; multiplying by θ^1 yields the spending on local services; dividing by w yields the labor demand due to the local services sector. The following term is labor demand in the tradables sector. These two labor demand sources must sum in equilibrium to the total labor supply.

In addition, the housing market must be in equilibrium:

$$\left(1-\theta^1-\theta^2\right)\left[wL^{TOT} + r(q,w,K) + p^H H\right] = p^H H. \tag{25}$$

Differentiating (24) and (25) with respect to L^{TOT} yields the following result on the response of wages and the housing price to immigration.

Proposition 3. *In the model with housing, the response of the local wage to an increase in immigration is given by:*

$$\frac{dw}{dL^{TOT}} = \frac{-\theta^2 w}{\theta^2(L^{TOT}+r_2) + (\theta^1+\theta^2)wr_{22}} < 0 \tag{26}$$

and the response of the housing price is given by:

$$\frac{dp^H}{dL^{TOT}} = \frac{(1-\theta^1-\theta^2)r_{22}w^2}{\left[\theta^2(L^{TOT}+r_2) + (\theta^1+\theta^2)wr_{22}\right]H} > 0. \tag{27}$$

When immigrants are added to the town labor force, the wage falls in terms of tradables, as in the basic model, and with the rise in local GDP and the drop in the wage, the number of varieties of local service rises, as in the basic model. However, the increase in local income also creates an increased demand for housing, driving up its price, which is a cost for local workers (but of course a benefit for owners of the local housing stock). In order to work out whether native-born workers benefit from the immigration or not, we need to trade off the drop in w and the rise in p^H against the drop in P^S. It is clear that there are cases in which real wages would rise but for the effect of the housing price. For example, consider the limiting case in which tradables technology is Ricardian (or in other words, let r_{22}, and thus the elasticity of labor demand in tradables, become arbitrarily large). In that case, from (26) the response of w to immigration becomes vanishingly small, but from (27), the response of the price of housing does not. In this case, the portion of the real wage in (23) that applied in the basic model rises (in other words, (19) rises), but if θ^1 and θ^2 are small enough the rise in the housing price will nonetheless lower the overall real wage. Of course, that will not imply a reduction in welfare, because the increased income to the owners of the housing stock must be accounted for, but it will mean a reduction in the utility of native-born workers. These observations are formalized as follows:

Proposition 4. In the model with a housing market, immigration will raise the real wage for native-born workers if and only if:

$$\theta^1 > \left(\frac{\sigma - 1}{\sigma}\right)\left(\frac{1 + (1-\theta^2)\phi_{L,T}\epsilon^D_{L,T}}{1 + \phi_{L,T}\epsilon^D_{L,T}}\right). \tag{28}$$

Condition (28) shows that, as before, immigrants increase real wages if and only if the weight on non-tradables is large enough. Further, it shows that the housing market makes it more likely that immigrants will *lower* the real wage. To see this, consider the case in which housing consumption has a zero weight in the utility function, so that $(1 - \theta^2) = \theta^1$; in this case it can easily be checked that (28) collapses to (20). Now, holding θ^1 constant and raising the weight on housing above zero reduces θ^2, which increases the right-hand side of (28). Clearly, this makes it less likely that (28) will be satisfied.

1.6 Adding worker mobility.

We have assumed to this point that native-born workers cannot relocate from this town, or new native-born workers from elsewhere in the country relocate to this town, once immigrants have chosen to enter. However, such relocation is an important part of the analysis of immigration. Borjas (2003) argues that because of mobility of native workers the whole country should be thought of as a single labor market; Saiz (2007) and Wozniak and Murray (2012), for example, examine various aspects of this mobility.

A really convincing account of intra-national mobility would require a dynamic model, such as for example Kennan and Walker (2011) or Artuç et al. (2010), but to capture the main idea here we accommodate intra-national mobility of native-born workers in a very simple way. Suppose that there are $\bar{L}$ native-born workers initially living in the town, and each one can move to another part of the country, receiving a real wage $\widehat{w}$ but paying a relocation disutility cost equal to τ, so that the net wage from moving is $\widetilde{w} \equiv \widehat{w} - \tau$. These opportunity wages and moving costs are idiosyncratic; a measure $G(\widetilde{w})$ of local workers have an outside net wage of less than or equal to $\widetilde{w}$, with $G(0) = 0$ and $\lim_{\widetilde{w} \to \infty} = \bar{L}$. At the same time, workers elsewhere in the country can come to the town if they wish; a worker's opportunity real wage in his or her home town is denoted $\widehat{w}^*$, with a moving cost of τ^*, so that the worker will move to the town we are focussing on if the real wage w^{REAL} thereby obtained satisfies $w^{REAL} - \tau^* > \widehat{w}^*$, or $w^{REAL} > \widetilde{w}^*$, where $\widetilde{w}^* \equiv \widehat{w}^* + \tau^*$. Again, the opportunity wages and moving costs are idiosyncratic; a measure $G^*(\widetilde{w}^*)$ of non-local workers have an outside net wage of less than or equal to $\widetilde{w}^*$, with $G^*(0) = 0$.

Now, the total labor supply in the town is endogenous, and can be written as the increasing and continuous function $L^{TOT}(w^{REAL}) \equiv G(w^{REAL}) + G^*(w^{REAL}) + L^I$, where L^I is the number of immigrants. (We ignore here the possibility that immigrants may themselves move to other towns after immigrating.) It should be emphasized that the size of the local labor force responds to a decline in the local real wage not only because a portion of local workers may choose to move elsewhere but because a portion of workers elsewhere in the country who otherwise may have chosen to move to this town instead choose to stay where they are.

All of the model up to now has been analyzed with an exogenous value of L^{TOT}, and has returned an equilibrium value of w^{REAL}. This relationship can be summarized in the curve DD in Figure 2. Panel (a) shows the case in which the 'labor glut' effect dominates the 'shot in the arm' effect, so a rise in L^{TOT} reduces the local real wage (precisely, condition (20) in the basic model or (28) in the housing model is *not* satisfied), and therefore the curve is downward-sloping. Panel (b) shows the opposite case in which the 'shot in the arm' effect dominates. Now, the possibility of labor mobility creates a new relationship between w^{REAL} and L^{TOT} summarized in the labor-supply function $L^{TOT}(w^{REAL})$ derived just above. This is represented by the curve SS in Figure 2, which must be upward-sloping. In each panel, the initial equilibrium is marked as point a and the equilibrium following increased immigration is marked as point b. Note that in the case of panel (b) there could be multiple equilibria; we will focus on the case of a stable equilibrium, which requires the SS curve to be steeper than the DD curve.

Now a rise in immigration creates a rightward shift in the SS curve. In Panel (a), this lowers the local real wage, which induces a net outflow of native-born workers from the town. In Panel (b), the shift *raises* the real wage, which induces a net *inflow* of native-born workers to the town. Therefore, the mobility of workers can be a way of testing the direction of the overall change in the local real wage. To summarize:

Proposition 4. *In the model with worker mobility, if*

$$\frac{dw^{REAL}}{dL^{TOT}} < 0, \tag{29}$$

(precisely, if condition (20) in the basic model or (28) in the housing model is not satisfied), then immigration to a town will induce a net outflow of native-born workers from the town. Otherwise, immigration will induce a net inflow.

In addition, note that in panel (a) the increase in employment that results from the immigration is less than $\triangle L^I$, while in panel (b) it is greater than $\triangle L^I$. It may seem paradoxical that the arrival of 1,000 immigrants will shift the local demand for labor curve to the right by only $(\theta)(1,000) < 1,000$ (as seen in Figure 1 and (18) for the version with no housing sector, or (24) for the version with a housing sector), and yet result in a new equilibrium with an increase in employment greater than $1,000$. One way of understanding this outcome is that when the shot-in-the-arm effect is strong, immigrants create a virtuous circle: The immigrants induce greater demand for local services, causing entry and creating a greater variety of local services; this makes the town a more attractive place to live, causing workers to move there from other locations; this in turn feeds local services demand again, amplifying the effect. We can summarize by saying that *when the shot-in-the-arm effect is weak, each immigrant creates less than one new local job, but when it is strong, each immigrant creates more than one new job.* (Of course, as before, this needs to be qualified by the fact that a portion of immigrants in practice will be dependents and not workers.)

These findings can naturally be useful for empirical work. The real wage (23) is not observable, because consumer price data will not normally include information on how many local restaurants there are in a neighborhood, for example, and how much they differ in menu and style. Therefore, although the wage in terms of tradables can be observed and correlated with movements in immigration, the theoretically grounded real wage, which is needed for welfare evaluation, cannot (and of course, it would need to be observed in each town, over time). But Proposition 4 tells us that we can see in what direction the real wage is moving simply by observing movements in aggregate employment or internal migration of workers.

1.7 Labor complementarities and other complications.

The stylized model presented above has been simplified to clarify the effects of immigration on local labor demand. A number of features that have been emphasized by other authors could be incorporated as well, which we may need to keep in mind while analyzing the empirics.

(i) Labor Complementarity. We have assumed throughout that immigrant labor is a perfect substitute for native-born labor. Some authors have emphasized the possibility that immigrants tend to have different skills than native-born workers and are hired to do different tasks (Ottaviano and Peri (2012) and Peri and Sparber (2009)). This can be accommodated in our model by assuming a production function in (9) for tradable industry i, for example, that is a function of the two kinds of labor separately as well as capital, with imperfect substitutability between the two. Without working out the details, it is clear that such a specification will dampen and perhaps reverse negative effects of immigration on w, and make the case of Panel (b) of Figure 2, with an upward sloping SS curve, more likely.

(ii) Local non-tradable inputs. Brezis and Krugman (1996) show that the presence of local non-traded inputs (including local parts producers and local services used by firms, such as repair, construction, couriers, catering, and the like) can affect the relationship between immigration and labor market outcomes dramatically. An increase in immigration expands the local labor force, making entry into the non-traded input sector profitable, which increases productivity and encourages capital inflows, ultimately raising local wages. This could be added to the model as well, producing the same sorts of effects as (i), but with a lag to allow for capital inflows.

(iii) Industry-switching costs. We have assumed for simplicity that any worker in a given town can move costlessly from one industry to another, so that in each town all workers receive the same wage. Obviously, this is not realistic, and it would imply that wage effects from immigration are identical in all industries within a given town.

A full incorporation of industry-switching costs would add a great deal of complexity (as in Artuç et al. (2010)), so we will simply acknowledge that a full model would have such costs and so a rise in demand for labor in one industry relative to another would generally result in both a movement of workers and a rise in that industry's relative wage. This is important to acknowledge in examining the empirical results.

With these theoretical points in hand, we now turn to empirics. We will be able to check for clues as to the strength of the shot-in-the-arm effect: The effect of immigrants on employment in non-tradable services relative to tradeables; the sign and magnitude of the effect on local wages; and movements of workers into or out of a location that has received an influx of immigrants.

2 Empirical approach.

To check on the strength the the 'shot-in-the-arm' effect, we check on the overall effect of immigration on the size of local employment; on the number of jobs created in the non-traded sector compared to the traded sector; and on wages.

2.1 The total employment effect.

The most straightforward method to assess the total employment effect would be to estimate:

$$\Delta E_m = \alpha_0 + \alpha_1 N_m + \alpha_2 X_m + \epsilon_m, \tag{30}$$

where ΔE_m is employment growth in location m between 1990 and 2000; N_m is the new immigrant population arriving in location m over the same decade; X_m is a set of location characteristics; and ϵ_m is an i.i.d error term. A value of α_1 in excess of unity would indicate a strong shot-in-the-arm effect. However, this approach is vulnerable to two major econometric problems, the likely endogeneity of N_m and scale effects, which we discuss in turn.

(i) *Endogeneity of immigrant inflows.* Immigrant flows are likely to respond to local labor-market conditions. It is natural to surmise that immigrants will be attracted to locations with booming labor markets or avoid areas with falling labor demand (a point confirmed by Cadena and Kovak (2013)), in which case N_m will be positively correlated with ϵ_m. On the other hand, Olney (2012) finds evidence that in his data immigrants, surprisingly, are attracted to locations with high unemployment, perhaps because of the availability of low-cost housing, which could generate the opposite correlation. Either way, an instrument for immigrant inflows is called for.

A well-known instrument is the 'supply-push' instrument developed by Card (2001), which is based on the initial distribution of immigrants of various nationalities across the country. In our case, the instrument takes the form:

$$\hat{N}_m^{CARD} = \sum_{s=1}^{S} N_s^{AGG} \left(\frac{P_{sm}^{90}}{\sum\limits_{m'=1}^{M} P_{sm'}^{90}} \right), \tag{31}$$

where N_s^{AGG} is the aggregate inflow of new immigrants from source country s and P_{sm}^{90} is the size of initial immigrant population from country s in location m. The term in parentheses is location m's initial share of immigrants from s, and the Card instrument is the predicted total inflow of new immigrants to location m assuming that all new immigrants will be allocated nationwide in the same proportions as their initial distribution.

We use the Card instrument, but to guard against endogeneity problems we also use another instrument of our own creation based on source-country shocks. It is conceivable that a country with a comparative advantage in a particular industry would send a particularly large number of immigrants to the US when that industry is booming, who would then be allocated to a particular locality where that industry is located, which has a historic concentration of immigrants from that country for that reason. In that case, the Card instrument would not be exogenous. The instrument we propose to avoid this possibility is similar in spirit to Pugatch and Yang (2011), and is constructed based on source-country-specific economic shocks such as natural disasters, civil and military conflicts, and negative real GDP growth events. To the extent that the occurrences of the above push-factors in source countries are independent of local economic conditions at any U.S. destination, it will provide plausible variations to identify the causal link between immigrant inflows and the local economic outcomes.

Formally, we denote by N_m, C, and S the number of new immigrants arriving in U.S. location m over 1990-2000, the number of different types of source country shocks, and the number of source countries in the sample, respectively. Then, the first stage regression equation is specified as:

$$N_m = \delta_0 + \sum_{c=1}^{C} \delta_c \sum_{s=1}^{S} P_{sm}^{90} Z_{cs} + \epsilon_m, \tag{32}$$

where Z_{cs} is the count of event c that occurred in source country s between 1990 and 2000; ϵ_m is a random component. In order to account for the fact that newly arriving immigrants are more likely to locate where established immigrant population form the same source country is large, we interact Z_{cs} with P^{90}_{sm}, the size of initial immigrant population from country s in location m. Our instrument is then the predicted immigrant inflows, $Y_m \equiv \hat{N}_m$, from (32). We use this as the instrument in our benchmark specification, and the Card instrument in robustness checks.

(ii) Scale effects and heteroskedasticity. A second reason equation (30) could provide misleading results is the presence of scale effects, a problem analyzed at length by Peri and Sparber (2011). Even if there is no causal connection between immigration and local employment, if each location's employment grows at 1% per year and each location receives immigrants equal to 1% of its initial population, large towns will show large numbers of immigrants entering and large numbers of new jobs compared to small towns, and α_1 will be estimated to have a positive value. At the same time, city size could be correlated with other factors relevant for employment growth, such as import competition afflicting local industries, which has been a dramatic feature of the experience of some of the largest US cities in recent years. For example, the second-largest city in our sample, Los Angeles, with the second-largest immigrant inflow, had negative employment growth over the 1990's, due to the loss of $200,000$ manufacturing jobs clearly caused by the rise of manufactured exports from low-wage economies and not by the expansion of the Los Angeles labor force. If we are unable to control adequately for these other factors and they are correlated with city size, specification (30) can be biased.

In regressions with the size of the labor force as the dependent variable, Peri and Sparber (2011) examine various solutions to this problem and find, with simulated data, that the most reliable solution is to normalize both the dependent variable and immigrant inflows by initial population. This is also used in similar situations by Card (2001) and Wright et al. (1997). Accordingly, our preferred specification for the total employment effect is:

$$\Delta E_m/P_m^{90} = \alpha_0 + \alpha_1 Y_m/P_m^{90} + \alpha_2 X_m + \epsilon_m, \tag{33}$$

To allow the employment levels to grow at different rates depending on the initial location characteristics, X_m includes the share of college graduates as well as the share of manufacturing workers in the labor force as of 1990. In addition, the population change between 1980 and 1990 was added to X_m in order to control for location-specific population growth trends. Again, α_1 is the main parameter of interest, and in accordance with Proposition 3, our interest is in whether or not it is greater than unity.

An additional reason for normalizing by initial population is heteroskedasticity. As suggested by Wozniak and Murray (2012) in an analogous situation, we have run regression (30) and then regressed the square residuals on initial city population and its square. Both variables were highly significant, suggesting that weighting the regression by the reciprocal of city size would be desirable. Normalizing by initial population is similar in its effect.

2.2 Non-traded share of employment effect.

While informative in assessing the *mean* effect of immigration across all the industries, the above specification does not account for the possibility of a *differential* effect on employment in the traded and non-traded sectors, as predicted by Proposition 2. To test this hypothesis, we need to develop an index of tradability to compare across industries. We defer details to the next section, but in brief we conjecture that employment in non-tradeable industries will be highly correlated with local income, since local non-traded output must be equal to local demand, while traded industries need show no such correlation. We therefore compute the correlation, *corr*, between local GDP and local employment of each industry and use this as a proxy for non-tradedness. Using this measure, we replace equation (33) with an equation in which each observation is an industry-location combination:

$$\Delta E_{jm}/P_m^{90} = \beta_0 + \beta_1 Y_m/P_m^{90} + \beta_2 corr_j Y_m/P_m^{90} + \beta_3 X_m + \phi_j + \epsilon_{jm}, \qquad (34)$$

where j indexes industries. The inclusion of the industry fixed effects, ϕ_j controls for any unobserved nation-wide trends in industry j employment, an important consideration in this context because one of the interesting trends in the 1990s has been the rise of the service sector.[10] The employment change in industry j caused by one more immigrant can be expressed as $(\beta_1 + \beta_2 corr_j)$. To the extent that more immigrants lead to a larger increase in non-tradables employment than tradables employment because immigrants increase local consumer demand for non-tradables – an outcome predicted by Proposition 2 provided that $\theta \geq \frac{1}{2}$ – we will observe $\beta_2 > 0$. Further, if we choose a cutoff value of θ, say, $\bar{\theta}$, such that we will call an industry i non-traded if and only if $\theta_j \geq \bar{\theta}$, then we can compute the effect of a marginal immigrant on non-traded employment as $\sum\limits_{j \ni \theta_j \geq \bar{\theta}} (\beta_1 + \beta_2 corr_j)$, and the

[10] Buera and Kaboski (2012) report that the non-tradeable service sector grew faster than tradeable sector in the post-1950 U.S. economy.

marginal effect on traded-industry employment as $\sum_{j \ni \theta_j < \bar{\theta}} (\beta_1 + \beta_2 corr_j)$.

2.3 Wage effects.

Finally, in order to measure the impacts of immigration on local wages, we move to data on individual workers. Consider the following regression:

$$\begin{aligned} log(w_{ijm}) &= \gamma_0 + \gamma_1 X_i + \gamma_2 yr2000_i + \gamma_3 yr2000_i corr_j \\ &\quad + \gamma_4 yr2000_i Y_m / P_m^{90} + \gamma_5 yr2000_i corr_j Y_m / P_m^{90} + \phi_j + \epsilon_{ijm}, \end{aligned} \tag{35}$$

where X_i is a vector of worker i's demographic characteristics including age, age squared, immigrant status, marital status, race and education; $yr2000_i$ is a dummy variable equal to one if worker i is observed in year 2000. Therefore, the inclusion of $yr2000_i$ and $yr2000_i corr_j$ in the regression controls for the time trend over the 1990s and its interaction with industry tradability. Any unobserved, time-invariant industry-specific variables are controlled for by ϕ_j.

The dependent variable, w_{ijm} is the nominal wage; dividing by the CPI would make no difference because the trend in measured CPI will be common to all workers and will be absorbed in γ_2. Since the true cost-of-living index depends on the price index for services (4) which is not observed (since it depends on the number of varieties of service available locally and on σ), the wage w_{ijm} on the left-hand side of (35) corresponds to the wage in terms of tradables in the theory model, rather than the real wage of (19) or (23).

The parameters of interest are γ_4 and γ_5, which would inform us of how immigration affects the wage in traded and non-traded industries. In the simple theory model presented earlier, we would have $\gamma_4 < 0$ and $\gamma_5 = 0$, because immigration lowers the wage in terms of tradeables,[11] and in that model labor is costlessly mobile across sectors so the wage would move in the same way in both traded and non-traded industries. If we allowed for costs of switching sectors, then to the extent that immigrants increase local services demand, we would expect γ_5 to be positive. If γ_4 and γ_5 are both close to zero, then immigration has only a small effect on the tradables wage (implying that $\phi_{L,T}$ or $\epsilon_{L,T}$ is small, from Proposition 1), and the effect of immigration on the real utility wage is likely to be positive.

To explore the possibility that the wage effects are different for different skill classes (for example, we would expect that the wages of a specific human-capital group that can be more easily substituted by immigrant skills would fall faster), we split the sample into four educational categories (less than high school; high school graduate; some college; college graduate), and allow the wage effects of immigration to vary by these categories. Then our main wage regression equation becomes:

$$\begin{aligned} log(w_{ijm}) &= \gamma_0 + \gamma_1 X_i + \gamma_2 yr2000_i + \gamma_3 yr2000_i corr_j \\ &\quad + \sum_k \gamma_{4k} educ_{ik} yr2000_i Y_m + \sum_k \gamma_{5k} educ_{ik} yr2000_i corr_j Y_m + \phi_m + \phi_j + \epsilon_{ijm}, \end{aligned} \tag{36}$$

where $educ_{ik}$ is an indicator equal to one if worker i is observed to be in educational category k. Therefore, by estimating γ_{4k} and γ_{5k}, we will be able to state whether, for each skill category, immigrants increase or reduce wage growth for trade industries and non-traded industries.

[11] In a model such as presented by Brezis and Krugman (1996), it is possible to have $\gamma_4 > 0$ because immigration improves productivity and induces capital inflows, which increase wages after a lag.

3 Data.

Our main data set is extracted from the 5% samples from the 1990 and 2000 US Censuses provided by the IPUMS project at the Minnesota Population Center of the University of Minnesota (Ruggles et al. (2010)).[12] The variables employed in the empirical analysis include year, age, gender, marital status, race, place of birth, year of immigration, educational attainment, employment status, industry, and income.

In order to investigate the local economic impacts of immigration, we need a definition of location. Two main candidates are available in IPUMS, the "CONSPUMA" variable and the "METAREA" variable. CONSPUMA's are a division of the entire United States into 543 similarly-sized units, which are consistently defined from 1980 to 2000. METAREA's are metropolitan areas with boundaries drawn in such a way as to contain both employment and residence for a typical worker in the city. By contrast, CONSPUMA's in many cases divide a city, so that immigrants to one CONSPUMA could cause employment effects that spill over to an adjacent CONSPUMA, and movement of residence of a worker from one neighborhood to another would show up as an employment loss from one CONSPUMA and a gain to the other even if the worker's job does not change. Therefore, although it does not cover the entire area of the U.S. and, therefore, it costs a significant number of observations, we prefer METAREA for our purpose.[13] We limit our attention to the metropolitan areas that are consistently defined from 1980 to 2000 census, which results in 219 METAREA's.

Following the convention in the literature, we define an immigrant as being either

[12] The Census data are publicly available at https://usa.ipums.org/usa/.

[13] Approximately, 31% of the sample observations in both Census years are missing "METAREA" information.

a noncitizen or a naturalized U.S. citizen. Then immigrants are considered as 'new' arrivals if year of immigration is reported to be after 1990.

Table 2 presents summary statistics for the 7,026,535 individual workers who are included in the estimation.[14] The average sample person is a 39-year-old, likely to be married. The sample consists of 78% white, 53% male. 15% of the sample are identified as immigrant. About 60% of the sample are observed to have college experience, while high-school dropouts account for 13% of the total. The two main outcome variables we consider are employment status and salary income. The employment status used in the regressions are based on the variable "EMPSTAT," which indicates whether the respondent was a part of the labor force and, if so, whether the person was working or searching for employment. We count the number of employed workers to compute the changes in employment level for each metarea in the employment regressions. In both Censuses, after excluding armed forces, about 70% of the sample are employed, while 26% report to be out of labor force. "INCWAGE" reports the pre-tax nominal wage or salary income received during the previous calendar year. We exclude observations with $400,000 or more and zero income in the wage regressions.

Turning to the construction of instrument variables in the first stage regression, we consider three source-country-specific economic shocks: natural disasters, civil and military conflicts, and negative real GDP growth events. Data on natural disaster events are obtained from EM-DAT: the International Disaster Database (http://www.emdat.be/), which contains core information on the occurrence and estimated direct and indirect losses from over 18,000 mass disasters in the world from 1900

[14]See Table 1 for details of the sample selection criteria.

to present. Following Yang (2008) and Hanson and McIntosh (2012), we consider a disaster as 'serious' if it affected 1,000 people or more. Then we count the number of serious natural disaster events that occurred during the 1990s for every country in the sample, which is to be merged with the US Censuses using the place of birth variable,"BPLD." Next, we use UCDP/PRIO Armed Conflict Dataset to track the occurrences of civil and military conflicts between 1990 and 2000. This is a conflict-year dataset maintained by Uppsala University with information on armed conflict where at least one party is the government of a state during 1946-2008.[15] Again, we count the number of armed conflicts that resulted in more than 1,000 battle-related deaths over the decade for each country. Finally, data on annual percentage growth rate of real GDP are obtained from the World Bank (http://data.worldbank.org/indicator/NY.GDP.MKTP.KD.ZG). We compute the number of years during the 1990s in which real GDP growth falls below zero for each country.[16]

One important requirement for studying the impacts of immigration on the local economy is an operable measure of 'tradability.' In order to identify the existence and magnitude of the shot-in-the-arm effect of immigration, we must make a clear distinction between non-traded industries, whose demand is likely boosted by immigration, and traded industries, whose demand is not. Despite the growing importance of the non-tradable service sector in the U.S. economy, little scholarly attention has been paid to it empirically, perhaps because of the lack of reliable measure of 'non-tradedness.'[17] We develop a new measure of industry 'tradability' by looking at,

[15] The dataset is available at http://www.prio.no/Data/Armed-Conflict/UCDP-PRIO/. See Gleditsch et al. (2002) for a complete description of the dataset.

[16] With the idea that economic recessions in larger countries are likely to cause more people to get affected, thereby resulting more frequent out-migrations, we interact it with the 1995 source-country population in the regression.

[17] One notable exception is Gervais and Jensen (2012). Our approach to measuring non-tradedness

for each industry, the correlation between local demand and supply across different locations in the U.S. For a non-traded service, local demand must equal local supply, while for a traded good supply can be located where production cost is minimized, regardless of where consumers reside, so the geographic correlation between supply and demand should be stronger for a non-traded than for a traded industry. To implement this idea, we first construct GDP for each metropolitan area (computed as the sum of incomes of all persons living there) as a proxy for local demand; and employment for every industry/location cell as a proxy for local supply. Then, we simply compute the correlation coefficient between the two variables across regions for each industry (of course, we are implicitly assuming that demand patterns for non-tradables do not vary too much from place to place).[18] Table 3 lists the top 10 most/least tradable industries according to our measure, which seems to conform to our priors regarding the degree of 'non-tradedness.' For example, retail bakeries or child day care services are widely perceived as non-traded service industry. On the other hand, mining or tobacco manufacturers are well-known examples of geographically concentrated, tradeable industries.

is inspired by their approach, but is much simpler and less ambitious. Considering a spatial mismatch between production and consumption as evidence of trade, they provide industry-level estimates of trade costs from a structural equilibrium model. However, because their estimates were obtained from microdata on U.S. service establishments and do not cover other important industry categories such as agricultural, mining, utilities and construction, they could not be directly applied to this study.

[18]Here, we use "CONSPUMA," instead of "METAREA," as the unit of geography, because production establishments for some industries are geographically concentrated outside of metropolitan areas. For example, a tiny fraction of workers employed in coal mines are located within metropolitan areas, and those who do are not a representative sample of coal miners nationwide. The correlation between local GDP and coal mining employment is 69% by METAREA, suggesting a fairly non-traded industry, but the correlation is -0.2% by CONSPUMA, suggesting a traded industry. Of course, coal mining is a traded industry, with production concentrated outside of major population centers and consumption concentrated within them.

4 Results

4.1 Impacts of source-country shocks on out-migration

Table 4 presents estimates of the relationship between the source-country push factors and the number of newly arriving immigrants into U.S. metropolitan areas over the 1990s as described in equation (32). Overall, the OLS regression results are statistically significant, with all the coefficients having the expected sign. The coefficient of 0.0157 indicates that one additional occurrence of armed conflicts in a source country is predicted to raise the total immigrant population by 15.7 in a U.S. metropolitan area where 1,000 immigrants from that country resided in 1990. Natural disasters are estimated to have smaller impacts on out-migration, each disaster event adding only 1.2 new immigrants to metro areas. On the other hand, economic recessions seem to have substantial impacts on immigration decisions as one additional year of negative real GDP growth in country s with a population of 10 million in 1995, is expected to result in 45.9 new immigrants arriving to a metro area with a 1990 immigrant population of 1,000 from country s.[19] The fitted values from this regression are normalized by 1990 population in the METAREA to serve as an instrument in the main regression.

[19] Note that negative real GDP growth events are weighted by 1995 source-country population (in 10,000s) to account for the possibility that a recession in a large country will result in more emigrants than a recession in a small one. This is not necessary for civil war or natural disasters because they are already scaled, since the cutoff for their respective indicator variables is 1,000 fatalities.

4.2 Employment regressions

Having constructed the instrument for immigrant inflows as the fitted values from the regression above, we proceed to estimate the impacts of immigration on local economic conditions. Table 5 presents estimates of the local employment effects of immigration. The first two columns of the table report the results from the standard OLS regression of equation (33), which shows a statistically significant positive effect of immigration on local employment growth. The next two columns show the results using the disaster IV, and the last two columns show results from the Card IV. The results consistently indicate a strong positive effect of immigrants on employment. An inflow of immigrants amounting to a one-percent rise in the local population relative to the 1990 metropolitan area population is predicted to provide an increase in total employment amounting to more than 3% of the 1990 population and an increase in native employment amounting to more than 2%, providing initial evidence of the 'shot-in-the-arm' effect of immigrant inflows. Essentially, each new immigrant is associated with an increase of two jobs for native-born workers. (Metropolitan area-specific population growth trends are also found to be important in explaining local employment growth over the 1990s, with a negative coefficient.)

While informative in gauging the net impacts of immigration on regional employment change, this approach has its limitations because it masks substantial variation across industries. Therefore, we re-estimate the model employing the measure of 'non-tradedness,' $corr$, as illustrated in equation (34) in order to account for the difference in industry tradability. Table 6 compares the OLS and IV results from estimating equation (34). Again, the OLS estimates of employment impact of immigration are larger in magnitude but the IV estimates are still positive and statistically significant. The third and fourth rows in Table 6 suggest that immigrant inflows lead to more rapid growth in non-traded services employment relative to tradable industries employment, because they show a consistently positive and significant interaction term between immigrant inflows and $corr_i$. Specifically, taking the estimates using the Card instrument, the arrival of $1,000$ immigrants is predicted to increase employment in the hair salon industry (the least tradable industry with $corr$ of 0.85) by 21 ($= (-0.006 + 0.0323 \times 0.85) \times 1,000$) for the full sample and by 16 ($= -0.039 + 0.0235 \times 0.85$) for the native sample, while having small negative employment impacts (-6 to -4) in the most tradable industries such as mining or tobacco manufactures.

The total effect of one more immigrant on employment implied by this regression is $\Delta \equiv \sum_{i=1}^{228}(\beta_1 + corr_i\beta_2)$, where β_1 is the coefficient on immigration flows and β_2 is the coefficient on the interaction with $corr_i$. The estimate of this value is presented at the bottom of the table, together with its standard error. Not surprisingly, the estimates are almost identical to the coefficient on immigrant flows in Table 5, and despite the insignificant coefficient on the intercept, Δ is significant at the 1% level. The results of Table 6 are summarized in Figure 3, which shows the effect of 1,000 new immigrants on employment in each industry, where the industries' values of $corr_i$ are measured on the horizontal axis and the employment effect on each industry is measured on the vertical axis. Clearly, the effect on non-traded employment is much stronger than the effect on traded employment.

To evaluate the overall employment impact on tradable industries and on non-tradable industries, we need to choose a threshold value for $corr$, below which we will call an industry 'tradable' and above which we will call it 'non-tradable.' There is necessarily some arbitrariness in such a choice. We use a threshold value of *corr* equal to 0.6; the results change little if the threshold is perturbed around this value.[20] We then add up the marginal employment effect across all non-traded industries, and then across all traded industries, and compare. Pursuing this we observe that, for the full-sample results from column 5 of Table 5, $1,000$ immigrants to a metropolitan area on average will create $2,435$ jobs in non-tradables industries and 568 jobs in tradable industries, for a total of $3,002$ new local jobs.[21] Thus, 81.1% of the newly-created jobs are in the non-traded sector.

It is instructive to note the relationship between these results and Moretti (2010), who studies the multiplier effect of one new tradables job on local non-tradables employment. Moretti finds that each tradables job generates 1.5 local non-tradables jobs on average. According to our results, if the only variation in the data came from immigration, then there would be four non-tradables jobs generated for each tradables job (80% to 20%), implying a Moretti multiplier more than twice what he found. However, there is no reason to expect that immigration is the only (or even the largest) source of local employment variation in the data; Moretti has in mind, for example, terms-of-trade improvements that raise labor demand in a given

[20]We follow the following reasoning. (i) We expect most, but not all, services to be non-traded, and most goods industries to be traded. (ii) If we classify each industry as a good or a service on the basis of the Census description of the industry, any threshold choice results in some services below the cutoff and some goods industries above it; any increase in the cutoff increases the former and decreases the latter. (iii) At the value $corr = 0.6$, the the number of non-traded goods industries and the number of traded service industries are equal at 22, out of a total of 228 industries. This cutoff yields 138 non-traded industries and 90 traded industries.

[21]Note that the estimate of total job creation is greater than for the metarea-level regression in Table 5. The reason appears to be that some cities with a large immigrant population, such as Los Angeles, were also dependent on industries that contracted over the 1990's due to trade pressures, such as durable manufactures. The metarea-industry-level regression purges the results of that industry-composition effect.

manufacturing industry; the Moretti multiplier from such a shock would presumably be smaller because the direct effect is to increase employment in the traded sector. (Indeed, if labor supply is perfectly inelastic, the multiplier from a terms-of-trade shock could not be positive because each new tradables job would require a *reduction* in non-tradables employment.) The estimated Moretti multiplier could be a weighted average of the low multiplier from such trade shocks and the high multiplier from immigration shocks.

Recall that Proposition 2 predicts that the non-tradeable sector's share of the employment increase exceeds θ, the share of non-tradeables in expenditure – or, in the extreme case of high tradables labor-demand elasticity or a small tradables sector, it will be equal to θ. Now, in equilibrium, the share of non-tradables in expenditure must equal their share in income, so we can estimate θ by adding up the income of all individuals in our sample who work in the non-tradables industries; doing the same for tradeable industries; and finding what fraction the former sum is of the total. We do this both with labor income (the IPUMS variable INCWAGE) and total income (the variable INCTOT), which presumably includes capital and rental income as well, which may or may not derive from the same industry as the labor income. Either way, the share of non-tradables in income, and therefore our estimate of θ, is 0.83. The share of non-tradables in immigrant-induced job creation is quite close to the expenditure share of non-tradables – the limiting case in Proposition 2.[22]

The overall message of Table 5 is that *on average, each immigrant generates about 2 jobs in the city in which he or she locates, about* 80% *of which are in the*

[22] If we raise the cutoff for tradability to $corr = 0.65$, non-tradables' share of employment gains becomes 72% and θ becomes 75%. If we lower it to $corr = 0.55$, non-tradables' share of employment gains becomes 88% and θ becomes 86%.

non-traded industries. From Proposition 4, this can be taken as evidence of a strong shot-in-the-arm effect.

Turning to the coefficients for the employment regression results by educational class (and focussing on native-born workers) in Table 7, we find that the immigration impacts on local employment growth remain significant in most industries regardless of educational class. In particular, it is noteworthy that the estimated value of β_2 in equation (34) is shown to be always significantly positive and increasing in educational attainment (second row of the table), indicating that the employment effect of immigrants is always strongest in non-traded industries, and more strongly so for more educated workers. The point estimates in the first and the last columns imply that in the least tradable industry (hair salons), an additional $1,000$ immigrants in a metropolitan area create nearly four times more new jobs for high skilled native workers than for low skilled (6.3 new hair-salon jobs for college graduates vs. 1.2 for high-school dropouts). Adding up across all industries, the increase in native employment would be 883 for college graduates, 443 for workers with some college, 311 for high-school graduates, and 145 for high-school dropouts. Assuming that labor supply elasticities are not significantly different across skill groups, the results seem to imply that immigrant inflows raise labor demand for high-skilled native workers more rapidly than for low-skilled. This finding is in line with the literature that emphasizes skill complementary effects of immigrants (Peri and Sparber, 2009): Although we have assumed away skill heterogeneity in our theoretical model, the results presented here lend support to imperfect substitutability between immigrant and native-born labor and suggest that the 'labor glut' effect could be more pronounced in the labor market for unskilled-native workers whose skills are more similar to immigrants' skills.

4.3 Wage regressions

Table 8 presents the results from estimating equations (35) and (36). All the relevant demographic characteristics were controlled as described in Section 2, although we choose to omit those coefficients from the table for the sake of brevity.[23] The first and the third columns show that the point estimates of γ_4 and γ_5 of equation (35) are all positive but statistically insignificant regardless of nativity. However, looking only at the individual coefficients is misleading; a test of joint significance is significant at the 1% level for both the full and native samples ($\chi^2 = 12.96$ and 17.93 respectively). Investigating the wage effect by industry, we find that the effect is statistically insignificant for a worker in the most tradable industries, but significant for a worker in the least tradable industries and also for the average worker.[24] A one-standard-deviation increase in normalized immigration (0.044 from Table 2; equivalent to 940 new immigrants in a average-sized city with the 1990 sample population of 21,383) leads to a point estimate of an increase in average native wage growth between 4.85% and 5.73% over the decade depending on how traded the industry is.

The finding that overall native wages are increased by immigration is at odds

[23]The coefficients on the worker control variables are as expected, in that there are statistically significant positive effects of being male, married, white and more educated. On the other hand, being an immigrant is predicted to lower the wage by 8.9%. The full results are available upon request.

[24]The hypotheses to be tested are $\gamma_4 + corr\gamma_5 = 0$ for $corr = -0.002$, $\overline{corr}$, and 0.855 respectively, where $\overline{corr}$ is the average of $corr_j$ across workers, or equivalently, the weighted average of $corr_j$ across industries with the weights given by the share of each industry in employment. In our data, $\overline{corr}$ takes a value of 0.7055. The χ^2 values for these hypothesis tests, with p-values in parentheses, are 12.74(0.0004), 12.21(0.0005), and 0.06(0.8012) for the full sample; and 15.66(0.0001), 17.89(0.000), and 2.61(0.1062) for the native-born sample.

with the simplest version of the theory model presented in Section 1, but it can easily be rationalized by adding non-traded inputs or labor complementarity as discussed in Section 1.7, together with some worker mobility costs to allow wages to differ across industries. More importantly, the result contrasts with most of the empirical literature, which mostly finds wage effects "small and clustered near zero" (Kerr and Kerr (2011), p.12). Part of the reason may be our distinction between tradable and non-tradable industries, which, as we have seen, differ sharply in their response to immigration. In addition, some other studies that have examined large-scale immigration events have looked at a much shorter time horizon than our 10-year horizon (Card (1990) and Friedberg (2001), for example). The mechanism of new firm formation may take time to respond to new immigrants (although Olney (2012) finds surprisingly quick firm entry in response to immigration), and both Ottaviano and Peri (2012) and Brezis and Krugman (1996) emphasize that capital flows may respond to immigration with a lag.

Moreover, some studies that have found negative wage effects, such as Borjas (2003), Aydemir and Borjas (2011) and Borjas et al. (2006) are actually asking a different question: These studies divide up the labor force into, say, 32 skill-experience cells and ask what is the effect of an increase in immigration within cell i on wages for native workers within cell i. This approach is more focussed on the effect of the *composition* of immigration on the *relative* native wages, rather than on the *total number* of immigrants on *absolute* wages. If a rise in total immigration changes all wages in some direction, that will be absorbed in the year fixed effects; holding the total number constant, a rise in immigrants within cell i then implies a change in that cell's *share* of the immigrant inflow, which can affect its wages relative to wages in other cells. Thus, the same data-generating process could generate both our results and the results in those papers.[25]

The second and the fourth columns of Table 8 decompose the samples into four educational groups by nativity. We will focus on the native-worker results of column 4. Again, most of the coefficient estimates associated with the wage effects of immigration are statistically insignificant, but the eight together corresponding to the γ_{4k}'s and γ_{5k}'s of equation (36) are jointly significant at the 1% level ($\chi^2 = 521.63$), and they are almost all positive. The point estimates of 0.396 and 0.665 imply that a one standard deviation increase in $\hat{N}_m/P_m^{90}$ (=0.044), is predicted to raise the nominal wage of high school dropouts in the hair salon industry 4.2% ((= 0.396 + 0.665×0.85)×0.044), while raising it in the coal mining industry by only 1.74% ((=0.396 + 0.665×(-0.002))×0.044). The effects are consistently stronger for non-traded industries and consistently stronger for more educated workers; for college graduates, the corresponding effects are 8.23% and 4.28% for hair salons and coal mining, respectively.

To sum up, we find that the wages of native-born workers in our data are increased by immigrants, at least in non-traded industries. Together with the previous findings that immigration increases employment in those industries relative to traded industries, the finding supports the hypothesis that immigration boosts labor demand in non-traded industries relative to traded industries.

[25] Put differently, suppose that the actual data-generating process follows $\log(w_{ct}) = \alpha_0 + \alpha_1 \log(N_t) + \alpha_2 \log(\frac{N_{ct}}{N_t})$, where w_{ct} is the wage in skill-experience cell c at date t, N_t is total immigration at date t, and N_{ct} is total immigration of workers in cell c at date t. There is nothing logically preventing α_1 from being positive and at the same time α_2 from being negative. The Borjas (2003) regression and others of that type, with time fixed effects, would estimate α_2, while the sort of regression we are running would be aimed at estimating α_1.

4.4 Do immigrants crowd out native workers?

The immigration literature has provided mixed evidence regarding the impact of immigration on the internal migration of native workforce. While Butcher and Card (1991) and Card (2001) find that native out-migration and immigrant inflows are largely unrelated, Borjas (2006) argues that immigration is associated with higher out-migration rates; Peri and Sparber (2011) survey work on this question. The simple empirical framework described above allows us to examine the differential impacts of immigration on the movements of workers by employment status.

More specifically, we employ the metarea-level employment regression equation in (33) but consider two additional dependent variables: change in the number of unemployed and change in the size of not-in-labor force (NILF). Column 1 through 6 in Table 9 presents regression results separately for natives and immigrants who arrived before 1990. The results are striking. The point estimates in the first three columns imply that 1,000 new immigrants are predicted to increase native employment by 1,690, native unemployment by 84, and native NILF by 521, which amounts to a net increase of 2,295 in native population in town. At the same time, the last three columns in the table show that $1,000$ newly arriving immigrants are expected to increase the established immigrant population who arrived in the U.S. before 1990 by 35.[26] However, care must be taken before concluding that higher immigrant populations *attract* workers *into* the town, because population increases could also be explained by decreases in outflows from affected metropolitan areas (Wozniak and

[26] In unreported results, we ran the same regressions for other various sub-groups in US Census, including female, black, and Hispanic population. We found that the same pattern holds with the exception of African Americans on whom we find no significant impact of immigration. The results are available upon request.

Murray (2012)). In order to address this issue, we limit the sample to include only those who moved into a different metropolitan area between 1995 and 2000 using the "MIGMET5" variable available in IPUMS and run the regressions.[27] The estimated coefficients in the last three columns of the table suggest that 1,000 new immigrants induces 992 workers to move into the town during the five year period. This provides strong evidence against native displacement hypothesis of immigration. Therefore, according to Proposition 4, we conclude that immigration increases native in-migration rates by raising the real wage through increased product diversity in the service industries.

4.5 Robustness

A potential issue with our estimations is that there may be some other trends that would affect both employment growth and immigrant inflows in a systematic manner, thereby generating a spurious correlation between them. One well-known global trend in the 1990s was increased openness to trade and particularly increased imports from lower-wage economies. To the degree that historic location decisions of immigrants were in part based on nativity-specific comparative advantage, immigrants might have had a tendency to move into (or stay away from) trade-vulnerable cities. Then, when the large import shocks occurred during the 1990's, newly-arriving immigrants could be settling in areas because of their immigrant networks that were also experiencing adverse shocks due to import competition, which would affect labor demand both directly through the traded-goods industry and indirectly through the

[27] "MIGMET5" reports the metropolitan area the respondent lived 5 years ago. Therefore, it allows us to compute the number of in-migrants between 1995-2000 in each metro area.

income shock that would affect demand for local services. This situation could give rise to an omitted variable bias; some measure of local income shocks due to trade shocks should be incorporated as a control.

As an example of how to address this concern, consider the North American Free Trade Agreement (NAFTA), which provided for free trade between the US, Canada and Mexico from the mid-1990's forward. This created a trade shock to any MA that was heavily invested in industries that were vulnerable to imports from Mexico (US tariffs against Canada were mostly gone by then due to a prior agreement). We follow McLaren and Hakobyan (2010) and consider the degree of pre-NAFTA trade protection measured by the average tariff to Mexican imports in each metarea in order to gauge the vulnerability of each location to trade with Mexico.[28] Specifically, we define the metarea average tariff weighted by industry employment share as:

$$loc\tau_{90}^{m} \equiv \frac{\sum_{j=1}^{N_j} L_{90}^{jm}\tau_{90}^{j}}{\sum_{j=1}^{N_j} L_{90}^{jm}}, \tag{37}$$

where N_j is the number of industries; L_{90}^{jm} is the number of employed workers in industry j at metarea m; τ_{90}^{j} is the US tariff on Mexican imports in industry j. To isolate the effect of anticipated tariff reduction from that of the realized tariff reduction, we also control for the actual tariff change between the two Census years as: $loc\Delta\tau_{90}^{m} \equiv \frac{\sum_{j=1}^{N_j} L_{90}^{jm}\Delta\tau_{90}^{j}}{\sum_{j=1}^{N_j} L_{90}^{jm}}$, where $\Delta\tau_{90}^{j} = \tau_{00}^{j} - \tau_{90}^{j}$.

The third and fourth columns of Table 10 show the estimation results when the two trade shock controls are included in the employment regression. The trade

[28] We drop agriculture due to the issue regarding aggregation of industries in the US Census as described in McLaren and Hakobyan (2010). In unreported results, we verified that including agriculture made no difference.

shocks themselves are insignificant, and both the signs and magnitudes of the estimates associated with immigrant inflows remain similar to the baseline results, which provides an evidence against the concern of omitted variable bias. The implied total employment effect of 1,000 immigrants is 1,917 jobs, somewhat more modest than before but still well above 1,000.

In addition, we examine whether the main results may be the driven by the control variable for population growth trends. In fact, due to the likely positive correlation between immigrant inflows and population growth trends, we expect that it would not affect the results much qualitatively. Nevertheless, we check how sensitive the estimates are to this additional control by excluding it from the regression equation (34). Comparing the results found in the last two columns of Table 10 with the baseline results, we see that omitting the population trend term makes very little change in the magnitude of the estimates; each 1,000 new immigrants are predicted to add 2,080 new jobs (1,647 for native workers) to a city in which he or she settles.

Next, there may be concerns regarding global trade or technology shocks which could affect the industry composition at the national level. Although we expect any unobserved industry-specific trends to be absorbed by the industry fixed effects in equation (33), as an additional robustness check, we choose to directly control for the national trend and global shocks for the tradeable industries. For this, we first compute for the projected employment change in each industry-metarea cell assuming that local industry employment growth will follow the national trend for that industry:

$$ProjE_{jm}^{90} = trend_j E_{jm}^{90}, \tag{38}$$

where $trend_j$ is the nation-wide employment growth rate over the 1990s in industry

j and E^{90}_{jm} is initial employment in industry j in location m. Then we interact the variable with a dummy variable for 'tradable' industry and include it in the regressions. Table 11 presents the results with different cutoff values for defining 'tradable' industry. We can confirm that regardless of the choice of the cutoff value, the main results do not change qualitatively. More importantly, when our preffered threshold value of *corr* equal to 0.6 is used, the aggregate employment impacts of 1,000 new immigrants turn out to be 2,078 new jobs, among which 92% are concentrated in the non-traded industries, remaining essentially the same as in the baseline case in Table 5.

Finally, there may be concerns that local labor-demand shocks are serially correlated, so that the local stock of immigrants in 1990 is a response to labor-demand shocks in the 1980's that have lingering after effects during the 1990's, calling into question the endogeneity of our instruments. To address this, we recalculate both our disaster IV and the Card IV using the 1980 distribution of immigrants instead of the 1990 distribution. The results are reported in Table 12. The first two columns report results with the retrofitted disaster IV, and the following two the retrofitted Card IV. Unfortunately, with the 1980's immigration distribution, the first-stage regression for the disaster IV fits poorly, and the instruments are too weak to be useful. However, the results from the Card IV are almost identical to the baseline results. Therefore, we conclude that our results are not caused by serially correlated labor demand shocks.

5 Conclusions.

We have studied the effect of immigration on local labor markets, emphasizing the effect of immigration on local labor *demand* as opposed to merely labor *supply*. We have first studied a stylized model of a local labor market that shows how the arrival of immigrants increases local aggregate income and thus the labor demand by the non-traded services sector. This effect, which we have labelled the 'shot-in-the-arm' effect, dampens the downward pressure the extra labor supply places on local wages, and also increases the variety of non-traded services available, which confers a benefit on all local consumers, native-born and immigrant. Consequently, even in a model in which immigration always lowers local wages in terms of tradeables, it *raises* real wages in terms of non-tradables, and depending on how strong the shot-in-the-arm effect is, it may raise real wages in terms of the overall consumer price index, raising utility for all local workers.

In that case, immigration into a town will tend to attract other native workers from elsewhere in the country, who will then create an additional 'shot in the arm' of their own, resulting in a virtuous cycle in which employment in the town has increased by more than the direct rise in the local labor force due to the immigrants. In that case, we can say that each immigrant generates more than one job. One the other hand, if the shot-in-the-arm effect is weak, real wages will fall, and native workers will flow out of the town; each immigrant can then be said to generate less than one job. Since real wages that take full account of diversity are difficult to measure, net flows of workers in response to immigration can be a useful indicator of the local net effects of immigration on the welfare of local workers.

We examine these effects empirically with a five-percent sample from the US Decennial Census. We use a novel method to divide industries into non-traded and traded, and find that the non-traded portion of the economy generates 83% of total income, which creates the potential for a large shot-in-the-arm effect. Using a new instrumental variable for local immigrant inflows based on adverse shocks in source countries plus historical ethnic patterns of immigrants across US localities, we find that $1,000$ new immigrants to a US Metropolitan Area (MA) generates approximately $2,200$ new local jobs, about 80% of which are in the non-traded sector. Further, we find that new immigrants tend to raise local wages even in terms of tradeables, at least for jobs in the non-traded sector (with positive but insignificant point estimates for tradeables jobs), and that new immigrants seem to attract native workers into the MA. Thus, the evidence appears to favor a strong shot-in-the-arm effect, and support the idea that workers in a given MA benefit from the arrival of more immigrants to that MA.

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Appendix

Proof of Proposition 1. From (10) and (18), labor market equilibrium can be written as:

$$wL^{TOT} = -wr_2(q, w, K) + \theta wL + \theta r\,(q, w, K)\,. \tag{39}$$

The left-hand side is total labor income and the right-hand side terms are, respectively, income to labor employed in tradables followed by two terms representing labor income in non-tradables. Differentiating with respect to L^{TOT} yields and solving for dw/dL^{TOT}:

$$\frac{dw}{dL^{TOT}} = \frac{-(1-\theta)w}{(1-\theta)(L^{TOT}+r_2)+wr_{22}} < 0. \tag{40}$$

Note that $(L^{TOT}+r_2)$ is just the amount of labor employed in the non-traded sector, and is therefore positive. Therefore the denominator of dw/dL^{TOT} is positive. This implies that the change in local income is:

$$\frac{dI}{dL^{TOT}} = \frac{d}{dL^{I}}\left[w(L^{N}+L^{I})+r(q,w,K)\right] = \frac{w^2 r_{22}}{(1-\theta)(L^{TOT}+r_2)+wr_{22}} > 0. \tag{41}$$

From (14), the effect on the equilibrium value of n is:

$$\frac{d\log n}{dL^{TOT}} = \frac{d\log E^{S}}{dL^{TOT}} - \frac{d\log w}{dL^{TOT}} = \frac{d\log I}{dL^{TOT}} - \frac{d\log w}{dL^{TOT}}. \tag{42}$$

Putting this together with (19) and (4), we can derive the effect of immigration on the local real wage:

$$
\begin{aligned}
\frac{d\ln(w^{REAL})}{dL^{TOT}} &= \frac{d\ln(w)}{dL^{TOT}} - \theta\frac{d\ln(P^S)}{dL^{TOT}} \\
&= \frac{d\ln(w)}{dL^{TOT}} - \left(\frac{\theta}{1-\sigma}\right)\frac{d\ln(n)}{dL^{TOT}} - \theta\frac{d\ln(w)}{dL^{TOT}} \\
&= \frac{d\ln(w)}{dL^{TOT}} - \left(\frac{\theta}{1-\sigma}\right)\frac{d\log I}{dL^{TOT}} + \left(\frac{\theta}{1-\sigma}\right)\frac{d\log w}{dL^{TOT}} - \theta\frac{d\ln(w)}{dL^{TOT}} \\
&= \left[-\left(\frac{1-\sigma+\theta\sigma}{1-\sigma}\right)(1-\theta) - \left(\frac{\theta}{1-\sigma}\right)\frac{w^2 r_{22}}{TOT}\right]\frac{1}{(1-\theta)(L^{TOT}+r_2)+wr_{22}}.
\end{aligned}
$$

Given that

$$\frac{w^2 r_{22}}{I} = \left(\frac{w|r_2|}{r}\right)\left(\frac{r}{I}\right)\left(\frac{wr_{22}}{|r_2|}\right) = \phi_{L,T}(1-\theta)\epsilon^D_{L,T}, \tag{43}$$

where $\phi_{L,T}$ is labor's share of costs in the traded sector and $\epsilon^D_{L,T}$ is the elasticity of labor demand in the traded sector, the stated condition follows mechanically. *Q.E.D.*

Proof of Proposition 2. Since $-r_{22}$ is the derivative of tradables labor demand with respect to the wage, clearly

$$\frac{dL^T}{dL^{TOT}} = -\frac{dw}{dL^{TOT}} r_{22}. \tag{44}$$

Using the expression for dw/dL^{TOT} derived in the proof of Proposition 1, the result follows immediately. *Q.E.D.*

Proof of Proposition 3. The derivative of equilibrium condition (24) with respect to immigrant labor is:

$$-[(1-\theta^1)(L^{TOT}+r_2)+wr_{22}]\frac{dw}{dL^{TOT}} + \theta^1 H\frac{dp^H}{dL^{TOT}} = (1-\theta^1)w \tag{45}$$

The derivative of equilibrium condition (25) with respect to immigrant labor is:

$$-(1-\theta^1-\theta^2)(L^{TOT}+r_2)\frac{dw}{dL^{TOT}}+(\theta^1+\theta^2)H\frac{dp^H}{dL^{TOT}}=(1-\theta^1-\theta^2)w \tag{46}$$

These two equations can be written in matrix form as:

$$A\begin{pmatrix}\frac{dw}{dL^{TOT}}\\ \frac{dp^H}{dL^{TOT}}\end{pmatrix}\equiv\begin{pmatrix}-[(1-\theta^1)(L^{TOT}+r_2)+wr_{22}] & \theta^1 H\\ -(1-\theta^1-\theta^2)(L^{TOT}+r^2) & (\theta^1+\theta^2)H\end{pmatrix}\begin{pmatrix}\frac{dw}{dL^{TOT}}\\ \frac{dp^H}{dL^{TOT}}\end{pmatrix}=\begin{pmatrix}(1-\theta^2)w\\ (1-\theta^1-\theta^2)w\end{pmatrix} \tag{47}$$

The inverse of the matrix A is:

$$\frac{1}{D}\begin{pmatrix}(\theta^1+\theta^2)H & -\theta^1 H\\ (1-\theta^1-\theta^2)(L^{TOT}+r_2) & -[(1-\theta^1)(L^{TOT}+r_2)+wr_{22}]\end{pmatrix}, \tag{48}$$

where $D\equiv-[\theta^2(L^{TOT}+r_2)+(\theta^1+\theta^2)wr_{22}]H<0$ is the determinant. The result follows mechanically. *Q.E.D.*

Proof of Proposition 4. First, note that because $(1-\theta^1-\theta^2)I=p^H H$,

$$\begin{aligned}\frac{d\log(I)}{dL^{TOT}} &= \frac{d\log(p^H)}{dL^{TOT}}\\ &= \left(\frac{1}{p^H}\right)\frac{(1-\theta^1-\theta^2)r_{22}w^2}{[\theta^2(L^{TOT}+r_2)+(\theta^1+\theta^2)wr_{22}]\,H}\\ &= \frac{r_{22}w^2}{[\theta^2(L^{TOT}+r_2)+(\theta^1+\theta^2)wr_{22}]\,I}\\ &= \left(\frac{w|r_2|}{r}\right)\left(\frac{r_{22}w}{|r_2|}\right)\left(\frac{r}{I}\right)\frac{1}{[\theta^2(L^{TOT}+r_2)+(\theta^1+\theta^2)wr_{22}]}\\ &= \frac{\phi_{L,T}\epsilon^D_{L,T}\theta^2}{[\theta^2(L^{TOT}+r_2)+(\theta^1+\theta^2)wr_{22}]}.\end{aligned}$$

Second, note that because of free entry in nontraded services, $\frac{d\log(n)}{dL^{TOT}} = \frac{d\log(I)}{dL^{TOT}} - \frac{d\log(w)}{dL^{TOT}}$ as implied by (14). These yield:

$$\begin{aligned}
\frac{d\ln(w^{REAL})}{dL^{TOT}} &= \frac{d\ln(w)}{dL^{TOT}} - \theta^1\frac{d\ln(P^S)}{dL^{TOT}} - (1-\theta^1-\theta^2)\frac{d\ln(p^H)}{dL^{TOT}} \\
&= \frac{d\ln(w)}{dL^{TOT}} - \frac{\theta^1}{1-\sigma}\frac{d\ln(n)}{dL^{TOT}} - \theta^1\frac{d\ln(w)}{dL^{TOT}} - (1-\theta^1-\theta^2)\frac{d\ln(p^H)}{dL^{TOT}} \\
&= \frac{d\ln(w)}{dL^{TOT}} - \frac{\theta^1}{1-\sigma}\frac{d\ln(I)}{dL^{TOT}} + \frac{\theta^1}{1-\sigma}\frac{d\ln(w)}{dL^{TOT}} - \theta^1\frac{d\ln(w)}{dL^{TOT}} - (1-\theta^1-\theta^2)\frac{d\ln(p^H)}{dL^{TOT}} \\
&= \left(1+\frac{\theta^1}{1-\sigma}-\theta^1\right)\frac{d\log(w)}{dL^{TOT}} - \left(\frac{\theta^1}{1-\sigma}+1-\theta^1-\theta^2\right)\frac{d\log(I)}{dL^{TOT}}
\end{aligned}$$

This can be combined with Proposition 3 to derive the effect of immigration on the real wage as follows:

$$\frac{d\ln(w^{REAL})}{dL^{TOT}} > 0 \iff -(1-\sigma+\theta^1\sigma) - (1-\theta^2-\sigma(1-\theta^1-\theta^2))\phi_{L,T}\epsilon^D_{L,T} < 0.$$

Rearranging gives the desired result. *Q.E.D.*

Tables.

Table 1: Sample Selection Criteria

Selection Criterion	Number Rejected	Number Remaining
Keep if in the 1990 or 2000 U.S. Censuses.	0	26,582,512
Keep if INCWAGE$< 400,000$.	5,960,707	20,621,805
Drop if age< 20 or age> 65.	5,006,240	15,615,565
Keep if in a consistently defined metarea.	5,367,572	10,247,993
Keep if IND1990< 900.	551,379	9,696,614
Keep if employed.	2,670,079	7,026,535

Table 2: Summary Statistics

	Mean	Std. Dev.	Min	Max	N
Individual-level					
Year	1995.3	4.985	1990	2000	7,026,535
Age	39.13	11.46	20	65	7,026,535
Male	0.532	0.498	0	1	7,026,535
Married	0.608	0.488	0	1	7,026,535
High school dropouts	0.131	0.338	0	1	7,026,535
High school graduates	0.263	0.440	0	1	7,026,535
Some college	0.314	0.464	0	1	7,026,535
College graduates	0.290	0.453	0	1	7,026,535
Immigrant	0.158	0.365	0	1	7,026,535
Salary income	29999.7	35894.2	0	354000	7,026,535
Metarea-level					
Population, 1990 (P_m^{90})	21383.7	43740.4	2397	433699	219
Population, 2000	25410.7	48574.2	2357	476833	219
New immigrants in the 1990s (N_m)	1590.9	5359.1	8	56491	219
Employment growth in the 1990s (ΔE_m)	2417.8	3916.9	-5993	28706	219
Share of college graduates in 1990	0.229	0.061	0.111	0.436	219
Share of manufacturing workers in 1990	0.192	0.078	0.039	0.463	219
Population growth trend in the 1980s	1392	11943	-48129	84335	219
$\Delta E_m/P_m^{90}$	0.180	0.266	-0.353	1.811	219
$\hat{N}_m/P_m^{90}$	0.047	0.044	0.003	0.330	219

Table 3: 10 Most and Least Tradable Industries

IND1990	Industry description	Corr.
772	Beauty shops	0.855
412	U.S. Postal Service	0.851
610	Retail bakeries	0.846
731	Personnel supply services	0.838
862	Child day care services	0.837
623	Apparel and accessory stores, except shoe	0.836
812	Offices and clinics of physicians	0.835
890	Accounting, auditing, and bookkeeping services	0.834
471	Sanitary services	0.827
510	Professional and commercial equipment and supplies	0.826
312	Construction and material handling machines	0.180
42	Oil and gas extraction	0.153
31	Forestry	0.145
220	Leather tanning and finishing	0.115
132	Knitting mills	0.098
311	Farm machinery and equipment	0.090
130	Tobacco manufactures	0.054
40	Metal mining	0.039
380	Photographic equipment and supplies	0.025
41	Coal mining	-0.002

Table 4: Stage 1 Regression Results

Dependent Variable: Newly arriving immigrants	
1990 Immigrant population×Armed conflicts	0.0157**
	(0.0063)
1990 Immigrant population×Natural disasters	0.0012
	(0.0008)
1990 Immigrant population×1995 Source-country population×(negative) GDP growth	4.59e-05***
	(1.05e-05)
Constant	358.7***
	(55.18)
Observations	219
R-Squared	0.96

Notes: Robust standard errors in parentheses; *, **, and *** indicate significance at the 10%, 5% and 1% levels, respectively.

Table 5: Metarea-level Employment Regression Results

	OLS		Disaster IV		Card IV	
Dependent Variable: Employment change	Full sample	Natives only	Full sample	Natives only	Full sample	Natives only
(Immigrant flow)/(1990 population)	3.0481***	2.1303***	3.9197***	3.0374***	2.9717**	2.2583**
	(.3917)	(.3658)	(1.2249)	(1.0376)	(1.1762)	(1.0114)
(Population change over the 1980s)/(1990 population)	−.1967***	−.1859***	−.2130***	−.2029***	−.1953***	−.1883***
	(.0392)	(.0366)	(.0451)	(.0417)	(.0472)	(.0435)
College graduates in 1990, per cent	−.3279	−.2952	−.5482	−.5244	−.3086	−.3275
	(.2903)	(.2711)	(.3745)	(.3430)	(.3545)	(.3282)
In manufacturing industries in 1990, per cent	.1556	.1580	.2036	.2080	.1514	.1650
	(.2168)	(.2025)	(.3705)	(.3510)	(.3813)	(.3582)
Constant	.0845	.0826	.0849	.0830	.0844	.0826
	(.0875)	(.0818)	(.1087)	(.0995)	(.1113)	(.0998)
Adj. R^2	.2539	.1836	.2366	.1601	.2537	.1831
No. of observations	219	219	219	219	219	219

Notes: Robust standard errors in parentheses; *, **, and *** indicate significance at the 10%, 5% and 1% levels, respectively.

Table 6: Metarea-industry-level Employment Regression Results

Dependent Variable: Employment change	OLS Full sample	OLS Natives only	Disaster IV Full sample	Disaster IV Natives only	Card IV Full sample	Card IV Natives only
(Immigrant flow)/(1990 population)	–.0038	–.0010	–.0094	–.0069	–.0060	–.0039
	(.0041)	(.0035)	(.0061)	(.0052)	(.0066)	(.0060)
(Immigrant flow)×Corr/(1990 population)	.0298***	.0183*	.0451***	.0344**	.0323*	.0235
	(.0111)	(.0094)	(.0170)	(.0143)	(.0174)	(.0153)
(Population change over the 1980s)/(1990 population)	–.0009***	–.0009***	–.0010***	–.0010***	–.0009***	–.0009***
	(.0002)	(.0002)	(.0002)	(.0002)	(.0002)	(.0002)
College graduates in 1990, per cent	–.0015	–.0014	–.0025	–.0024	–.0013	–.0014
	(.0015)	(.0014)	(.0018)	(.0016)	(.0017)	(.0016)
In manufacturing industries in 1990, per cent	.0008	.0008	.0010	.0010	.0007	.0008
	(.0018)	(.0017)	(.0018)	(.0017)	(.0018)	(.0017)
Constant	.0001	–.0007	.0003	–.0005	.0002	–.0006
	(.0006)	(.0005)	(.0006)	(.0005)	(.0007)	(.0006)
Industry fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Total change in employment (Δ)	3.161***	2.241***	3.962***	3.087***	2.999**	2.289**
	(.826)	(.705)	(.740)	(1.067)	(1.195)	(1.034)
Adj. R^2	.2417	.2167	.2399	.2141	.2416	.2166
No. of observations	46508	46252	46508	46252	46508	46252

Notes: Robust standard errors in parentheses are clustered by metarea; *, **, and *** indicate significance at the 10%, 5% and 1% levels, respectively; Total employment effect of one additional immigrant is computed as $\Delta \equiv \sum_{i=1}^{228}(\beta_1 + corr_i\beta_2)$, where β_1 is the intercept and β_2 is the coefficient on the interaction.

Table 7: Native Employment Regression Results by Educational Class

Dependent Variable: Employment change	High school dropout	High school grad	Some college	College grad
(Immigrant flow)/(1990 population)	–.0010	.0003	–.0008	–.0038
	(.0017)	(.0024)	(.0015)	(.0030)
(Immigrant flow)×Corr/(1990 population)	.0040*	.0049	.0085**	.0169*
	(.0022)	(.0034)	(.0042)	(.0097)
(Population change over the 1980s)/(1990 population)	–.0001***	–.0003***	–.0004***	–.0004***
	(.0000)	(.0001)	(.0001)	(.0001)
College graduates in 1990, per cent	–.0001	–.0012**	–.0015**	.0004
	(.0003)	(.0005)	(.0006)	(.0006)
In manufacturing industries in 1990, per cent	.0000	.0002	.0004	.0007
	(.0005)	(.0007)	(.0006)	(.0006)
Constant	–.0004***	–.0001	.0003	–.0003
	(.0001)	(.0002)	(.0002)	(.0002)
Industry fixed effects	Yes	Yes	Yes	Yes
Total change in employment (Δ)	.317	.737**	.963***	1.416**
	(.199)	(.344)	(.343)	(.681)
Adj. R^2	.0508	.1652	.2422	.2559
No. of observations	34583	42050	41789	36920

Notes: Disaster IV used as instrument for immigrant flow. Robust standard errors in parentheses are clustered by metarea; *, **, and *** indicate significance at the 10%, 5% and 1% levels, respectively; Total employment effect of one additional immigrant is computed as $\Delta \equiv \sum_{i=1}^{228}(\beta_1 + corr_i\beta_2)$, where β_1 is the intercept and β_2 is the coefficient on the interaction.

Table 8: Wage Regression Results

Dependent Variable: Log Wage	Full sample	Full sample	Natives only	Natives only
(Year = 2000)	0.259***	0.255***	0.208***	0.210***
	(0.0353)	(0.034)	(0.039)	(0.039)
Corr×(Year = 2000)	-0.006	0.002	0.053	0.055
	(0.062)	(0.061)	(0.056)	(0.056)
(Immigrant flow)×(Year = 2000)	0.156		1.103	
	(0.610)		(0.683)	
Corr×(Immigrant flow)×(Year = 2000)	1.225		0.233	
	(0.835)		(0.876)	
(Less than high school)×(Immigrant flow)×(Year = 2000)		-1.187*		0.396
		(0.638)		(0.678)
(High school grad)×(Immigrant flow)×(Year = 2000)		0.308		0.966
		(0.687)		(0.823)
(Some college)×(Immigrant flow)×(Year = 2000)		1.237*		1.791**
		(0.723)		(0.807)
(College grad)×(Immigrant flow)×(Year = 2000)		0.506		0.976
		(1.059)		(1.091)
Corr×(Less than high school)×(Immigrant flow)×(Year = 2000)		2.304***		0.665
		(0.927)		(0.906)
Corr×(High school grad)×(Immigrant flow)×(Year = 2000)		0.651		-0.057
		(0.933)		(1.066)
Corr×(Some college)×(Immigrant flow)×(Year = 2000)		-0.427		-1.026
		(0.991)		(1.115)
Corr×(College grad)×(Immigrant flow)×(Year = 2000)		1.406		1.046
		(1.372)		(1.376)
Industry fixed effects	Yes	Yes	Yes	Yes
Observations	6,467,192	6,467,192	5,466,920	5,466,920
R-squared	0.343	0.344	0.348	0.348

Notes: Disaster IV used as instrument for immigrant flow. Robust standard errors in parentheses are clustered by metarea, industry and year; *, **, and *** indicate significance at the 10%, 5% and 1% levels, respectively.

Table 9: Population Change Regression Results

Dependent Variable: Change in	Natives			Pre-1990 Immigrants			Post-1995 In-migrants		
	Emp.	Unemp.	NILF	Emp.	Unemp.	NILF	Emp.	Unemp.	NILF
(Immigrant flow)/(1990 population)	1.690***	0.084***	0.521**	0.185***	0.006	0.161***	0.653***	0.054***	0.285***
	(0.414)	(0.019)	(0.013)	(0.042)	(0.005)	(0.024)	(0.155)	(0.009)	(0.063)
(Population change over the 1980s)/(1990 population)	-0.126***	-0.001	-0.035***	-0.000	0.001	0.005**	0.020	0.002***	0.019***
	(0.037)	(0.001)	(0.012)	(0.003)	(0.001)	(0.002)	(0.014)	(0.001)	(0.005)
In manufacturing industries in 1990, per cent	0.107	-0.016*	-0.053	-0.032	-0.003	-0.031**	-0.146*	-0.022***	-0.146***
	(0.209)	(0.009)	(0.070)	(0.021)	(0.003)	(0.012)	(0.078)	(0.004)	(0.032)
College graduates in 1990, per cent	0.305	0.022*	0.073	0.038	-0.001	0.014	0.423***	-0.008	-0.016
	(0.265)	(0.012)	(0.088)	(0.027)	(0.003)	(0.015)	(0.099)	(0.006)	(0.040)
Constant	-0.074	-0.006	0.004	-0.005	0.000	-0.001	0.057	0.013***	0.076***
	(0.093)	(0.004)	(0.031)	(0.009)	(0.001)	(0.005)	(0.034)	(0.002)	(0.014)
Observations	219	219	219	219	217	219	219	219	219
R-squared	0.139	0.123	0.111	0.107	0.020	0.217	0.187	0.246	0.219

Notes: Disaster IV used as instrument for immigrant flow. Standard errors in parentheses; *, **, and *** indicate significance at the 10%, 5% and 1% levels, respectively.

Table 10: Robustness Check (I)

Dependent Variable: Employment change	Card instrument		Trade shock controls		Without pop. growth trend	
	Full sample	Natives only	Full sample	Natives only	Full sample	Natives only
(Immigrant flow)/(1990 population)	–.0005	–.0001	–.0037	–.0021	–.0031	–.0015
	(.0023)	(.0020)	(.0027)	(.0023)	(.0029)	(.0024)
(Immigrant flow)×Corr/(1990 population)	.0103	.0075	.0204**	.0145*	.0206**	.0147**
	(.0075)	(.0061)	(.0095)	(.0074)	(.0095)	(.0073)
(Population change over the 1980s)/(1990 population)	–.0006**	–.0007***	–.0006**	–.0006***		
	(.0002)	(.0002)	(.0002)	(.0002)		
In manufacturing industries in 1990, per cent	.0004	.0005	.0007	.0007	.0025	.0025
	(.0020)	(.0018)	(.0016)	(.0014)	(.0020)	(.0018)
College graduates in 1990, per cent	.0033	.0021	–.0018	–.0018	–.0016	–.0016
	(.0024)	(.0019)	(.0017)	(.0015)	(.0016)	(.0014)
Local average tariff in 1990 (agric = 0)			–.6251	–.5401		
			(.4076)	(.3810)		
Change in local average tariff in 1990 (agric = 0)			–.7104	–.6155		
			(.4498)	(.4203)		
Constant	–.0008	–.0014*	.0002	–.0006	–.0002	–.0009*
	(.0010)	(.0008)	(.0007)	(.0005)	(.0007)	(.0005)
Industry fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R^2	.2272	.2083	.2352	.2147	.2310	.2094
No. of observations	46508	46252	46508	46252	46508	46252

Notes: Disaster IV used as instrument for immigrant flow, except for the first two columns. Robust standard errors in parentheses are clustered by metarea; *, **, and *** indicate significance at the 10%, 5% and 1% levels, respectively.

Table 11: Robustness Check (II)

National trend controlled for:	Every industry	Corr.<0.8	Corr.<0.6	Corr.<0.4	Corr.<0.2	No industry
Dependent Variable: Employment change	Full sample	Full sample	Full sample	Full sample	Full sample	Full sample
(Immigrant flow)/(1990 population)	.0019	–.0035*	–.0113***	–.0120***	–.0124***	–.0124***
	(.0019)	(.0020)	(.0025)	(.0025)	(.0026)	(.0026)
(Immigrant flow)×Corr/(1990 population)	.0128***	.0216***	.0344***	.0356***	.0363***	.0362***
	(.0048)	(.0040)	(.0034)	(.0034)	(.0034)	(.0034)
(Population change over the 1980s)/(1990 population)	–.0005**	–.0006**	–.0006**	–.0006**	–.0006**	–.0006**
	(.0002)	(.0002)	(.0003)	(.0003)	(.0003)	(.0003)
In manufacturing industries in 1990, per cent	.0021	.0021	.0021	.0020	.0021	.0021
	(.0022)	(.0022)	(.0022)	(.0022)	(.0022)	(.0022)
College graduates in 1990, per cent	–.0033*	–.0030*	–.0022	–.0023	–.0022	–.0022
	(.0017)	(.0017)	(.0017)	(.0017)	(.0017)	(.0017)
National industry employment growth trend	1.1457***	1.0976***	.9816***	.5047*	–.0806	
	(.1055)	(.1163)	(.2664)	(.2892)	(.4211)	
Constant	.0000	.0002	.0004	.0004	.0004	.0004
	(.0006)	(.0006)	(.0006)	(.0006)	(.0006)	(.0006)
Adj. R^2	.2327	.1886	.0698	.0361	.0298	.0298
No. of observations	43718	43718	43718	43718	43718	43718

Notes: Disaster IV used as instrument for immigrant flow. Robust standard errors in parentheses are clustered by metarea; *, **, and *** indicate significance at the 10%, 5% and 1% levels, respectively.

Table 12: Robustness Check (III)

Dependent Variable: Employment change	Disaster IV (1980 weights) Full sample	Disaster IV (1980 weights) Natives only	Card IV (1980 weights) Full sample	Card IV (1980 weights) Natives only
(Immigrant flow)/(1990 population)	–.0031	–.0003	–.0140*	–.0108
	(.0062)	(.0057)	(.0079)	(.0074)
(Immigrant flow)×Corr/(1990 population)	.0173	.0092	.0440**	.0338*
	(.0187)	(.0162)	(.0205)	(.0182)
(Population change over the 1980s)/(1990 population)	–.0008***	–.0008***	–.0009***	–.0009***
	(.0002)	(.0002)	(.0002)	(.0002)
College graduates in 1990, per cent	.0003	–.0001	–.0011	–.0013
	(.0018)	(.0016)	(.0017)	(.0016)
In manufacturing industries in 1990, per cent	.0004	.0005	.0007	.0008
	(.0019)	(.0018)	(.0018)	(.0017)
Constant	.0000	–.0008	.0003	–.0005
	(.0007)	(.0006)	(.0007)	(.0006)
Industry fixed effects	Yes	Yes	Yes	Yes
Total change in employment (Δ)	1.628	1.165	2.772**	2.106**
	(1.323)	(1.093)	(1.272)	(1.067)
Adj. R^2	.2377	.2142	.2408	.2157
No. of observations	46508	46252	46508	46252

Notes: Robust standard errors in parentheses are clustered by metarea; *, **, and *** indicate significance at the 10%, 5% and 1% levels, respectively; Total employment effect of one additional immigrant is computed as $\Delta \equiv \sum_{i=1}^{228}(\beta_1 + corr_i\beta_2)$, where β_1 is the intercept and β_2 is the coefficient on the interaction.

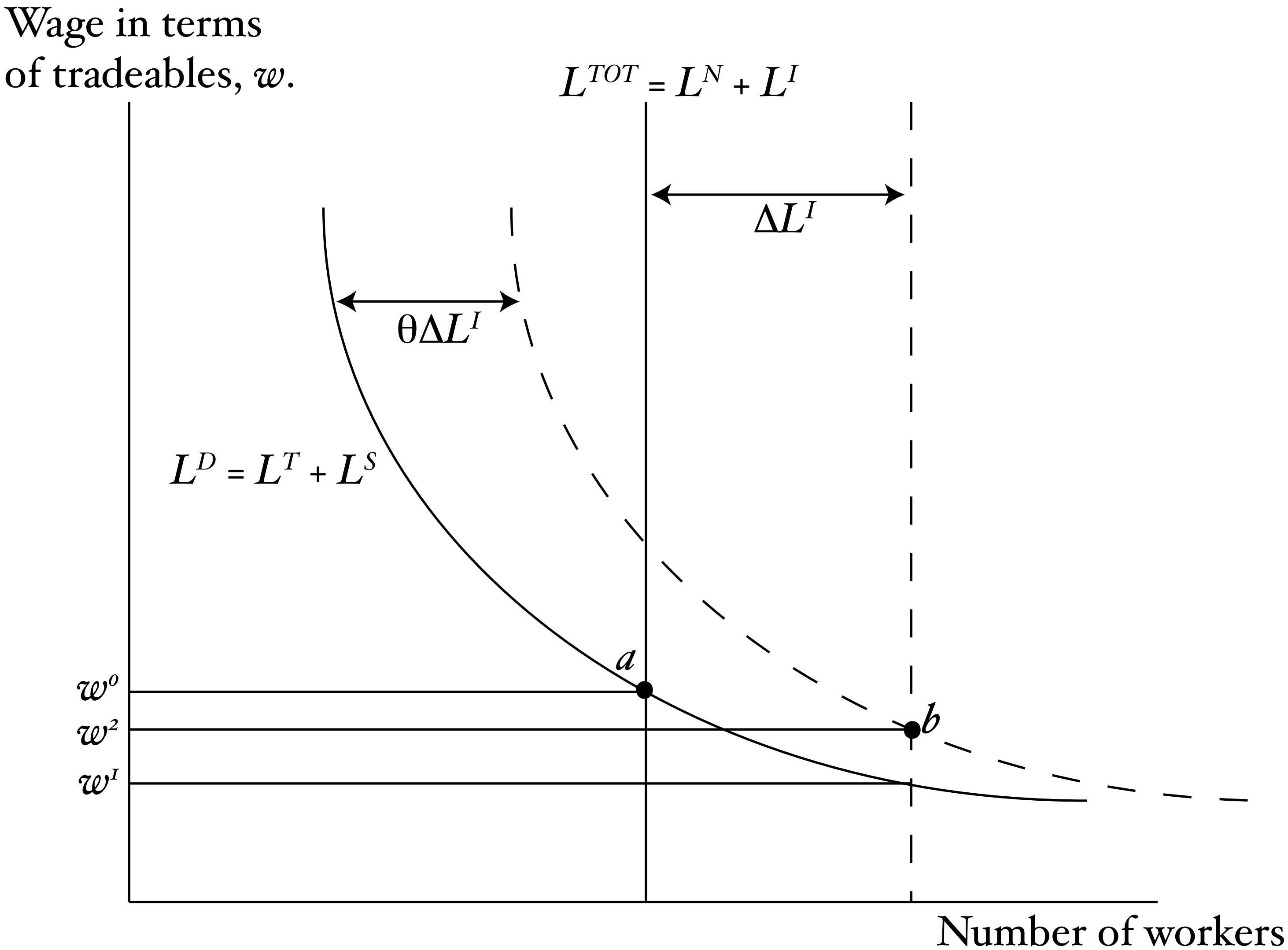

Figure 1: The effect of immigration
with inelastic and immobile labor supply.

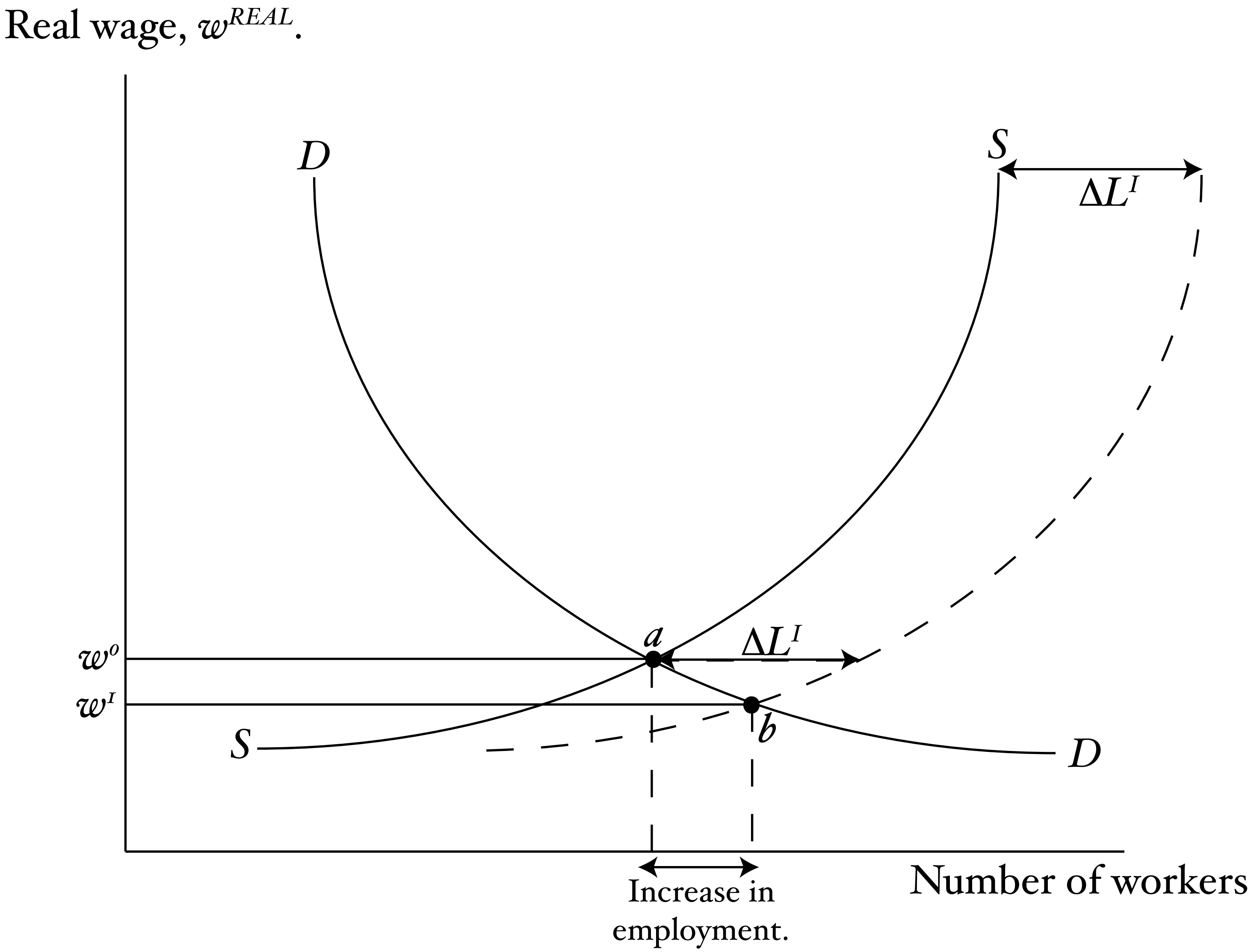

Figure 2(a): The effect of immigration when the 'shot-in-the-arm' effect is weak.

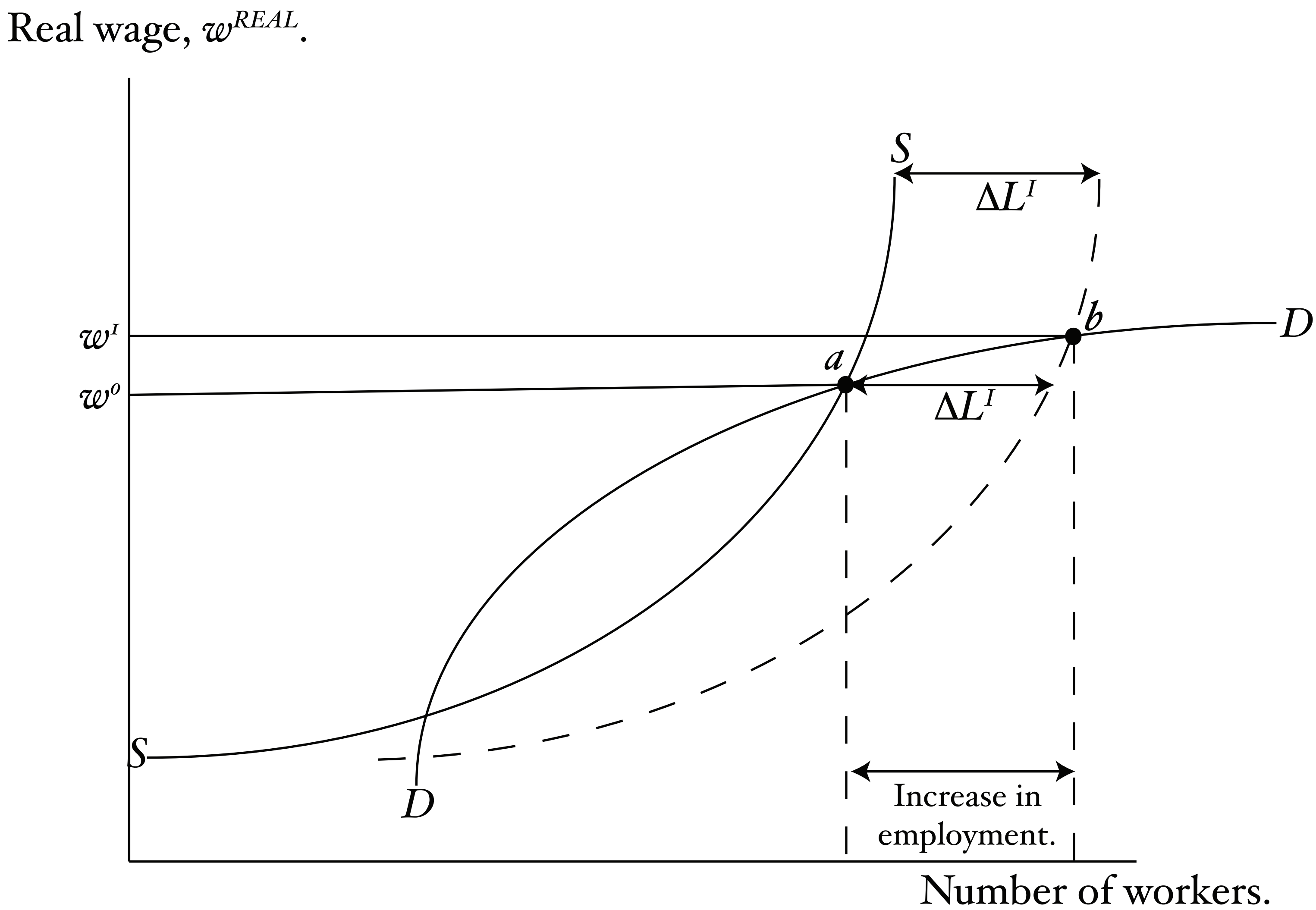

Figure 2(b): The effect of immigration when the 'shot-in-the-arm' effect is strong.

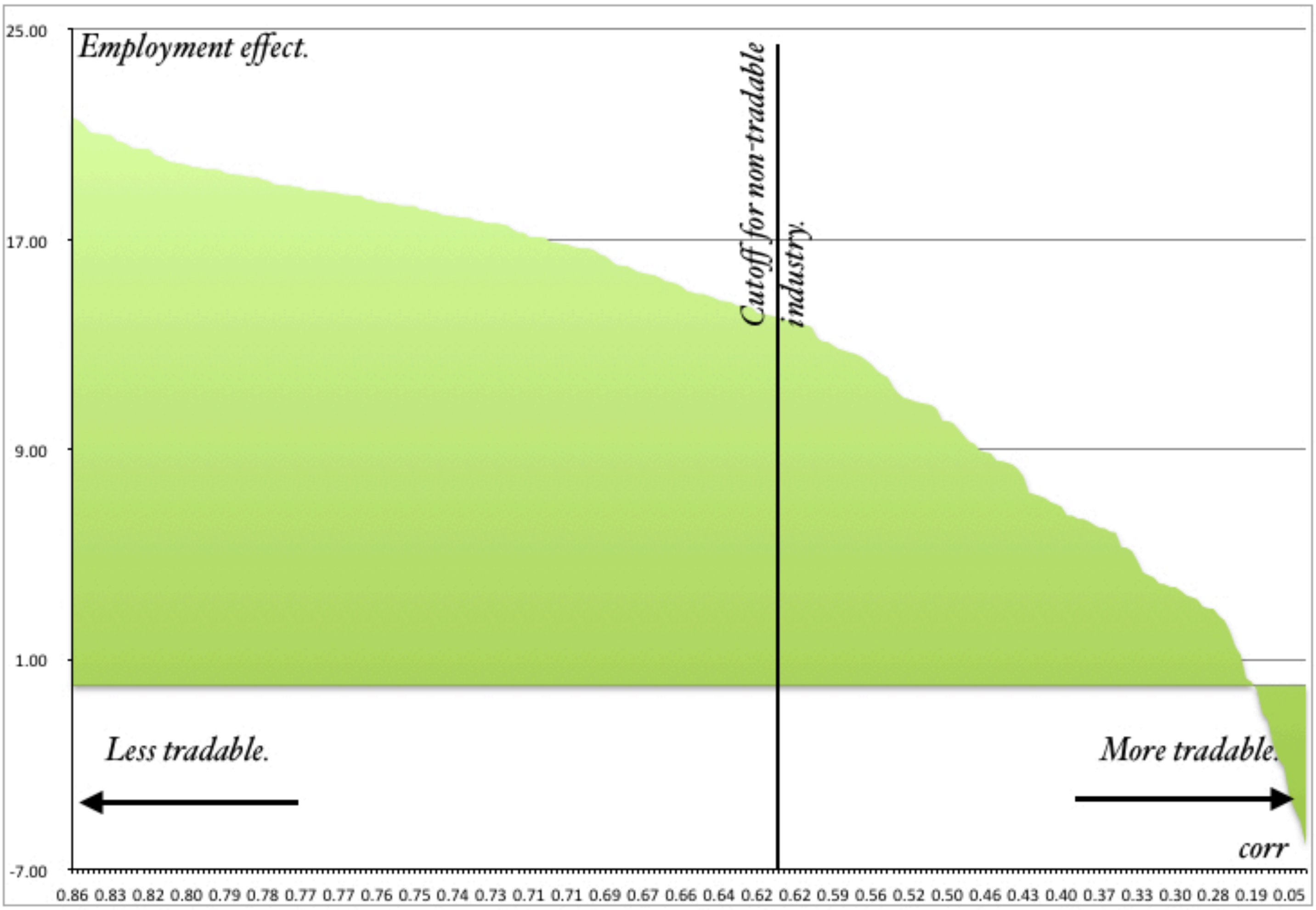

Figure 3: The employment effect of immigrants, by industry.