## Online Appendix (not for publication)

## A Proofs

In this section, we provide proofs of Theorem 1, Corollary 1, Lemma 1, and Proposition 1.

## A. 1 Proof of Theorem 1

In this section, we prove Theorem 1 using the contraction mapping theorem. Recall that the system of Equations $F: \mathbb{R}_{++}^{N \times K} \rightarrow \mathbb{R}_{++}^{N \times K}$ are written as:

$$
F(\mathbf{x})_{i k} \equiv \sum_{j} K_{i j, k} \prod_{l=1}^{K}\left(x_{j, l}\right)^{\alpha_{k, l}} \prod_{l=1}^{K}\left(x_{i, l}\right)^{\lambda_{k, l}} \prod_{m=1}^{M} P_{m}\left(\mathbf{x}_{j}\right)^{\gamma_{k, m}} \prod_{m=1}^{M} P_{m}\left(\mathbf{x}_{i}\right)^{\chi_{k, m}},
$$

where $Q_{m}(\cdot)$ are nested CES aggregating functions:

$$
P_{m}\left(\mathbf{x}_{j}\right) \equiv\left(\sum_{l \in S_{m}} \frac{1}{\left|S_{m}\right|}\left(\left(\sum_{n \in T_{l}} \frac{1}{\left|T_{n}\right|}\left(x_{j, n}\right)^{\delta_{m, l}}\right)^{\frac{1}{\delta_{m, l}}}\right)^{\beta_{m}}\right)^{\frac{1}{\beta_{m}}}
$$

where $\delta_{m, l}>0$ and $\beta_{m}>0$ for all $m$ and $l,\left\{K_{i j, k}, U_{l}, T_{j, n}\right\}$ are all strictly positive parameter values; $S_{m}$ and $T_{l, m}$ are (weak) subsets of $\{1, \ldots, K\}$; and $\left\{\alpha_{k, l}, \lambda_{k, l}, \gamma_{k, m}, \chi_{k, p}\right\}$ are all realvalued.

It proves helpful to instead consider an equivalent function $G: \mathbb{R}^{N \times K} \rightarrow \mathbb{R}^{N \times K}$ :

$$
G(\mathbf{x}) \equiv \log \sum_{j} K_{i j, k} \prod_{l=1}^{K}\left(\exp x_{j, l}\right)^{\alpha_{k, l}} \prod_{l=1}^{K}\left(\exp x_{i, l}\right)^{\lambda_{k, l}} \prod_{m=1}^{M} \exp Q_{m}\left(\mathbf{x}_{j}\right)^{\gamma_{k, m}} \prod_{m=1}^{M} \exp Q_{m}\left(\mathbf{x}_{i}\right)^{\chi_{k, m}}
$$

where:

$$
Q_{m}\left(\mathbf{x}_{j}\right) \equiv \log \left(\sum_{l \in S_{m}} \frac{1}{\left|S_{m}\right|}\left(\left(\sum_{n \in T_{l}} \frac{1}{\left|T_{n}\right|}\left(\exp x_{j, n}\right)^{\delta_{m, l}}\right)^{\frac{1}{\delta_{m, l}}}\right)^{\beta_{m}}\right)^{\frac{1}{\beta_{m}}}
$$

Clearly if there is any fixed point $\tilde{\mathbf{x}}^{*} \in \mathbb{R}^{N \times K}$ such that $G\left(\tilde{\mathbf{x}}^{*}\right)=\tilde{\mathbf{x}}^{*}$ implies that $\mathbf{x}^{*} \equiv$ $\exp \left(\tilde{\mathbf{x}}^{*}\right) \in \mathbb{R}_{++}^{N \times K}$ is a fixed point for $F$, i.e. $F\left(\mathbf{x}^{*}\right)=\mathbf{x}^{*}$ (where it is understood that the exponential function is element by element).

For any $\mathbf{x}$ and $\mathbf{y}$ in $\mathbb{R}^{N \times K}$, consider the "max" metric $d(\mathbf{x}, \mathbf{y})=\max _{i, k}\left|x_{i, k}-y_{i, k}\right|$. Then $\left(\mathbb{R}^{N \times K}, d\right)$ is a complete metric space so that by the contraction mapping theorem, there exists a unique $\tilde{\mathbf{x}}^{*} \in \mathbb{R}^{N \times K}$ such that $G\left(\tilde{\mathbf{x}}^{*}\right)=\tilde{\mathbf{x}}^{*}$ (and hence there exists a unique $\mathbf{x}^{*} \in \mathbb{R}_{++}^{N \times K}$ ) if there exists a $\rho \in[0,1)$ such that for all $\mathbf{x}$ and $\mathbf{y}$ in $\mathbb{R}^{N \times K}$ we have $d(G(\mathbf{x}), G(\mathbf{y})) \leq \rho \times$ $d(\mathbf{x}, \mathbf{y})$. We define $\rho \equiv \max _{k \in\{1, \ldots, K\}}\left(\sum_{m=1}^{M}\left|\gamma_{k, m}\right|+\sum_{l=1}^{K}\left|\alpha_{k, l}\right|+\sum_{m=1}^{M}\left|\lambda_{k, m}\right|+\sum_{m=1}^{M}\left|\chi_{k, m}\right|\right)$, and show in the following that $d(G(\mathbf{x}), G(\mathbf{y})) \leq \rho \times d(\mathbf{x}, \mathbf{y})$, as required.

First, choose any two $\mathbf{x}$ and $\mathbf{y}$ in $\mathbb{R}^{N \times K}$. We then can calculate the metric of $G(\mathbf{x})$ and
$G(\mathbf{y}):$

$$
\begin{align*}
d(G(\mathbf{x}), G(\mathbf{y}))= & \max _{i, k} \mid \log \sum_{j} K_{i j, k} \exp \left(\sum_{l=1}^{K} \alpha_{k, l} x_{j, l}+\sum_{m=1}^{M} \gamma_{k, m} Q_{j, m}\left(\mathbf{x}_{j}\right)+\sum_{m=1}^{M} \chi_{k, m} Q_{j, m}\left(\mathbf{x}_{i}\right)\right) \Longleftrightarrow \\
& -\log \sum_{j} K_{i j, k} \exp \left(\sum_{l=1}^{K} \alpha_{k, l} y_{j, l}+\sum_{m=1}^{M} \gamma_{k, m} Q_{j, m}\left(\mathbf{y}_{j}\right)+\sum_{m=1}^{M} \chi_{k, m} Q_{j, m}\left(\mathbf{y}_{i}\right)\right) \mid \\
= & \max _{i, k}\left|\log \frac{\sum_{j} K_{i j, k} \exp \left(\sum_{l=1}^{K} \alpha_{k, l} x_{j, l}+\sum_{m=1}^{M} \gamma_{k, m} Q_{j, m}\left(\mathbf{x}_{j}\right)+\sum_{m=1}^{M} \chi_{k, m} Q_{j, m}\left(\mathbf{x}_{i}\right)\right)}{\sum_{j} K_{i j, k} \exp \left(\sum_{l=1}^{K} \alpha_{k, l} y_{j, l}+\sum_{m=1}^{M} \gamma_{k, m} Q_{j, m}\left(\mathbf{y}_{j}\right)+\sum_{m=1}^{M} \chi_{k, m} Q_{j, m}\left(\mathbf{y}_{i}\right)\right)}\right| \Longleftrightarrow \\
= & \max _{i, k}\left|\log \sum_{j} C_{i j, k}\left(\exp \left(\begin{array}{c}
\sum_{m=1}^{M} \gamma_{l=1}^{K} \alpha_{k, l}\left(x_{j, l}-y_{j, l}\right)+ \\
\sum_{m=1}^{M} \chi_{k, m}\left(Q_{j, m}\left(\mathbf{x}_{j}\right)-Q_{j, m}\left(\mathbf{x}_{j}\right)\right)+ \\
\left.\mathbf{x}_{j, m}\left(\mathbf{y}_{i}\right)\right)
\end{array}\right)\right)\right|, \tag{14}
\end{align*}
$$

where $C_{i j, k} \equiv \sum_{j} \frac{K_{i j, k} \exp \left(\sum_{l=1}^{K} \alpha_{k, l} y_{j, l}+\sum_{m=1}^{M} \gamma_{k, m} Q_{j, m}\left(\mathbf{y}_{j}\right)+\sum_{m=1}^{M} \chi_{k, m} Q_{j, m}\left(\mathbf{y}_{i}\right)\right)}{\sum_{j} K_{i j, k} \exp \left(\sum_{l=1}^{K} \alpha_{k, l} y_{j, l}+\sum_{m=1}^{M} \gamma_{k, m} Q_{j, m}\left(\mathbf{y}_{j}\right)++\sum_{m=1}^{M} \chi_{k, m} Q_{j, m}\left(\mathbf{y}_{i}\right)\right)}$. Note that $\sum_{j} C_{i j, k}=$ 1 for all $i$ and $k$.

Second, note that we can bound the difference in the CES aggregate functions $Q_{m}(\cdot)$ as follows:

$$
\begin{aligned}
& \left|Q_{j, m}\left(\mathbf{x}_{j}\right)-Q_{j, m}\left(\mathbf{y}_{j}\right)\right|=\left\lvert\, \log \left(\sum_{l \in S_{m}} \frac{1}{\left|S_{m}\right|}\left(\left(\sum_{n \in T_{l}} \frac{1}{\left|T_{n}\right|}\left(\exp \left(x_{j, n}\right)\right)^{\delta_{m, l}}\right)^{\frac{1}{\delta_{m, l}}}\right)^{\beta_{m}}\right)^{\frac{1}{\beta_{m}}} \Longleftrightarrow\right. \\
& \left.-\log \left(\sum_{l \in S_{m}} \frac{1}{\left|S_{m}\right|}\left(\left(\sum_{n \in T_{l}} \frac{1}{\left|T_{n}\right|}\left(\exp \left(y_{j, n}\right)\right)^{\delta_{m, l}}\right)^{\frac{1}{\delta_{m, l}}}\right)^{\beta_{m}}\right)^{\frac{1}{\beta_{m}}} \right\rvert\, \\
& =\left|\frac{1}{\beta_{m}} \log \left(\frac{\sum_{l \in S_{m}}\left(\left(\sum_{n \in T_{l}} \frac{1}{\left|T_{n}\right|}\left(\exp \left(x_{j, n}\right)\right)^{\delta_{m, l}}\right)^{\frac{1}{\delta_{m, l}}}\right)^{\beta_{m}}}{\sum_{l \in S_{m}}\left(\left(\sum_{n \in T_{l}} \frac{1}{\left|T_{n}\right|}\left(\exp \left(y_{j, n}\right)\right)^{\delta_{m, l}}\right)^{\frac{1}{\delta_{m, l}}}\right)^{\beta_{m}}}\right)\right| \Longleftrightarrow \\
& =\left|\frac{1}{\beta_{m}} \log \left(\sum_{l \in S_{m}}\left(\lambda_{l}\left(\sum_{n \in T_{l}} \omega_{n, l} \exp \left(\delta_{m, l}\left(x_{j, n}-y_{j, n}\right)\right)\right)^{\frac{1}{\delta_{m, l}}}\right)^{\beta_{m}}\right)\right| \text {, } \\
& \text { where } \omega_{n, l} \equiv \frac{\left(\exp \left(y_{j, n}\right)\right)^{\delta_{m, l}}}{\sum_{n \in T_{l}}\left(\exp \left(y_{j, n}\right)\right)^{\delta_{m, l}}} \text { and } \lambda_{l} \equiv \frac{\left(\left(\frac{1}{\left|T_{n}\right|} \sum_{n \in T_{l}}\left(\exp \left(y_{j, n}\right)\right)^{\delta_{m, l}}\right)^{\frac{1}{\delta_{m, l}}}\right)^{\beta_{m}}}{\sum_{l \in S_{m}}\left(\left(\sum_{n \in T_{l}} \frac{1}{\left|T_{n}\right|}\left(\exp \left(y_{j, n}\right)\right)^{\delta_{m, l}}\right)^{\frac{1}{\delta_{m, l}}}\right)^{\beta_{m}}} \text {. Note that }
\end{aligned}
$$ $\omega_{n, l} \geq 0$ and $\sum_{n \in T_{l}} \omega_{n, l}=1$ and, similarly, $\lambda_{l} \geq 0$ and $\sum_{l \in S_{m}} \lambda_{l}=1$, i.e. both $\omega_{n, l}$ and $\lambda_{l}$

are weights. As a result we have:

$$
\begin{align*}
& \left|Q_{j, m}\left(\mathbf{x}_{j}\right)-Q_{j, m}\left(\mathbf{y}_{j}\right)\right|=\left|\frac{1}{\beta_{m}} \log \left(\sum_{l \in S_{m}}\left(\lambda_{l}\left(\sum_{n \in T_{l}} \omega_{n, l} \exp \left(\delta_{m, l}\left(x_{j, n}-y_{j, n}\right)\right)\right)^{\frac{1}{\delta_{m, l}}}\right)^{\beta_{m}}\right)\right| \Longrightarrow \\
& \left|Q_{j, m}\left(\mathbf{x}_{j}\right)-Q_{j, m}\left(\mathbf{y}_{j}\right)\right| \leq \frac{1}{\beta_{m}} \log \left(\sum_{l \in S_{m}}\left(\left(\sum_{n \in T_{l}} \omega_{n, l} \exp \left(\delta_{m, l}\left(\max _{i, k}\left|x_{i, k}-y_{i, k}\right|\right)\right)\right)^{\frac{1}{\delta_{m, l}}}\right)^{\beta_{m}} \times \lambda_{l}\right) \Longleftrightarrow \\
& \left|Q_{j, m}\left(\mathbf{x}_{j}\right)-Q_{j, m}\left(\mathbf{y}_{j}\right)\right| \leq \max _{i, k}\left|x_{i, k}-y_{i, k}\right| \tag{15}
\end{align*}
$$

Third, we apply Equation (15) and the fact that $\sum_{j} C_{i j, k}=1$ to derive the following bound:

$$
\left.\begin{array}{rl}
\sum_{j} C_{i j, k}\left(\exp \left(\begin{array}{c}
\sum_{l=1}^{K} \alpha_{k, l}\left(x_{j, l}-y_{j, l}\right)+ \\
\sum_{m=1}^{M} \gamma_{k, m}\left(Q_{j, m}\left(\mathbf{x}_{j}\right)-Q_{j, m}\left(\mathbf{y}_{j}\right)\right)+ \\
\sum_{m=1}^{M} \chi_{k, m}\left(Q_{j, m}\left(\mathbf{x}_{i}\right)-Q_{j, m}\left(\mathbf{y}_{i}\right)\right)
\end{array}\right)\right.
\end{array}\right) \leq \sum_{j} C_{i j, k}\left(\exp \left(\begin{array}{c}
\sum_{l=1}^{K}\left|\alpha_{k, l}\right|\left|x_{j, l}-y_{j, l}\right|+ \\
\sum_{m=1}^{M}\left|\gamma_{k, m}\right|\left|\left(Q_{j, m}\left(\mathbf{x}_{j}\right)-Q_{j, m}\left(\mathbf{y}_{j}\right)\right)\right|+  \tag{16}\\
\sum_{m=1}^{M}\left|\chi_{k, m}\right|\left|Q_{j, m}\left(\mathbf{x}_{i}\right)-Q_{j, m}\left(\mathbf{y}_{i}\right)\right|
\end{array}\right) .\right.
$$

Finally, applying Equation (16) to Equation (14) yields:

$$
d(G(\mathbf{x}), G(\mathbf{y})) \leq \rho \times d(\mathbf{x}, \mathbf{y})
$$

as required.

## A. 2 Proof of Corollary 1

We first derive two equilibrium equations from the four conditions defining the equilibrium presented in Section 4.3. We then apply Theorem 1 to this system of equations.

Suppose migration costs are symmetric. Recall the first equilibrium condition requires both:

$$
\begin{gathered}
L_{i}^{n, s}\left(\frac{w_{i}^{n, s}}{P_{i}} u_{i}^{n, s}\right)^{-\theta^{n, s}}=\sum_{j \in \mathcal{N}}\left(\mu_{j i}^{n, s}\right)^{-\theta^{n, s}}\left(\Pi_{j}^{n, s}\right)^{-\theta^{n, s}} L_{j}^{n, s} \\
\left(\Pi_{i}^{n, s}\right)^{\theta^{n, s}} \equiv \sum_{j \in \mathcal{N}}\left(\mu_{i j}^{n, s}\right)^{-\theta^{n, s}}\left(\frac{w_{j}^{n, s}}{P_{j}} u_{j}^{n, s}\right)^{\theta^{n, s}}
\end{gathered}
$$

It turns out that this set of two equations can be simplified to a single equation when migration costs are symmetric. To see this, suppose that the following relationship holds true for some scalar $\kappa^{n, s}>0$ :

$$
L_{i}^{n, s}\left(\frac{w_{i}^{n, s}}{P_{i}} u_{i}^{n, s}\right)^{-\theta^{n, s}}=\kappa^{n, s}\left(\Pi_{i}^{n, s}\right)^{\theta^{n, s}}
$$

Then the first equation becomes:

$$
\begin{aligned}
L_{i}^{n, s}\left(\frac{w_{i}^{n, s}}{P_{i}} u_{i}^{n, s}\right)^{-\theta^{n, s}} & =\sum_{j \in \mathcal{N}}\left(\mu_{j i}^{n, s}\right)^{-\theta^{n, s}}\left(\Pi_{j}^{n, s}\right)^{-\theta^{n, s}} L_{j}^{n, s} \Longleftrightarrow \\
\kappa\left(\Pi_{i}^{n, s}\right)^{\theta, s} & =\sum_{j \in \mathcal{N}}\left(\mu_{j i}^{n, s}\right)^{-\theta^{n, s}}\left(\frac{w_{j}^{n, s}}{P_{j}} u_{j}^{n, s}\right)^{\theta^{n, s}} \kappa \Longleftrightarrow \\
\left(\Pi_{i}^{n, s}\right)^{\theta^{n, s}} & =\sum_{j \in \mathcal{N}}\left(\mu_{i j}^{n, s}\right)^{-\theta^{n, s}}\left(\frac{w_{j}^{n, s}}{P_{j}} u_{j}^{n, s}\right)^{\theta^{n, s}}
\end{aligned}
$$

where the last line imposed symmetry. Hence both equations in the system are identical given the above relationship. This allows us to consider a single non-linear equation:

$$
\begin{equation*}
L_{i}^{n, s}=\kappa^{n, s} \sum_{j \in \mathcal{N}}\left(\mu_{j i}^{n, s}\right)^{-\theta^{n, s}}\left(\frac{w_{i}^{n, s}}{P_{i}} u_{i}^{n, s}\right)^{\theta^{n, s}}\left(\frac{w_{j}^{n, s}}{P_{j}} u_{j}^{n, s}\right)^{\theta^{n, s}} . \tag{17}
\end{equation*}
$$

Similarly, suppose trade costs are symmetric. Recall the fourth equilibrium condition requires that both:

$$
\begin{aligned}
Y_{i}^{\sigma} Q_{i}^{1-\sigma} & =\sum_{j \in \mathcal{N}} \tau_{i j}^{1-\sigma} P_{j}^{\sigma-1} Y_{j} \\
P_{i}^{1-\sigma} & \equiv \sum_{j \in \mathcal{N}} \tau_{j i}^{1-\sigma} Y_{i}^{1-\sigma} Q_{i}^{\sigma-1}
\end{aligned}
$$

Suppose that the following relationship holds true for some scalar $\kappa>0$ :

$$
\begin{align*}
Y_{i}^{\sigma} Q_{i}^{1-\sigma} & =\kappa P_{i}^{1-\sigma} \Longleftrightarrow \\
P_{i} & =\kappa^{\frac{1}{\sigma-1}} Y_{i}^{-\frac{\sigma}{\sigma-1}} Q_{i} \tag{18}
\end{align*}
$$

then the first equation becomes:

$$
\begin{aligned}
Y_{i}^{\sigma} Q_{i}^{1-\sigma} & =\sum_{j \in \mathcal{N}} \tau_{i j}^{1-\sigma} P_{j}^{\sigma-1} Y_{j} \Longleftrightarrow \\
\kappa P_{i}^{1-\sigma} & =\sum_{j \in \mathcal{N}} \tau_{i j}^{1-\sigma}\left(\kappa Y_{j}^{-\sigma} Q_{j}^{\sigma-1}\right) Y_{j} \Longleftrightarrow \\
P_{i}^{1-\sigma} & =\sum_{j \in \mathcal{N}} \tau_{j i}^{1-\sigma} Y_{j}^{1-\sigma} Q_{j}^{\sigma-1}
\end{aligned}
$$

where the last line imposed symmetry of trade costs. Hence the two equations are identical.

This allows us to consider a single non-linear equation:

$$
\begin{align*}
Y_{i}^{\sigma} Q_{i}^{1-\sigma} & =\kappa \sum_{j \in \mathcal{N}} \tau_{i j}^{1-\sigma} Y_{j}^{1-\sigma} Q_{j}^{\sigma-1} \Longleftrightarrow \\
Y_{i} & =\kappa \sum_{j \in \mathcal{N}} \tau_{i j}^{1-\sigma}\left(Y_{i}^{1-\sigma} Q_{i}^{\sigma-1}\right)\left(Y_{j}^{1-\sigma} Q_{j}^{\sigma-1}\right) \tag{19}
\end{align*}
$$

Substituting the price index equation (18) into the migration equation (17) yields:

$$
\begin{aligned}
L_{i}^{n, s} & =\kappa^{n, s} \sum_{j \in \mathcal{N}}\left(\mu_{j i}^{n, s}\right)^{-\theta^{n, s}}\left(\frac{w_{i}^{n, s}}{P_{i}} u_{i}^{n, s}\right)^{\theta^{n, s}}\left(\frac{w_{j}^{n, s}}{P_{j}} u_{j}^{n, s}\right)^{\theta^{n, s}} \Longleftrightarrow \\
L_{i}^{n, s} & =\frac{\kappa^{n, s}}{\kappa^{\frac{2 \theta^{n, s}}{\sigma-1}}} \sum_{j \in \mathcal{N}}\left(\mu_{j i}^{n, s}\right)^{-\theta^{n, s}}\left(\frac{w_{i}^{n, s}}{Y_{i}^{-\frac{\sigma}{\sigma-1}} Q_{i}} u_{i}^{n, s}\right)^{\theta^{n, s}}\left(\frac{w_{j}^{n, s}}{Y_{j}^{-\frac{\sigma}{\sigma-1}} Q_{j}} u_{j}^{n, s}\right)^{\theta^{n, s}}
\end{aligned}
$$

Moreover, using the equilibrium equation (3) for wages from the first order conditions of the producer (the third equilibrium condition):

$$
w_{i}^{n, s}=A_{i}^{n, s} Y_{i} Q_{i}^{\frac{1-\rho}{\rho}}\left(Q_{i}^{s}\right)^{\left(\frac{1}{\rho s}-\frac{1}{\rho}\right)}\left(L_{i}^{n, s}\right)^{-\frac{1}{\rho_{s}}}
$$

we have:

$$
\begin{align*}
L_{i}^{n, s}= & \frac{\kappa^{n, s}}{\kappa^{\frac{2 n, s}{\sigma-1}}} \sum_{j \in \mathcal{N}}\left(\mu_{j i}^{n, s}\right)^{-\theta^{n, s}}\left(\frac{w_{i}^{n, s}}{Y_{i}^{-\frac{\sigma}{\sigma-1}} Q_{i}} u_{i}^{n, s}\right)^{\theta^{n, s}}\left(\frac{w_{j}^{n, s}}{Y_{j}^{-\frac{\sigma}{\sigma-1}} Q_{j}} u_{j}^{n, s}\right)^{\theta^{n, s}} \Longleftrightarrow \\
L_{i}^{n, s}= & \tilde{\kappa}^{n, s} \sum_{j \in \mathcal{N}}\left(\frac{A_{i}^{n, s} u_{i}^{n, s} A_{j}^{n, s} u_{j}^{n, s}}{\mu_{i j}^{n, s}}\right)^{\theta^{n, s}}\left(Y_{i}^{\frac{2 \sigma-1}{\sigma-1}} Q_{i}^{-\frac{2 \rho-1}{\rho}}\left(Q_{i}^{s}\left(\frac{1}{\rho_{s}-\frac{1}{\rho}}\right)\left(L_{i}^{n, s}\right)^{-\frac{1}{\rho_{s}}}\right)^{\theta^{n, s}}\right. \\
& \times\left(Y_{j}^{\frac{2 \sigma-1}{\sigma-1}} Q_{j}^{-\frac{2 \rho-1}{\rho}}\left(Q_{j}^{s}\right)^{\left(\frac{1}{\rho_{s}}-\frac{1}{\rho}\right)}\left(L_{j}^{n, s}\right)^{-\frac{1}{\rho_{s}}}\right)^{\theta^{n, s}} \tag{20}
\end{align*}
$$

We apply Theorem 1 to the system of equations (19) and (20). Note that the second equilibrium condition defines how $Q_{i}$ and $Q_{s}$ are functions of the $\left\{L_{i}^{n, s}\right\}_{n \in\{M, U\}}^{s \in\{h, l\}}$. Recall that Theorem 1 applies to any system of Equations $F: \mathbb{R}_{++}^{N \times K} \rightarrow \mathbb{R}_{++}^{N \times K}$ are written as:

$$
F(\mathbf{x})_{i k} \equiv \sum_{j} K_{i j, k} \prod_{l=1}^{K}\left(x_{j, l}\right)^{\alpha_{k, l}} \prod_{l=1}^{K}\left(x_{i, l}\right)^{\lambda_{k, l}} \prod_{m=1}^{M} Q_{m}\left(\mathbf{x}_{j}\right)^{\gamma_{k, m}} \prod_{m=1}^{M} Q_{m}\left(\mathbf{x}_{i}\right)^{\chi_{k, m}}
$$

where $Q_{m}(\cdot)$ are nested CES aggregating functions:

$$
Q_{m}\left(\mathbf{x}_{j}\right) \equiv\left(\sum_{l \in S_{m}} U_{l}\left(\left(\sum_{n \in T_{l, m}} T_{j, n}\left(x_{j, n}\right)^{\delta_{m, n}}\right)^{\frac{1}{\delta_{m, n}}}\right)^{\beta_{m}}\right)^{\frac{1}{\beta_{m}}}
$$

$\left\{K_{i j, k}, U_{l}, T_{j, n}\right\}$ are all strictly positive parameter values; $S_{m}$ and $T_{l, m}$ are (weak) subsets of $\{1, \ldots, K\}$; and $\left\{\alpha_{k, l}, \lambda_{k, l}, \gamma_{k, m}, \chi_{k, p}\right\}$ are all real-valued.

Equations (19) and (20) are one such system where $N$ is the number of locations, $K=5$ is the number of endogenous variables in each location (corresponding to the four types of labor $L_{i}^{h, M}, L_{i}^{h, U}, L_{i}^{l, M}, L_{i}^{l, U}$ and the income in each location $Y_{i}$, using the production function - equilibrium condition ), and $M=3$ (one CES aggregate for high-skill labor $Q^{h}$, one CES for low-skill labor $Q^{l}$, and one nested CES aggregate across both high and low-skill labor $Q)$. Under the assumptions that $\rho_{s}>\rho$ for $s \in\{h, l\}, \rho>\frac{1}{2}$ and $\sigma>1$, Theorem 1 provides the following sufficient conditions for uniqueness:

$$
\begin{gathered}
\theta^{n, s}<\frac{1}{2}\left(\frac{\sigma-1}{4 \sigma-3}\right) \forall n \in\{M, U\}, s \in\{h, l\} \\
\sigma<\frac{5}{4}
\end{gathered}
$$

as claimed.

## A. 3 Proof of Lemma 1

First, note that we can immediately construct the total income of a location from the location observables as follows: $Y_{i}=\sum_{n \in\{U, M\}, s \in\{h, l\}} w_{i}^{n, s} L_{i}^{n, s}$. Noting that $Y_{i}=p_{i} Q_{i}$ as well and rearranging Equation (8), we have:

$$
\begin{aligned}
& p_{i}^{\sigma-1}=\sum_{j=1}^{N} \tau_{i j}^{1-\sigma} P_{j}^{\sigma-1}\left(\frac{Y_{j}}{Y_{i}}\right) \\
& P_{i}^{1-\sigma}=\sum_{j=1}^{N} \tau_{j i}^{1-\sigma} p_{j}^{1-\sigma}
\end{aligned}
$$

An immediate application of Theorem 3 of Allen, Arkolakis, and Li (2016) tells us that there exists a unique (to-scale) set of $p_{i}^{1-\sigma}$ and $P_{i}^{1-\sigma}$ consistent with observed trade costs $\left\{\tau_{i j}^{1-\sigma}\right\}$ and incomes $\left\{Y_{i}\right\}$.

Identifying amenities proceeds in a similar way. Define $W_{i}^{n, s} \equiv \frac{w_{i}^{n, s}}{P_{i}} u_{i}^{n, s}$ as the welfare of worker of type $\{n, s\}$ in location $i$. Rearranging equation (7) then yields:

$$
\begin{aligned}
\left(W_{i}^{n, s}\right)^{-\theta^{n, s}} & =\sum_{j \in \mathcal{N}}\left(\mu_{j i}^{n, s}\right)^{-\theta^{n, s}}\left(\Pi_{j}^{n, s}\right)^{-\theta^{n, s}} \frac{L_{j 0}^{n, s}}{L_{i}^{n, s}} \\
\left(\Pi_{i}^{n, s}\right)^{\theta^{n, s}} & =\sum_{j \in \mathcal{N}}\left(\mu_{i j}^{n, s}\right)^{-\theta^{n, s}}\left(W_{j}^{n, s}\right)^{\theta^{n, s}}
\end{aligned}
$$

Again, an immediate application of Theorem 3 of Allen, Arkolakis, and Li (2016) tells us that there exists a unique (to-scale) set of $\left(W_{i}^{n, s}\right)^{\theta^{n, s}}$ and $\left(\Pi_{i}^{n, s}\right)^{\theta^{n, s}}$ consistent with observed migration costs $\left\{\left(\mu_{i j}^{n, s}\right)^{-\theta^{n, s}}\right\}$ and populations $\left\{\frac{L_{j,}^{n, s}}{L_{i}^{n, s}}\right\}$.

## A. 4 Proof of Proposition 1

We express the (unobserved) productivities of each type of labor as a function of the local factor price (which from above can be recovered from the data using the market clearing condition). First, taking ratios of United States and Mexican born workers, Equation (3) implies:

$$
\frac{A_{i}^{M, s}}{A_{i}^{U, s}}=\left(\frac{w_{i}^{M, s}}{w_{i}^{U, s}}\right)\left(\frac{L_{i}^{M, s}}{L_{i}^{U, s}}\right)^{\frac{1}{\rho_{s}}} \forall s \in\{h, l\},
$$

so that given observed relative wages and populations (along with the known elasticity of substitution $\rho_{s}$ ), relative productivities of United States to Mexican workers of the same skill group within location are observed. Hence, once the productivity of U.S. workers of a skill group is recovered, we can immediately deduce the productivity of Mexican workers in that skill group.

We proceed by identifying the price and quantity of skilled workers within a location (an identical derivation holds for low-skilled workers). Using the CES aggregate of the price of high-skill workers, we have:

$$
\begin{aligned}
\left(p_{i}^{h}\right)^{1-\rho_{h}} & =\left(A_{i}^{M, h}\right)^{\rho_{h}}\left(w_{i}^{M, h}\right)^{1-\rho_{h}}+\left(A_{i}^{U, h}\right)^{\rho_{h}}\left(w_{i}^{U, h}\right)^{1-\rho_{h}} \Longleftrightarrow \\
\left(p_{i}^{h}\right)^{1-\rho_{h}} & =\left(A_{i}^{U, h}\right)^{\rho_{h}}\left(\left(\frac{A_{i}^{M, h}}{A_{i}^{U, h}}\right)^{\rho_{h}}\left(w_{i}^{M, h}\right)^{1-\rho_{h}}+\left(w_{i}^{U, h}\right)^{1-\rho_{h}}\right) \Longleftrightarrow \\
p_{i}^{h} & =\left(A_{i}^{U, h}\right)^{-\frac{\rho_{h}}{\rho_{h}-1}}\left(\left(\frac{A_{i}^{M, h}}{A_{i}^{U, h}}\right)^{\rho_{h}}\left(w_{i}^{M, h}\right)^{1-\rho_{h}}+\left(w_{i}^{U, h}\right)^{1-\rho_{h}}\right)^{\frac{1}{1-\rho_{h}}} \Longleftrightarrow \\
p_{i}^{h} & =\left(A_{i}^{U, h}\right)^{-\frac{\rho_{h}}{\rho_{h}-1}} \tilde{p}_{i}^{h}
\end{aligned}
$$

where $\tilde{p}_{i}^{h} \equiv\left(\left(\frac{A_{i}^{M, h}}{A_{i}^{U, h}}\right)^{\rho_{h}}\left(w_{i}^{M, h}\right)^{1-\rho_{h}}+\left(w_{i}^{U, h}\right)^{1-\rho_{h}}\right)^{\frac{1}{1-\rho_{h}}}$ can be recovered from observed data. That is, the high-skill price is identified up to the United States high skilled productivity in a location.

Similarly, using the CES aggregate of the quantity of high-skill, we have:

$$
\begin{aligned}
& Q_{i}^{h}=\left(A_{i}^{U, h}\right)^{\frac{\rho_{h}}{\rho_{h}-1}}\left(\frac{A_{i}^{M, h}}{A_{i}^{U, h}}\left(L_{i}^{M, h}\right)^{\frac{\rho_{h}-1}{\rho_{h}}}+\left(L_{i}^{U, h}\right)^{\frac{\rho_{h}-1}{\rho_{h}}}\right)^{\frac{\rho_{h}}{\rho_{h}-1}} \Longleftrightarrow \\
& Q_{i}^{h}=\left(A_{i}^{U, h}\right)^{\frac{\rho_{h}}{\rho_{h}-1}} \tilde{Q}_{i}^{h}
\end{aligned}
$$

where $\tilde{Q}_{i}^{h} \equiv\left(\frac{A_{i}^{M, h}}{A_{i}^{U, h}}\left(L_{i}^{M, h}\right)^{\frac{\rho_{h}-1}{\rho_{h}}}+\left(L_{i}^{U, h}\right)^{\frac{\rho_{h}-1}{\rho_{h}}}\right)^{\frac{\rho_{h}}{\rho_{h}-1}}$ can be recovered from observed data.
Combining the above expressions for prices and quantity yields:

$$
\begin{aligned}
& p_{i}^{h}\left(Q_{i}^{h}\right)^{\frac{1}{\rho}}=\tilde{p}_{i}^{h}\left(A_{i}^{U, h}\right)^{\frac{\rho_{h}}{-\rho_{h}-1}} \times\left(\left(A_{i}^{U, h}\right)^{\frac{\rho_{h}}{\rho_{h}-1}} \tilde{Q}_{i}^{h}\right)^{\frac{1}{\rho}} \Longleftrightarrow \\
& p_{i}^{h}\left(Q_{i}^{h}\right)^{\frac{1}{\rho}}=\tilde{p}_{i}^{h}\left(\tilde{Q}_{i}^{h}\right)^{\frac{1}{\rho}}\left(A_{i}^{U, h}\right)^{\left(\frac{\rho_{h}}{\rho_{h}-1}\right)\left(\frac{1}{\rho}-1\right)}
\end{aligned}
$$

Since the same expression holds for low-skill workers, we can combine these results with the first order condition $p_{i}^{h}\left(Q_{i}^{h}\right)^{\frac{1}{\rho}}=p_{i}^{l}\left(Q_{i}^{l}\right)^{\frac{1}{\rho}}$ to yield:

$$
\begin{gathered}
\tilde{p}_{i}^{h}\left(\tilde{Q}_{i}^{h}\right)^{\frac{1}{\rho}}\left(A_{i}^{U, h}\right)^{\left(\frac{\rho_{h}}{\rho_{h}-1}\right)\left(\frac{1}{\rho}-1\right)} \\
=\tilde{p}_{i}^{l}\left(\tilde{Q}_{i}^{l}\right)^{\frac{1}{\rho}}\left(A_{i}^{U, l}\right)^{\left(\frac{\rho_{l}}{\rho_{l}-1}\right)\left(\frac{1}{\rho}-1\right)} \Longleftrightarrow \\
\left(A_{i}^{U, l}\right)^{\left(\frac{\rho_{l}}{\rho_{l}-1}\right)\left(1-\frac{1}{\rho}\right)}
\end{gathered}=\frac{\tilde{p}_{i}^{U, h}\left(\tilde{Q}_{i}^{h}\right)^{\frac{1}{\rho}}}{\left.\tilde{p}_{h}^{l}\left(\tilde{Q}_{i}^{l}\right)^{\frac{1}{\rho}}\right)\left(1-\frac{1}{\rho}\right)}
$$

Finally, we define $x_{i} \equiv \frac{\left(A_{i}^{U, h}\right)^{\left(\frac{\rho_{h}}{\rho_{h}-1}\right)\left(1-\frac{1}{\rho}\right)}}{\left(A_{i}^{U, l}\right)^{\left(\frac{\rho_{l}}{\rho_{l}-1}\right)\left(1-\frac{1}{\rho}\right)}}=\left(\frac{\left(A_{i}^{U, h}\right)^{\left(\frac{\rho_{h}}{\rho_{h}-1}\right)}}{\left(A_{i}^{U, l}\right)^{\left(\frac{\rho_{l}}{\rho_{l}-1}\right)}}\right)^{-(1-\rho) \frac{1}{\rho}}$ (which can be recovered from data using the above expression) and use the CES aggregate expression for prices to derive an expression for the United States high skilled workers:

$$
\begin{aligned}
& p_{i}^{1-\rho}=\left(p_{i}^{h}\right)^{1-\rho}+\left(p_{i}^{l}\right)^{1-\rho} \Longleftrightarrow \\
& p_{i}^{1-\rho}=\left(\left(A_{i}^{U, h}\right)^{-\frac{\rho_{h}}{\rho_{h}-1}} \times \tilde{p}_{i}^{h}\right)^{1-\rho}+\left(\left(A_{i}^{U, l}\right)^{-\frac{\rho_{l}}{\rho_{l}-1}} \times p_{i}^{l}\right)^{1-\rho} \Longleftrightarrow \\
& p_{i}^{1-\rho}=\left(\left(A_{i}^{U, h}\right)^{-\frac{\rho_{h}}{\rho_{h}-1}} \times \tilde{p}_{i}^{h}\right)^{1-\rho}+\left(\left(A_{i}^{U, l}\right)^{-\frac{\rho_{l}}{\rho_{l}-1}} \times p_{i}^{l}\right)^{1-\rho} \Longleftrightarrow \\
& p_{i}^{1-\rho}=\left(A_{i}^{U, h}\right)^{-\frac{\rho_{h}}{\rho_{h}-1}(1-\rho)}\left(\left(\tilde{p}_{i}^{h}\right)^{1-\rho}+\left(\frac{\left(A_{i}^{U, h}\right)^{\frac{\rho_{h}}{\rho_{h}-1}}}{\left(A_{i}^{U, l}\right)^{\frac{\rho_{l}}{\rho_{l}-1}}}\right)^{(1-\rho)}\left(p_{i}^{l}\right)^{1-\rho} \Longleftrightarrow\right. \\
& p_{i}^{1-\rho}=\left(A_{i}^{U, h}\right)^{-\frac{\rho_{h}}{\rho_{h}-1}(1-\rho)}\left(\left(\tilde{p}_{i}^{h}\right)^{1-\rho}+x_{i}^{-\rho}\left(\tilde{p}_{i}^{l}\right)^{1-\rho}\right) \Longleftrightarrow \\
& A_{i}^{U, h}=\left(\left(\left(\left(\tilde{p}_{i}^{h}\right)^{1-\rho}+x_{i}^{-\rho}\left(\tilde{p}_{i}^{l}\right)^{1-\rho}\right)^{\frac{1}{1-\rho}}\right) / p_{i}\right)^{\frac{\rho_{h}-1}{\rho_{h}}}
\end{aligned}
$$

Finally, we recover $A_{i}^{U, l}$ in all locations:

$$
\left(\frac{\left(A_{i}^{U, h}\right)^{\left(\frac{\rho_{h}}{\rho_{h}-1}\right)\left(1-\frac{1}{\rho}\right)}}{x_{i}}\right)^{\frac{1}{\left(\frac{\rho_{l}}{\rho_{l}-1}\right)\left(1-\frac{1}{\rho}\right)}}=\left(A_{i}^{U, l}\right)
$$

As a result, we have recovered the productivity of all labor types solely as a function of observables and model elasticities. Note that because the factor price is only recovered up to scale (see Lemma 1), each productivity is only recovered up to scale.

Identifying amenities is simpler. Recall that $W_{i}^{n, s} \equiv \frac{w_{i}^{n, s}}{P_{i}} u_{i}^{n, s}$ is the welfare of worker of type $\{n, s\}$ in location $i$. From Lemma 1, there exists a unique (to-scale) set of $\left(W_{i}^{n, s}\right)^{\theta^{n, s}}$ consistent with observed migration costs $\left\{\left(\mu_{i j}^{n, s}\right)^{-\theta^{n, s}}\right\}$ and populations $\left\{\frac{L_{j, 0}^{n, s}}{L_{i}^{n, s}}\right\}$. Since $w_{i}^{n, s}$ is observable in the data and $P_{i}$ is uniquely (to-scale) recovered from the data (see Lemma 1), the amenity of each type of worker is immediately recovered from the following expression:

$$
u_{i}^{n, s}=W_{i}^{n, s} /\left(\frac{w_{i}^{n, s}}{P_{i}}\right)
$$

as required.

## B Data appendix

## B. 1 United States Data

We follow the replication files provided by Ottaviano and Peri (2012) and Borjas, Grogger, and Hanson (2012) and define our sample variables in the same way:

- Our primary sample is all individuals aged 18-64 (inclusive).
- We drop people in group quarters (inlist(gq, $\mathbf{0 , 3 , 4}$ ))
- We define education as low education if the person has complete high school or less (educ variable less than or equal to category 6). We define education as high education if the person has completed some college (educ variable greater than or equal to category 7).
- We define experience as age minus first time worked, where we assume first time worked is 17 for workers with no HS degree, 19 for HS graduates, 21 for workers with some college, and 23 for college graduates. We then drop if experience $<1 \mid$ experience $>40$.
- We use the CPI - U variable to deflate the wage variables into constant year 2000 dollars
- We calculate the usual hours of work per week. Before 1980 and from 2008, we use the midpoint of the aggregated variable wkswork2. For the other years, we use the value reported in the variable hrswork2.
- We sum the variable PERWT to get the total counts of individuals.

Further sample selection rules

- We include both males and females in the analysis. Ottaviano and Peri (2012)and Borjas, Grogger, and Hanson (2012) consider only males
- For computing population counts, we drop self-employed people (classwkrd<20 | classwkrd $>\mathbf{2 8}$ ). We keep people who did not work the last week (this is in contrast to B/OP who drop this. We are interested in employment as an outcome)
- For computing average wages, we drop self-employed people, those with zero wage income, and those who with 0 hours of regular work. Average income is weighted by the number of hours worked.


## B. 2 Mexican data

We follow the same definitions as above as closely as possible to define analgous variables in the Mexican Census.

## B. 3 Geographic concordances

We are restricted to using geographical variables that are available in the public use files. The primary variable is the PUMA (public use microdata areas). PUMAS are redefined after each Census year. We use the IPUMS variable cpuma0010, which provides consistent groupings of PUMAS from 2000-2015 for our primary analysis.

## B. 4 Matrícula Database

One of the data sets used in this study was constructed from the administrative records of the Mexican Matrícula Consular. The original source did not provide numeric identifiers for place of birth or residency, but the names of these locations. In this appendix we describe how we constructed our data set from this records. We will do so in two parts: first merging places of residency to PUMAs in the United States and then merging place of birth to GEOLEV2 locations in Mexico ${ }^{29}$

## Place of residency in the United States

The raw data gives us two pieces of information regarding place of residency, "Current State" and "Current Municipality". The field "Current Municipality" is vague and was interpreted by applicants in different ways, some providing a county, others a city. Furthermore, it is common to use unofficial names, e.g. "LA" for "Los Angeles". To match theses localities to PUMAs, we made use of a crosswalk provided by the Missouri Census Data Center. ${ }^{30}$ It contains the names of all counties, minor civil divisions, cities, villages, towns, etc. in the United States We matched these with the Matrícula data set using the Stata function reclink. After this, we hand-coded the unmatched localities with the highest numbers of Matrículas cards. One example of such location is "LA", which the algorithm could not recognize as being "Los Angeles". This procedure yields the following results: $92 \%$ of the Matrículas Consularess were matched to a PUMA, $7 \%$ did not have place of residency in the raw data and $1 \%$ were not matched.

## Place of birth in Mexico

The raw data gives us two pieces of information regarding place of birth, "State of Birth" and "Municipality of Birth". Again, the field "Municipality of Birth" was interpreted by applicants in different ways. To match these to Municipality codes, we used a list of all geographical divisions of Mexico provided by the Instituto Nacional de Estadistica y Geografia ${ }^{31}$ and the Stata function reclink. As above, we hand-coded the unmatched localities with the highest numbers of Matrículas cards. Finally we used the dictionaries provides by IPUMS to aggregate municipalities to GEOLEV2 areas. This procedure yields the following results:

[^0]$86 \%$ of the Matrículas Consularess were matched to a GEOLEV2, $7 \%$ did not have place of birth in the data and $7 \%$ were not matched.

## B. 5 Verification of Matrícula database

First, we show that the Matrícula counts correlate with measures of migrants from the ACS. Because the stock of migrants at a point in time depends on both the inflows of new migrants and the outflows of pre-existing migrants, we consider three different measures, shown in Appendix Table 2. The first panel considers the elasticity of migrant stocks in the ACS to the number of Matrículas Consularess. We find an elasticity of 6.1 (across all migrants) and an elasticity of 7.7 (for low-educated migrants in the ACS). We then do the same exercise considering a fixed cohort of individuals, born between 1940-1987, to hold constant population growth. We find similar elasticities of 4.6 and 6.1. The second panel considers the correlation between the stock of migrants in levels and the number of Matrículas in levels. We find that each additional Matrícula is associated with an increase of between 0.4 migrants in the $\mathrm{ACS}^{32}$ and 0.42 for the stock of lower-educated migrants. Considering only male migrants and Matrículas issued to males, we find a point estimate of 0.60 . The point estimates using the fixed cohort are larger, at $0.48,0.52$, and 0.77 respectively. The third panel considers the change in the stock of migrants and the level of Matrículas. We find that each additional Matrícula is associated with a net change in the stock of between 0.03-0.07 migrants, although the point estimates are smaller for the fixed cohort estimates.

Next, we repeat the same exercise using Mexican Census data. The population growth rate in Mexico is about twice that of the United States and so we focus on the fixed cohort numbers, although both are included in the table for completeness. Appendix Table ?? shows that the number of Matrículas Consularess correlates negatively with population stocks in the Mexican Census. This is the expected direction because migrants are people who are not living in Mexico. We find that each additional Matrícula is associated with between 14-24 fewer working age people (Panel b) and a change in the stock of Mexican working-age population of between 0.6-1.5 (Panel c) in an Mexican municipality.

[^1]Appendix Table 1: Geographical location of migrants: ACS and Matrícula

|  | $2005 / 2006$ |  |  |  | $2010-2012$ |  |
| :--- | :---: | :---: | :---: | :---: | :---: | :---: |
|  | Matricula | ACS | ACS: recent | Matricula | ACS | ACS: recent |
| Demographics |  |  |  |  |  |  |
| Female | 0.362 | 0.332 | 0.263 | 0.395 | 0.358 | 0.288 |
| High education | 0.035 | 0.000 | 0.000 | 0.039 | 0.000 | 0.000 |
| Destinations |  |  |  |  |  |  |
| California | 0.379 | 0.374 | 0.251 | 0.313 | 0.355 | 0.249 |
| Texas | 0.154 | 0.181 | 0.162 | 0.216 | 0.186 | 0.188 |
| Illinois | 0.093 | 0.068 | 0.050 | 0.075 | 0.068 | 0.052 |
| Arizona | 0.036 | 0.049 | 0.061 | 0.030 | 0.037 | 0.025 |
| Nevada | 0.029 | 0.021 | 0.023 | 0.021 | 0.021 | 0.014 |
| Georgia | 0.027 | 0.028 | 0.049 | 0.030 | 0.027 | 0.038 |
| Florida | 0.025 | 0.030 | 0.050 | 0.028 | 0.026 | 0.031 |
| Colorado | 0.022 | 0.023 | 0.027 | 0.024 | 0.022 | 0.021 |
| North Carolina | 0.022 | 0.025 | 0.042 | 0.037 | 0.027 | 0.040 |
| Washington | 0.021 | 0.021 | 0.025 | 0.011 | 0.024 | 0.026 |
| New Mexico | 0.012 | 0.010 | 0.009 | 0.013 | 0.011 | 0.008 |
| All other states | 0.182 | 0.170 | 0.250 | 0.203 | 0.196 | 0.309 |
| N (average per year) | 887,564 | $5,928,770$ | $1,291,722$ | 841,503 | $5,627,935$ | 573,386 |
| Notes: Table shows share of migrants in each state. Data source: Matrícula Consular database, 2005, 2006, |  |  |  |  |  |  |
| 2010; ACS 2005-2012. Only migrants with high-school education or lower included from ACS. |  |  |  |  |  |  |

Appendix Table 2: Comparing Matrículas and ACS Mexican-born

|  | All |  |  | Fixed cohort (born 1940-1987) |  |  |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: |
|  |  | (2) | (3) | (4) <br> All ACS | (5) | (6) |
| Panel (a): Log-Log |  |  |  |  |  |  |
| Log num matr | $\begin{gathered} 0.061 \\ 0.021^{* *} \end{gathered}$ | $\begin{gathered} 0.077 \\ 0.022^{* * *} \end{gathered}$ |  | $\begin{gathered} 0.046 \\ 0.021^{*} \end{gathered}$ | $\begin{gathered} 0.061 \\ 0.022^{* *} \end{gathered}$ |  |
| Log num male matr |  |  | $\begin{aligned} & 0.030 \\ & 0.020 \end{aligned}$ |  |  | $\begin{aligned} & 0.021 \\ & 0.020 \end{aligned}$ |
| N <br> yearFE <br> cpumaFE | $\begin{gathered} 8287 \\ \text { yes } \\ \text { yes } \end{gathered}$ | $\begin{gathered} 7856 \\ \text { yes } \\ \text { yes } \end{gathered}$ | $\begin{gathered} 8057 \\ \text { yes } \\ \text { yes } \end{gathered}$ | $\begin{gathered} 8251 \\ \text { yes } \\ \text { yes } \end{gathered}$ | $\begin{gathered} 7802 \\ \text { yes } \\ \text { yes } \end{gathered}$ | $\begin{gathered} 8005 \\ \text { yes } \\ \text { yes } \end{gathered}$ |
| Panel (b): Level-Level |  |  |  |  |  |  |
| Num matr | $\begin{gathered} 0.402 \\ 0.017^{* * *} \end{gathered}$ | $\begin{gathered} 0.419 \\ 0.017^{* * *} \end{gathered}$ |  | $\begin{gathered} 0.482 \\ 0.021^{* * *} \end{gathered}$ | $\begin{gathered} 0.517 \\ 0.022^{* * *} \end{gathered}$ |  |
| Num male matr |  |  | $\begin{gathered} 0.598 \\ 0.024^{* * *} \end{gathered}$ |  |  | $\begin{gathered} 0.766 \\ 0.030^{* * *} \end{gathered}$ |
| N <br> yearFE <br> cpumaFE | $\begin{gathered} 11858 \\ \text { yes } \\ \text { yes } \end{gathered}$ | $\begin{gathered} 11858 \\ \text { yes } \\ \text { yes } \end{gathered}$ | $\begin{gathered} 11858 \\ \text { yes } \\ \text { yes } \end{gathered}$ | $\begin{gathered} 11858 \\ \text { yes } \\ \text { yes } \end{gathered}$ | $\begin{gathered} 11858 \\ \text { yes } \\ \text { yes } \end{gathered}$ | $\begin{gathered} 11858 \\ \text { yes } \\ \text { yes } \end{gathered}$ |
| Panel (c): First diff-level |  |  |  |  |  |  |
| Num matr | $\begin{gathered} 0.053 \\ 0.018^{* *} \end{gathered}$ | $\begin{aligned} & 0.031 \\ & 0.017 \end{aligned}$ |  | $\begin{aligned} & 0.008 \\ & 0.018 \end{aligned}$ | $\begin{gathered} -0.021 \\ 0.017 \end{gathered}$ |  |
| Num male matr |  |  | $\begin{gathered} 0.069 \\ 0.024^{* *} \end{gathered}$ |  |  | $\begin{aligned} & 0.004 \\ & 0.024 \end{aligned}$ |
| N yearFE cpumaFE | $\begin{gathered} 10780 \\ \text { yes } \\ \text { ves } \end{gathered}$ | $\begin{gathered} 10780 \\ \text { yes } \\ \text { yes } \end{gathered}$ | $\begin{gathered} 10780 \\ \text { yes } \\ \text { yes } \end{gathered}$ | $\begin{gathered} 10780 \\ \text { yes } \\ \text { yes } \end{gathered}$ | $\begin{gathered} 10780 \\ \text { yes } \\ \text { yes } \end{gathered}$ | $\begin{gathered} 10780 \\ \text { yes } \\ \text { ves } \end{gathered}$ |

Notes: Data compares Matrículas and Mexican-born population in the ACS. Period: 2005-2010;2012-2015.

Appendix Table 3: Comparing Matrículas and Mexican census

|  | All |  |  | Fixed cohort (born 1940-1987) |  |  |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: |
|  | (1) | (2) | (3) | (4) | (5) | (6) |
|  | All | Male | Low-ed | All | Male | Low-ed |
| Panel (a): Log-Log |  |  |  |  |  |  |
| Log num matr | 0.017 | 0.026 |  | -0.009 | -0.004 |  |
|  | 0.008* | 0.008** |  | 0.009 | 0.008 |  |
| Log num male matr |  |  | 0.002 |  |  | -0.017 |
|  |  |  | 0.007 |  |  | 0.007* |
| N <br> yearFE <br> geolev2FE | 6046 | 6046 | 6371 | 6012 | 6012 | 6353 |
|  | yes | yes | yes | yes | yes | yes |
|  | yes | yes | yes | yes | yes | yes |
| Panel (b): Level-Level |  |  |  |  |  |  |
| Num matr | 17.442 | 0.607 |  | -18.126 | -22.878 |  |
|  | $0.624^{* * *}$ | 0.447 |  | $0.627^{* * *}$ | 0.685*** |  |
| Num male matr |  |  | 13.776 |  |  | -14.472 |
|  |  |  | $0.507 * * *$ |  |  | 0.594*** |
| N <br> yearFE <br> geolev2FE | 6054 | 6046 | 6379 | 6020 | 6012 | 6361 |
|  | yes | yes | yes | yes | yes | yes |
|  | yes | yes | yes | yes | yes | yes |
| Panel (c): First diff-sum of level |  |  |  |  |  |  |
| 5-year sum matr | -0.188 | -0.194 |  | -0.614 | -1.374 |  |
|  | $0.034^{* * *}$ | $0.035^{* * *}$ |  | $0.035^{* * *}$ | $0.037 * * *$ |  |
| 5 -year sum male matr |  |  | -0.299 |  |  | -0.587 |
|  |  |  | 0.033*** |  |  | 0.032 ${ }^{* * *}$ |
| N <br> yearFE <br> geolev2FE | 4662 | 4644 | 4662 | 4662 | 4644 | 4662 |
|  | yes | yes | yes | yes | yes | yes |
|  | yes | yes | yes | yes | yes | yes |

Notes: Data compares Matrículas and population in Mexican Census. Mexican Census data from 2005 and 2010. Matrícula data from 2005-2010.

Appendix Table 4: Comparison: Pew Matrícula applicants vs ACS Mexican-born

|  | Pew | 2005 ACS (all) | 2005 ACS (6 states) |
| :--- | :---: | :---: | :---: |
| Share male | 0.59 | 0.54 | 0.52 |
| Age | 31.29 | 36.26 | 36.96 |
| High school educ or less | 0.94 | 0.87 | 0.86 |
| Married | 0.46 |  |  |
| In U.S. for less than 5 years | 0.39 | 0.21 | 0.17 |
| Avg weekly earnings | 334.51 | 441.71 | 451.07 |
| No. obs (unweighted) | 4836 | 62871 | 45683 |

Notes: Data source: Pew Matrícula survey. Pew survey conducted in CA, NY, IL, GA, TX, NC, between July 2004-Jan 2005.

Appendix Table 5: Gravity equations: Matrícula data (robustness: unweighted)

|  | OLS |  | RF |  | IV |  |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: |
|  | (1) | (2) | (3) | (4) | (5) | (6) |
|  | Log(x) | Log(1+x) | $\log (\mathrm{x})$ | Log(1+x) | Log(x) | $\log (1+\mathrm{x})$ |
|  | $\mathrm{b} / \mathrm{se}$ | b/se | b/se | $\mathrm{b} / \mathrm{se}$ | $\mathrm{b} / \mathrm{se}$ | $\mathrm{b} / \mathrm{se}$ |
| Post x change log traveltime | -0.029 | -0.219 |  |  | -0.311 | -0.375 |
|  | 0.060 | 0.009*** |  |  | 0.193 | $0.023 * * *$ |
| Post x change log travel time (pred) |  |  | -0.214 | -0.301 |  |  |
|  |  |  | 0.133 | 0.019*** |  |  |
| N | 451074 | 4969692 | 451074 | 4969692 | 451074 | 4969692 |
| First-stage F stat |  |  |  |  | 753.28 | 4968.09 |
| Mean change travel time var. | 0.036 | 0.018 | 0.017 | 0.018 | 0.036 | 0.018 |
| Destination-year FE | yes | yes | yes | yes | yes | yes |
| Origin-year FE | yes | yes | yes | yes | yes | yes |
| Pair FE | yes | yes | yes | yes | yes | yes |
| SE clustered at: | no | no | no | no | no | no |
| whatSE | pair | pair | pair | pair | pair | pair |

Notes: Data: 2006 and 2010 Matrícula database. Each observation is an origin (Mexican municipality) destination (U.S. PUMA) pair. Log change travel time is the log change in travel time for the least-cost path between the origin and destination pair. Log change travel time (pred) is the change in travel time for the predicted wall expansion.

Appendix Table 6: First stage for gravity equations: Matrícula data

|  | $(1)$ | $(2)$ |
| :--- | :---: | :---: |
|  | $x>0$ | All |
| Dep var: Post x change log travel time | $\mathrm{b} / \mathrm{se}$ | $\mathrm{b} / \mathrm{se}$ |
| Post x change log travel time (pred) | 0.656 | 0.797 |
|  | $0.034^{* * *}$ | $0.027^{* * *}$ |
| N | 451074 | 4969692 |
| First-stage F stat | 382.87 | 858.60 |
| Mean change travel time var. | 0.017 | 0.018 |
| Destination-year FE | yes | yes |
| Origin-year FE | yes | yes |
| Pair FE | yes | yes |
| WLS | yes | yes |
| whatSE | pair | pair |

Notes: Data: 2006 and 2010 Matrícula database. Each observation is an origin (Mexican municipality) - destination (U.S. PUMA) pair. Log change travel time is the log change in traveltime for the least-cost path between the origin and destination pair. Log change travel time (pred) is the change in travel time for the predicted wall expansion.

Appendix Table 7: Fence expansion and choice of crossing location (EMIF data)

|  | $(1)$ |
| :--- | :---: |
|  |  |
| Indicator crossing location | $\mathrm{b} / \mathrm{se}$ |
| Log distance to destination | -0.046 |
|  | $0.022^{* *}$ |
| Log distance to origin | -0.014 |
|  | 0.015 |
| Fence Expansion | -0.030 |
|  | $0.017^{*}$ |
| Origin-destination FE | 568378 |
| Crossing location FE | 0.059 |
| IndividualFE | Yes |
| CrossLocFE | Yes |
| Notes: This table estimates a choice |  |
| model at the individual level (hold- |  |
| ing constant the origin and destina- |  |
| tion) of which of the 17 EMIF border |  |
| crossing points to chose. The stan- |  |
| dard errors are multi-way clustered |  |
| in each of the included fixed effects. |  |

Appendix Table 8: Effect of the wall on population (Simple instrument)


Notes: Data: 20000 Census, 2005 ACS, 2010 ACS. Using network instrument. Recent migrant is a migrant who has been in the U.S. for five years or less. Established migrants have been in the U.S. for longer than five years. Latino migrants are all migrants born in Central or South America. Non-Latino migrants are migrants not born in Central or South America. Controls for log distance to border, population growth between 1990-2000, industry share in 2000 for agriculture, manufacturing, and construction, and the Mian/Sufi housing shock included. Standard errors clustered by state.

Appendix Table 9: Effect of the wall on population (Network instrument)


Notes: Data: 20000 Census, 2005 ACS, 2010 ACS. Using network instrument. Recent migrant is a migrant who has been in the U.S. for five years or less. Established migrants have been in the U.S. for longer than five years. Latino migrants are all migrants born in Central or South America. Non-Latino migrants are migrants not born in Central or South America. Controls for log distance to border, population growth between 1990-2000, industry share in 2000 for agriculture, manufacturing, and construction, and the Mian/Sufi housing shock included. Standard errors clustered by state.

Appendix Table 10: Predicting pop change in Mexico: three measures (rf)

|  | $(1)$ <br> $\mathrm{b} / \mathrm{se}$ | $(2)$ <br> $\mathrm{b} / \mathrm{se}$ | $(3)$ <br> $\mathrm{b} / \mathrm{se}$ |
| :--- | :---: | :---: | :---: |
| Dep var: $\log \left(N_{d t} / N_{d t-1}\right)$ |  |  |  |
| Low-educ pop | -14.641 |  |  |
| Simple | 48.810 |  |  |
|  |  | 0.901 |  |
| Network |  | 1.987 | 2.086 |
|  |  |  | 2.931 |
| GE Network | 0.090 | 0.206 | 0.506 |
| F (inst) |  |  |  |
| No. of migrants in US |  |  |  |
| Simple |  |  |  |
|  |  | -5.207 |  |
| Network |  |  |  |
|  |  |  | 13.263 |

Notes: Standard errors clustered at the state level. Sample is 2000 and 2010 Mexican Censuses.

Appendix Table 11: Migration rate: ENOE data

| Dep var: rate per 10,000 | Out <br> b/se | $\begin{aligned} & \text { In } \\ & \text { b/se } \end{aligned}$ | $\begin{aligned} & \text { Net } \\ & \text { b/se } \end{aligned}$ | Out <br> b/se | $\begin{gathered} \text { In } \\ \mathrm{b} / \mathrm{se} \end{gathered}$ | $\begin{aligned} & \text { Net } \\ & \text { b/se } \end{aligned}$ | $\begin{aligned} & \text { Out } \\ & \mathrm{b} / \mathrm{se} \end{aligned}$ | $\begin{gathered} \text { In } \\ \mathrm{b} / \mathrm{se} \end{gathered}$ | Net <br> b/se |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| Post X wall (pred. 1\% change in migrants) | 0.510 | 0.583 | -0.073 | 0.269 | 0.182 | 0.087 | 0.330 | 0.171 | 0.159 |
|  | 0.300* | $0.197^{* * *}$ | 0.260 | 0.272 | 0.203 | 0.100 | 0.272 | 0.202 | 0.106 |
| Post X log dist border |  |  |  |  |  |  | 0.003 | -0.001 | 0.004 |
|  |  |  |  |  |  |  | 0.002 | 0.002 | 0.001*** |
| N | 4941 | 4941 | 4941 | 4931 | 4931 | 4931 | 4931 | 4931 | 4931 |
| clusterSE | state | state | state | state | state | state | state | state | state |
| stateYrFE | no | no | no | yes | yes | yes | yes | yes | yes |

Notes: Data: 2005/2006 (pre) and 2010-2012 (post) ENOE household data. Measure of wall shock is the network instrument. Migration rates computed from the ENOE following the Mexican Statistical Agency methodological guidelines (INEGI (2012)). If the wall reduced migration out of Mexico then we expect a negative coefficient.

Appendix Table 12: Bilateral gravity estimation (iv spec)

|  | Mexico |  | US |  |
| :--- | :---: | :---: | :---: | :---: |
|  | $(1)$ | $(2)$ | $(3)$ | $(4)$ |
|  | $\log (\mathrm{x})$ | $\log (1+\mathrm{x})$ | $\log (\mathrm{x})$ | $\log (1+\mathrm{x})$ |
|  | $\mathrm{b} / \mathrm{se}$ | $\mathrm{b} / \mathrm{se}$ | $\mathrm{b} / \mathrm{se}$ | $\mathrm{b} / \mathrm{se}$ |
| Post X change log traveltime | -0.295 | -0.237 |  |  |
|  | $0.043^{* * *}$ | $0.010^{* * *}$ |  |  |
| N | 510434 | 15836814 | 182178 | 2272712 |

Notes: Each observation is a geolev2-cpuma0010-year pair. Maximum sample size is 2331 Mexican origins * (2331 Mexican destinations +1066 US destinations) * 2 years $=15.8$ million for Mexico, and 1066 US origins*1066 US destinations $* 2$ years $=2.3$ million for the US. We do not observe US to Mexico flows. Within-U.S. migration flows are not affected by the wall and so there is no estimated coefficient for the U.S., the regressions are included for completeness and to show the sample size.

Appendix Table 13: Correlation of pair fixed effects with geographical variables

|  | Baseline |  | RF |  | IV |  |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: |
|  | (1) <br> $\log (\mathrm{x})$ <br> b/se | $\begin{gathered} (2) \\ \log (1+\mathrm{x}) \\ \mathrm{b} / \mathrm{se} \\ \hline \end{gathered}$ | (3) <br> $\log (\mathrm{x})$ <br> b/se | $\begin{gathered} (4) \\ \log (1+\mathrm{x}) \\ \mathrm{b} / \mathrm{se} \\ \hline \end{gathered}$ | (5) <br> $\log (\mathrm{x})$ <br> b/se | $\begin{gathered} (6) \\ \log (1+\mathrm{x}) \\ \mathrm{b} / \mathrm{se} \\ \hline \end{gathered}$ |
| Log distance | $\begin{gathered} -0.253 \\ 0.000^{* * *} \end{gathered}$ | $\begin{gathered} -0.365 \\ 0.002^{* * *} \end{gathered}$ | $\begin{gathered} -0.253 \\ 0.000^{* * *} \end{gathered}$ | $\begin{gathered} -0.365 \\ 0.002^{* * *} \end{gathered}$ | $\begin{gathered} -1.803 \\ 0.001^{* * *} \end{gathered}$ | $\begin{gathered} -1.471 \\ 0.005^{* * *} \end{gathered}$ |
| Cross border | $\begin{gathered} 0.292 \\ 0.011^{* * *} \end{gathered}$ | $\begin{gathered} 0.414 \\ 0.053^{* * *} \end{gathered}$ | $\begin{gathered} 0.268 \\ 0.011^{* * *} \end{gathered}$ | $\begin{gathered} 0.386 \\ 0.053^{* * *} \end{gathered}$ | $\begin{gathered} -6.773 \\ 0.048^{* * *} \end{gathered}$ | $\begin{gathered} 3.121 \\ 0.130^{* * *} \end{gathered}$ |
| Cross border X log distance | $\begin{gathered} 0.042 \\ 0.002^{* * *} \end{gathered}$ | $\begin{gathered} -0.323 \\ 0.007^{* * *} \end{gathered}$ | $\begin{gathered} 0.045 \\ 0.002^{* *} \end{gathered}$ | $\begin{gathered} -0.319 \\ 0.007^{* * *} \end{gathered}$ | $\begin{gathered} 1.594 \\ 0.007^{* * *} \end{gathered}$ | $\begin{gathered} 0.784 \\ 0.018^{* * *} \end{gathered}$ |
| N | 9054763 | 346306 | 9054763 | 346306 | 9054763 | 346306 |
| Notes: Each observation is a geolev2-cpuma0010-year pair. Maximum sample size is 2331 Mexican origins (2331 Mexican destinations +1066 US destinations $)+1066$ US origins*1066 US destinations $=9.05$ million We do not observe US to Mexico flows. Log distance overland is the log overland distance between an origin and destination. We assign the log average distance within an origin for non-migrants (moves between the same origin and destination). |  |  |  |  |  |  |

Appendix Table 14: Gravity equations:
Trade data

|  | $(1)$ | $(2)$ |
| :--- | :---: | :---: |
| Post x change log | 0.171 |  |
| traveltime | $(0.673)$ |  |
| Log overland |  | $-1.249^{* * *}$ |
| distance |  | $(0.032)$ |
| Log overland |  | $-0.564^{* * *}$ |
| distance * international |  | $(0.153)$ |
| Constant |  | $3.922^{* * *}$ |
|  |  | $(0.207)$ |
| Origin-year FE | Yes | Yes |
| Destination-year FE | Yes | Yes |
| Origin-destination FE | Yes | No |
| R-squared | 0.978 | 0.968 |
| Observations | 6422 | 7011 |

Notes: Each observations is a U.S. state to U.S./Mexico state pair in either 2007 or 2012. The dependent variable is the $\log$ value of trade flows in column 1 and the log value of trade flows normalized by own trade flows in column 2. (The normalized trade flows imply the origin-year and destination-year fixed effects are the same and allow the recovery of the constant). Overland distance is the distance along the shortest overland route between origin and destination. Traveltime is the distance along the shortest overland route that avoids a border wall. Both overland distance and traveltime are averaged across all locations (Mexican municipalities and U.S. PUMAs) within the state-year pair. Standard errors clustered by origin-destination pair. Stars indicate statistical significance: ${ }^{*} \mathrm{p}<.10^{* *} \mathrm{p}<.05^{* * *} \mathrm{p}<.01$.

Appendix Table 15: Estimation of production function elasticities: First stage

|  | Mex./U.S.: Low skill <br> (1) | Mex./U.S.: High skill <br> (2) | High/low skill <br> (3) |
| :---: | :---: | :---: | :---: |
| Simple average wall exposure |  |  |  |
| Simple average wall exposure | 33.874* | 15.541 | -18.481** |
|  | (18.625) | (15.871) | (7.675) |
| ...X Mexico | -153.877 | -235.757 | -116.782 |
|  | (209.293) | (283.587) | (191.707) |
| F-statistic | 1.820 | 0.782 | 3.149 |
| Network wall exposure |  |  |  |
| Network wall exposure | 15.430** | 7.937* | -8.907*** |
|  | (5.928) | (4.350) | (2.204) |
| ...X Mexico | -30.055*** | -29.842*** | -7.274 |
|  | (10.367) | (10.158) | (12.484) |
| F-statistic | 4.866 | 4.512 | 9.036 |
| GE network wall exposure |  |  |  |
| GE network wall exposure | 19.569** | 9.986 | -10.968*** |
|  | (8.620) | (6.818) | (3.365) |
| ...X Mexico | $-40.802^{* * *}$ | -40.532*** | -0.728 |
|  | (13.250) | (11.759) | (11.250) |
| F-statistic | 4.803 | 6.155 | 5.906 |
| ControlsFixed Effects | None | None | None |
|  | State | State | State |
| Standard ErrorsWeighting | State clusters | State clusters | State clusters |
|  | Pre-pop. | Pre-pop. | Pre-pop. |
| Sample | U.S. and Mex. | U.S. and Mex. | U.S. and Mex. |
| Observations | 3392 | 3392 | 3392 |

Notes: Ordinary least squares. Each observation is a (log) difference in a U.S. or Mexico location pre- and post- the SFA. Preand post- data come from the 2000 and 2010 censuses in Mexico, respectively; pre- data in the U.S. comes from the 2000 census and post-data come from an average of the 2010-2012 ACS. The dependent variable is the change in the relative population shares. The independent variable (the instrument) is either a simple average fence exposure which is the unweighted average fence exposure across all origins; a network wall exposure which is a weighted average fence exposure across all origins, where the weights are the pre-period migration flows; or a $G E$ network wall exposure which in addition to weighting flows by pre-period mirgation flows also accounts for substitution in migration across different destinations by correcting for each orgin's market access; see the text for details. Standard errors are reported in parentheses. Stars indicate statistical significance: * p<. 10 ** $\mathrm{p}<.05^{* * *} \mathrm{p}<.01$

Appendix Table 16: Estimation of migration elasticities: First stage

|  | (1) | (2) | (3) | (4) | (5) |
| :---: | :---: | :---: | :---: | :---: | :---: |
| Simple average wall exposure |  |  |  |  |  |
| Simple average wall exposure | $\begin{gathered} -23.537^{* * *} \\ (5.708) \end{gathered}$ | $\begin{gathered} -12.559 \\ (12.922) \end{gathered}$ | $\begin{gathered} -3.686 \\ (4.208) \end{gathered}$ | $\begin{gathered} -0.050 \\ (5.965) \end{gathered}$ | $\begin{gathered} -5.027 \\ (4.991) \end{gathered}$ |
| ...X Mexico | $\begin{gathered} -3.195 \\ (81.381) \end{gathered}$ | $\begin{gathered} -55.140 \\ (97.026) \end{gathered}$ | $\begin{gathered} 177.362 \\ (151.998) \end{gathered}$ | $\begin{aligned} & 287.775^{*} \\ & (146.874) \end{aligned}$ | $\begin{aligned} & -23.385 \\ & (79.459) \end{aligned}$ |
| F-statistic | 8.555 | 0.720 | 1.037 | 1.922 | 0.571 |
| Network wall exposure |  |  |  |  |  |
| Network wall exposure | $\begin{gathered} -7.838^{* * *} \\ (1.194) \end{gathered}$ | $\begin{gathered} -2.926 \\ (2.823) \end{gathered}$ | $\begin{gathered} -1.790 \\ (1.452) \end{gathered}$ | $\begin{gathered} 0.380 \\ (0.960) \end{gathered}$ | $\begin{gathered} -1.869^{* *} \\ (0.715) \end{gathered}$ |
| ...X Mexico | $\begin{gathered} 4.402 \\ (2.918) \end{gathered}$ | $\begin{gathered} -0.211 \\ (5.584) \end{gathered}$ | $\begin{gathered} 0.796 \\ (10.555) \end{gathered}$ | $\begin{gathered} 2.514 \\ (4.836) \end{gathered}$ | $\begin{aligned} & -1.493 \\ & (2.944) \end{aligned}$ |
| F-statistic | 22.372 | 0.749 | 0.765 | 0.265 | 4.111 |
| GE network wall exposure |  |  |  |  |  |
| GE network wall exposure | $\begin{gathered} -9.248^{* * *} \\ (1.291) \end{gathered}$ | $\begin{gathered} -3.275 \\ (3.187) \end{gathered}$ | $\begin{gathered} -1.251 \\ (1.885) \end{gathered}$ | $\begin{gathered} 1.050 \\ (0.961) \end{gathered}$ | $\begin{aligned} & -1.463 \\ & (0.975) \end{aligned}$ |
| ...X Mexico | $\begin{gathered} 5.386 \\ (3.596) \end{gathered}$ | $\begin{gathered} 1.551 \\ (7.263) \end{gathered}$ | $\begin{gathered} 1.799 \\ (12.429) \end{gathered}$ | $\begin{gathered} 0.408 \\ (5.569) \end{gathered}$ | $\begin{gathered} -2.064 \\ (3.810) \end{gathered}$ |
| F-statistic | 26.322 | 0.563 | 0.221 | 0.632 | 1.584 |
| Controls | None | None | None | None | None |
| Fixed Effects | State | State | State | State | State*Type |
| Standard Errors | State clusters | State clusters | State clusters | State clusters | State clusters |
| Weighting | Pre-pop. | Pre-pop. | Pre-pop. | Pre-pop. | Pre-pop. |
| Sample | U.S. and Mex. | U.S. and Mex. | U.S. and Mex. | U.S. and Mex. | U.S. and Mex. |
| Observations | 3392 | 3392 | 3392 | 3392 | 13568 |

Notes: Ordinary least squares. Each observation is a (log) difference in a U.S. or Mexico location pre- and post- the SFA. Preand post- data come from the 2000 and 2010 censuses in Mexico, respectively; pre- data in the U.S. comes from the 2000 census and post-data come from an average of the $2010-2012$ ACS. The dependent variable is the ( $\log$ ) change in the real wage, where the nominal wages are observed and the price indices are calculated from the trade destination fixed effect and the estimated trade elasticity. The independent variable (the instrument) is either a simple average fence exposure which is the unweighted average fence exposure across all origins; a network wall exposure which is a weighted average fence exposure across all origins, where the weights are the pre-period migration flows; or a $G E$ network wall exposure which in addition to weighting flows by pre-period mirgation flows also accounts for substitution in migration across different destinations by correcting for each orgin's market access; see the text for details. Standard errors are reported in parentheses. Stars indicate statistical significance: * p<. 10 ${ }^{* *} \mathrm{p}<.05^{* * *} \mathrm{p}<.01$.

Appendix Table 17: Robustness of estimated structural parameters: Simple instrument

|  | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| EoS between Mex. and | $3.715^{* * *}$ | 3.515*** | $3.130^{* * *}$ | 3.962 | 3.724*** | $3.808^{* * *}$ | 4.685 | $3.203^{* * *}$ | 3.938*** | 3.305*** |
| U.S. low skill ( $\rho_{l}$ ) | (0.853) | (1.241) | (1.050) | (4.768) | (0.931) | (1.093) | (10.195) | (0.623) | (0.846) | (0.615) |
| EoS between Mex. and | 24.912 | -5.575 | -6.792 | -2.935 | 8.297 | 361.748 | -1.567 | $2.288^{* * *}$ | 7.559 | 2.480*** |
| U.S. high skill ( $\rho_{h}$ ) | (265.660) | (22.164) | (34.024) | (5.627) | (22.830) | (6.5e+04) | (2.535) | (0.391) | (13.328) | (0.590) |
| EoS between high and | 1.693*** | 1.182*** | 1.578* | 1.565*** | 1.698*** | 1.578*** | 0.956 ** | 1.539*** | 1.984*** | 1.556*** |
| low skill ( $\rho$ ) | (0.416) | (0.299) | (0.807) | (0.341) | (0.381) | (0.271) | (0.397) | (0.325) | (0.676) | (0.349) |
| EoS between goods | 1.373*** | 0.964*** | 1.179*** | 1.348*** | 1.256*** | 1.574*** | 1.010*** | $2.216^{* * *}$ | 1.754 | 2.107*** |
| produced in different locations ( $\sigma$ ) | (0.390) | (0.105) | (0.387) | (0.353) | (0.293) | (0.460) | (0.049) | (0.696) | (2.533) | (0.525) |
| Mex. Low skill | -0.949 | 0.118 | -0.596* | -0.421** | -0.753* | -0.858* | -0.005 | -1.329 | -1.685 | -1.268 |
| migration elasticity ( $\theta_{l}^{M}$ ) | (0.583) | (0.166) | (0.308) | (0.182) | (0.425) | (0.439) | (0.011) | (0.884) | (1.667) | (0.837) |
| Mex. High skill | 0.994 | -0.289 | 0.634 | 0.802 | 0.755 | 1.365 | $0.053 *$ | 1.391 | 1.540 | 1.110 |
| migration elasticity ( $\theta_{h}^{M}$ ) | (1.103) | (0.191) | (0.615) | (0.677) | (0.838) | (1.519) | (0.029) | (2.514) | (3.840) | (2.957) |
| U.S. Low skill | 0.173 | 0.014 | 0.003 | 1.264 | -0.024 | 0.516 | -0.146 | -1.430 | -4.713 | -1.019 |
| migration elasticity ( $\theta_{l}^{U}$ ) | (0.986) | (0.100) | (0.658) | (1.912) | (0.497) | (1.342) | (0.343) | (6.096) | (14.563) | (3.712) |
| U.S. High skill | 0.260 | -0.184** | 1.149 | 0.208 | 2.176 | -2.038 | 0.012 | $-2.534$ | -1.888*** | $-2.666$ |
| migration elasticity $\left(\theta_{h}^{U}\right)$ | (1.049) | (0.088) | (1.133) | (0.984) | (2.847) | (2.589) | (0.043) | (2.334) | (0.500) | (2.655) |
| Pooled migration | 0.057 $(0.582)$ | ${ }_{(0.034}$ | -0.119 | -0.470 | ${ }^{0.053}$ | ${ }^{0.210}$ | -0.009 | ${ }^{0.861}$ | -0.961 | 0.939 |
| elasticity $(\bar{\theta})$ | (0.582) | (0.031) | (0.352) | (0.410) | (0.368) | (1.008) | (0.023) | (4.779) | (1.476) | (4.843) |
| Controls: |  |  |  |  |  |  |  |  |  |  |
| 1990-2000 pop. growth (by type) | No | Yes | No | No | No | No | Yes | No | No | No |
| 2000-2005 pop. growth (by type) | No | No | Yes | No | No | No | Yes | No | No | No |
| Distance to border (log) | No | No | No | Yes | No | No | Yes | No | No | No |
| 2000 U.S. Ag. employ. share | No | No | No | No | Yes | No | Yes | No | No | No |
| Housing shock | No | No | No | No | No | Yes | Yes | No | No | No |
| IV construction: |  |  |  |  |  |  |  |  |  |  |
| IV interacted with.. | Country | Country | Country | Country | Country | Country | Country | None | Country | None |
| Wall location used.. | Predicted | Predicted | Predicted | Predicted | Predicted | Predicted | Predicted | Predicted | Actual | Predicted |
| Sample | U.S. and Mex. | U.S. and Mex. | U.S. and Mex. | U.S. and Mex. | U.S. and Mex. | U.S. and Mex. | U.S. and Mex. | U.S. and Mex. | U.S. and Mex. | U.S. only |
| Fixed Effects | State | State | State | State | State | State | State | State | State | State |
| Weighting | Pre-pop. | Pre-pop. | Pre-pop. | Pre-pop. | Pre-pop. | Pre-pop. | Pre-pop. | Pre-pop. | Pre-pop. | Pre-pop. |
| Standard errors | State clusters | State clusters | State clusters | State clusters | State clusters | State clusters | State clusters | State clusters | State clusters | State clusters |

[^2]Appendix Table 18: Robustness of estimated structural parameters: Network instrument

|  | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| EoS between Mex. and | 4.492*** | 3.949*** | 3.707** | 4.267 | 4.217*** | 4.651** | 2.873 | 3.467** | 4.920*** | $3.975^{* * *}$ |
| U.S. low skill ( $\rho_{l}$ ) | (1.513) | (1.476) | (1.615) | (5.348) | (1.006) | (1.819) | (2.423) | (1.353) | (0.847) | (0.666) |
| EoS between Mex. and | 8.797 | -10.945 | 35.493 | -27.584 | 5.048 | 9.666 | -4.463 | 1.613 | 4.369 | 2.612* |
| U.S. high skill ( $\rho_{h}$ ) | (11.884) | (15.961) | (228.280) | (106.803) | (4.013) | (15.122) | (3.738) | (1.382) | (2.785) | (1.349) |
| EoS between high and | 1.930*** | 1.575*** | 1.831** | 2.028** | $1.946^{* * *}$ | 1.840*** | 1.448* | 1.442*** | 1.711*** | $1.668^{* * *}$ |
| low skill ( $\rho$ ) | (0.529) | (0.567) | (0.898) | (0.919) | (0.496) | (0.466) | (0.834) | (0.118) | (0.264) | (0.266) |
| EoS between goods | $2.977^{* * *}$ | $1.087^{* * *}$ | $2.140^{* * *}$ | $3.158^{* * *}$ | $2.708^{* * *}$ | 3.024*** | 1.022** | 3.940 | $2.149^{* * *}$ | $2.501^{* * *}$ |
| produced in different locations ( $\sigma$ ) | (0.420) | (0.333) | (0.485) | (0.399) | (0.570) | (0.151) | (0.429) | (5.069) | (0.604) | (0.304) |
| Mex. Low skill | -1.096** | -0.335 | -1.045** | -0.789** | -1.339* | -1.002** | -0.033 | -1.111* | -0.155 | -1.092** |
| migration elasticity ( $\theta_{l}^{M}$ ) | (0.513) | (0.363) | (0.507) | (0.337) | (0.686) | (0.465) | (0.028) | (0.610) | (0.274) | (0.550) |
| Mex. High skill | 1.193 | 0.913 | 1.144 | 1.185 | 0.841 | 1.253 | 0.160 | 1.218 | 2.149 | 0.670 |
| migration elasticity ( $\theta_{h}^{M}$ ) | (1.806) | (1.197) | (1.773) | (1.665) | (1.158) | (1.888) | (0.101) | (1.823) | (1.657) | (1.050) |
| U.S. Low skill | 1.187 | 0.177 | 0.897 | -0.959 | 1.229 | 1.503 | 0.021 | 1.189 | 2.082 | 1.209 |
| migration elasticity ( $\theta_{l}^{U}$ ) | (1.828) | (0.259) | (1.933) | (0.835) | (1.271) | (2.450) | (0.211) | (1.961) | (2.111) | (1.756) |
| U.S. High skill | -11.653 | 0.633** | -8.406 | 4.698 | -4.947 | -10.355 | 0.171 | -11.408 | -9.754 | -31.514 |
| migration elasticity ( $\theta_{h}^{U}$ ) | (22.237) | (0.272) | (27.219) | (16.269) | (9.386) | (15.942) | (0.173) | (18.611) | (7.569) | (149.214) |
| Pooled migration | -0.389 | 0.074 | -0.557 | -0.390 | -0.359 | -0.397 | -0.014 | -0.158 | 0.546 | 1.156 |
| elasticity ( $\bar{\theta}$ ) | (0.512) | (0.143) | (0.492) | (0.386) | (0.719) | (0.529) | (0.051) | (0.573) | (0.595) | (0.781) |
| Controls: |  |  |  |  |  |  |  |  |  |  |
| 1990-2000 pop. growth (by type) | No | Yes | No | No | No | No | Yes | No | No | No |
| 2000-2005 pop. growth (by type) | No | No | Yes | No | No | No | Yes | No | No | No |
| Distance to border (log) | No | No | No | Yes | No | No | Yes | No | No | No |
| 2000 U.S. Ag. employ. share | No | No | No | No | Yes | No | Yes | No | No | No |
| Housing shock | No | No | No | No | No | Yes | Yes | No | No | No |
| IV construction: |  |  |  |  |  |  |  |  |  |  |
| IV interacted with.. | Country | Country | Country | Country | Country | Country | Country | None | Country | None |
| Wall location used.. | Predicted | Predicted | Predicted | Predicted | Predicted | Predicted | Predicted | Predicted | Actual | Predicted |
| Sample | U.S. and Mex. | U.S. and Mex. | U.S. and Mex. | U.S. and Mex. | U.S. and Mex. | U.S. and Mex. | U.S. and Mex. | U.S. and Mex. | U.S. and Mex. | U.S. only |
| Fixed Effects | State | State | State | State | State | State | State | State | State | State |
| Weighting | Pre-pop. | Pre-pop. | Pre-pop. | Pre-pop. | Pre-pop. | Pre-pop. | Pre-pop. | Pre-pop. | Pre-pop. | Pre-pop. |
| Standard errors | State clusters | State clusters | State clusters | State clusters | State clusters | State clusters | State clusters | State clusters | State clusters | State clusters |

Notes: This table shows the estimated structural parameters for under a variety of alternative specifications. Every row is a result from a different regression; in each regression, each observation is a (log) difference in a U.S. or Mexico location pre- and post- the SFA. Pre- and post- data come from the 2000 and 2010 censuses in Mexico, respectively; pre- data in the U.S. comes from the 2000 census and post-data come from an average of the 2010-2012 ACS. Column (1) summarize the preferred results presented in Tables 5, 6, and 7. Columns (2) - (7) include additional control variables including the 1990-2000 population growth rate of each of the four types of labor, the 2000-2005 population growth rate of each of the four types of labor, the (log) distance to the border, the year 2000 agricultural employment share of each U.S. location, and a measure of the housing shock from Mian and Sufi (2014). Column (8) requires the instrument to have the same impact in the U.S. and Mexico by removing the country interaction. Column (9) constructs the instrument using the actual location of the border wall expansion (instead of the predicted location due to geography along the border). Column (10) restricts the analysis to U.S. locations only. Standard errors are reported in parentheses. Stars indicate statistical significance: ${ }^{*} \mathrm{p}<.10{ }^{* *} \mathrm{p}<.05{ }^{* * *} \mathrm{p}<.01$.

Appendix Figure 1: Example of border walls


Appendix Figure 2: Wall expansion by year


Notes: Source: Data shared by Guerrero and Castañeda (2017).

Appendix Figure 3: Matrícula database: Migration to CA
(a) Destination: California


Notes: Source: 2006 Matrícula Consular database.

Appendix Figure 4: Matrícula database: migration to Texas
(a) Destination: Texas


Notes: Source: 2006 Matrícula Consular database.

Appendix Figure 5: Matrícula gravity: Event study


Notes: Data: 2005, 2006, 2010, 2012-2015 Matrícula database. Figure plots the coefficient, by year, on log change travel time from a gravity regression. Regression weighted by flows. Standard errors clustered at the pair level.

Appendix Figure 6: Event studies (unweighted)

Panel (i): United States


Notes: Figure shows the predicted change in low-skill Mexican born for each of the three instruments. Panel (i) considers the effect on destinations in the United States. Panel (ii) considers the effect on origins in Mexico. Instruments defined in text.

Appendix Figure 7: Event studies (no controls)

## Panel (i): United States



Notes: Figure shows the predicted change in low-skill Mexican born for each of the three instruments. Panel (i) considers the effect on destinations in the United States. Panel (ii) considers the effect on origins in Mexico. Instruments defined in text.


Appendix Figure 9: Apprehensions of Mexican and non-Mexican nationals by border sector
(a) Mexican nationals
(b) Non-Mexican nationals



Notes: Figure shows apprehensions of Mexican and non-Mexican nationals on the United StatesMexico border between 2000 and 2015 fiscal year for each of the nine border sectors. The three Texan border sectors with little wall are bolded. Data source: United States Customs and Border Patrol. Downloaded: 1/14/2018.https://www.cbp.gov/sites/default/files/assets/ documents/2017-Dec/BP\%20Total\%20Apps\%2C\%20Mexico\%2C\%200TM\%20FY2000-FY2017.pdf

Appendix Figure 10: Migration rates from ENOE


Notes: Data source: ENOE survey. Wall exposure is measured by the network instrument. Migration rates computed from the ENOE following the Mexican Statistical Agency methodological guidelines (INEGI (2012)).

Appendix Figure 11: Counterfactual wall expansion


Notes: Figure shows the expansion of the wall. We fill in the wall based on our geographical prediction of where the wall was built, filling in the next $25 \%$ and $50 \%$ of the remaining pixels.


[^0]:    ${ }^{29}$ PUMAs and GEOLEV2 are time-invariant geographical divisions provided by IPUMS, which are comparable to counties, but usually larger. More details in https://usa.ipums.org/usa/
    ${ }^{30}$ http://mcdc.missouri.edu/websas/geocorr2k.html
    ${ }^{31}$ See "Catálogo de Claves de Entidades Federativas y Municipios" in http://www.inegi.org.mx/ default.aspx.

[^1]:    ${ }^{32}$ We should expect this value to be less than one: demographers estimate that the ACS and the Census under-count unauthorized migration by 8-13\% Passel and Cohn (2016).

[^2]:    Notes: This table shows the estimated structural parameters for under a variety of alternative specifications. Every row is a result from a different regression; in each regression, each observation is a (log) difference in a U.S. or Mexico location pre- and postthe SFA. Pre- and post- data come from the 2000 and 2010 censuses in Mexico, respectively; pre- data in the U.S. comes from the 2000 census and post-data come from an average of the $2010-2012$ ACS. Column (1) summarize the preferred results presented in
    Tables 5,6 , and 7 . Columns (2) - (7) include additional control variables including the $1990-2000$ population growth rate of each of the four types of labor, the $2000-2005$ population growth rate of each of the four types of labor, the (log) distance to the border, the year 2000 agricultural employment share of each U.S. location, and a measure of the housing shock from Mian and Sufi (2014). Column (8) requires the instrument to have the same impact in the U.S. and Mexico by removing the country interaction. Column
    ${ }^{(9)}$ constructs the instrument using the actual location of the border wall expansion (instead of the predicted location due to geography along the border). Column (10) restricts the analysis to U.S. locations only. Standard errors are reported in parentheses.
    Stars indicate statistical significance: * $\mathrm{p}<.10^{* *} \mathrm{p}<.05$ *** $\mathrm{p}<.01$.

