Online Appendix

A1 Proof of Proposition A1

Proposition A1:

Let $|l|$ and $|g_k|$ denote, respectively, the number of workers classified as worker type l and the number of workers whose job match would be classified as group g (either stayers or new hires among those in l) if hired by position k (a subset of the workers in $l(g)$). In addition, let $n(l)$ denote the share of all workers assigned to worker type l, so that $|l| = n(l)I$. Further, define C_l as the mean value of $e^{-\frac{r_i}{\sigma}}$ for a given worker type l. Define $S_{g|l,k}$ as the share of workers of worker type l who would be assigned to group g if they filled position k (i.e. the share of workers who are incumbents at the firm if $z(g) = 1$, the share who would be within-industry job movers if $z(g) = 2$, and the share who would be industry switchers if $z(g) = 0$), and define $\overline{S}_{g|l,f}$ to be the mean of $S_{g|l,k}$ among all k assigned to position type f. Suppose the following assumptions hold:

$$\text{\textit{Assumption 1:}}\quad \frac{1}{|g_k|}\sum_{i:g(i,k)=g} e^{-\frac{r_i}{\sigma}} \approx \frac{1}{|l|}\sum_{i:l(i)=l(g)} e^{-\frac{r_i}{\sigma}} = C_{l(g)}\ \forall (g,k) \tag{9}$$

$$\text{\textit{Assumption 2:}}\quad S_{g|l,k} \approx \overline{S}_{g|l,f}\ \forall\, k,\ \forall\, g \tag{10}$$

Then the equilibrium aggregate group-level choice probabilities can be written as follows:

$$P(g|f) = \frac{e^{\frac{\theta_g}{\sigma}}\overline{S}_{g|l,f}n(l)C_l}{\sum_{l'\in\mathcal{L}}\sum_{g'\in(l,f)} e^{\frac{\theta_{g'}}{\sigma}}\overline{S}_{g'|l',f}n(l')C_{l'}} \tag{11}$$

Proof: Building off the second welfare theorem, Shapley and Shubik (1972) show that Walrasian equilibrium assignment in this game maximizes a linear programming problem. This then implies that the unique stable assignment can also be found by solving the dual problem: identifying a set of worker utility values $\{r_i\}$ and position profit values $\{q_k\}$ that minimize the total "cost" of all workers and positions, $\sum_{i\in\mathcal{I}} r_i + \sum_{k\in\mathcal{K}} q_k$, subject to the constraint that these values cannot violate the underlying joint surplus values: $r_i + q_k \geq \pi_{ik}\ \forall\ (i,k)$. Crucially, inspection of the problem reveals that the stable assignment is fully determined by the joint surplus values $\{\pi_{ik}\}$; no separate information on the worker and firm components π^i_{ik} and π^k_{ik} is needed. Following GS, this dual problem yields the following conditions that define the optimal assignment:

$$\mu_{ik} = 1 \text{ iff } k \in \arg\max_{k\in\mathcal{K}\cup 0} \pi_{ik} - q_k \text{ and } i \in \arg\max_{i\in\mathcal{I}\cup 0} \pi_{ik} - r_i \tag{12}$$

Given optimal worker and position payoffs $\{r_i\}$ and $\{q_k\}$ from the dual solution, Shapley and

Shubik (1972) show how to decentralize this optimal assignment via a set of earnings transfers w_{ik}:

$$w_{ik} = \pi_{ik}^k - q_k \tag{13}$$

Because $r_i + q_k = \pi_{ik} \equiv \pi_{ik}^i + \pi_{ik}^k$ for any matched pair (i, k) in the stable match, this implies:

$$w_{ik} = r_i - \pi_{ik}^i \tag{14}$$

Using (13) and (14), the conditions (12) can be rewritten as the standard requirements that worker and establishment choices must be utility- and profit-maximizing, respectively:

$$\mu_{ik} = 1 \text{ iff } k \in \arg\max_{k \in \mathcal{K} \cup 0} \pi_{ik}^i + w_{ik} \text{ and } i \in \arg\max_{i \in \mathcal{I} \cup 0} \pi_{ik}^k - w_{ik} \tag{15}$$

Given candidate equilibrium payoffs $\{r_i\}$ combined with the i.i.d. Type 1 EV assumption for ϵ_{ik}, Decker et al. (2013) show that the probability that hiring (or retaining) i maximizes k's payoff is given by:

$$P(i|k) = \frac{e^{\frac{\theta_g - r_i}{\sigma}}}{\sum_{i' \in \mathcal{I}} e^{\frac{\theta_{g'} - r_{i'}}{\sigma}}} \tag{16}$$

Next, note that the law of total probability implies:

$$\begin{aligned} P(g|f) &= \sum_{k \in f} P(g|f,k)P(k|f) = \frac{1}{|f|} \sum_{k \in f} P(g|k) = \frac{1}{|f|} \sum_{k \in f} \sum_{i:g(i,k)=g} P(i|k) \\ &= \frac{1}{|f|} \sum_{k \in f} \sum_{i:g(i,k)=g} \frac{e^{\frac{\theta_g - r_i}{\sigma}}}{\sum_{i' \in \mathcal{I}} e^{\frac{\theta_{g'} - r_{i'}}{\sigma}}} = \frac{1}{|f|} \sum_{k \in f} \frac{(e^{\frac{\theta_g}{\sigma}})(\sum_{i:g(i,k)=g} e^{\frac{-r_i}{\sigma}})}{\sum_{i' \in \mathcal{I}} e^{\frac{\theta_{g'} - r_{i'}}{\sigma}}}, \end{aligned} \tag{17}$$

where $|f|$ captures the number of positions k assigned to position type f.

Assumption 1 imposes that the mean exponentiated worker utility values $e^{\frac{-r_i}{\sigma}}$ vary minimally across groups g featuring the same worker type $l(g)$. Given the characteristics used to define l and g in the empirical application, this states that existing employees (potential stayers) and non-employees of each establishment (both from the same industry and from other industries) have approximately the same mean value of r_i among workers whose initial jobs were in the same local area and pay category. In other words, the payoffs that workers in the same initial earnings and age class require in equilibrium will not differ systematically across establishments within a small local area. This becomes a better approximation as more characteristics and categories are used to define a worker type $l(i)$.

Assumption 2 imposes that the share of potential stayers vs. new hires from the same and from different industries among workers from each worker type l is common across establishments within position type f. In the chosen context, this means that establishments in the same geographic area, industry supersector, and establishment size and average pay categories have roughly the same number and past pay and age composition of employees. This assumption is necessary because the probability of filling a position with an existing employee depends on how many employees one already has, so that without it the worker retention rate depends on sizes and worker type compositions of establishments that are at risk of retaining a worker.

Importantly, Assumptions 1 and 2 are only necessary to isolate the surplus from hiring a within-firm incumbent relative to a worker from another firm within the same census tract. Violations lead to slight over or understatement of deviations among (l, f) type combinations from the average surplus premium for job staying in the population. In the absence of Assumption 1, the probability that a worker is an establishment stayer instead of a mover depends on the kinds of workers within the worker type that sorted into particular establishments within the firm type. If the establishments that are experiencing job loss within the firm type are particularly populated at baseline by workers with higher required r_i levels relative to the mean for their type, then the job retention rate predicted under Assumption 1 might slightly overstate how much retention would really occur. As long as there is not extreme segregation by workers' unmodeled utility requirements across establishments within a firm type, the predicted probabilities are unlikely to be very sensitive to Assumption 1.

Similarly, when Assumption 2 fails, it is possible that some establishments within a position type have disproportionate shares of type l workers at baseline relative to others. Because the job retention rate does not increase linearly with the share of potential job stayers for given surplus premium from job retention, changes in the concentration of potential stayers within particular establishments slightly changes the predicted share of (l, f) matches that consist of job stayers rather than job movers.

Note first that Assumption 2 implies that $|g_k| \equiv S_{g|l,k} n(l(g))I \approx \overline{S}_{g|l,f} n(l(g))I$. Thus, Assumptions 1 and 2 together imply:

$$\sum_{i:g(i,k)=g} e^{-\frac{r_i}{\sigma}} \approx \overline{S}_{g|l(g),f(g)} n(l(g))(I)C_{l(g)}. \tag{18}$$

Applying this result to the last expression in (17), one obtains:

$$\begin{aligned}
P(g|f) &= \sum_{k\in f}(\frac{1}{|f|})\frac{e^{\frac{\theta_g}{\sigma}}\sum_{i:g(i,k)=g} e^{-\frac{r_i}{\sigma}}}{\sum_{i'\in\mathcal{I}} e^{\frac{\theta_{g'}-r_{i'}}{\sigma}}} = \sum_{k\in f}(\frac{1}{|f|})\frac{e^{\frac{\theta_g}{\sigma}}\sum_{i:g(i,k)=g} e^{-\frac{r_i}{\sigma}}}{\sum_{l'\in\mathcal{L}}\sum_{g'\in(l,f)}\sum_{i':g(i',k)=g'} e^{\frac{\theta_{g'}-r_{i'}}{\sigma}}} \\
&= \sum_{k\in f}(\frac{1}{|f|})\frac{e^{\frac{\theta_g}{\sigma}}\overline{S}_{g|l,f}n(l)(I)C_l}{\sum_{l'\in\mathcal{L}}\sum_{g'\in(l,f)} e^{\frac{\theta_{g'}}{\sigma}}\overline{S}_{g'|l',f}n(l')(I)C_{l'}} \\
&= \frac{e^{\frac{\theta_g}{\sigma}}\overline{S}_{g|l,f}n(l)(I)C_l}{\sum_{l'\in\mathcal{L}}\sum_{g'\in(l,f)} e^{\frac{\theta_{g'}}{\sigma}}\overline{S}_{g'|l',f}n(l')(I)C_{l'}}\sum_{k\in f}(\frac{1}{|f|}) = \frac{e^{\frac{\theta_g}{\sigma}}\overline{S}_{g|l,f}n(l)C_l}{\sum_{l'\in\mathcal{L}}\sum_{g'\in(l,f)} e^{\frac{\theta_{g'}}{\sigma}}\overline{S}_{g'|l',f}n(l')C_{l'}}
\end{aligned} \tag{19}$$

This concludes the proof.

A2 Proof of Proposition 1

Proposition 1:

Define the set $\Theta^{D-in-D} \equiv \{\frac{(\theta_g-\theta_{g'})-(\theta_{g''}-\theta_{g'''})}{\sigma} \,\forall\, (g,g',g'',g'''): l(g)=l(g''), l(g')=l(g'''), f(g)=f(g'), f(g'')=f(g''')\}$*. Given knowledge of* Θ^{D-in-D}*, a set* $\tilde{\Theta}=\{\tilde{\theta}_g \,\forall\, g \in \mathcal{G}\}$ *can be constructed such that the unique group level assignment* $P^{CF}(g)$ *that satisfies the market-clearing conditions (8) using* $\theta_g^{CF}=\tilde{\theta}_g \,\forall\, g$ *and arbitrary marginal PMFs for worker and position types* $n^{CF}(*)$ *and* $h^{CF}(*)$ *will also satisfy the corresponding market-clearing conditions using* $\theta_g^{CF}=\theta_g \,\forall\, g \in \mathcal{G}$ *and the same PMFs* $n^{CF}(*)$ *and* $g^{CF}(*)$*. Furthermore, denote by* $\tilde{\mathbf{C}}^{\mathbf{CF}} \equiv \{\tilde{C}_1^{CF},\ldots,\tilde{C}_L^{CF}\}$ *and* $\mathbf{C}^{\mathbf{CF}} \equiv \{C_1^{CF},\ldots,C_L^{CF}\}$ *the utility vectors that clear the market using* $\theta_g^{CF}=\tilde{\theta}_g$ *and using* $\theta_g^{CF}=\theta_g$*, respectively. Then* $\tilde{\mathbf{C}}^{\mathbf{CF}}$ *will satisfy* $\tilde{C}_l^{CF}=C_l^{CF}e^{\frac{-\Delta_l}{\sigma}} \,\forall\, l \in \mathcal{L}$ *for some set of worker type-specific constants* $\{\Delta_l : l \in [1,L]\}$ *that is invariant to the choices of* $n^{CF}(*)$ *and* $h^{CF}(*)$*.*

Proof: We prove Proposition 1 by construction.

Let $z(i,k)$ represent a trichotomous variable that takes on the value of 1 if the firms associated with positions $j(i)$ and k are the same $(1(m(j)=m(k)))$, 2 if the industries (but not the firms) associated with positions $j(i)$ and k are the same $(1(s(j)=s(k))\&m(j)\neq m(k))$ and 0 otherwise. Recall also that all job matches assigned to the same match group g share values of the worker and establishment characteristics that define the worker and position types l and f, respectively, as well as the value of $z(i,k)$. Thus, one can write $l(g)$, $f(g)$ and $z(g)$ for any group g. Let the worker types be ordered (arbitrarily) from $l=1\ldots l=L$, and let the position types be ordered (arbitrarily) from $f=1\ldots f=F$. Let $g(l,f,z)$ denote the group associated with worker type l, position type f, and existing worker indicator z. Assume that the set $\Theta^{D-in-D}=\{\frac{(\theta_g-\theta_{g'})-(\theta_{g''}-\theta_{g'''})}{\sigma} \,\forall\, (g,g',g'',g''')\}$ is known, since a consistent estimator for each element of the set can be obtained via adjusted log odds ratios, as described in Section 3. Consider defining the set of alternative group-level joint surplus values $\tilde{\Theta}=\{\tilde{\theta}_g\}$ as follows:

$$\tilde{\theta}_{g'} = 0 \,\forall\, g' : (l(g')=1 \text{ and/or } f(g')=1) \text{ and } z(g')=0 \tag{20}$$

$$\tilde{\theta}_{g'} = \frac{(\theta_{g'}-\theta_{g(1,f(g'),0)})-(\theta_{g(l(g'),1,0)}-\theta_{g(1,1,0)})}{\sigma} \,\forall\, g' : (f(g')\neq \text{ and } l(g')\neq 1) \text{ and/or } z(g')\neq 0 \tag{21}$$

Under the definitions in (20) and (21), we have:

$$\frac{(\tilde{\theta}_g-\tilde{\theta}_{g'})-(\tilde{\theta}_{g''}-\tilde{\theta}_{g'''})}{\sigma} = \frac{(\theta_g-\theta_{g'})-(\theta_{g''}-\theta_{g'''})}{\sigma}$$
$$\forall\, (g,g',g'',g'''): l(g)=l(g''), l(g')=l(g'''), f(g)=f(g'), f(g'')=f(g''') \tag{22}$$

Thus, the appropriate difference-in-differences using elements of $\tilde{\Theta}$ match their analogues among the true surpluses in Θ^{D-in-D}, so that all the information about Θ in the identified set Θ^{D-in-D} is retained. And unlike the true set Θ, the construction of $\tilde{\Theta}$ only requires knowledge of Θ^{D-in-D}.

Next, note that the elements of $\tilde{\Theta}$ can be written in the following form:

$$\tilde{\theta}_g = \theta_g + \Delta^1_{l(g)} + \Delta^2_{f(g)} \; \forall \; g \in \mathcal{G}, \text{ where} \tag{23}$$

$$\Delta^1_{l(g)} = \theta_{g(l(g),1,0)} - \theta_{g(1,1,0)} \quad \text{and} \quad \Delta^2_{f(g)} = \theta_{g(1,f(g),0)} \tag{24}$$

where $\mathcal{G}$ is the set of all possible match groups. In other words, each alternative surplus $\tilde{\theta}_g$ equals the true surplus θ_g plus a constant $(\Delta^1_{l(g)})$ that is common to all groups featuring the same worker type and a constant $(\Delta^2_{f(g)})$ that is common to all groups featuring the same position type.

Next, recall that there exists a unique aggregate assignment associated with each combination of marginal worker and position type distributions $n^{CF}(l)$ and $h^{CF}(f)$ and set of group-level surpluses, including $\tilde{\Theta}$. Let $\tilde{P}^{CF}(*) \equiv P^{CF}(*|\tilde{\Theta}, \tilde{C}^{CF}_2, \ldots, \tilde{C}^{CF}_L))$ represent the assignment that results from combining arbitrary marginals $n^{CF}(l)$ and $h^{CF}(f)$ with $\tilde{\Theta}$. $\tilde{\mathbf{C}}^{\mathbf{CF}} = [1, \tilde{C}^{CF}_2 \ldots \tilde{C}^{CF}_L]$ denotes the vector of mean exponentiated utility values for each worker type l (with $\tilde{C}^{CF}_1$ normalized to 1) that solves the system of excess demand equations below, and thus yields $\tilde{P}^{CF}(g) \; \forall \; g \in \mathcal{G}$ when plugged into equation (5) along with the elements of $\tilde{\Theta}$, n^{CF} and $\overline{S}^{CF}_{g'|l(g'),d}$:

$$\begin{aligned} &\sum_{f \in \mathcal{F}} h^{CF}(f)(\sum_{g:l(g)=2} P^{CF}(g|f, \tilde{\Theta}, \tilde{\mathbf{C}}^{\mathbf{CF}})) = n^{CF}(2) \\ &\vdots \\ &\sum_{f \in \mathcal{F}} h^{CF}(f)(\sum_{g:l(g)=L} P^{CF}(g|f, \tilde{\Theta}, \tilde{\mathbf{C}}^{\mathbf{CF}})) = n^{CF}(l) \end{aligned} \tag{25}$$

We wish to show that $\tilde{P}^{CF}(*) \equiv P^{CF}(*|\tilde{\Theta}, \tilde{\mathbf{C}}^{\mathbf{CF}})$ will be identical to the alternative unique counterfactual equilibrium assignment $P^{CF}(*|\Theta, \mathbf{C}^{\mathbf{CF}})$ that combines the same arbitrary marginal distributions $n^{CF}(l)$ and $h^{CF}(f)$ with the set Θ instead of $\tilde{\Theta}$. Here, $\mathbf{C}^{\mathbf{CF}} = [1, C^{CF}_2 \ldots C^{CF}_L]$ denotes a vector of l-type-specific mean exponentiated utility values that clears the market by satisfying the following alternative excess demand equations:[49]

$$\begin{aligned} &\sum_{f \in \mathcal{F}} h^{CF}(f)(\sum_{g:l(g)=2} P^{CF}(g|f, \Theta, \mathbf{C}^{\mathbf{CF}})) = n^{CF}(2) \\ &\vdots \\ &\sum_{f \in \mathcal{F}} h^{CF}(f)(\sum_{g:l(g)=L} P^{CF}(g|f, \Theta, \mathbf{C}^{\mathbf{CF}})) = n^{CF}(l) \end{aligned} \tag{26}$$

Since all other terms are shared by the systems (25) and (26), it suffices to show that $P^{CF}(g|f, \tilde{\Theta}, \tilde{\mathbf{C}}^{\mathbf{CF}}) =$

[49]Note that we have suppressed the dependence of $P^{CF}(*|\Theta, \mathbf{C}^{\mathbf{CF}}, n^{CF}(l), h^{CF}(f), \overline{S}_{g|l,f})$ on $n^{CF}(l)$, $h^{CF}(f)$, and $\overline{S}_{g|l,f}$ because these are held fixed across the two alternative counterfactual simulations.

$P^{CF}(g|f,\Theta,\mathbf{C^{CF}}))\ \forall\, g \in \mathcal{G}$ for some vector $\mathbf{C^{CF}}$. Consider the following vector $\mathbf{C^{CF}}$:

$$C_l^{CF} = \tilde{C}_l^{CF} e^{\frac{\Delta_l^1}{\sigma}}\ \forall\, l \in [2,\ldots,L] \tag{27}$$

where Δ_l^1 is as defined in (24). For an arbitrary choice of g, we obtain:

$$P^{CF}(g|f(g),\tilde{\Theta},\tilde{\mathbf{C}}^{\mathbf{CF}}) = \frac{e^{\frac{\tilde{\theta}_g^{CF}}{\sigma}}\overline{S}_{g|l(g),f(g)}^{CF} n^{CF}(l(g))\tilde{C}_l^{CF}}{\sum_{l'\in\mathcal{L}}\sum_{g'\in(l',f)} e^{\frac{\tilde{\theta}_{g'}^{CF}}{\sigma}}\overline{S}_{g'|l'(g'),f(g)}^{CF} n^{CF}(l')\tilde{C}_{l'}^{CF}}$$

$$= \frac{e^{\frac{(\theta_g^{CF}+\Delta_{l(g)}^1+\Delta_{f(g)}^2)}{\sigma}}\overline{S}_{g|l(g),f(g)}^{CF} n^{CF}(l(g))C_l^{CF}e^{\frac{-\Delta_l^1}{\sigma}}}{\sum_{l'\in\mathcal{L}}\sum_{g'\in(l',f)} e^{\frac{(\theta_{g'}^{CF}+\Delta_{l(g')}^1+\Delta_{f(g')}^2)}{\sigma}}\overline{S}_{g'|l'(g'),f(g)}^{CF} n^{CF}(l')C_{l'}^{CF}e^{\frac{-\Delta_{l'}^1}{\sigma}}}$$

$$= e^{\frac{\Delta_{l(g)}^1}{\sigma}}e^{\frac{\Delta_{f(g)}^2}{\sigma}}e^{\frac{-\Delta_{l(g)}^1}{\sigma}}\frac{e^{\frac{\theta_g^{CF}}{\sigma}}\overline{S}_{g|l(g),f(g)}^{CF} n^{CF}(l(g))C_l^{CF}}{e^{\frac{\Delta_{f(g)}^2}{\sigma}}\sum_{l'\in\mathcal{L}} e^{\frac{\Delta_{l(g')}^1}{\sigma}}e^{\frac{-\Delta_{l(g')}^1}{\sigma}}\sum_{g'\in(l',f)} e^{\frac{\theta_{g'}^{CF}}{\sigma}}\overline{S}_{g'|l'(g'),f(g)}^{CF} n^{CF}(l')C_{l'}^{CF}}$$

$$= \frac{e^{\frac{\theta_g^{CF}}{\sigma}}\overline{S}_{g|l(g),f(g)}^{CF} n^{CF}(l(g))C_l^{CF}}{\sum_{l'\in\mathcal{L}}\sum_{g'\in(l',f)} e^{\frac{\theta_{g'}^{CF}}{\sigma}}\overline{S}_{g'|l'(g'),f(g)}^{CF} n^{CF}(l')C_{l'}^{CF}} = P^{CF}(g|f,\Theta,\mathbf{C^{CF}}) \tag{28}$$

This proves that $P^{CF}(g|f,\Theta,\mathbf{C^{CF}})$ also satisfies the market clearing conditions (26) above, and will therefore be the unique group-level assignment consistent with marketwide equilibrium and stability. Thus, we have shown that the counterfactual assignment that is recovered when using an alternative set of surpluses $\tilde{\Theta}$ derived from the identified set Θ^{D-in-D} will in fact equal the counterfactual assignment we desire, which is based on the true set of joint surplus values Θ. Furthermore, while worker-type specific mean utility values $\tilde{\mathbf{C}}^{\mathbf{CF}}$ that clear the market given $\tilde{\Theta}$ will differ for each worker type from the corresponding vector $\mathbf{C^{CF}}$ based on the true surplus set Θ, these differences are invariant to the marginal worker type and position type distributions $n^{CF}(l)$ and $h^{CF}(f)$ used to define the counterfactual. This implies that differences in utility gains caused by alternative counterfactuals among worker types are identified, permitting comparisons of the utility incidence of alternative labor supply or demand shocks. This concludes the proof.

A3 Proof of Proposition A2

Proposition A2:

Suppose the following assumptions hold:

1') *The assumptions laid out in sections 2 and 3 continue to hold. Namely, each joint surplus π_{ik} is additively separable in the group-level and idiosyncratic components, the vector of idiosyncratic components ϵ_{ik} is independently and identically distributed, and follows the type 1 extreme* *value distribution, and Assumptions 1 and 2 hold.*

2') *The set of destination positions $k \in \tilde{\mathcal{K}}$ that will be filled in the stable counterfactual assignment are known in advance, and the set of destination positions $k \in \tilde{\mathcal{K}}$ that will remain unfilled in the stable counterfactual assignment are ignorable, in the sense that their existence does not change the assignment nor the division of surplus among the remaining set of positions $\mathcal{K}$ and set of workers $\mathcal{I}$.*

3') $\frac{1}{|g_i|} \sum_{k:g(i,k)=g} e^{-\frac{q_k}{\sigma}} \approx \frac{1}{|f|} \sum_{k:f(k)=f(g)} e^{-\frac{q_k}{\sigma}} = C_{f(g)} \; \forall (g,i)$.

4') $P(g|i, f(g)) \approx P(g|l(g), f(g)) \; \forall (g,i)$.

Then the group-level assignment $P^{CF}(g)$ that satisfies the following $L-1$ excess demand equations represents the unique group-level equilibrium assignment $P^{CF^*}(g)$ consistent with the unique worker/position level stable matching μ^{CF}:

$$
\begin{aligned}
&\sum_{f \in \mathcal{F}} h^{CF}(f) \Big(\sum_{g:l(g)=2} P^{CF}(g|f, C_2^{CF}, \ldots, C_L^{CF} \Big) = n^{CF}(2) \\
&\vdots \\
&\sum_{f \in \mathcal{F}} h^{CF}(f) \Big(\sum_{g:l(g)=L} P^{CF}(g|f, C_2^{CF}, \ldots, C_L^{CF} \Big) = n^{CF}(L)
\end{aligned}
\tag{29}
$$

where $P^{CF}(g|f, C_2^{CF}, \ldots, C_L^{CF})$ is given by:

$$
P^{CF}(g|f) = \frac{e^{\frac{\theta_g^{CF}}{\sigma}} \overline{S}^{CF}_{g|l(g),f} n^{CF}(l(g)) C_l^{CF}}{\sum_{l' \in \mathcal{L}} \sum_{g' \in (l,f)} e^{\frac{\theta_{g'}^{CF}}{\sigma}} \overline{S}^{CF}_{g'|l(g'),d} n^{CF}(l') C_{l'}^{CF}} \; \forall \, f \in [1, \ldots, F] \tag{30}
$$

Proof: Proposition A2 states that assignment $P^{CF}(g)$ implied by the vector of mean utility values $\mathbf{C^{CF}} = [1, C_2, \ldots, C_L^{CF}]$ that solves the system of equations (29) in fact represents the unique group-level stable (and equilibrium) assignment $P^{CF^*}(g)$.

First, note that if unfilled positions are ignorable for the counterfactual assignment, then we can focus on finding a stable assignment of a restricted version of the assignment game in which only remaining K positions need to be considered. As discussed in section 3.2, Assumption 2' implicitly requires that no position that remains unfilled is ever the second-best option for any worker who takes a job in the destination period.

Furthermore, Assumption 2' imposes that each of the remaining positions will be filled in any stable matching. Recall that stability in the individual-level matching μ^{CF} requires:

$$\mu_{ik}^{CF} = 1 \text{ iff } k \in \arg\max_{k \in \tilde{\mathcal{K}} \cup 0} \pi_{ik} - q_k^{CF} \text{ and } i \in \arg\max_{i \in \tilde{\mathcal{I}} \cup 0} \pi_{ik} - r_i^{CF} \tag{31}$$

Assumption 2' allows us to replace $i \in \arg\max_{i \in \tilde{\mathcal{I}} \cup 0} \pi_{ik} - r_i^{CF}$ with $i \in \arg\max_{i \in \tilde{\mathcal{I}}} \pi_{ik} - r_i^{CF}$. In other words, we assume in advance that the individual rationality conditions that any proposed match yield a higher payoff to the position than remaining vacant, $\pi_{ik} - r_i > \pi_{0k}$ when $\mu_{ik} = 1$, are satisfied and can be ignored. Implicitly, this requires that the joint surpluses to workers and firms from matching up are sufficiently large relative to both workers' and firms' outside options.[50] Imposing Assumption 2' may cause utility losses among local workers from negative local labor demand shocks to be overstated, since some workers would likely find jobs at positions that were not willing to hire at the original wage level but would enter the labor market at lower wage levels. Conversely, gains to local workers from positive shocks may be understated, since some local firms that filled positions at the original wage levels might choose to remain vacant (or move to other locations) when competition for local workers becomes more fierce.

In our applications the number of positions that will be filled is greater than the number of workers seeking positions (I). In order to be able to consistently allocate workers to match groups, even when they move to (or remain in) nonemployment, we define a "nonemployment" position type as the last position type F. Because the number of workers who end up nonemployed is assumed to be known, we allocate enough "nonemployment" positions within type F, $h^{CF}(F)$, so that the number of workers I equals the number of "positions" K, once K includes the dummy nonemployment positions. We then normalize this common number of workers and firm positions (assumed to be very large) to be 1, and reinterpret $n^{CF}(l)$ and $h^{CF}(f)$ as probability mass functions providing shares of the relevant worker and position populations rather than counts.

As discussed in section 3, Assumption 1', when combined with the stability conditions (31), implies that the probability that a given position k will be filled by a particular worker i is given by the logit form (16). When combined with Assumptions 1 and 2 (also cited by Assumption 1'), this implies that the group-level conditional choice probability $P(g|f)$ takes the form (30) for any position types f that are composed of positions k (as derived in section 3).

However, the statement of Proposition A2 makes clear that the form (30) also holds for the last type F, which contains the "dummy" unemployment positions whose "choices" will be workers becoming unemployed. The stability conditions (31) do not provide any justification for why these dummy nonemployment positions should be filled via the same logit form as the other position types that consist of actual positions at firms. Thus, these dummy positions, and the assumption that the probability distribution over alternative groups representing different worker and job match characteristics $(l(g), z(g))$ follows the logit form, are mere computational devices to calculate the equilibrium assignment. That this computational device in fact yields the unique stable assignment

[50] This implicitly requires that the unobserved draws ϵ_{0k} for position vacancy values are taken from a bounded distribution rather than the Type 1 extreme value distribution.

for the counterfactual labor market is the primary reason Proposition A2 requires a proof.

However, the stability conditions and Assumption 1' imply that the probability that a given worker i will choose a particular position k (where $k = 0$ represents nonemployment) is also given by the logit form (Decker et al. (2013)):

$$P^{CF}(k|i) = \frac{e^{\frac{\theta_g^{CF} - q_k^{CF}}{\sigma}}}{\sum_{k' \in \mathcal{K} \cup 0} e^{\frac{\theta_{g'}^{CF} - q_{k'}^{CF}}{\sigma}}} \tag{32}$$

This can then be aggregated (using the same steps as in section A1) to provide an expression for the probability that a randomly chosen worker from a given worker type l matches with a position that yields a transition assigned to group g:

$$P^{CF}(g|l) = \frac{1}{|l|} \sum_{i \in l} \frac{(e^{\frac{\theta_g^{CF}}{\sigma}})(\sum_{k: g(i,j(i),k)=g} e^{\frac{-q_k^{CF}}{\sigma}})}{\sum_{k' \in \mathcal{K} \cup 0} e^{\frac{\theta_{g'}^{CF} - q_{k'}^{CF}}{\sigma}}} \tag{33}$$

Assumptions 3' and 4', which are analogues to Assumptions 1 and 2 in section 3, allow us to simply this expression to the following:

$$P^{CF}(g|l) = \frac{e^{\frac{\theta_g^{CF}}{\sigma}} \overline{S}_{g|l(g),d}^{CF} h^{CF}(f(g)) \tilde{C}_f^{CF}}{\sum_{f' \in \mathcal{F}} \sum_{g' \in (l, f')} e^{\frac{\theta_{g'}^{CF}}{\sigma}} \overline{S}_{g'|l(g'),d}^{CF} h^{CF}(f') \tilde{C}_{f'}^{CF}} \; \forall \, l \in [1, \ldots, L] \tag{34}$$

Assumption 3' states that the discounted profits of alternative positions k of the same position type f are roughly the same. This implies that the profit share that workers must provide to the position in a stable matching is approximately the same for their existing positions as for other positions in the same local area with the same industry and establishment size and establishment average pay categories, and can be summarized by a parameter C_f^{CF} that is defined at the position type level.

Taken literally (given the characteristics we use to define groups), Assumption 4' states that every worker of the same worker type starts the year in firms with the same number of destination positions, which clearly does not hold. More broadly, though, Assumptions 3' and 4' allow us to replace the term $\sum_{k: g(i,k)=g} e^{\frac{-q_k^{CF}}{\sigma}}$ that depends on the individual i with an expression $P^{CF}(g|l, f(g)) h^{CF}(f(g)) \tilde{C}_{f(g)}^{CF}$ that depends on only group and destination-type level terms. Essentially, we assume that ignoring within-worker type variation in the number of positions at which they would be stayers (due to different establishment sizes of initial job matches) when aggregating is not generating significant bias in the counterfactual assignment and incidence estimates.

Under Assumptions 1' through 4', the group-level stable matching must satisfy the following market clearing conditions, which specify that supply must equal demand for each position type f:

$$\sum_{l \in \mathcal{L}} n^{CF}(l) (\sum_{g: f(g)=2} P^{CF^*}(g|l, \tilde{\mathbf{C}}^{\mathbf{CF}}) = h^{CF}(2) \tag{35}$$

$$\vdots \tag{36}$$

$$\sum_{l\in\mathcal{L}} n^{CF}(l)(\sum_{g:f(g)=F} P^{CF*}(g|l,\mathbf{\tilde{C}^{CF}}) = h^{CF}(F) \tag{37}$$

where $\mathbf{\tilde{C}^{CF}}$ represents the $F-1$ length vector = $[1, \tilde{C}_2^{CF}, \ldots, \tilde{C}_F^{CF}]$ and each conditional probability $P^{CF*}(g|l,\mathbf{\tilde{C}^{CF}})$ takes the form in (34).

Assumption 2' allows us to ignore the possibility that supply might exceed demand for some position types (implying some vacant positions). In this alternative position-side system of equations, the expressions for each conditional probability $P^{CF*}(g|l)$ do in fact stem directly from the necessary stability conditions. And all of the feasibility conditions for a stable matching are incorporated into the zero-excess demand equations (since $P^{CF*}(g|l)$ sum to 1 by construction, the assignment $P^{CF*}(g)$ that satisfies this system necessarily sums to the worker-type PMF $n^{CF}(l)$). Thus, one can apply the proof by Decker et al. (2013) that there exists a unique group-level assignment that satisfies all of the group-level feasibility and stability conditions (and is thus consistent with a stable matching in the assignment game defined at the level of worker-position matches).

If one wished, one could directly compute the unique group-level counterfactual assignment $P^{CF*}(g|l)$ by finding a $F-1$ length vector $\mathbf{\tilde{C}^{CF}}$ that solved this system, and constructing the implied assignment by plugging this vector into the conditional probability expressions (34). However, when $F \gg L$, solving this system is considerably more computationally burdensome than solving the worker-side counterpart (29), which features $L-1$ equations. Thus, the remainder of this proof is devoted to showing that any assignment $P^{CF}(g)$ implied by a solution to (29) must equal the assignment $P^{CF*}(g)$ implied by a solution to (37). And since we know that the latter solution represents the unique group-level matching consistent with stability in the assignment game, the former solution must also be unique, and must also represent the group-level matching consistent with stability in the assignment game. Essentially, this amounts to showing that the device of adding "dummy" nonemployment positions present in (29) appropriately incorporates the surpluses π_{i0} that workers obtain from staying single.

Consider an L length vector $\mathbf{C^{CF}} = [1, C_2^{CF}, \ldots, C_L^{CF}]$ that solves (29) and yields assignment $P^{CF}(g)$. We will show that one can use $\mathbf{C^{CF}}$ to construct an alternative F length vector $\mathbf{\tilde{C}^{CF}} = [1, \tilde{C}_2^{CF}, \ldots, \tilde{C}_F^{CF}]$ that solves (37), and that the assignment it generates, $P^{CF*}(g)$, equals $P^{CF}(g)$.

We propose the following vector $\mathbf{\tilde{C}^{CF}}$:

$$\tilde{C}_f^{CF} = \frac{\sum_{l=1}^{L} \sum_{g':(l(g'),f(g'))=(l,F)} e^{\frac{\theta_{g'}}{\sigma}} n^{CF}(l) \overline{S}_{g'|l,F} C_l^{CF}}{\sum_{l=1}^{L} \sum_{g':(l(g'),f(g'))=(l,f)} e^{\frac{\theta_{g'}}{\sigma}} n^{CF}(l) \overline{S}_{g'|l,f} C_l^{CF}} \; \forall\, f \in [1,\ldots,F] \tag{38}$$

Here, the numerator captures the inclusive value (as defined by Menzel (2015)) associated with the nonemployment position type F, while the denominator captures the inclusive value for the chosen position type f. This implies that $\tilde{C}_F^{CF} = 1$. While any position type could be chosen as the one whose mean exponentiated profit value is normalized, normalizing the nonemployment type is particularly appealing, since it implies "profit" values of 0 for the dummy nonemployment position type F ($\tilde{C}_F^{CF} = e^{\bar{q}_F} = e^0 = 1$).

Let λ represent the inclusive value of the unemployment position type F, the numerator in (38):

$$\lambda = \sum_{l=1}^{L} \sum_{g':(l(g'),f(g'))=(l,F)} e^{\frac{\theta_{g'}}{\sigma}} n^{CF}(l) \overline{S}_{g'|l,F}^{CF} C_l^{CF} \tag{39}$$

Note that λ is independent of position type. We begin by showing that the assignments implied by the vectors $[C_1^{CF}, \ldots, C_L^{CF}]$ and $[C_1^{CF}, \ldots, \tilde{C}_F^{CF}]$ are identical: $P^{CF}(g) = P^{CF^*}(g)$.

Since $\mathbf{C}^{CF}$ solves the worker-side system of excess demand equations (29), we know that

$$\begin{aligned}
&\sum_{f'\in\mathcal{F}} h^{CF}(f') \sum_{g'\in(l,f')} \frac{e^{\frac{\theta_{g'}^{CF}}{\sigma}} \overline{S}_{g'|l,f'}^{CF} n^{CF}(l) C_l^{CF}}{\sum_{l'=1}^{L} \sum_{g':(l(g'),f(g'))=(l',f)} e^{\frac{\theta_{g'}}{\sigma}} n^{CF}(l') \overline{S}_{g'|l',f} C_{l'}^{CF}} = n^{CF}(l)\ \forall\, l \in [1, L] \\
&\Rightarrow \sum_{f'\in\mathcal{F}} \sum_{g'\in(l,f')} \frac{e^{\frac{\theta_{g'}^{CF}}{\sigma}} \overline{S}_{g'|l,f'}^{CF} h^{CF}(f')}{\sum_{l=1}^{L} \sum_{g':(l(g'),f(g'))=(l,f)} e^{\frac{\theta_{g'}}{\sigma}} n^{CF}(l) \overline{S}_{g'|l,f} C_l^{CF}} = \frac{1}{C_l^{CF}}\ \forall\, l \in [1, L] \\
&\Rightarrow \sum_{f'\in\mathcal{F}} \sum_{g'\in(l,f')} \frac{e^{\frac{\theta_{g'}^{CF}}{\sigma}} \overline{S}_{g'|l,f'}^{CF} h^{CF}(f')}{\frac{\lambda}{\tilde{C}_{f'}^{CF}}} = \frac{1}{C_l^{CF}}\ \forall\, l \in [1, L] \\
&\Rightarrow \sum_{f'\in\mathcal{F}} \sum_{g'\in(l,f')} e^{\frac{\theta_{g'}^{CF}}{\sigma}} \overline{S}_{g'|l,f'}^{CF} h^{CF}(f') \tilde{C}_{f'}^{CF} = \frac{\lambda}{C_l^{CF}}\ \forall\, l \in [1, L]
\end{aligned} \tag{40}$$

We can now proceed:

$$\begin{aligned}
&P^{CF^*}(g) = n^{CF}(l) P^{CF^*}(g|l) = n^{CF}(l) \frac{e^{\frac{\theta_g^{CF}}{\sigma}} \overline{S}_{g|l,f}^{CF} h^{CF}(f) \tilde{C}_f^{CF}}{\sum_{f'\in\mathcal{F}} \sum_{g'\in(l,f')} e^{\frac{\theta_{g'}^{CF}}{\sigma}} \overline{S}_{g'|l,f'}^{CF} h^{CF}(f') \tilde{C}_{f'}^{CF}} \\
&= \frac{n^{CF}(l) e^{\frac{\theta_g^{CF}}{\sigma}} \overline{S}_{g|l,f}^{CF} h^{CF}(f) \tilde{C}_f^{CF} C_l^{CF}}{\lambda} \\
&= h^{CF}(f) \frac{e^{\frac{\theta_g^{CF}}{\sigma}} n^{CF}(l) \overline{S}_{g|l,f}^{CF} \lambda C_l^{CF}}{\lambda \sum_{l'=1}^{L} \sum_{g':(l(g'),f(g'))=(l',f)} e^{\frac{\theta_{g'}}{\sigma}} f^{CF}(l') \overline{S}_{g'|l',f} C_{l'}^{CF}} \\
&= h^{CF}(f) P^{CF}(g|f) = P^{CF}(g)
\end{aligned} \tag{41}$$

It remains to show that the chosen $\mathbf{\tilde{C}^{CF}}$ vector (38) solves (37). Consider the left-hand side of the excess demand equation for an arbitrary position type f in the system (37). One can write:

$$\sum_{l=1}^{L} \sum_{g:(l(g),f(g))=(l,f)} n^{CF}(l) P^{CF^*}(g|l, \Theta^{CF}, \tilde{\mathbf{C}}^{CF})$$

$$
\begin{aligned}
&= \sum_{l=1}^{L} \sum_{g:(l(g),f(g))=(l,f)} h^{CF}(f) P^{CF}(g|f, \Theta^{CF}, \mathbf{C}^{CF}) \\
&= h^{CF}(f) \sum_{l=1}^{L} \sum_{g:(l(g),f(g))=(l,f)} P^{CF}(g|f, \Theta^{CF}, \mathbf{C}^{CF}) \\
&= h^{CF}(f) \sum_{g:f(g)=f} P^{CF}(g|f, \Theta^{CF}, \mathbf{C}^{CF}) \\
&= h^{CF}(f) \qquad (42)
\end{aligned}
$$

where the last line imposes that $P^{CF}(g|f)$ is a (conditional) probability distribution and thus sums to one. Since we have proved that the implied "demand" by workers for positions of an arbitrary position type equals the "supply" $h^{CF}(f)$, we have proved that $\tilde{C}^{CF}$ solves the system (37).

Notice that the expression for the proposed equilibrium mean ex post profit vector (38) has value beyond its use in proving proposition A1. Once the L-vector of mean ex post utilities $\{C_l^{CF}\}$ for each worker type have been computed, one can use (38) to directly calculate the mean ex post profit vector for each position type f without having to solve a system of $F-1$ equations. This is quite valuable when $F \gg L$, as it is in our application. Of course, the equivalent mapping can be inferred by symmetry for the opposite case where $L \gg F$:

$$
C_l^{CF} = \frac{\sum_{f=1}^{F} \sum_{g':(l(g'),f(g'))=(L,f)} e^{\frac{\theta_{g'}}{\sigma}} h^{CF}(f) \overline{S}_{g'|L,f} \tilde{C}_f^{CF}}{\sum_{f=1}^{F} \sum_{g':(l(g'),f(g'))=(l,f)} e^{\frac{\theta_{g'}}{\sigma}} h^{CF}(f) \overline{S}_{g'|l,f} \tilde{C}_f^{CF}} \; \forall \, l \in [1, \ldots, L] \qquad (43)
$$

In section 3.2 we showed that these vectors are sufficient to determine both the worker and position type-level incidence of any counterfactual shocks to the composition or spatial distribution of labor supply and/or labor demand. Thus, at least in cases where the proposed model is a reasonable approximation of the functioning of the labor market (and housing supply is sufficiently elastic and agglomeration effects and other product market spillovers are second order), a proper welfare analysis of such shocks only requires solving at most $\min\{L, F\}$ non-linear excess demand equations. Since an analytical Jacobian can be derived and fed as an input to non-linear equations solvers, relatively large scale assignment problems featuring thousands of types on one side of the market (and perhaps more on the opposite side) can be solved within a matter of minutes.

A4 Estimating the Value of σ

We attempt to estimate σ, the standard deviation of the unobserved match-level component ϵ_{ik}, by exploiting the evolution in the composition of U.S. worker and position types $n^y(l)$ and $h^y(f)$ across years y. Specifically, we estimate the set of group-level surpluses $\{\theta_g^{2003}\}$ from the observed 2003-2004 matching. Then, holding these surplus values fixed, we combine $\{\theta_g^{2003}\}$ with $n^y(l)$ and $h^y(f)$ from each other year $y \in [2004, 2012]$ to generate counterfactual assignments and changes in scaled mean (exponentiated) utility values $\{C_l^{CF}\}$ for each worker type. These counterfactuals predict how mean worker utilities by skill/location combination would have evolved given the observed compositional changes in labor supply and demand had the underlying surplus values $\{\theta_g\}$ been constant and equal to $\{\theta_g^{2003}\}$ throughout the period.

To the extent that most of evolution in the utility premia enjoyed by workers in particular locations and skill categories was due primarily to changes in supply and demand composition rather than changes in the moving costs, recruiting costs, tastes, and relative productivities that compose the joint surplus values $\{\theta_g\}$, these counterfactual predictions will be reasonable approximations of the realized evolution of ex post utility over time by worker type. Recall that $C_l^{CF} \approx \frac{1}{|l|} \sum_{i:l(i)=l} e^{\frac{-r_i^{CF}}{\sigma}}$. Thus, if ex post utility r_i^{CF} does not vary too much across individuals within a worker type, so that Jensen's inequality is near equality and $\frac{1}{|l^y|} \sum_{i:l(i)=l} e^{\frac{-r_i^{CF,y}}{\sigma^y}} \approx e^{\frac{\overline{r}_l^{CF,y}}{\sigma^y}}$, then taking logs yields $ln(C_l^{CF,y}) \approx \frac{\overline{r}_l^{CF,y}}{\sigma^y}$.

Next, we form the corresponding changes in observed annual earnings for each worker type in each year, $\overline{Earn}_l^{y+1} - \overline{Earn}_l^{y}$.[51] We then run the following regression at the l-type level for each year $y \in [2004 - 2012]$:

$$\overline{Earn}_l^{y+1} - \overline{Earn}_l^{y} = \beta_0^y + \beta_1^y(ln(C_l^{CF,y+1}) - ln(C_l^{CF,y})) + \nu_l^y \qquad (44)$$

Recall that the $\overline{r}_l^{CF,y}$ values represent predicted money metric utility gains, and are thus denominated in dollars. However, even if the surplus values $\{\theta_g\}$ are time invariant over the chosen period (and the other assumptions of the assignment model specified above all hold, including the approximations just described), dollar-valued mean utility gains would not equal mean annual earnings gains for a given worker type if its workers systematically moved to jobs featuring better or worse amenities, avoided more moving/recruiting training costs, or moved to jobs featuring better or worse continuation values. However, if such changes in other sources of utility nearly cancel out among workers assigned to the same worker type (for all worker types), then $\overline{r}_l^{CF,y+1} - \overline{r}_l^{CF,y}$ should approximately equal $\overline{Earn}_l^{y+1} - \overline{Earn}_l^{y}$. This implies that $\beta_1^y \approx \sigma^y$.

As noted in Section 5.1, the worker type space depends on which location is considered the target location for the shock, with the geographic units that partially define worker types becoming more aggregated farther from the shock. To address this issue, in practice we constructed separate true and counterfactual earnings changes and estimated equation (44) for the collapsed worker type spaces associated with each possible target PUMA among the sample states, and averaged the estimates of β_1 across all regressions satisfying a minimum R^2 threshold of .1 to obtain $\hat{\beta}_1^y$.[52] The estimates of

[51] Note that while worker earnings in initial job matches were used to assign workers to skill categories, to this point we have not used observed worker earnings in destination positions to identify any other parameters.

[52] A few PUMAs and states experienced relatively little year-to-year change in the distribution of employment across position types, so that the counterfactual earnings forecasts predicted true earnings changes poorly. In this case, the R^2 from the regression was very low, and β_1^y was badly identified. The results become far more stable across the remaining alternative type spaces when a minimum R^2 was imposed to eliminate the few badly identified estimates, which tended to produce outliers.

$\hat{\beta}_1^y$ are fairly consistent across years, so we use the mean estimate across all years, $\overline{\sigma} = 18,420$, to produce dollar values for all the results relating to utility gains presented in the paper.

Clearly, given the additional strong assumptions required, this approach represents a relatively crude attempt to calibrate σ. Indeed, further efforts could conceivably be taken to exclude worker types l' whose surplus values $\{\theta_g : l(g) = l'\}$ were known to be changing over the chosen time period, or to allow θ_g to evolve in a particular parametric fashion. In fact, GS discuss how a vector of σ values associated with different types or combinations of types based on observed characteristics might potentially be jointly estimated with other model parameters (thereby allowing heteroskedasticity across types in the idiosyncratic match component). Since the focus in this paper is primarily on examining relative incidence across different worker types from shocks featuring different changes in labor demand composition, we opted for the simpler, more transparent approach.

A5 Using Transfers to Decompose the Joint Surpluses $\{\theta_g\}$

This appendix examines whether observing equilibrium transfers, denoted w_{ik}, allows the identification of additional parameters of interest. In CS's assignment model, the unobserved match-level heterogeneity is assumed to take the form $\epsilon_{ik} = \epsilon^1_{l(i)k} + \epsilon^2_{if(k)}$, so that aggregate surplus is left unchanged when two pairs of job matches (i, k) and (i', k') belonging to the same group g swap partners. The elimination of any true (i, k) match-level surplus component implies that equilibrium transfers cannot vary among job matches belong to the same group g, so that $w_{ik} = w_{g(i,k)} \; \forall \, (i, k)$.[53] GS show that under this assumption, observing the (common) group-level transfers w_g would be sufficient to decompose the group-level mean joint surplus θ_g into the worker and position's respective pre-transfer payoffs, which we denote θ^l_g and θ^f_g, respectively.

Because the model proposed in section 2 does not impose the additive separability assumption $\epsilon_{ik} = \epsilon^1_{l(i)k} + \epsilon^2_{if(k)}$, equilibrium transfers will in general vary among (i, k) pairs within the same group g. Given the substantial earnings variance within observed groups g regardless of the worker, position, and job match characteristics used to define g, the CS restriction on the nature of unobserved match-level heterogeneity would be strongly rejected in the labor market context.

However, one can still consider whether the observed transfers $\{w_{ik}\}$ identify additional objects. From section 2.1, equilibrium transfers are related to equilibrium worker and position payoffs via:

$$w_{ik} = \pi^f_{ik} - q_k \tag{45}$$

$$w_{ik} = r_i - \pi^l_{ik} \tag{46}$$

Next, recall from equation (6) that under Assumptions 1 and 2 in Proposition A1 the log odds that a randomly chosen position from arbitrary position type f will choose a worker whose hire would be

[53] If $w_{ik} > w_{i'k'}$ for any two matched pairs (i, k) and $(i'k')$ such that $g(i, k) = g(i', k')$, then (i', k) would form a blocking pair by proposing a surplus split between them featuring a transfer between w_{ik} and $w_{i'k'}$, thus undermining the stability of the proposed matching.

assigned to group g_1 relative to g_2 are given by:

$$\ln(\frac{P(g_1|d)}{P(g_2|f)}) = \ln(P(g_1|f)) - \ln(P(g_2|f)) = \frac{\theta_{g_1}}{\sigma} + \ln(\overline{S}_{g_1|l(g_1),f}) + \ln(n(l(g_1))) + \ln(C_{l(g_1)}) - \frac{\theta_{g_2}}{\sigma} - \ln\overline{S}_{g_2|l(g_2),f}) - \ln(n(l(g_2))) - \ln(C_{l(g_2)}) \quad (47)$$

Since $\ln(\overline{S}_{g_1|l(g_1),f})$, $\ln(\overline{S}_{g_2|l(g_2),f})$, $\ln(n(l(g_1)))$, and $\ln(n(l(g_2)))$ are all observed (or, if a large sample is taken, extremely precisely estimated), one can form adjusted log odds:

$$\ln(\frac{\hat{P}_{g_1|f}/(\overline{S}_{g_1|l(g_1),f})n(l(g_1)))}{\hat{P}_{g_2|f}/(\overline{S}_{g_2|l(g_2),f}n(l(g_2)))}) = (\frac{\theta_{g_1} - \theta_{g_2}}{\sigma}) + (\ln(C_{l(g_1)}) - \ln(C_{l(g_2)})) \quad (48)$$

Under Assumption 1, C_l is the mean of exponentiated (and rescaled) equilibrium utility payoffs owed to workers $i : l(i) = l$:

$$C_l = \frac{1}{|l|} \sum_{i:l(i)=l(g)} e^{-\frac{r_i}{\sigma}} \approx \sum_{\frac{1}{g_k}} \sum_{i:g(i,k)=g} e^{-\frac{r_i}{\sigma}} \; \forall \, k \quad (49)$$

Plugging (46) into (49) and then (49) into (48) yields:

$$\ln(\frac{\hat{P}_{g_1|f}/(\overline{S}_{g_1|l(g_1),f}n(l(g_1)))}{\hat{P}_{g_2|f}/(\overline{S}_{g_2|l(g_2),f}n(l(g_2)))}) = (\frac{\theta_{g_1} - \theta_{g_2}}{\sigma}) + (\ln(\frac{1}{|l|} \sum_{i:l(i,j(i))=l(g_1)} e^{-\frac{w_{ik}+\pi^l_{ik}}{\sigma}}) - \ln(\frac{1}{|l|} \sum_{i:l(i,j(i))=l(g_2)} e^{-\frac{w_{ik}+\pi^l_{ik}}{\sigma}})) \quad (50)$$

It is not immediately obvious how to use equation (50) to recover parameters of interest. Only when one adds further assumptions that are at odds with the structure of the model can one recover an expression that mirrors the one in CS. Specifically, suppose the following assumptions hold:

$$\begin{aligned} & r_i \approx r_{l(i)} \; \forall \, i : l(i) = l \; \forall l \in \mathcal{L} \\ & \pi^l_{ik} = \pi^l_{g(i,k)} \equiv \theta^l_g \; \forall \, (i,k) : g(i,k) = g \; \forall \, g \in \mathcal{G} \\ & w_{ik} = w_{g(i,k)} \forall \, (i,k) : g(i,k) = g \; \forall \, g \in \mathcal{G} \end{aligned} \quad (51)$$

These assumptions are extremely unlikely to hold in any stable matching if there is meaningful variance in ϵ_{ik} among the (i,k) pairs within the same group g. Nonetheless, they yield:

$$\begin{aligned} \ln(\frac{\hat{P}_{g_1|f}/(\overline{S}_{g_1|l(g_1),f}n(l(g_1)))}{\hat{P}_{g_2|f}/(\overline{S}_{g_2|l(g_2),f}n(l(g_2)))}) &= (\frac{\theta_{g_1} - \theta_{g_2}}{\sigma}) + (\ln(e^{-r_{l(g_1)}}) - \ln(e^{-r_{l(g_2)}})) \\ &= (\frac{\theta_{g_1} - \theta_{g_2}}{\sigma}) + \frac{-r_{l(g_1)} + r_{l(g_2)}}{\sigma} = (\frac{\theta_{g_1} - \theta_{g_2}}{\sigma}) + (\frac{-(w_{g_1} + \theta^l_{g_1}) + (w_{g_2} + \theta^l_{g_2})}{\sigma}) \\ &= \frac{\theta^f_{g_1} - \theta^f_{g_2} + (w_{g_2} - w_{g_1})}{\sigma} \end{aligned} \quad (52)$$

Given an estimate of σ based on multiple markets (as described in Appendix A4) and data on mean annual earnings for each match group $g \in \mathcal{G}$, one could identify the difference in the position component of the joint surplus for arbitrary groups g_1 and g_2. This provides information about the relative profit contributions of different types of workers for each type of position before such workers salaries are considered. Note that one could still not separate the training cost, recruiting cost, current revenue contribution, and continuation value components of θ_g^f without additional data.

A similar progression using adjusted log odds based on the worker side conditional probabilities $P(g_1|l_1)$ and $P(g_2|l_1)$ would yield an estimate of the corresponding difference in the worker components of the joint surplus $\theta_{g_1}^l - \theta_{g_2}^l$ for any two groups featuring the same worker type. Since one such group could represent nonemployment, this approach would provide estimates of the desirability of working at various types of firms in various locations for zero pay relative to nonemployment. These values identify the reservation salary necessary to convince each worker type to take (or continue) a position of each type. Again, one could not disentangle the moving cost, search cost, non-wage amenity value, and continuation value components of the surplus without further data.

Because 1) we deem the assumptions (51) to be antithetical to the spirit of the model and at odds with the data, and 2) other than estimating σ, the use of transfers is not necessary to fulfill the primary aim of the paper, evaluating the utility and employment incidence across worker types of alternative local labor demand shocks, we do not make further use of the observed annual earnings distributions in the destination period.

A6 Imputing Missing Transitions Involving Unemployment and Missing Match Group Characteristics

Recall that nonemployed workers are only included in the sample in a given year if they are observed resuming work in a future year. This requirement is imposed so as to better distinguish unemployed workers from those exiting the labor force, but it creates the likely possibility of undercounting employment-to-unemployment (E-to-U) and unemployment-to-unemployment (U-to-U) transitions toward the end of the sample, when high shares of unemployment spells are right-censored due to data availability.[54] In addition, the inability to observe the characteristics of those working in states that did not approve the use of their LEHD data creates a further need for imputation for employment-to-employment (E-to-E) and unemployment-to-employment (U-to-E) transitions originating in out-of-sample states. This appendix describes how data from the harmonized American Community Survey (hereafter ACS) series created by IPUMS along with official unemployment statistics from the Bureau of Labor Statistics (hereafter BLS) were used to address these problems.

[54] Since nearly all states enter the sample well before the years used for this analysis, the analogous risk of undercounting unemployment-to-employment transitions is negligible.

A6.1 E-to-U and U-to-U Transitions

Note first that a match count must be generated for each match group g classified as an E-to-U transition, which consists of a combination of origin location, age category, and earnings quartile (since there is a single unemployment position type). Because the 1% ACS sample is too small to generate accurate E-to-U counts at even the PUMA level, we construct population-weighted E-to-U ACS counts by initial state, age, and earnings group, and re-scale each count so that the aggregate stock of E-to-U transitions matches the count of workers unemployed between more than 26 and less than 52 weeks from the BLS for the chosen year.[55] For in-sample initial states, we impute a match group g for each implied individual from the rescaled ACS counts by combining the ACS characteristics with a draw from the observed conditional empirical distribution of origin tracts given origin state among E-to-U transitions in the LEHD. E-to-U counts of transitions from the ACS that originate out of sample are aggregated across states, leaving 12 groups corresponding to the combinations of the three age categories and four initial earnings quartiles.

For U-to-U transitions, we begin with age-specific counts of long-term unemployment ($>$ 52 weeks) from the BLS, and distribute them across origin and destination states according to the joint distribution of state pairs among ACS U-to-U counts. We then impute an origin tract for each U-to-U transition from an in-sample state by drawing from the conditional empirical distribution of origin tracts given origin state and age group among the combined pool of E-to-U and E-to-E LEHD transitions that end in the observed state, so as to ensure appropriate support among origin tracts.

A6.2 E-to-E and U-to-E Transitions

Note that full match group counts are observed for all E-to-E transitions among in-sample states. Since we aggregate out-of-sample destination positions to a single type, in-sample to out-of-sample E-to-E match counts are also fully observed (by combining the absence of observed earnings with the provided indicator for non-zero earnings somewhere in the U.S.). E-to-E match counts among out-of-sample states require an initial earnings quartile and age to be assigned. We draw this using the distribution of initial earnings quartiles$\times$ age combinations among LEHD in-sample observations. E-to-E match counts from out-of-sample to in-sample states are completed similarly, except that the distribution of earnings quartiles also conditions on destination state, industry, firm size, and firm average pay as well as on being a state switcher.

U-to-E transitions in a fashion analogous to that of E-to-E transitions, except that an initial location must be imputed as well. If the worker has worked in-sample previously, we use the most recently observed employer tract as the worker's initial location. For those without previously observed employers (mostly young new entrants to the labor market), we use the same method for drawing origin tracts that was detailed for U-to-U transitions in the previous subsection.

[55] Because we use a 50% random sample of LEHD transitions, we multiply estimated E-to-U counts (and U-to-U counts) by .5.

A7 Smoothing Procedure

In this appendix we describe how we smooth the empirical distribution of job matches across groups, $\hat{P}(g)$, prior to estimation in order to generate accurate estimates of the set of identified joint surplus difference-in-differences Θ^{D-in-D}. We smooth for two reasons. First, such smoothing serves as a "noise infusion" technique that removes the risk that individual or establishment identities could be revealed by any estimates presented in the paper, as required of all research results generated from confidential microdata in Federal Statistical Research Data Centers (FSRDCs). Second, smoothing is necessary because there are sufficiently few observations per match group such that many match groups are rarely (or never) observed in a given matching despite substantial underlying matching surpluses simply due to sampling error. Essentially, $\hat{P}(g)$ is only a consistent estimator of $P(g)$ as the number of observed job matches per group I/G approaches infinity.

We overcome this sampling error problem by assuming that the underlying frequency $P(g)$ with which a job match belongs to a particular match group is a smooth function of the observed characteristics that define group g (following Hotz and Miller (1993) and Arcidiacono and Miller (2011)). This permits the use of a kernel density estimator that computes a weighted average of the empirical probabilities $\hat{P}(g')$ of "nearby" groups g' that feature "similar" vectors of characteristics to generate a well-behaved approximation of $P(g)$ from the noisy empirical distribution $\hat{P}(g)$.

Such smoothing introduces two additional challenges. First, excessive smoothing across other match groups erodes the signal contained in the data about the degree of heterogeneity in the relative surplus from job matches featuring different combinations of worker characteristics, establishment characteristics, and origin and destination locations. Since highlighting the role of such heterogeneity in forecasting the incidence of labor market shocks is a primary goal of the paper, decisions about the appropriate bandwidth must be made with considerable thought. The second, related challenge consists of identifying which of the worker and position characteristics that defines other groups makes them "similar", in the sense that the surplus $\{\theta_{g'}\}$ is likely to closely approximate the surplus θ_g whose estimate we wish to make more precise.

Recall that each group $g \equiv g(l, f, z)$ is a combination of 1) the origin establishment location (which we denote $loc(l)$), workers' initial age category (denoted $age(l)$), workers' initial earnings quartile (or unemployment status) at the origin establishment (denoted $earn(l)$), and an indicator for whether the worker's initial industry matches that of the job stimulus ($sameind(l)$); 2) the destination establishment's location ($loc(f)$), size category ($f\_size(f)$), average earnings category ($f\_earn(f)$), and industry supersector ($ind(f)$); and 3) the trichotomous indicator $z(i, k)$ that equals '1' when establishment $j(i)$ and establishment k are the same ($z(i, k) = 1$), '2' when these establishments are different but share an industry, and '0' when $j(i)$ and k are in different industries.

Given the goal of accurately characterizing incidence at a very high spatial resolution, we wish to preserve as accurately as possible any signal in the data about the structure of spatial ties between nearby local areas. Thus, wherever possible the kernel estimator should place non-zero weight only on alternative groups g' that share the same origin and destination locations

$(loc(l(g)) = loc(l(g'))$ and $loc(f(g)) = loc(f(g')))$. Similarly, we posit that an establishment's combination of size, average pay, and industry is more important than its location in determining the initial earnings and age categories of the worker that generates the most surplus. Let $wchar(l(g)) \equiv [earn(l), age(l), sameind(l)]$ denote the non-location worker characteristics. To develop a smoothing approach that embodies these principles, we first exploit the fact that $P(g)$ can be written as $P(g|f) * h(f(g))$, and then decompose $P(g|f)$ via:

$$
\begin{aligned}
P(g|f) &= P([l(g), f(g), z(g)]|f) \\
&= P([loc(l(g)), wchar(l(g)), z(g)]|f) \\
&= P(loc(l(g))|wchar(l(g)), z(g), f)P([wchar(l(g)), z(g)]|f) \qquad (53)
\end{aligned}
$$

where we use the definition of g, the set of characteristics that define $l(g)$ and $z(g)$, and the low of total probability. We use separate kernel density estimator procedures to estimate $P(loc(l(g))|wchar(l(g)), z(g), f(g))$ and $P(wchar(l(g)), z(g))|f(g))$.

Consider first the estimation of $P(loc(l(g))|wchar(l(g), z(g), f(g))$. For job stayer groups $(z(g) = 1)$, $P(loc(l(g))|wchar(l(g)), 1(z(g) = 1), f) = 1(loc(l(g)) = loc(f(g)))$, since a potential stayer associated with a particular position type must have already been working at the same location in the origin period (since we treat establishments that switch locations as different establishments for computational reasons). Thus, no smoothing of this component is necessary for such groups. For groups with $z(g) = 0$ or $z(g) = 2$, this is the conditional probability that a particular new hire would be originally located at location $loc(l)$, given the hired worker's initial earnings, age, the position's type f, and whether the worker would be an industry stayer or switcher. Let $K^{dist}(g, g')$ denote the metric capturing the similarity of alternative groups g' and g for the purpose of estimating the propensity for establishments of type f to hire workers from a particular location (conditional on the other worker characteristics). As discussed above, wherever possible we only assign finite distance $K^{dist}(g, g') < \infty$ (i.e. non-zero weight) to empirical conditional probabilities $P(loc(l(g'))|wchar(l(g')), z(g'), f(g'))$ of alternative groups g' that feature both the same origin location $loc(l(g')) = loc(l(g))$ *and* destination location $loc(f(g')) = loc(f(g))$.[56]

$K^{dist}(g, g')$ assigns the smallest distance to alternative groups g' that also feature the same position type $(f(g') = f(g))$, so that g and g' only differ in the non-location characteristics of hired workers. The closer $wchar(l(g'))$ is to $wchar(l(g'))$ (based on mahalanobis distance for the naturally ordered earnings and age categories), the smaller is the assigned distance $K^{dist}(g, g')$, but the profile flattens so that all groups g' that differ from g' only due to $wchar(l(g'))$ contribute to the weighted average. $K^{dist}(g, g')$ assigns larger (but still finite) distance to groups g' whose position types also differ on establishment size, avg. pay, or industry dimensions. The more different the establishment composition of the group, the smaller is its weight, with the profile again flattening so that all groups g' featuring the same origin and destination locations receive non-zero weight. Thus,

[56] There are a very small number of worker and position types that are never observed in any job match. By necessity, we put positive weight on groups featuring nearby origin or destination locations in such cases.

groups with less similar worker and establishment characteristics receive non-negligible weight only when there are too few observations from groups with more similar worker and establishment characteristics to form reliable estimates. The weight assigned to a particular alternative group g' also depends on the number of observed new hires made by $f(g')$ at a particular combination of non-location worker characteristics $wchar(l(g'))$, denoted $N^{dist}(g')$ below, since this determines the signal strength of the empirical CCP $P(loc(l(g')|wchar(l(g')), z(g), f(g'))$. Thus, we have:

$$P(loc(l(g))|wchar(l(g)), z(g), f(g)) \approx \\ \sum_{g'} (\frac{\phi(K^{dist}(g', g) N^{dist}(g'))}{\sum_{g''} \phi(K^{dist}(g'', g) N^{dist}(g''))} \hat{P}(loc(l(g'))|wchar(l(g')), z(g'), f(g')) \tag{54}$$

where $\phi(*)$ is the density function of the t distribution with 5 degrees of freedom (used as the kernel density), and $\frac{\phi(K^{dist}(g',g)N^{dist}(g'))}{\sum_{g''} \phi(K^{dist}(g'',g)N^{dist}(g''))}$ is the weight given to nearby match group g'.[57]

Next, consider the estimation of $P(wchar(l(g)), z(g)|f)$ and the conditional probabilities that either a job stayer, industry stayer, or industry mover with particular non-location characteristics will be hired to fill a position of position type f. Let $K^{wchar}(g, g')$ represent the metric capturing how similar alternative groups g' are to g for the purpose of estimating the propensity for firms of type f to hire (or retain) workers with particular non-location characteristics.

$K^{wchar}(g, g')$ assigns infinite distance (i.e. zero weight) to groups g' featuring different combos of establishment size, average pay, industry, and match characteristic $z(g)$ than the target group g. $K^{wchar}(g, g')$ assigns small distances to the conditional probabilities for groups g' representing hiring new (retaining) workers with the same non-location characteristics $wchar(l(g)) = wchar(l(g'))$ among firms from the same position type $f(g) = f(g')$ who are hiring workers from nearby locations. The distance metric increases in the tract pathlength between $loc(l(g'))$ and $loc(l(g'))$, but flattens beyond a threshold distance, so that groups featuring all origin locations (but shared values of other characteristics) contribute to the estimate.

Larger (but finite) distance values for $K^{wchar}(g, g')$ are assigned to conditional probabilities from groups g' that feature different (but nearby) destination locations (so $f(g) \neq f(g')$ but has the same combination of non-location position characteristics). Again, the distance metric increases in the pathlength between $loc(f(g))$ and $loc(f(g'))$, but eventually flattens at a large but non-infinite value. As before, the weight given to a group g' also depends on the precision of its corresponding number of total hires made by firms of the position type $f(g')$, which is proportional to $h(f(g'))$.

Again, the motivation here is that targeted worker characteristics and the retention/new hire decision (conditional on the utility bids required by workers in different locations) is likely to be driven more by an establishment's production process (proxied by size, mean pay, and industry) than by its location. Since there still may be spatially correlated unobserved heterogeneity in pro-

[57]The degrees-of-freedom choice is effectively a bandwidth choice, since a larger number of degrees of freedom generates less smoothing (smaller weight in the tails). 5 is used as the bandwidth for both this and the kernel densities presented below. The results are insensitive to moderate changes in bandwidth choice, but choosing a very large bandwidth results in very volatile simulation estimates across target tracts, highlighting the need for smoothing.

duction processes conditional on the other establishment observables, we place greater weight on the worker composition/retention decisions of proximate firms. More distant firms receive non-negligible weight only when too few local observations exist to form reliable estimates. The estimator for $P(wchar(l(g))|f)$ can be expressed via:

$$P(wchar(l(g)), z(g))|f(g)) \approx \sum_{g'} \left(\frac{\phi(K^{wchar}(g', g)h(f(g')))}{\sum_{g''} \phi(K^{wchar}(g'', g)h(f(g'')))} \hat{P}(wchar(l(g')), z(g'))|f(g')) \right. \tag{55}$$

Bringing the pieces together, this customized smoothing procedure has a number of desirable properties. First, by requiring the same origin and destination locations as a necessary condition for non-zero weight when estimating the propensity for particular position types to hire workers from each location, one can generate considerable precision in estimated CCPs without imposing assumptions about the spatial links between locations. Second, at the same time, one can still use information contained in the hiring and retention choices of more distant establishments to learn about the propensity for establishments of different sizes, pay levels, and industries to retain and hire workers at different skill levels and from unemployment. Third, the procedure places non-trivial weight on match groups featuring less similar worker and establishment characteristics only when there are too few observed hires/retentions made by establishments associated with groups featuring very similar characteristics to yield reliable estimates. Fourth, overall the estimated probabilities $P(g|f)$ place weight on many groups, so that no element of the resulting smoothed distribution contains identifying worker or establishment information, eliminating disclosure risk.

A8 Model Validation

The simulations consider relatively large, locally focused labor demand shocks, but the estimated surplus parameters $\hat{\Theta}^{D-in-D}$ that underlie them are identified from millions of quotidian job transitions driven by small firm expansions/contractions and worker retirements and preference or skill changes over the life cycle that generate considerable offsetting churn in the U.S. labor market. Thus, one might reasonably wonder whether parameters governing ordinary worker flows are capable of capturing the response to sizable, locally focused positive or negative shocks. To address this concern, in this section we describe and present results from a model validation exercise in which surplus parameters estimated on pre-shock ordinary worker flows were used to forecast the reallocation of workers after actual local economic shocks observed in the LEHD sample.

Specifically, 421 shocks to employment in a census tract were identified in the LEHD sample that satisfied the following criteria: 1) the shock occurred in a sample state during the years 2003 - 2012; 2) exactly one establishment experienced an employment change of at least 100 workers (usually a closing or opening); 3) at least 100 more or 100 fewer positions were filled in the chosen census tract than the year before; 4) the change in the number of positions constituted at least 10%

and at most 200% of the total number of filled positions in the chosen census tract in the prior year; 5) The chosen tract featured at least 200 positions in the year prior to the shock; 6) no other tract in the same PUMA experienced an offsetting shock more than 50% as large as the shock to the chosen tract; and 7) less than 50% of the change in number of positions filled in the year of the shock was offset by a shock to the same tract in the opposite direction the following year.

These criteria ensure that a sufficient number of states report data in both the shock year and the prior year to properly capture any worker reallocation, that the shock was likely to be demand-driven and big enough to represent a meaningful disruption to both the chosen tract and the surrounding area, and that the shock was sufficiently persistent to rule out the possibility of a spuroius "shock" due to a reporting error by a large firm in the unemployment insurance data.

To create a forecast of the worker reallocations that a given shock occurring in year y would engender, the full set of model parameters was estimated based on the nationwide sample of worker transitions between years $y-2$ and $y-1$, using the same procedures for smoothing and aggregating types featuring distant locations described in Section 5.1. A counterfactual allocation was then generated by holding fixed the estimated surplus parameters but imposing the marginal distributions of origin and position types from the pair of years capturing the shock, $f^{y-1}(l)$ and $h^{y}(f)$. Since the exact composition of the shock (as reflected in $h^{y}(f)$) is built into the forecast, the test of the model is the degree to which the particular flows of workers of different worker types to particular destination position types that resulted from the shock can be predicted.

We assess the accuracy of the forecast using the index of dissimilarity, which measures the percentage of predicted job matches that must be reassigned to a different match group to perfectly match the distribution of actual job matches across groups. It sums the absolute differences in the share of all matches assigned to g in the forecast and the actual data across all match groups g and multiplies by one-half: $\sum_g \frac{1}{2}|\hat{P}(g) - P(g)|$. Since most shock-induced reallocation likely occurs among workers initially near the target tract, we evaluate forecast accuracy only among groups featuring workers who were working or most recently working in the PUMA of the target tract.

To help understand the sources of improvements and shortfalls in model fit, we also compute the index of dissimilarity between the true allocation and several alternative forecasts. The first is a standard parametric conditional logit specification, in which the probability that a random position of type f is filled by a worker whose match would be assigned to group g is given by $P^{y}(g|f) = \frac{e^{X_g^y \lambda}}{\sum_{g'} e^{X_{g'}^y \lambda}}$, where X_g^y includes a substantial set of regressors constructed for year y that capture the kinds of predictors of joint surplus that researchers often use, and λ is the corresponding vector of parameters estimated from the relationship between the previous year's data, $P^{y-1}(g|f)$ and X_g^{y-1}. The regressors include full sets of dummies for the following categorical variables: origin-destination distance bins using tract pathlength within PUMA, PUMA pathlength within state, and state pathlength between states, initial earnings quartile $\times$ supersector dummies, age category $\times$ supersector dummies, initial earnings $\times$ firm size quartile dummies, age category $\times$ firm size quartile dummies, initial earnings $\times$ firm average pay quartile dummies, and age category $\times$ firm average pay quartile dummies. The regressors also include indicators for whether the group g is associated with job stayers ($1(z(g) = 1)$) or industry stayers among firm movers ($1(z(g) = 2)$), the worker type frequency $n(l(g))$ interacted with the geographic category of the position type associated with g (tract, PUMA, or state), an interaction between $n(l(g))$ and an indicator for whether $f(g)$ represents the "nonemployment" position type, and dummies for whether the origin and position types associated with match group g share a PUMA and share a state.

The second alternative forecast simply imposes that the CCPs that existed between $y-2$ and $y-1$ also hold during the shock year, so that $P^y(g) = \hat{P}^{y-1}(g|f)h^y(f)$. The third forecast mimics the second, except that the smoothing procedure described in Section A7 is applied to the $y-2$ data prior to constructing $\hat{P}^{y-1}(g|f)$. Like much research on either worker job search or firm job filling, all these alternative forecasts ignore the problem's two-sided nature, and thus do not impose that the proposed allocation satisfies the marginal distribution of worker types, $n^{y-1}(l)$. The fourth forecast uses Choo and Siow (2006)'s version of the model, in which the idiosyncratic job match-level surplus component ϵ_{ik} is replaced by two terms capturing surplus interactions between worker and position type and worker type and position rather than between worker and position: $\epsilon^1_{if(k)} + \epsilon^2_{l(i),k}$. This comparison is useful for assessing the importance of assumptions about correlation structure among unobserved components in driving predictions about counterfactual assignments.

The final five alternative forecasts all consider simplified versions of the baseline model in which we eliminate heterogeneity in surplus values among 1) non-location firm characteristics, 2) non-location worker characteristics, 3) non-location worker and firm characteristics, 4) industry stayers vs. movers among job switchers, and 5) job stayers vs. job movers, respectively. Comparisons of these forecasts with the baseline specification reveal which dimensions of heterogeneity are important for the accuracy of out-of-sample predictions at different levels of aggregation.

Table 8 contains the results of this exercise. All entries consist of averages across all 421 shocks considered. The two-sided matching model, with parameters estimated from the previous period, would need to reallocate 35.1% of job matches of workers originating in the target PUMA to other groups g to perfectly match the true within-PUMA distribution. However, predicting the exact joint distribution of origin tract and initial earnings and age categories among workers hired separately for positions defined by tract/size/avg. pay/industry combinations is quite a tall order. Comparing across columns, we see that the parametric logit, despite over 100 regressors, performs considerably worse: 45.8% of transitions starting in the relevant PUMA must be reallocated to a different match group to match the actual post-shock allocation. Holding fixed the full prior year CCP distribution (cols. 3 and 8) performs slightly worse than the two-sided estimator within the target PUMA (35.3% misallocated), while smoothing the CCPs does not help at this level of aggregation (35.6)%. The Choo-Siow model matches the baseline model by this metric, with 35.1% misallocated.

For many purposes, however, forecasting exactly the right origin and destination tracts of transitions may be less important than correctly assessing the degree to which the disruption dissipates farther from the shock. To this end, row 2 reports results in which groups are combined that feature the same worker and establishment characteristics as well as origin and destination locations that belong to the same distance bin (using 14 bins), so that the dissimilarity index is computed over a somewhat coarser set of match groups. Only 11.1% of matches within the target PUMA are now misallocated by the two-sided forecast, with the two CCP forecasts following suit (with smoothing now improving the forecast slightly), suggesting that a substantial share of "incorrect" predictions might nonetheless be sufficiently accurate for most purposes. The parametric logit, by contrast, still performs poorly (36.2%). Furthermore, row 3 shows that combining groups featuring the same distance bins and worker earnings and age categories but different establishment size, average pay, and industry categories reduces the index of dissimilarity to 2.3% for workers originating in the targeted PUMA. This is despite the fact that $P(g)$ still contains 1,500 match groups with only 155 restrictions imposed by $n(l)$ and $h(f)$. Furthermore, the two-sided model significantly outperforms the simpler smoothed and unsmoothed CCP models at this level of aggregation (3.7% and 3.8%, respectively), and slightly outperforms the Choo-Siow model (3.7%). This suggests that the two-sided matching model matches well the locations of job movers and stayers, but is slightly less effective at matching small differences in the establishment characteristics of the jobs to which workers move.

The disaggregated baseline model also generates much more accurate predictions than the five alternative versions from Table A17 that restrict surplus heterogeneity across worker types, firm types, or mover/stayer status. After aggregating to distance bins and across non-location firm characteristics, the baseline model (2.3%) dramatically outperforms the version of the model with no heterogeneity in firm characteristics (13.0%), despite the fact that the ability to match destination firm characteristics is no longer being assessed. Removing heterogeneity in non-location worker instead of firm characteristics also reduces the goodness of fit (8.6%), while removing both sets causes a required reallocation share of 19.2%. Dropping the distinction between job stayers and movers is inconsequential at this level of aggregation, but causes extremely poor predictions (73.5%) for the full group space that tries to predict which types of workers make job transitions.

For other purposes, the primary goal of a forecast might be to properly predict the geographic and skill incidence of unemployment. To this end, row 4 computes the index of dissimilarity exclusively over the set of groups featuring workers entering or exiting unemployment, so that the exercise is to predict the location and initial earnings and age categories of those losing jobs and the firm composition of those finding jobs (separately by worker initial location). Using the full set of locations, the worker or firm types of only 3.3% of within-PUMA workers entering or exiting unemployment would need to be altered in order for the two-sided prediction to match the allocation that actually occurred. The two-sided estimator easily outperforms the CCP estimators (both estimators are around 9%), and slightly outperforms the Choo-Siow model within the target PUMA (4.2%) Aggregating locations into 14 distance bins (row 5) shows that the two-sided predictions only badly predicts origin and destination locations for 1.0% of unemployment entrants and exiters originating in the PUMA, suggesting that it predicts quite well the geographic and skill incidence of changes in unemployment following the shocks considered. Taken together, the model does quite a good job of predicting the reallocation of workers across job types and particularly across employment/unemployment status that follows major local labor market shocks.

Table A1: Summary Statistics from the Smoothed Sample Describing Heterogeneity in the Spacial Scope of Labor Markets by Worker and Establishment Characteristics

Panel A: By Worker Earnings or Age Category

		Share of All Transitions						Share of Job to Job Transitions					
Worker Subpop.	% of Pop.	Unemp. to Unemp.	Unemp. to Emp.	Emp. to Unemp.	Stay at Same Job	Same Ind.	Diff. Ind.	Same PUMA	New PUMA, Same State	New State	< 10 Miles	10-250 Miles	>250 Miles
All		0.028	0.093	0.028	0.695	0.073	0.083	0.277	0.576	0.148	0.303	0.517	0.180
Unemployment	0.120	0.229	0.771					0.288	0.617	0.095	0.314	0.554	0.131
1st Earn. Q.	0.217			0.057	0.703	0.099	0.141	0.295	0.551	0.153	0.313	0.507	0.180
2nd Earn. Q.	0.221			0.032	0.790	0.082	0.097	0.279	0.558	0.163	0.302	0.510	0.188
3rd Earn. Q.	0.221			0.021	0.831	0.075	0.073	0.251	0.563	0.186	0.282	0.504	0.214
4th Earn. Q.	0.221			0.016	0.846	0.073	0.065	0.216	0.551	0.233	0.264	0.456	0.280
Age < 30	0.308	0.028	0.181	0.040	0.529	0.091	0.130	0.267	0.581	0.152	0.294	0.521	0.185
Age 31-50	0.427	0.028	0.061	0.024	0.742	0.073	0.071	0.260	0.555	0.185	0.293	0.491	0.217
Age >50	0.264	0.026	0.041	0.018	0.821	0.049	0.045	0.265	0.556	0.179	0.292	0.497	0.211

Panel B: By Destination Establishment Pay Quartile and Size Quartile

		Share of All Transitions						Share of Job to Job Transitions					
Estab. Subpop.	% of Pop.	Unemp. to Unemp.	Unemp. to Emp.	Emp. to Unemp.	Stay at Same Job	Same Ind.	Diff. Ind.	Same PUMA	New PUMA, Same State	New State	< 10 Miles	10-250 Miles	>250 Miles
FE Quartiles 1 & 2	0.519		0.141		0.683	0.082	0.094	0.290	0.545	0.165	0.301	0.507	0.192
FE Quartile 3	0.241		0.059		0.793	0.069	0.079	0.269	0.556	0.175	0.296	0.505	0.199
FE Quartile 4	0.240		0.045		0.803	0.072	0.081	0.222	0.558	0.221	0.288	0.448	0.264
FS < Median	0.514		0.117		0.700	0.085	0.097	0.308	0.505	0.187	0.332	0.472	0.197
FS > Median	0.486		0.077		0.780	0.067	0.076	0.219	0.610	0.172	0.252	0.523	0.224

Panel C: By Destination Establishment Industry

		Share of All Transitions						Share of Job to Job Transitions					
Estab. Industry	% of Pop.	Unemp. to Unemp.	Unemp. to Emp.	Emp. to Unemp.	Stay at Same Job	Same Ind.	Diff. Ind.	Same PUMA	New PUMA, Same State	New State	< 10 Miles	10-250 Miles	>250 Miles
Nat. Resources	0.018		0.131		0.693	0.076	0.101	0.386	0.391	0.224	0.192	0.561	0.248
Construction	0.049		0.113		0.690	0.091	0.106	0.242	0.535	0.223	0.247	0.531	0.222
Manufacturing	0.089		0.054		0.829	0.035	0.081	0.339	0.490	0.172	0.296	0.518	0.187
Wholesale/Retail	0.204		0.107		0.733	0.077	0.083	0.234	0.570	0.196	0.251	0.522	0.228
Information	0.023		0.068		0.752	0.062	0.118	0.226	0.585	0.190	0.320	0.434	0.246
Financial Activities	0.059		0.061		0.761	0.074	0.104	0.237	0.601	0.162	0.297	0.493	0.211
Prof. Bus. Services	0.143		0.119		0.661	0.091	0.129	0.228	0.584	0.189	0.281	0.478	0.242
Ed. & Health	0.224		0.069		0.796	0.078	0.057	0.308	0.537	0.155	0.344	0.487	0.169
Leis. & Hosp.	0.113		0.179		0.621	0.116	0.084	0.298	0.525	0.177	0.336	0.468	0.196
Oth. Serv.	0.031		0.122		0.722	0.038	0.118	0.301	0.531	0.168	0.353	0.458	0.190
Government	0.047		0.036		0.880	0.025	0.059	0.344	0.544	0.112	0.319	0.520	0.162

Notes: "Unemployed": Workers who were unemployed in the prior year. "Earn. Q.": Workers in the chosen quartile of the distribution of annualized earnings based on pro-rating earnings in full quarters. "FE Quartile": Firms (SEINs) in the chosen quartile of the (worker-weighted) firm distribution of per-worker annual earnings. "FS <(>) Median": Firms below (above) the median of the worker-weighted firm employment distribution. *: For initially unemployed workers, the share of unemployment-to-employment transitions by distance category is reported in place of share of job-to-job transitions. The locations of initially unemployed workers are assumed to be the location of their most recent employer if previously observed working, otherwise they are imputed from the conditional distribution among job-to-job transitions of origin locations given the destination employer location.

"Nat. Resources": Natural Resources. "Wholesale/Retail": Wholesale/Retail Trade and Transportation. "Prof. Bus. Services": Professional & Business Services. "Ed. & Health": Education and Healthcare. "Leis. & Hosp.": Leisure and Hospitality. "Oth. Serv.": Other Services (includes repair, laundry, security, personal services).

Table A2: Specifications for the Baseline Set of Counterfactual Labor Demand Shocks

Spec. No.	Number of Jobs	Firm Avg. Earn. Quartile	Firm Size Quartile	Industry Supersector	Shock Type
1	250	2	1	Information	Stimulus
2	250	2	4	Information	Stimulus
3	250	4	1	Information	Stimulus
4	250	4	4	Information	Stimulus
5	250	2	1	Manufacturing	Stimulus
6	250	2	4	Manufacturing	Stimulus
7	250	4	1	Manufacturing	Stimulus
8	250	4	4	Manufacturing	Stimulus
9	250	2	1	Trade/Trans./Utilities	Stimulus
10	250	2	4	Trade/Trans./Utilities	Stimulus
11	250	4	1	Trade/Trans./Utilities	Stimulus
12	250	4	4	Trade/Trans./Utilities	Stimulus
13	250	2	1	Prof. & Bus. Services	Stimulus
14	250	2	4	Prof. & Bus. Services	Stimulus
15	250	4	1	Prof. & Bus. Services	Stimulus
16	250	4	4	Prof. & Bus. Services	Stimulus
17	250	2	1	Education & Health	Stimulus
18	250	2	4	Education & Health	Stimulus
19	250	4	1	Education & Health	Stimulus
20	250	4	4	Education & Health	Stimulus
21	250	2	1	Leisure & Hospitality	Stimulus
22	250	2	4	Leisure & Hospitality	Stimulus
23	250	4	1	Leisure & Hospitality	Stimulus
24	250	4	4	Leisure & Hospitality	Stimulus
25	250	2	1	Government	Stimulus
26	250	2	4	Government	Stimulus
27	250	4	1	Government	Stimulus
28	250	4	4	Government	Stimulus
29	250	2	1	Other Services	Stimulus
30	250	2	4	Other Services	Stimulus
31	250	4	1	Other Services	Stimulus
32	250	4	4	Other Services	Stimulus

Table A3: Assessing the Impact of Stimulus Packages That Create 250 Jobs by Pathlength Distance from Focal Tract Across Several Outcomes (Averages Across All Stimulus Compositions)

Distance from Target Tract	Share of JtJ Dest.	Initial Locations	Prob. of Stim. Job	Share of Stim Jobs	Change in P(Employed)	Share of Emp. Gains	Avg. Welfare Change ($)	Share of Wel. Gains
Target Tract	0.032	2.0E-05	0.005	0.034	0.001	0.006	322	0.009
			(3.0E-05)	(1.6E-04)	(4.7E-06)	(2.5E-05)	(10)	(4.1E-05)
1 Tct Away	0.057	1.1E-04	0.002	0.051	3.2E-04	0.009	105	0.015
			(9.1E-06)	(1.9E-04)	(1.9E-06)	(3.2E-05)	(3)	(5.5E-05)
2 Tcts Away	0.061	2.4E-04	0.001	0.053	1.4E-04	0.012	51	0.019
			(3.0E-06)	(1.7E-04)	(5.8E-07)	(3.6E-05)	(1)	(5.8E-05)
3+ Tcts w/in PUMA	0.122	0.001	2.8E-04	0.123	7.0E-05	0.032	26	0.055
			(7.1E-07)	(2.5E-04)	(1.7E-07)	(6.5E-05)	(0.4)	(1.3E-04)
1 PUMA Away	0.082	0.001	1.6E-04	0.094	4.6E-05	0.028	17	0.051
			(6.4E-07)	(2.5E-04)	(1.4E-07)	(6.6E-05)	(0.3)	(1.4E-04)
2 PUMAs Away	0.137	0.004	8.1E-05	0.132	3.1E-05	0.051	11	0.092
			(2.3E-07)	(2.6E-04)	(7.0E-08)	(8.4E-05)	(0.2)	(1.8E-04)
3+ PUMAs w/in State	0.328	0.055	2.4E-05	0.302	1.6E-05	0.243	7	0.399
			(7.2E-08)	(0.001)	(3.4E-08)	(0.001)	(0.1)	(0.001)
1 State Away	0.028	0.053	1.3E-06	0.035	2.6E-06	0.072	0.8	0.099
			(5.1E-09)	(1.4E-04)	(3.4E-09)	(1.7E-04)	(0.0)	(2.5E-04)
2+ States Away	0.036	0.262	2.1E-07	0.028	1.0E-06	0.141	0.1	0.070
			(5.3E-10)	(7.1E-05)	(4.4E-10)	(1.3E-04)	(0.0)	(8.2E-05)
Out of Sample	0.117	0.622	4.7E-07	0.148	1.3E-06	0.407	0.1	0.191
			(7.3E-10)	(2.3E-04)	(6.5E-10)	(2.1E-04)	(0.0)	(2.6E-04)

Notes: The column labeled “Share of JtJ Dest.” displays the observed share of all job-to-job transitions among 2012 and 2013 dominant jobs whose origin-destination distance fell into the distance bins given by the row labels. The column labeled “Initial Locations” captures the share of workers for whom the distance between their origin position and the targeted census tract fell into the chosen bin (averaged over 300 simulations featuring different target census tracts). The column labeled “Prob. of Stim. Job” indicates the probability that a randomly chosen worker in the row distance bin will receive one of the 250 new positions generated by the simulated stimulus package. The column labeled “Change in P(Employed)” indicates the change in the probability that a randomly chosen worker in the row distance bin will be employed in the destination year as a consequence of the simulated stimulus package. The column labeled “Avg. Welfare Change” indicates the change in job-related welfare (scaled to be equivalent to $ of 2023 annual earnings) that a randomly chosen worker in the distance bin indicated by the row label will experience as a consequence of the simulated stimulus package. The columns labeled “Share of Stim. Jobs”, “Share of Emp. Gains” and “Share of Wel. Gains” indicate the share of all stimulus jobs and total employment and welfare gains, respectively, generated by the simulated stimulus package that accrue to workers in the distance bin indicated by the row label.

“Target Tract” indicates that the worker’s origin establishment was in the tract receiving the stimulus package. 1/2/3+ Tct(s) Away” indicates that the origin establishment was one, two, or 3 or more tracts away (by tract pathlength) within the same PUMA. “1/2/3+ PUMAs Away” and “1/2+ States Away” indicate the PUMA pathlength (if within the same state) and state pathlength (if in different states), respectively. “Out of Sample” indicates that the worker’s origin establishment was not among the 19 states providing data in the sample.

Standard errors are provided in parentheses, and are based on the sampling distribution among the sample of 300 target tracts simulated for each stimulus package specification.

Table A4: Assessing the Impact of Stimulus Packages That Create 250 Jobs by Distance in Miles from Focal Tract Across Several Outcomes (Averages Across All Stimulus Compositions)

Distance from Centroid of Target Tract	Share of JtoJ Dest.	Initial Locations	Prob. of Stim. Job	Share of Stim. Jobs	Change in P(Employed)	Share of Emp. Gains	Avg. Welfare Gain ($)	Share of Wel. Gains
Within 1 Mile	0.032	8.1E-05	0.003	0.040	4.6E-04	0.007	164	0.013
1-2 Miles Away	0.053	2.1E-04	0.001	0.031	1.9E-04	0.006	55	0.010
3-5 Miles Away	0.093	0.001	0.001	0.095	1.9E-04	0.022	69	0.037
6-11 Miles Away	0.120	0.002	0.001	0.113	2.1E-04	0.030	74	0.053
11-26 Miles Away	0.160	0.003	0.001	0.151	1.5E-04	0.046	54	0.081
26-50 Miles Away	0.070	0.002	2.1E-04	0.064	6.1E-05	0.024	24	0.043
51-100 Miles Away	0.063	0.002	9.0E-05	0.056	3.7E-05	0.027	14	0.051
101-250 Miles Away	0.202	0.026	1.2E-05	0.100	9.9E-06	0.094	4	0.168
>250 Miles Away	0.092	0.342	1.1E-06	0.202	1.9E-06	0.336	0.4	0.354
Out of Sample	0.117	0.622	4.7E-07	0.148	1.3E-06	0.407	0.1	0.191

Notes: See Table A3 for expanded definitions of the outcomes in the column labels. The row labels define sets of workers for whom the distance between the establishment associated with their origin dominant jobs and the census tract receiving the simulated stimulus package fell in the listed distance bin.

Table A5: Assessing the Value of Restricting Stimulus Jobs to Workers Within the Target PUMA: Spatial Employment and Welfare Incidence for Restricted and Unrestricted Stimulus Packages (Each Featuring 250 Positions at a Large High-Paying Manufacturing Firm)

Distance from Target Tract	Change in P(Employed)		Share of Emp. Gains		Avg. Welfare Change ($)		Share of Wel. Gains	
	Unres.	Res.	Unres.	Res.	Unres.	Res.	Unres.	Res.
Target Tract	0.001	0.005	0.004	0.028	296	2076	0.009	0.050
1 Tct Away	2.5E-04	0.001	0.008	0.039	98	474	0.015	0.067
2 Tcts Away	1.2E-04	4.9E-04	0.010	0.039	49	176	0.019	0.061
3+ Tcts w/in PUMA	6.1E-05	1.6E-04	0.028	0.069	27	81	0.056	0.114
1 PUMA Away	3.9E-05	3.7E-05	0.025	0.024	17	16	0.048	0.044
2 PUMAs Away	2.8E-05	2.6E-05	0.046	0.043	12	11	0.087	0.078
3+ PUMAs w/in State	1.6E-05	1.5E-05	0.236	0.215	7	6	0.385	0.334
1 State Away	2.5E-06	2.5E-06	0.070	0.068	0.8	0.8	0.092	0.086
2+ States Away	1.1E-06	9.4E-07	0.144	0.128	0.1	0.1	0.069	0.055
Out of Sample	1.3E-06	1.1E-06	0.429	0.346	0.2	0.1	0.220	0.113

Notes: See Table A3 for expanded definitions of the row labels and the outcomes in the column labels. Table entries consist of various measures of incidence by worker initial distance from the target census tract from a stimulus package consisting of 250 new jobs at large (employment above the worker-weighted median), high-paying (4th quartile of avg. worker pay) manufacturing firms. Columns labeled "Res." report results from specifications in which the new positions are constrained to be filled by workers initially working (or most recently working) in the same PUMA as the targeted tract, while columns labeled "Unres." report results from specifications in which the new positions may be filled by any worker in the nation.

Table A6: Shares of Nationwide Employment and Utility Gains Induced by Job Stimuli among Worker Initial Earnings, Age, and Industry Categories: Stimuli Consist of 250 Jobs at Firms in Different Firm Size/Firm Average Earnings Quartiles (Averaged across Different Firm Industries)

Worker	Share of Employment Gains					Share of Welfare Gains				
Category	Avg.	Sm./Low	Lg./Low	Sm./Hi	Lg./Hi	Avg.	Sm./Low	Lg./Low	Sm./Hi	Lg./Hi
Unemployment	0.438	0.450	0.447	0.431	0.423	0.120	0.131	0.134	0.109	0.105
1st Earn Q.	0.237	0.237	0.238	0.236	0.239	0.198	0.208	0.207	0.187	0.188
2nd Earn Q.	0.141	0.138	0.139	0.142	0.144	0.217	0.219	0.218	0.216	0.217
3rd Earn Q.	0.096	0.093	0.093	0.099	0.100	0.225	0.219	0.219	0.230	0.232
4th Earn Q.	0.088	0.083	0.083	0.093	0.094	0.241	0.223	0.223	0.258	0.258
Age $\leq$ 30	0.403	0.405	0.417	0.392	0.398	0.323	0.331	0.341	0.307	0.312
Age 31-50	0.398	0.396	0.389	0.405	0.402	0.425	0.417	0.412	0.436	0.434
Age $\geq$ 51	0.199	0.200	0.195	0.204	0.200	0.253	0.251	0.248	0.257	0.254
Diff. Ind.	0.934	0.931	0.935	0.933	0.935	0.885	0.878	0.891	0.881	0.892
Same Ind.	0.067	0.069	0.065	0.067	0.065	0.115	0.122	0.109	0.119	0.108

Notes: See Table 2 for expanded definitions of worker subpopulations captured by the row labels. See Table 3 for expanded definitions of the establishment size/avg. pay combinations captured by the column labels. The first five columns capture the share of employment gains in the destination year attributable to a 250 job stimulus package accruing to workers whose employment status or earnings in the origin year places them in the earnings/age/industry category listed by the row label. The last five columns capture the share of all stimulus-driven welfare gains (scaled to be equivalent to $ of 2023 annual earnings) accruing to workers in each earnings/age/industry category. Columns 1 and 6 average across all 32 stimulus package specifications. Each of columns 2-5 and 7-10 averages results across 8 stimulus packages featuring jobs with establishments in the same firm size quartile/firm average pay quartile combination but in different industry supersectors (as well as simulated 300 simulations for each stimulus package specification featuring different target census tracts)

Table A7: Cumulative Shares of Employment and Welfare Gains due to a Job Stimulus Accruing to Workers within Different Distances from Focal Tract: Stimuli Consist of 250 New Jobs at Firms in Alternative Industries (Averaged Across Firm Size and Average Earnings Combos)

Panel A: Cumulative Shares of Unemployment Gains

Distance from		Industry							
Focal Tract	Avg.	Info.	Manu.	Trd./Tns.	Prof. Bus.	Ed./Hlth	Lei/Hosp.	Gov.	Oth. Serv.
Focal Tract	0.006	0.005	0.006	0.005	0.005	0.007	0.006	0.006	0.006
1 Tct Away	0.015	0.013	0.015	0.014	0.013	0.018	0.016	0.015	0.016
2 Tcts Away	0.026	0.023	0.027	0.025	0.024	0.031	0.027	0.027	0.027
3+ Tcts w/in PUMA	0.058	0.053	0.059	0.054	0.055	0.066	0.059	0.061	0.059
1 PUMA Away	0.087	0.080	0.087	0.080	0.083	0.097	0.087	0.090	0.088
2 PUMAs Away	0.138	0.131	0.138	0.129	0.133	0.149	0.138	0.143	0.139
3+ PUMAs w/in State	0.380	0.372	0.380	0.372	0.372	0.394	0.377	0.394	0.380
1 State Away	0.452	0.446	0.450	0.444	0.444	0.465	0.449	0.466	0.451
2+ States Away	0.593	0.588	0.591	0.587	0.587	0.605	0.591	0.605	0.592
Out of Sample	1	1	1	1	1	1	1	1	1
Within 10 Miles	0.066	0.062	0.066	0.060	0.063	0.074	0.066	0.068	0.067
Within 250 Miles	0.257	0.250	0.256	0.249	0.252	0.271	0.255	0.266	0.258

Panel B: Cumulative Shares of Welfare Gains

Distance from		Industry							
Focal Tract	Avg.	Info.	Manu.	Trd./Tns.	Prof. Bus.	Ed./Hlth	Lei/Hosp.	Gov.	Oth. Serv.
Focal Tract	0.009	0.007	0.010	0.009	0.008	0.013	0.010	0.009	0.009
1 Tct Away	0.025	0.021	0.025	0.023	0.022	0.031	0.025	0.026	0.026
2 Tcts Away	0.044	0.039	0.045	0.041	0.039	0.053	0.044	0.046	0.045
3+ Tcts w/in PUMA	0.099	0.091	0.102	0.093	0.091	0.115	0.098	0.103	0.099
1 PUMA Away	0.150	0.140	0.152	0.142	0.142	0.170	0.149	0.155	0.149
2 PUMAs Away	0.242	0.233	0.243	0.232	0.232	0.266	0.241	0.249	0.240
3+ PUMAs w/in State	0.641	0.634	0.639	0.635	0.626	0.667	0.638	0.659	0.630
1 State Away	0.740	0.736	0.735	0.734	0.726	0.764	0.739	0.757	0.724
2+ States Away	0.809	0.807	0.804	0.803	0.797	0.831	0.810	0.826	0.797
Out of Sample	1	1	1	1	1	1	1	1	1
Within 10 Miles	0.112	0.106	0.113	0.105	0.108	0.128	0.113	0.115	0.113
Within 250 Miles	0.455	0.447	0.453	0.447	0.445	0.482	0.453	0.465	0.448

Notes: See Tables A3 and 1 for expanded definitions of the row and column labels. Each entry provides the share of net employment gains attributable to a 250 job stimulus package accruing to workers whose distance between their origin jobs and the census tract receiving the stimulus package is less than or within the distance bin indicated in the row label. Different columns consider average employment impacts from stimuli featuring jobs in different industry supersectors. Each column averages results across four stimulus packages with the same industry supersector but in different categories of the establishment size and average worker earnings.

Table A8: Share of Nationwide Employment and Utility Gains From New Stimulus Positions by Distance from Focal Tract: Stimuli Consist of 250 New Positions in Alternative Combinations of Firm Size Quartile/Firm Average Pay Quartile (Averaged Across Industry Supersectors)

Distance from	Share of Employment Gains				Share of Utility Gains			
Focal Tract	Sm./Low	Lg./Low	Sm./Hi	Lg./Hi	Sm./Low	Lg./Low	Sm./Hi	Lg./Hi
Target Tract	0.006	0.006	0.005	0.005	0.010	0.009	0.010	0.009
1 Tct Away	0.017	0.016	0.014	0.013	0.026	0.025	0.025	0.024
2 Tcts Away	0.030	0.028	0.025	0.023	0.046	0.044	0.043	0.042
3+ Tcts w/in PUMA	0.065	0.061	0.055	0.052	0.103	0.100	0.097	0.096
1 PUMA Away	0.095	0.091	0.081	0.079	0.156	0.152	0.146	0.146
2 PUMAs Away	0.149	0.144	0.130	0.127	0.251	0.247	0.234	0.236
3+ PUMAs w/in State	0.396	0.394	0.365	0.365	0.658	0.660	0.620	0.626
1 State Away	0.468	0.467	0.436	0.436	0.760	0.762	0.716	0.721
2+ States Away	0.608	0.607	0.579	0.579	0.830	0.833	0.786	0.789
Out of Sample	1	1	1	1	1	1	1	1
Within 10 Miles	0.072	0.069	0.062	0.060	0.116	0.113	0.111	0.110
Within 250 Miles	0.272	0.268	0.245	0.243	0.471	0.468	0.439	0.442

Notes: See Table A3 for expanded definitions of the row labels. See Table 3 for expanded definitions of the establishment size/avg. pay combinations captured by the column labels. The first four columns capture the share of all net employment gains attributable to a 250 job stimulus package for workers whose distance between their origin jobs and the census tract receiving the stimulus package is below or within in the distance bin indicated in the row label. The last four columns capture the share of all stimulus-driven utility gains accruing to workers below or within in each distance bin. Different columns consider average employment impacts from stimuli featuring jobs with establishments from different combinations of firm size and firm average worker categories. Each column averages results across 8 stimulus packages featuring jobs with establishments in the same firm size quartile/firm average pay quartile combination but in different industry supersectors (as well as across 300 simulations for each stimulus package specification featuring different target census tracts).

Table A9: Cumulative Shares of Employment and Welfare Losses From a Plant Closing Removing 250 Positions at Large High-Paying Manufacturing Firms in the Target Tract Accruing to Workers in Different Distance Bins from the Target Tract by Worker Subpopulation

Panel A: Cumulative Share of Employment Losses

	Earnings Quartile					Age			Ind. Status	
Distance Bin	Unemp	1st Q.	2nd Q.	3rd Q.	4th Q.	$<= 30$	$31-50$	> 50	Diff Ind.	Same Ind.
Target Tract	0.005	0.022	0.091	0.217	0.291	0.051	0.098	0.121	0.003	0.612
1 Tct Away	0.010	0.028	0.098	0.224	0.299	0.057	0.105	0.127	0.009	0.623
2 Tcts Away	0.018	0.035	0.106	0.232	0.307	0.066	0.112	0.134	0.016	0.632
Over 3 Tcts within PUMA	0.039	0.056	0.129	0.253	0.323	0.087	0.133	0.153	0.037	0.653
1 PUMA Away	0.058	0.076	0.148	0.269	0.336	0.108	0.151	0.169	0.056	0.668
2 PUMAs Away	0.095	0.110	0.180	0.298	0.359	0.143	0.182	0.198	0.090	0.689
3+ PUMAs w/in State	0.346	0.291	0.346	0.449	0.489	0.354	0.370	0.372	0.301	0.769
1 State Away	0.383	0.324	0.378	0.476	0.509	0.389	0.401	0.401	0.337	0.782
2+ States Away	0.575	0.500	0.535	0.610	0.608	0.572	0.557	0.547	0.517	0.840
Out of Sample	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
Within 10 miles	0.044	0.055	0.127	0.254	0.327	0.088	0.136	0.155	0.040	0.648
Within 250 miles	0.220	0.217	0.279	0.383	0.422	0.256	0.283	0.291	0.203	0.733

Panel B: Cumulative Share of Welfare Losses

	Earnings Quartile					Age			Ind. Status	
Distance Bin	Unemp	1st Q.	2nd Q.	3rd Q.	4th Q.	$<= 30$	$31-50$	> 50	Diff Ind.	Same Ind.
Target Tract	0.012	0.068	0.203	0.398	0.534	0.198	0.379	0.439	0.006	0.779
1 Tct Away	0.026	0.081	0.216	0.409	0.548	0.211	0.392	0.452	0.019	0.792
2 Tcts Away	0.046	0.098	0.232	0.422	0.560	0.227	0.406	0.465	0.036	0.802
Over 3 Tcts within PUMA	0.099	0.144	0.274	0.454	0.584	0.268	0.439	0.494	0.080	0.823
1 PUMA Away	0.146	0.189	0.311	0.482	0.603	0.304	0.466	0.519	0.121	0.837
2 PUMAs Away	0.237	0.265	0.370	0.526	0.636	0.368	0.513	0.562	0.194	0.857
3+ PUMAs w/in State	0.732	0.643	0.645	0.735	0.810	0.690	0.740	0.766	0.576	0.930
1 State Away	0.787	0.692	0.683	0.763	0.829	0.731	0.768	0.792	0.624	0.939
2+ States Away	0.869	0.784	0.759	0.821	0.872	0.808	0.825	0.846	0.716	0.963
Out of Sample	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
Within 10 miles	0.106	0.144	0.271	0.454	0.593	0.271	0.443	0.496	0.088	0.820
Within 250 miles	0.504	0.489	0.540	0.649	0.722	0.548	0.640	0.680	0.409	0.899

Notes: See Table A3 for expanded definitions of the distance bins represented by the row labels. See Table 4 for expanded definitions of the worker subpopulations indicated by the column labels. Each entry gives the cumulative share of employment losses (Panel A) or utility losses (Panel B) among workers whose initial location is closer than or within the distance bin associated with the row label and who belong to the subpopulation associated with the column sublabel due to a simulated plant closing in which 250 positions are removed at large, high-paying manufacturing firms. The average is taken across 200 simulations featuring different target census tracts.

Table A10: Change in Probability of Destination Employment (or Unemployment) at Different Distances from Focal Tract after an Establishment Closing Removing 250 Positions at either Manufacturing or Retail Firms for Workers Initially Employed in the Focal Tract by Worker Subpopulation

Panel A: Large High-Paying Manufacturing

		Earnings Quartile					Age			Ind. Status	
Distance Bin	All	Unemp	1st Q.	2nd Q.	3rd Q.	4th Q.	$<= 30$	$31-50$	> 50	Diff Ind.	Same Ind.
Unemployment	0.007	0.001	0.003	0.006	0.009	0.008	0.006	0.007	0.007	2.3E-04	0.016
Target Tract	-0.046	-0.003	-0.012	-0.030	-0.050	-0.069	-0.041	-0.051	-0.040	-0.001	-0.112
1 Tct Away	0.002	2.0E-05	4.4E-04	0.002	0.002	0.002	0.002	0.002	0.001	-1.3E-05	0.004
2 Tcts Away	0.002	8.1E-05	0.001	0.002	0.003	0.002	0.002	0.002	0.002	-8.1E-06	0.005
3+ Tcts w/in PUMA	0.005	2.8E-04	0.002	0.003	0.006	0.007	0.004	0.005	0.004	3.3E-05	0.011
1 PUMA Away	0.003	2.9E-04	0.001	0.003	0.003	0.004	0.003	0.003	0.002	9.1E-05	0.006
2 PUMAs Away	0.003	3.2E-04	0.001	0.003	0.004	0.004	0.003	0.003	0.003	1.0E-04	0.009
3+ PUMAs w/in State	0.010	0.001	0.003	0.006	0.011	0.016	0.009	0.012	0.009	2.3E-04	0.028
1 State Away	0.002	7.6E-05	2.1E-04	0.001	0.002	0.004	0.002	0.002	0.001	3.7E-05	0.004
2+ States Away	0.003	1.6E-04	2.8E-04	0.001	0.002	0.006	0.003	0.004	0.002	4.7E-05	0.007
Out of Sample	0.011	1.2E-04	0.002	0.005	0.010	0.018	0.007	0.013	0.010	1.0E-04	0.024

Panel B Large Low-Paying Retail

		Earnings Quartile					Age			Ind. Status	
Distance Bin	All	Unemp	1st Q.	2nd Q.	3rd Q.	4th Q.	$<= 30$	$31-50$	> 50	Diff Ind.	Same Ind.
Unemployment	0.007	0.001	0.011	0.008	0.005	0.004	0.008	0.006	0.005	1.8E-04	0.018
Target Tract	-0.036	-0.002	-0.053	-0.045	-0.034	-0.027	-0.046	-0.033	-0.025	-0.001	-0.098
1 Tct Away	0.001	4.9E-05	0.001	0.001	0.001	0.001	0.001	0.001	0.001	5.0E-06	0.003
2 Tcts Away	0.001	4.6E-05	0.002	0.001	0.001	0.001	0.001	0.001	0.001	2.8E-06	0.003
Over 3 Tcts within PUMA	0.003	1.7E-04	0.004	0.004	0.003	0.002	0.004	0.003	0.002	3.4E-05	0.008
1 PUMA Away	0.002	1.3E-04	0.003	0.003	0.002	0.002	0.003	0.002	0.001	4.6E-05	0.006
2 PUMAs Away	0.005	2.6E-04	0.007	0.006	0.004	0.003	0.006	0.004	0.003	8.7E-05	0.012
3+ PUMAs w/in State	0.013	0.001	0.018	0.016	0.013	0.011	0.017	0.011	0.008	2.1E-04	0.034
1 State Away	0.001	9.1E-05	0.001	0.001	0.001	0.001	0.001	0.001	0.001	3.0E-05	0.003
2+ States Away	0.001	1.2E-04	0.002	0.001	0.001	0.001	0.001	0.001	0.001	3.7E-05	0.003
Out of Sample	0.003	6.1E-05	0.005	0.005	0.003	0.003	0.004	0.003	0.003	5.7E-05	0.009

Notes: See Table A3 for expanded definitions of the distance bins represented by the row labels. See Table 4 for expanded definitions of the worker subpopulations indicated by the column sublabels. Each entry gives the change in the probability of employment at a location whose distance falls into the distance bin associated with the row label among workers initially belonging to the subpopulation associated with the column sublabel and working in the previous year (or most recently working) in the focal census tract. The changes in employment probability are due to a simulated plant closing in which 250 positions are removed at either large, high-paying manufacturing firms (Panel A) or large, low-paying wholesale/retail firms (Panel B). Each entry represents an average over 200 simulations featuring different target census tracts. The entries in the row labeled "Unemployment" provides the change in the share of workers who stay or become unemployed due to the plant closing.

Table A11: Comparing the Impact of Plant Closings and Openings at Different Scales and Distances from Focal Tract on Employment and Welfare Outcomes

Panel A: Employment Outcomes

Distance from Focal Tract	Change in P(Employed): Plant Opening 125	250	500	Plant Closing 125	250	500	Share of Employment Gains or Losses: Plant Opening 125	250	500	Plant Closing 125	250	500
Target Tract	1.2E-04	2.3E-04	4.3E-04	-.003	-.007	-.016	0.005	0.005	0.004	0.075	0.086	0.099
1 Tct Away	8.7E-05	1.7E-04	3.2E-04	-6.6E-05	-1.2E-04	-2.2E-04	0.013	0.012	0.012	0.082	0.092	0.105
2 Tcts Away	5.5E-05	1.1E-04	2.0E-04	-4.4E-05	-8.0E-05	-1.4E-04	0.023	0.022	0.021	0.090	0.100	0.113
3+ Tcts w/in PUMA	2.8E-05	5.6E-05	1.1E-04	-2.4E-05	-4.6E-05	-8.6E-05	0.047	0.047	0.046	0.111	0.120	0.132
1 PUMA Away	1.8E-05	3.6E-05	7.2E-05	-1.6E-05	-3.0E-05	-5.6E-05	0.069	0.068	0.067	0.130	0.138	0.149
2 PUMAs Away	1.2E-05	2.5E-05	5.0E-05	-1.1E-05	-2.1E-05	-4.1E-05	0.106	0.106	0.104	0.164	0.171	0.180
3+ PUMAs w/in State	6.8E-06	1.4E-05	2.7E-05	-6.0E-06	-1.2E-05	-2.3E-05	0.322	0.321	0.320	0.361	0.365	0.369
1 State Away	1.3E-06	2.7E-06	5.3E-06	-1.2E-06	-2.4E-06	-4.7E-06	0.357	0.356	0.355	0.393	0.397	0.401
2+ States Away	5.7E-07	1.1E-06	2.3E-06	-5.3E-07	-1.1E-06	-2.1E-06	0.531	0.531	0.530	0.558	0.560	0.563
Out of Sample	7.4E-07	1.5E-06	3.0E-06	-6.9E-07	-1.4E-06	-2.7E-06	1	1	1	1	1	1

Panel B: Welfare Outcomes

Distance from Focal Tract	Change in E[Welfare] (in 2012 $): Plant Opening 125	250	500	Plant Closing 125	250	500	Share of Welfare Gains or Losses: Plant Opening 125	250	500	Plant Closing 125	250	500
Target Tract	93	176	325	-4645	-8176	-13065	0.018	0.018	0.017	0.367	0.357	0.333
1 Tct Away	55	108	204	-43	-80	-141	0.044	0.043	0.042	0.380	0.370	0.346
2 Tcts Away	32	62	120	-25	-46	-83	0.071	0.070	0.068	0.394	0.384	0.360
Over 3 Tcts within PUMA	14	29	56	-13	-25	-47	0.128	0.127	0.125	0.427	0.418	0.394
1 PUMA Away	9	18	36	-8	-16	-30	0.176	0.175	0.173	0.456	0.446	0.423
2 PUMAs Away	6	12	23	-5	-11	-20	0.254	0.253	0.250	0.505	0.496	0.473
3+ PUMAs w/in State	3	6	12	-3	-5	-11	0.610	0.609	0.607	0.746	0.737	0.719
1 State Away	0	1	2	0	-1	-2	0.653	0.652	0.651	0.775	0.767	0.750
2+ States Away	0	0	0	0	0	0	0.746	0.745	0.744	0.834	0.828	0.815
Out of Sample	0	0	0	0	0	0	1	1	1	1	1	1

Notes: See Table A3 for expanded definitions of the distance bins captured by the row labels, as well as definitions of the outcome measures used in both panels. The column subheadings "125", "250", and "500" indicate the number of jobs in the focal tract that were either added in "plant opening" simulations or removed in "plant closing" simulations whose incidence is summarized in the chosen column. Each "plant opening" or "plant closing" adds positions to or removes positions from large, high-paying manufacturing establishments.

Table A12: Heterogeneity in the Change in P(Employed) and Cumulative Share of Total Employment Gains by Distance from Focal Tract Across Various Categories of Focal Tracts

Panel A: Urbanicity and # Jobs within 5 Miles

Distance from	Change in P(Employed)					Share of Employment Gains				
Focal Tract	All	Rural	Urban	Low	High	All	Rural	Urban	Low	High
Target Tract	0.001	0.002	0.001	0.002	4.4E-04	0.006	0.012	0.003	0.013	0.003
1 Tct Away	3.2E-04	0.001	8.6E-05	0.001	4.7E-05	0.015	0.030	0.006	0.029	0.006
2 Tcts Away	1.4E-04	2.3E-04	5.5E-05	3.0E-04	4.1E-05	0.026	0.047	0.013	0.047	0.014
3+ Tcts w/in PUMA	7.0E-05	9.3E-05	4.5E-05	1.0E-04	3.1E-05	0.058	0.088	0.037	0.088	0.037
1 PUMA	4.6E-05	4.8E-05	3.2E-05	4.9E-05	2.7E-05	0.087	0.114	0.067	0.117	0.066
2 PUMAs Away	3.1E-05	3.1E-05	2.6E-05	3.1E-05	2.5E-05	0.138	0.167	0.113	0.172	0.114
3+ PUMAs w/in State	1.6E-05	1.8E-05	1.1E-05	1.8E-05	1.3E-05	0.380	0.295	0.480	0.310	0.437
1 State Away	2.6E-06	3.2E-06	2.2E-06	3.0E-06	2.3E-06	0.452	0.392	0.526	0.401	0.497
2+ States Away	1.0E-06	1.1E-06	9.5E-07	1.1E-06	1.0E-06	0.593	0.553	0.642	0.556	0.622
Out of Sample	1.3E-06	1.4E-06	1.1E-06	1.4E-06	1.2E-06	1	1	1	1	1

Panel B: Two-Bedroom Apartment Rent and Poverty Rate

Distance from	Change in P(Employed)					Share of Employment Gains				
Focal Tract	All	Cheap	Expen.	Low	High	All	Cheap	Expen.	Low	High
Target Tract	0.001	0.002	3.3E-04	0.001	0.001	0.006	0.011	0.003	0.004	0.008
1 Tct Away	3.2E-04	0.001	8.0E-05	1.9E-04	4.0E-04	0.015	0.025	0.007	0.010	0.018
2 Tcts Away	1.4E-04	2.7E-04	5.1E-05	1.1E-04	1.7E-04	0.026	0.041	0.015	0.019	0.030
3+ Tcts w/in PUMA	7.0E-05	1.2E-04	3.3E-05	5.2E-05	8.7E-05	0.058	0.084	0.036	0.047	0.067
1 PUMA	4.6E-05	6.3E-05	2.4E-05	4.5E-05	5.3E-05	0.087	0.118	0.057	0.072	0.100
2 PUMAs Away	3.1E-05	4.0E-05	1.9E-05	2.8E-05	3.3E-05	0.138	0.173	0.101	0.125	0.147
3+ PUMAs w/in State	1.6E-05	2.3E-05	9.2E-06	1.4E-05	1.8E-05	0.380	0.288	0.483	0.393	0.384
1 State Away	2.6E-06	3.0E-06	2.1E-06	2.7E-06	2.5E-06	0.452	0.384	0.517	0.460	0.457
2+ States Away	1.0E-06	1.1E-06	9.6E-07	1.0E-06	1.0E-06	0.593	0.547	0.635	0.599	0.596
Out of Sample	1.3E-06	1.4E-06	1.1E-06	1.3E-06	1.3E-06	1	1	1	1	1

Notes: See Table A3 for expanded definitions of the distance bins captured by the row labels. The first five columns of Panel A provide the estimated change in the probability of employment in the destination year caused by a 250 job stimulus package for workers whose distance between their origin jobs and the census tract receiving the stimulus package place them in the distance bin indicated in the row label. The next five columns of Panel A provide the share of total stimulus-driven employment gains that accrue to workers whose distance between their origin jobs and the census tract receiving the stimulus package place them below or within the distance bin indicated in the row label. Each column displays the average employment outcome by distance bin among a subset of simulations featuring focal census tracts whose characteristics align with the column label. "All": An average of all 300 target census tracts chosen as sites of simulated stimulus packages. "Rural"/"Urban": An average over the 60 census tracts featuring the lowest/highest residential density (residents per square mile) among the full 300 target tracts simulated. "Low"/"High": In Panel A (B), an average over the 60 census tracts featuring the smallest/largest number of jobs within 5 miles (poverty rate) among the full 300 target tracts simulated. "Cheap"/Expen.": An average over the 60 census tracts featuring the cheapest/most expensive rent for a two-bedroom apartment among the full 300 target tracts simulated.

Table A13: Heterogeneity in the Average Welfare Gain and Cumulative Share of Total Welfare Gains by Distance from Focal Tract Across Various Categories of Focal Tracts

Panel A: Urbanicity and # Jobs within 5 Miles

Distance from	Avg. Welfare Gain ($)					Share of Welfare Gains				
Focal Tract	All	Rural	Urban	Small	Large	All	Rural	Urban	Small	Large
Target Tract	322	805	216	878	132	0.009	0.020	0.004	0.021	0.004
1 Tct Away	105	239	23	301	16	0.025	0.049	0.009	0.048	0.011
2 Tcts Away	51	90	16	110	14	0.044	0.079	0.018	0.077	0.024
3+ Tcts within PUMA	26	37	14	39	11	0.099	0.152	0.054	0.150	0.064
1 PUMA Away	17	20	10	19	9	0.150	0.201	0.103	0.202	0.115
2 PUMAs Away	12	14	8	13	9	0.242	0.306	0.174	0.308	0.196
3+ PUMAs w/in State	7	8	4	8	5	0.641	0.537	0.736	0.554	0.703
1 State Away	1	1	1	1	1	0.740	0.683	0.793	0.685	0.777
2+ States Away	0	0	0	0	0	0.809	0.759	0.855	0.756	0.845
Out of Sample	0	0	0	0	0	1	1	1	1	1

Panel B: Two-Bedroom Apartment Rent and Poverty Rate

Distance from	Avg. Welfare Gain ($)					Share of Welfare Gains				
Focal Tract	All	Cheap	Expen.	Low	High	All	Cheap	Expen.	Low	High
Target Tract	322	747	96	200	394	0.009	0.019	0.004	0.005	0.013
1 Tct Away	105	264	26	69	127	0.025	0.043	0.012	0.016	0.030
2 Tcts Away	51	114	15	36	60	0.044	0.071	0.022	0.031	0.051
3+ Tcts within PUMA	26	49	10	19	31	0.099	0.149	0.054	0.079	0.114
1 PUMA Away	17	26	8	16	19	0.150	0.213	0.085	0.125	0.171
2 PUMAs Away	12	17	6	10	12	0.242	0.319	0.155	0.217	0.253
3+ PUMAs w/in State	7	11	3	6	7	0.641	0.541	0.748	0.649	0.645
1 State Away	1	1	1	1	1	0.740	0.687	0.789	0.743	0.743
2+ States Away	0	0	0	0	0	0.809	0.754	0.851	0.814	0.812
Out of Sample	0	0	0	0	0	1	1	1	1	1

Notes: See Table A3 for expanded definitions of the distance bins captured by the row labels. The first five columns provide the estimated gain in expected welfare (scaled in $ of 2023 annual earnings) in the destination year caused by a 250 job stimulus package for workers whose distance between their origin jobs and the census tract receiving the stimulus package place them in the distance bin indicated in the row label. The next five columns provide the share of total stimulus-driven welfare gains that accrue to workers whose distance between their origin jobs and the census tract receiving the stimulus package place them below or within the distance bin indicated in the row label. Each column displays the average welfare outcome by distance bin among a subset of simulations featuring focal census tracts whose characteristics align with the column label. "All": An average of all 300 target census tracts chosen as sites of simulated stimulus packages. "Rural"/"Urban": An average over the 60 census tracts featuring the lowest/highest residential density (residents per square mile) among the full 300 target tracts simulated. "Low"/"High": In Panel A (B), an average over the 60 census tracts featuring the smallest/largest number of jobs within 5 miles (poverty rate) among the full 300 target tracts simulated. "Cheap"/Expen.": An average over the 60 census tracts featuring the cheapest/most expensive rent for a two-bedroom apartment among the full 300 target tracts simulated.

Table A14: Regressions Predicting Local Employment and Welfare Incidence Using Standardized Tract Characteristics: Stimuli Adding 250 Positions at Large High-Paying Manufacturing Firms

		All Target PUMA Workers				Low-Paid Target PUMA Workers				All Low-Paid U.S.	
Variable	Mean (S.D.)	Emp. Gain	Emp. Share	Wel. Gain	Wel. Share	Emp. Gain	Emp. Share	Wel. Gain	Wel. Share	Emp. Share	Wel. Share
Pop. Density	4887	-6.2E-06	-0.0055	-2.9	-0.0125	-6.1E-06	-0.0033	-2.1	-0.0033	0.0022	-0.0011
	(6866)	(4.0E-06)	(0.0008)	(1.3)	(0.0016)	(6.9E-06)	(0.0005)	(1.1)	(0.0005)	(0.0005)	(0.0006)
Rent (Two-Bed)	1087	-5.0E-05	-0.0129	-20.9	-0.0284	-7.9E-05	-0.0076	-20.1	-0.0097	0.0100	-0.0049
	(462)	(5.0E-06)	(0.0009)	(1.6)	(0.0020)	(8.5E-06)	(0.0007)	(1.4)	(0.0006)	(0.0006)	(0.0008)
Poverty Rate	0.155	1.0E-05	0.0009	2.5	0.0012	1.9E-05	0.0008	1.9	0.0000	0.0001	-0.0011
	(0.112)	(4.0E-06)	(0.0007)	(1.2)	(0.0016)	(6.8E-06)	(0.0005)	(1.1)	(0.0005)	(0.0004)	(0.0006)
Job Density	2707	3.1E-06	0.0007	1.8	0.0017	4.2E-06	0.0003	1.4	0.0003	-0.0014	-0.0008
	(9960)	(3.2E-06)	(0.0006)	(1.0)	(0.0013)	(5.5E-06)	(0.0004)	(0.9)	(0.0004)	(0.0004)	(0.0005)
Median Income	58050	-3.2E-05	-0.0009	-11.2	-0.0037	-4.5E-05	-0.0004	-10.5	-0.0028	0.0009	-0.0043
	(27190)	(5.6E-06)	(0.0010)	(1.8)	(0.0023)	(9.6E-06)	(0.0007)	(1.6)	(0.0007)	(0.0006)	(0.0009)
Jobs w/in 5 Mi.	113100	-5.4E-05	-0.0016	-13.8	0.0018	-8.7E-05	-0.0013	-12.7	-0.0020	0.0002	-0.0019
	(137300)	(4.2E-06)	(0.0008)	(1.3)	(0.0017)	(7.2E-06)	(0.0006)	(1.4)	(0.0006)	(0.0005)	(0.0006)
% College Grad.	0.279	2.9E-05	0.0032	13.5	0.0133	4.7E-05	0.001313.	2	0.0045	-0.0063	0.0020
	(0.186)	(4.5E-06)	(0.0008)	(1.4)	(0.0018)	(7.7E-06)	(0.0006)	(1.3)	(0.0006)	(0.0005)	(0.0007)
% PUMA Same Ind.	0.082	1.1E-05	0.0004	11.2	0.0069	1.2E-05	-0.0002	10.0	0.0020	0.0000	0.0034
	(0.044)	(3.1E-06)	(0.0006)	(1.0)	(0.0013)	(5.3E-06)	(0.0004)	(0.9)	(0.0004)	(0.0003)	(0.0005)
Outcome Mean	–	1.9E-04	0.0514	58.1	0.0987	3.4E-04	0.0342	53.2	0.0318	0.6579	0.2853
R^2	–	0.262	0.203	0.306	0.177	0.224	0.165	0.323	0.245	0.187	0.118
N	–	3200	3200	3200	3200	3200	3200	3200	3200	3200	3200

Notes: This table reports regression coefficients and their accompanying standard errors (in parentheses) from tract-level regressions based on 3200 simulated stimulus packages creating 250 new positions at large, high-paying manufacturing firms in different randomly chosen focal tracts. Simulated employment and welfare outcomes listed in the column label are regressed on standardized versions of the tract characteristics associated with the focal tract that are listed in the row labels. Tract characteristics were collected by Chetty and Hendren (2018). The first four columns consider as regressands mean outcomes and shares of aggregate gains accruing workers initially in the focal PUMA receiving the stimulus, while the next four display the same regressands computed for the low-paid subset of focal PUMA workers (initially in the bottom two earnings quartiles). The final two columns display shares of employment and welfare gains accruing to low-paid workers nationally (rather than high-paid or initially unemployed workers). "Pop. Density": The focal tract's number of residents per square mile. "Rent (Two-Bed)": The focal tract's average monthly rent for a two-bedroom apartment. "Poverty Rate": The focal tract's share of households below the federal poverty line. "Job Density": The focal tract's employment per square mile. "Median Income": The focal tract's household median income. "Jobs w/in 5 Mi.": The number of jobs within 5 miles of the focal tract. "% College Grad.": The share of the focal tract's adult residents who are college graduates. "% PUMA Same Ind.": The share of the focal PUMA;s residents who were initially employed in firms in the manufacturing industry.

Table A15: Regressions Predicting Local Employment and Welfare Incidence Using Standardized Tract Characteristics: Stimuli Adding 250 Positions at Large Low-Paying Retail Firms

		All Target PUMA Workers				Low-Paid Target PUMA Workers				All Low-Paid U.S.	
Variable	Mean (S.D.)	Emp. Gain	Emp. Share	Wel. Gain	Wel. Share	Emp. Gain	Emp. Share	Wel. Gain	Wel. Share	Emp. Share	Wel. Share
Pop. Density	4887	-5.8E-06	-0.0051	-2.8	-0.0127	-4.7E-06	-0.0034	-2.2	-0.0044	0.0028	-0.0004
	(6866)	(4.1E-06)	(0.0008)	(1.0)	(0.0013)	(8.1E-06)	(0.0006)	(1.3)	(0.0006)	(0.0004)	(0.0004)
Rent (Two-Bed)	1087	-5.1E-05	-0.0126	-19.7	-0.0296	-9.1E-05	-0.0083	-24.4	-0.0126	0.0125	-0.0012
	(462)	(5.0E-06)	(0.0010)	(1.3)	(0.0016)	(9.9E-06)	(0.0008)	(1.6)	(0.0007)	(0.0005)	(0.0005)
Poverty Rate	0.155	1.1E-05	0.0009	1.5	-0.0004	2.5E-05	0.0010	2.2	-0.0001	0.0009	0.0001
	(0.112)	(4.0E-06)	(0.0008)	(1.0)	(0.0013)	(7.9E-06)	(0.0006)	(1.3)	(0.0006)	(0.0004)	(0.0004)
Job Density	2707	1.1E-06	0.0004	1.0	0.0013	2.0E-06	0.0001	1.1	0.0003	-0.0010	-0.0003
	(9960)	(3.2E-06)	(0.0006)	(0.8)	(0.0010)	(6.4E-06)	(0.0005)	(1.1)	(0.0005)	(0.0003)	(0.0003)
Median Income	58050	-3.2E-05	-0.0008	-7.4	-0.0034	-5.4E-05	-0.0005	-8.9	-0.0021	0.0022	-0.0006
	(27190)	(5.7E-06)	(0.0011)	(1.4)	(0.0018)	(1.1E-05)	(0.0009)	(1.8)	(0.0008)	(0.0005)	(0.0006)
Jobs w/in 5 Mi.	113100	-5.8E-05	-0.0017	-12.3	0.0020	-1.1E-04	-0.0019	-16.2	-0.0023	0.0001	-0.0011
	(137300)	(4.3E-06)	(0.0008)	(1.1)	(0.0013)	(8.4E-06)	(0.0007)	(1.4)	(0.0006)	(0.0004)	(0.0004)
% College Grad.	0.279	2.1E-05	0.0009	8.5	0.0089	4.1E-05	-0.0002	11.0	0.0035	-0.0083	-0.0003
	(0.186)	(4.6E-06)	(0.0009)	(1.2)	(0.0015)	(9.1E-06)	(0.0007)	(1.5)	(0.0007)	(0.0004)	(0.0005)
% PUMA Same Ind.	0.177	-2.8E-05	-0.0081	-4.5	-0.0098	-5.6E-05	-0.0067	-6.3	-0.0055	-0.0015	-0.0004
	(0.032)	(3.1E-06)	(0.0006)	(0.8)	(0.0010)	(6.2E-06)	(0.0005)	(1.0)	(0.0005)	(0.0003)	(0.0003)
Outcome Mean	–	-2.0E-04	0.0545	48.7	0.0883	4.2E-04	0.0422	63.7	0.0411	0.6871	0.3450
R^2	–	0.280	0.222	0.311	0.272	0.247	0.191	0.299	0.285	0.357	0.027
N	–	3200	3200	3200	3200	3200	3200	3200	3200	3200	3200

Notes: This table reports regression coefficients and their accompanying standard errors (in parentheses) from tract-level regressions based on 2500 simulated stimulus packages creating 250 new positions at large, low-paying retail firms in different randomly chosen focal tracts. Simulated employment and welfare outcomes listed in the column label are regressed on standardized versions of the tract characteristics associated with the focal tract that are listed in the row labels. Tract characteristics were collected by Chetty and Hendren (2018). The first four columns consider as regressands mean outcomes and shares of aggregate gains accruing workers initially in the focal PUMA receiving the stimulus, while the next four display the same regressands computed for the low-paid subset of focal PUMA workers (initially in the bottom two earnings quartiles). The final two columns display shares of employment and welfare gains accruing to low-paid workers nationally (rather than high-paid or initially unemployed workers). "Pop. Density": The focal tract's number of residents per square mile. "Rent (Two-Bed)": The focal tract's average monthly rent for a two-bedroom apartment. "Poverty Rate": The focal tract's share of households below the federal poverty line. "Job Density": The focal tract's employment per square mile. "Median Income": The focal tract's household median income. "Jobs w/in 5 Mi.": The number of jobs within 5 miles of the focal tract. "% College Grad.": The share of the focal tract's adult residents who are college graduates. "% PUMA Same Ind.": The share of the focal PUMA;s residents who were initially employed in firms in the retail/wholesale industry.

Table A16: Assessing Robustness to Model Assumptions: Employment and Welfare Incidence from Plant Opening Simulations for Alternative Models

Panel A: Employment Outcomes

	Change in P(Employed)					Share of Employment Gains				
Distance from Focal Tract	Base Spec.	Job Mult.	Endo. Vac.	Choo Siow	Endo. Surp.	Base Spec.	Job Mult.	Endo. Vac.	Choo Siow	Endo. Surp.
Target Tract	6.7E-04	4.0E-04	6.3E-04	5.3E-04	7.8E-04	0.004	0.002	0.004	0.004	0.006
1 Tct Away	2.5E-04	2.7E-04	2.4E-04	2.3E-04	2.3E-04	0.008	0.005	0.008	0.007	0.007
2 Tcts Away	1.2E-04	2.2E-04	1.2E-04	1.1E-04	1.2E-04	0.010	0.011	0.010	0.009	0.010
3+ Tcts w/in PUMA	6.1E-05	1.7E-04	5.9E-05	5.6E-05	6.7E-05	0.028	0.042	0.028	0.025	0.031
1 PUMA Away	3.9E-05	6.1E-05	3.8E-05	3.9E-05	3.9E-05	0.025	0.022	0.025	0.023	0.025
2 PUMAs Away	2.8E-05	4.2E-05	2.7E-05	2.8E-05	2.8E-05	0.046	0.042	0.046	0.038	0.046
3+ PUMAs w/in State	1.6E-05	2.4E-05	1.6E-05	1.6E-05	1.6E-05	0.236	0.217	0.236	0.219	0.234
1 State Away	2.5E-06	4.2E-06	2.5E-06	2.6E-06	2.5E-06	0.070	0.069	0.070	0.073	0.069
2+ States Away	1.1E-06	1.9E-06	1.0E-06	1.1E-06	1.1E-06	0.144	0.150	0.144	0.154	0.144
Out of Sample	1.3E-06	2.3E-06	1.3E-06	1.3E-06	1.3E-06	0.429	0.441	0.429	0.448	0.428
< 10 miles away						0.056	0.054	0.056	0.052	0.058
< 250 miles away						0.235	0.231	0.235	0.212	0.237

Panel B: Welfare Outcomes

	Avg. Welfare Gain ($)					Share of Welfare Gains				
Distance from Focal Tract	Base Spec.	Job Mult.	Endo. Vac.	Choo Siow	Endo. Surp.	Base Spec.	Job Mult.	Endo. Vac.	Choo Siow	Endo. Surp.
Target Tract	296	342	267	349	417	0.009	0.006	0.009	0.006	0.015
1 Tct Away	98	137	90	150	108	0.015	0.013	0.015	0.014	0.017
2 Tcts Away	49	85	46	74	65	0.019	0.019	0.019	0.018	0.025
3+ Tcts within PUMA	27	60	25	41	33	0.056	0.067	0.055	0.051	0.066
1 PUMA Away	17	33	17	27	17	0.048	0.052	0.048	0.046	0.046
2 PUMAs Away	12	21	11	19	12	0.087	0.092	0.087	0.082	0.084
3+ PUMAs w/in State	7	11	7	11	7	0.385	0.378	0.386	0.365	0.371
1 State Away	1	1	1	1	1	0.092	0.089	0.092	0.092	0.088
2+ States Away	0	0	0	0	0	0.069	0.063	0.069	0.078	0.069
Out of Sample	0	0	0	0	0	0.220	0.221	0.221	0.247	0.219
¡ 10 miles away						0.108	0.111	0.107	0.100	0.127
¡ 250 miles away						0.436	0.453	0.434	0.413	0.448

Notes: See Table A3 for expanded definitions of the distance bins captured by the row labels, as well as definitions of the outcome measures used in both panels. The mean outcomes displayed for each of four alternative models are averages over 300 simulations with different focal tracts featuring the creation of 250 positions at large, high-paying manufacturing firms. "Base. Spec.": The baseline assignment model described in Sections 2, 3, and 5; "Job Mult.": the baseline assignment model is augmented with a job multiplier process in which the original 250 manufacturing positions spawn additional service-sector jobs throughout the target PUMA, using a high-tech manufacturing multiplier of 1.71 from Bartik and Sotherland (2019); "Endo. Vac.": the baseline assignment model is augmented by allowing nearby firms to endogenously adjust the number of positions they wish to fill in response to stimulus-induced increases in required pay per efficiency unit of labor. Final equilibrium is determined by the convergence of a fixed point. "Choo Siow": the assignment model uses a Choo-Siow structure in which idiosyncratic part of the surplus consists of a worker-type × firm component and a worker × firm type component rather than a worker × firm component. "Endo. Surp.": The plant opening shock is allowed to change joint surplus values in addition to adding local positions to be filled. Surplus changes for all groups featuring within-PUMA worker and firm types are estimated using the average of revealed surplus changes based on worker reallocations from a set of observed high-paying manufacturing establishment openings between 2003 and 2012.

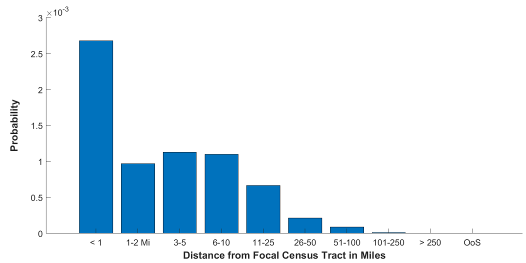
Table A17: Mean Simulated Welfare Gain for Local (Target Tract) Workers by Initial Earnings or Same Industry/Different Industry Category for Various Ways of Restricting Heterogeneity When Modeling the Joint Surplus from Forming Job Matches

Row	Main Spec.	No Firm Char.	No Worker Char.	No Same Ind.	No Same Firm
All	296	252	216	358	8633
Unemployed	267	383	288	302	276
1st Earn. Q.	201	261	201	256	4480
2nd Earn. Q.	274	228	206	320	7373
3rd Earn. Q.	362	219	208	415	13096
4th Earn. Q.	464	206	215	629	21990
Diff. Ind.	244	235	200	350	8503
Same. Ind.	1137	689	529	517	9270

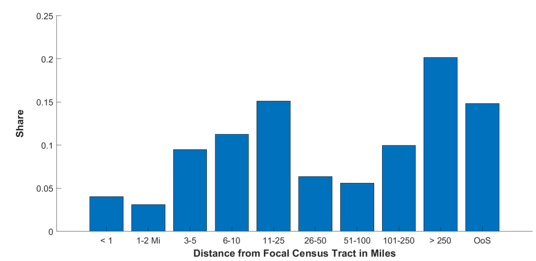
Notes: See Table 4 for expanded definitions of the worker subpopulations captured by the row labels. "Main Spec.": Main specification featuring unrestricted heterogeneity in match surpluses across worker-type/firm-type/job stayer combinations. "No Firm Char.": Removes any heterogeneity in match surpluses by non-location firm characteristics (industry, firm size, firm average pay). "No Worker Char.": Removes any heterogeneity in match surpluses by non-location worker characteristics (initial earnings quartile and age). "No Same Ind.": Removes heterogeneity in match surpluses based on whether the worker is staying within the same industry, conditional on changing firm. "No Same Firm": Removes heterogeneity in match surpluses based on whether the worker is being retained by the same firm.

Figure A1: Comparing the Spatial Distributions of P(Stimulus Job), Change in P(Employed), and Change in Average Welfare, along with Shares of Stimulus Jobs, Additional Employment and Additional Welfare: Average across All Simulated Stimuli, Distance Measured in Miles

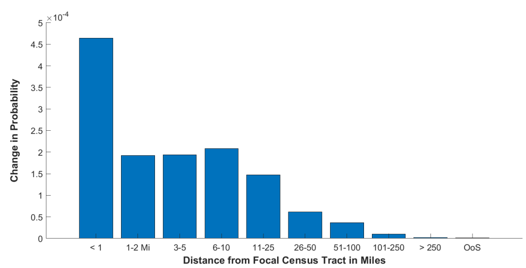
(a) Probability of Obtaining a Stimulus Job



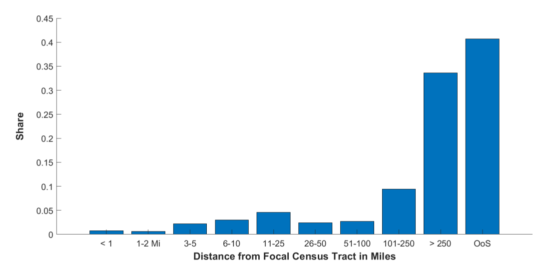
(b) Share of All Stimulus Jobs



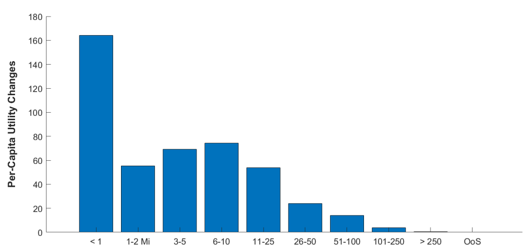
(c) Change in P(Employed)



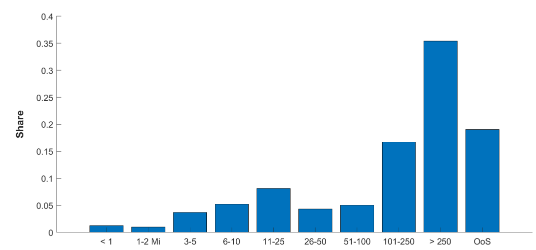
(d) Share of Employment Gains



(e) Avg. Welfare Gain (in 2023 $)



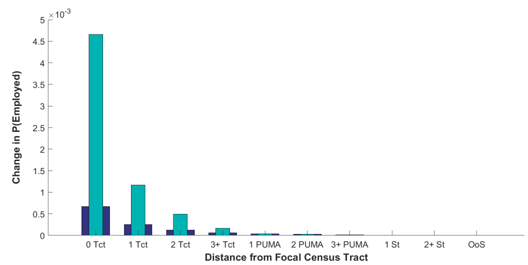
(f) Share of Welfare Gains



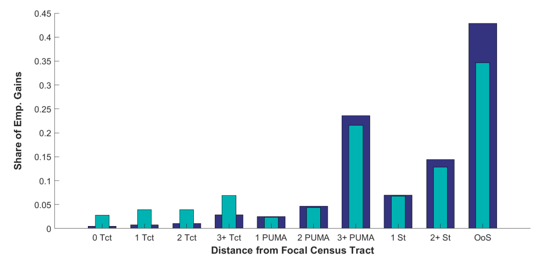
Notes:The bar heights in Figure A1a capture the average probability of obtaining a stimulus job among workers whose number of miles between their initial establishments and the census tract receiving the simulated stimulus package fell into the distance bins indicated by the bar labels. These probabilities average across different demographic categories and across stimulus packages featuring different firm compositions. Figure A1b displays the share of all stimulus jobs generated by the stimulus that redounds to workers in the chosen distance bin. Figures A1c and A1d display the corresponding gains in employment probability and shares of national employment gains accruing to workers in each distance bin, while Figures A1e and A1f display the corresponding expected welfare gains and shares of national welfare gains accruing to workers in each distance bin. Each bar represents an average over 300 simulations featuring different target census tracts as well as over 32 packages for each these 300 simulations featuring different firm composition (combinations of industry supersector and firm size and average pay categories). “OoS” indicates that the worker’s position was in an out-of-sample state.

Figure A2: Assessing the Value of Restricting Stimulus Jobs to Fill Positions With Workers from the Target PUMA: Spatial Employment and Welfare Incidence for Restricted and Unrestricted 250-Position Stimulus Packages

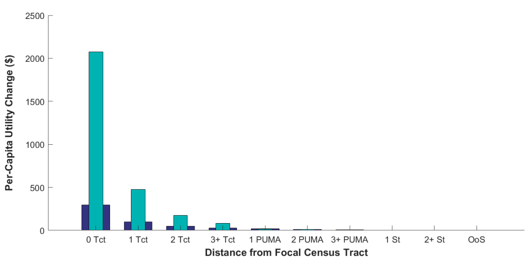
(a) Change in P(Employed)



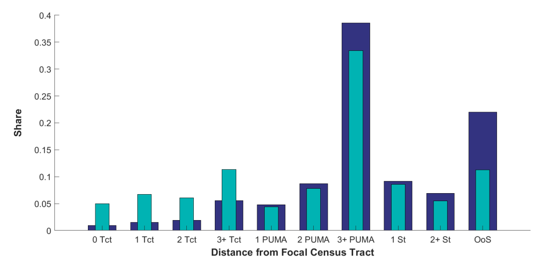
(b) Share of Employment Gains



(c) Avg. Welfare Gain ($)



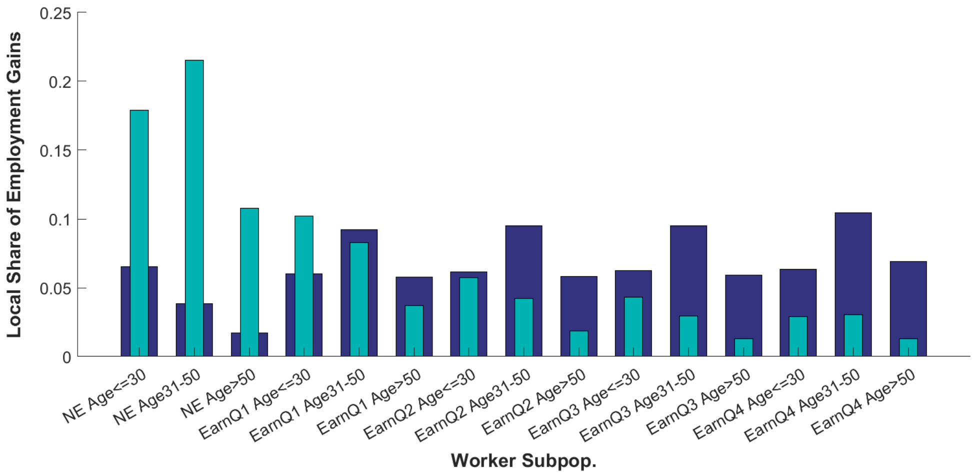
(d) Share of Welfare Gains



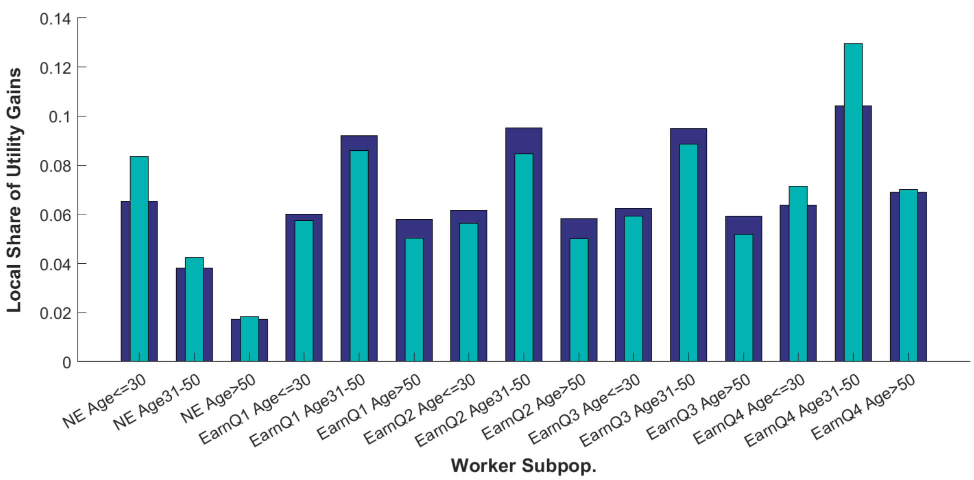
Notes: The bar heights capture the average measure of stimulus incidence associated with the chosen figure from a 250 person stimulus package among workers whose geographic distance between their initial establishments and the census tract receiving the simulated stimulus package fell into the distance bins indicated by the labels. The thin, light blue bars capture the case in which the new positions are restricted to be filled by existing workers within the targeted PUMA, while the wide, dark blue bars capture the case in which new positions can be filled by any worker. Each bar represents an average over 300 simulations featuring different target census tracts as well as over 32 packages for each these 300 simulations featuring different firm composition (combinations of industry supersector and firm size and average pay categories). "0/1/2/3+ Tct" indicates that the origin establishment was in the target tract or was one, two, or 3 or more tracts away (by tract pathlength) within the same PUMA. "1/2/3+ PUMA" and "1/2+ State" indicate the PUMA pathlength (if within the same state) and state pathlength (if in different states), respectively. "OoS" indicates that the worker's position was in an out-of-sample state.

Figure A3: Comparing Shares of Focal Tract Employment and Utility Gains with Initial Focal Tract Workforce Shares Among Workers from Different Initial Earnings/Age Combinations: Average across All Simulated Stimuli

(a) Share of Focal Tract Net Employment Gains

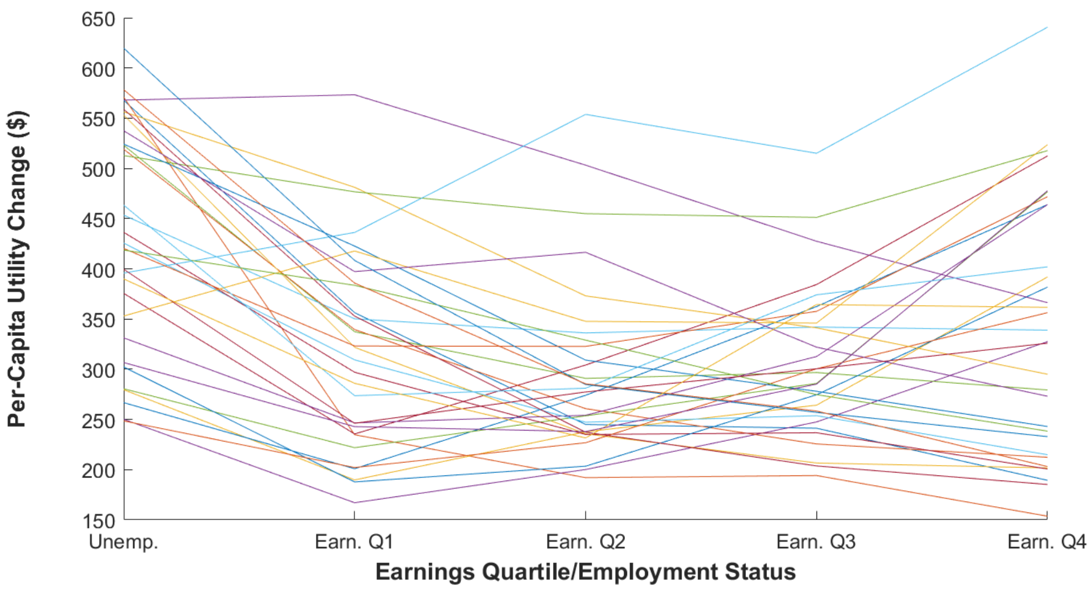


(b) Share of Focal Tract Utility Gains



Notes: The heights of the wider bars within a particular group in Figures A3a and A3b capture the initial share of the focal tract workforce associated with the subpopulation defined by the combination of earnings category and age category given by the label, while the heights of the narrower bars capture this subpopulation's share of the employment and job-related utility gains accruing to workers in the tract receiving the newly created jobs. Averages are taken across stimulus packages featuring different firm supersector/size/avg. pay compositions, as well as across 300 simulations featuring different targeted census tracts for each firm composition.

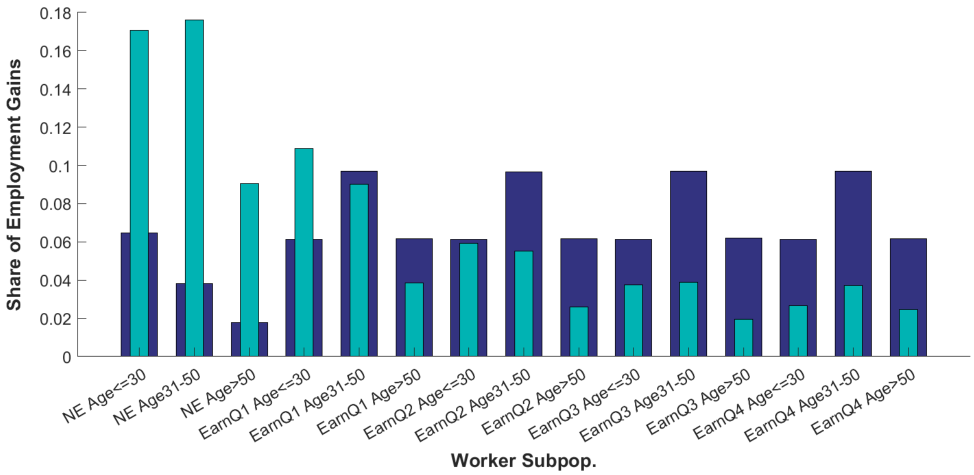
Figure A4: Expected Utility Changes Among Workers from the Targeted Tract by Initial Earnings/Employment Status: All Stimulus Packages



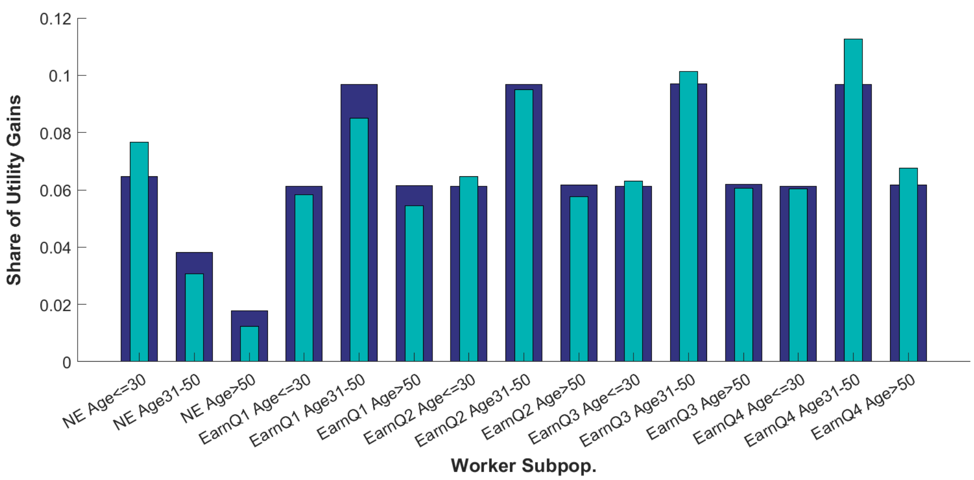
Notes: Each line traces the expected welfare gain among focal tract workers generated by a stimulus package featuring 250 positions among firms with a particular combination of supersector, firm size, and firm average pay categories across alternative unemployment or earnings quartile categories. 32 different lines corresponding to 32 different firm supersector/size/pay level compositions are displayed. Averages are taken across 300 simulations featuring different targeted census tracts for each supersector/firm size/firm avg. pay combo. "Unemp.": Workers who were not employed in the previous year. "Earn Q1/Q2/Q3/Q4": Workers whose pay at their dominant job in the previous year placed them in the 1st/2nd/3rd/4th quartile of the national age-adjusted annualized earnings distribution.

Figure A5: Comparing Shares of National Employment and Utility Gains with National Workforce Shares Among Workers from Different Initial Earnings/Age Combinations: Average across All Simulated Stimuli

(a) Share of Additional Employment



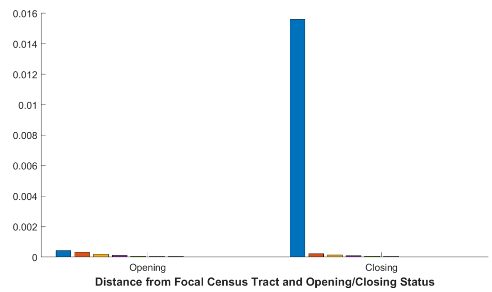
(b) Share of Total Utility Gains



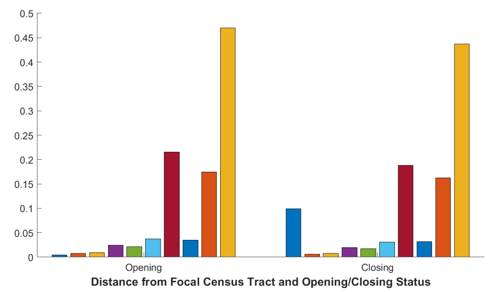
Notes: The heights of the wider bars within a particular group in Figures A5a and A5b capture the initial share of the national workforce associated with the subpopulation defined by the combination of earnings category and age category given by the label, while the heights of the narrower bars capture this subpopulation's share of the national employment and job-related utility gains created by the local job creation package. Averages are taken across job creation packages featuring 250 positions from different firm supersector/size/avg. pay compositions, as well as across 300 simulations featuring different targeted census tracts for each firm composition.

Figure A6: Asymmetry in Employment and Welfare Incidence from Plant Openings and Closings of Equivalent Magnitude

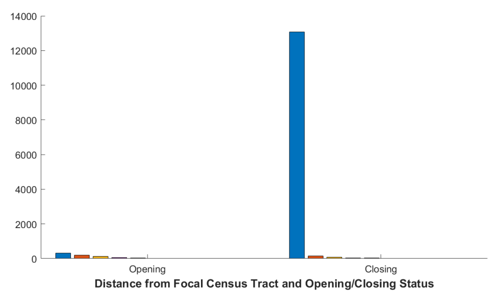
(a) Change in P(Employed)



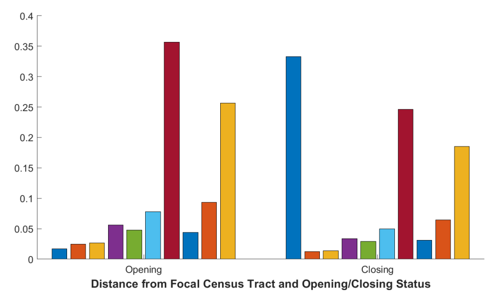
(b) Share of Employment Gains



(c) Avg. Welfare Gain (in 2023 $)



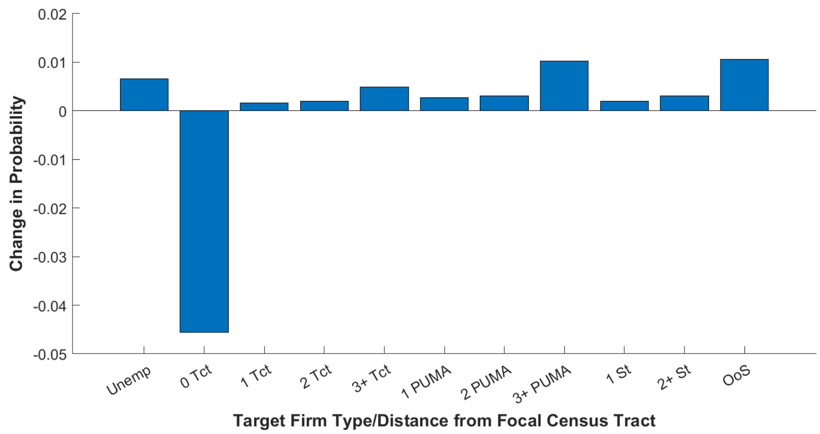
(d) Share of Welfare Gains



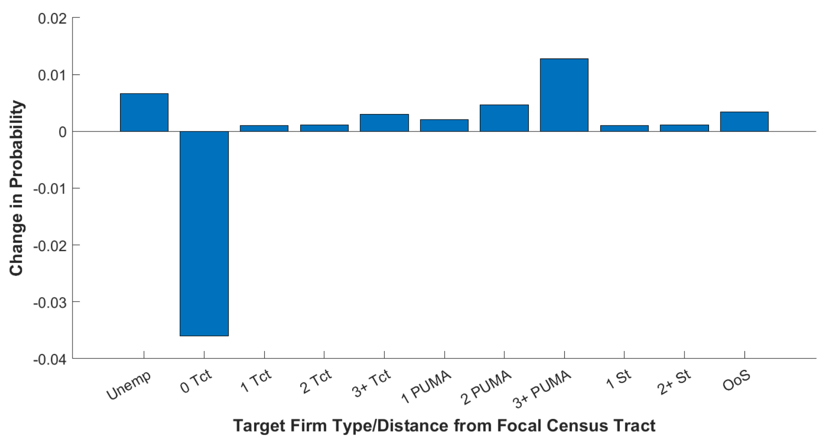
Notes: The bar heights within a particular group in Figures A6a-A6d capture the average value of the incidence measure associated with the figure from pairs of simulated plant openings and closings among workers whose geographic distance between their initial establishments and the census tract experiencing the disaster fell into the distance bins defined in Figure 2. Each opening or closing is associated with the creation or removal of 250 positions at large, high paying manufacturing firms in the focal tract. For each opening or closing, averages are taken across 200 simulations featuring different targeted census tracts.

Figure A7: Comparing Changes in the Distribution of Employment Locations (or Unemployment) for Focal Tract Workers after Plant Closings that Remove 250 Positions from either Large High-Paying Manufacturing Firms or Large Low-Paying Retail Firms

(a) High-Paid Manufacturing



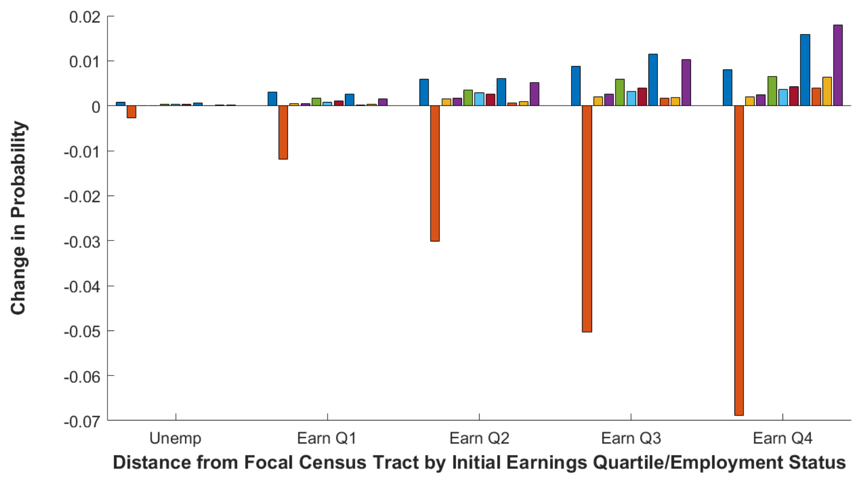
(b) Low-Paid Retail



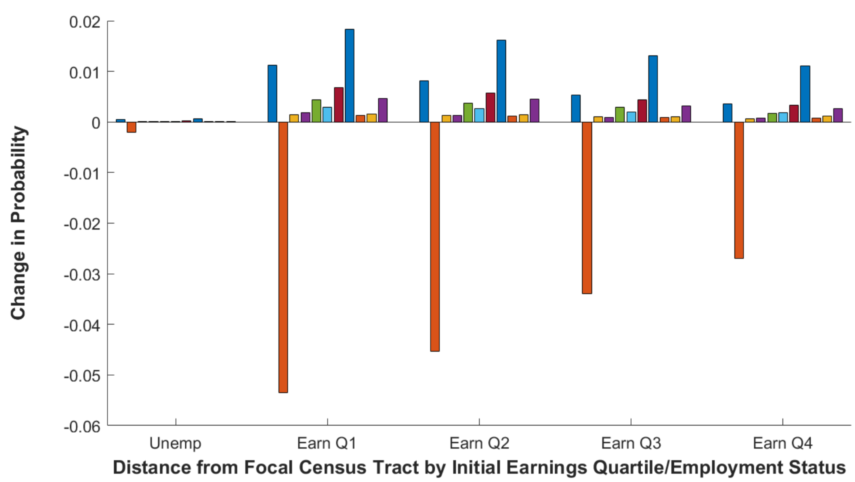
Notes: The bar heights in Figures A7a and A7b capture the impact of experiencing a plant or store closing, respectively, that removes 250 positions on the probability that a worker employed in the previous year (or most recently employed) in the targeted tract would be employed at a position whose distance from the targeted census tract fell into the distance bins defined in Figure 2 (or become/remain unemployed, the leftmost bar in each group). For both plant and store closings, averages are taken across 200 simulations featuring different targeted census tracts.

Figure A8: Sensitivity of the Change in the Distribution of Employment Locations (or Nonemployment) following Plant and Store Closings to the Match between Workers' Initial Earnings/Employment Status and the Closing Firm's Sector and Pay Level

(a) High-Paying Manufacturing: Change in Distribution of Destinations by Initial Earnings/Employment Status



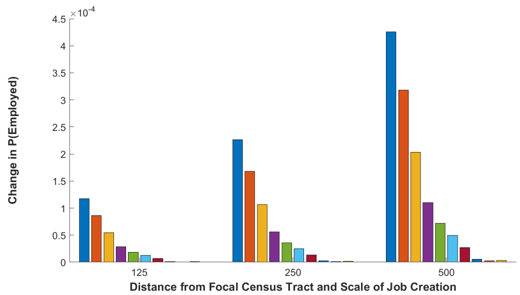
(b) Low-Paying Retail: Change in Distribution of Destinations by Initial Earnings/Employment Status



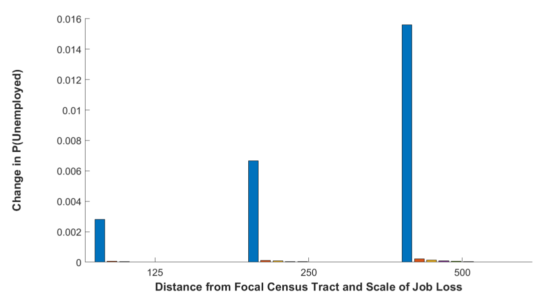
Notes: The bar heights within a particular group in Figures A8a and A8b capture the impact of experiencing a plant closing or store closing that removes 500 jobs in the target tract on the probability that a worker employed in the previous year (or most recently employed) in the targeted tract would be employed at a position whose geographic distance from the target tract fell into the distance bins defined in Figure A7a (or become/remain unemployed, the leftmost bar in each group). Each group of bars captures the change in destination employment probabilities among workers from the initial earnings/employment status given by the label. "Unemp": Workers who were unemployed in the origin year. "Earn Q1/Q2/Q3/Q4": Workers whose pay at their dominant job in the origin year placed them in the 1st/2nd/3rd/4th Quartile of the national age-adjusted annualized earnings distribution. Figure A8a considers a plant closing that removes 250 positions from large, high-paying manufacturing firms, while Figure A8b considers a store or mall closing that removes 250 positions from large, low-paying retail firms. For both plant and store closings, averages are taken across 200 simulations featuring different targeted census tracts.

Figure A9: Employment and Welfare Incidence from Plant Openings and Closings of Different Magnitudes: 125, 250, and 500 Jobs Created or Removed

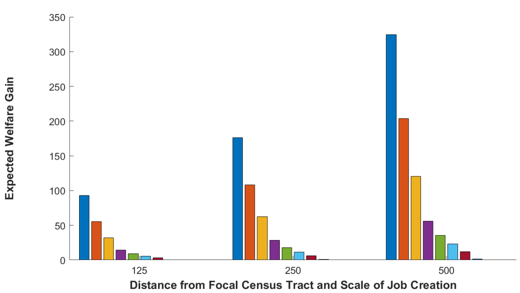
(a) Change in P(Employed): Openings



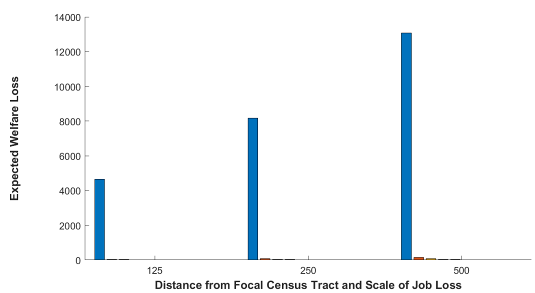
(b) Change in P(Unemployed): Closings



(c) Avg. Welfare Gain (in 2023 $): Openings



(d) Avg. Welfare Loss (in 2023 $): Closings



Notes: The bar heights within a particular group in Figures A9a-A9d capture the average value of the incidence measure associated with the figure from pairs of simulated plant openings and closings among workers whose geographic distance between their initial establishments and the census tract experiencing the disaster fell into the distance bins defined in Figure 2. Each opening or closing is associated with the creation or removal of 125, 250, or 500 positions at large, high paying manufacturing firms in the focal tract. For each opening or closing of each scale, averages are taken across 200 simulations featuring different targeted census tracts.

Figure A10: Heterogeneity in the Geographic Concentration of Several Incidence Measures Across Various Subsets of Focal Tracts

Notes: The bar heights within a particular group in Figures A10a-A10d capture the average measure of stimulus incidence associated with the chosen figure from a 250 job stimulus package among workers whose geographic distance between their initial establishments and the census tract receiving the simulated stimulus package fell into the distance bins defined in Figure 2. Each group of bars displays this incidence distribution across distance bins for a particular subset (indicated by the group's label) of the 300 simulations featuring different focal tracts. In addition to averaging over the simulations featuring different target tracts within the chosen subset, the displayed results also average over different stimuli featuring the same target census tract but different firm compositions. "All": Average is taken among all 300 target tracts. "Rural"/"Urban": Average is taken among the 60 target tracts with the smallest/largest residential population density. "Lo Rent"/"Hi Rent": Average is taken among the 60 target tracts with the lowest/highest rent for a two bedroom apartment. "Lo Pov"/"Hi Pov": Average is taken among the 60 target tracts with the lowest/highest household poverty rate.