Can Sorting Models Help Us Evaluate the Employment Effects of Environmental Regulations?

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Can models of worker and household sorting be used to consistently evaluate environmental regulations that affect the demand for labor? We take the first steps toward building unemployment into a model of sorting across the housing and labor markets. To demonstrate how the model could, in principle, be used to assess a prospective regulation, we build a "layoff simulator" for Northern California. Our simulator replicates stylized facts about earnings losses from mass layoffs. Moreover, the simulator suggests that earnings losses may be a poor proxy for welfare if unemployment increases the probability of migration. Finally, we find that the state of the business cycle (recession vs. expansion) is important for predicting changes in earnings and welfare.

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How important are the employment effects of federal regulations? Some regulatory evaluations include estimates for the number of jobs that are expected to be created or destroyed, but there is no widely accepted framework for monetizing these effects. Five consecutive years of high unemployment have motivated policymakers to look for ways to integrate employment effects into benefit-cost analyses (OMB 2012). Most of the discussion to date has focused on ideas for adjusting measures of lost earnings to anticipate the duration of unemployment (Mansur and Posner 2012). In this paper, we extend the literature to begin to consider spatial aspects of the problem.

The majority of job searches are inherently spatial.[1] A worker's job location limits where he can live, and his house location limits where he can work. These constraints link the housing and labor markets in ways that influence the spatial mobility of the labor force. For example, according to the American Housing Survey, "new job or job transfer" is the second most frequently cited reason for moving out of a former dwelling.[2] Likewise, "convenient to job" is the most frequently cited reason for selecting a new neighborhood. These statistics reinforce the need to consider the implications of layoffs for spatial mobility. If an unemployed worker's best job offer is far from his house, then he may decide to move. If he perceives the quality of life in his new neighborhood to be lower (higher) than his old neighborhood, then he may experience a significant welfare loss (gain) in addition to any change in earnings.

Equilibrium models of Tiebout sorting are often used to predict the welfare effects of policies that influence the quality of life by altering the spatial distribution of public goods. Most applications assume the policy has no effect on wages or employment (Kuminoff, Smith, and Timmins 2013). However, a few recent studies have adapted the canonical Tiebout framework to model links between work-

[1] Approximately 75% of U.S. workers report that they spend no time telecommuting (Noonan and Glass, 2012).
[2] The most frequently cited reason is "to establish own household". See appendix tables A1 and A2 for a historical summary of key findings from the Census Bureau's American Housing Survey from 1999 through 2009.

ers' participation in the housing and labor markets (e.g. Kuminoff 2010, Bishop 2011, Mangum 2012). In this paper, we extend Kuminoff's model to develop a framework for evaluating the welfare effects of a prospective regulation that would improve environmental quality while simultaneously generating layoffs. In order to assess the potential importance of labor market migration for the welfare effects of layoffs, we build a "layoff simulator" for Northern California.

I. Overview of Methods and Results

Our analysis is based on a model of how people decide where to live and work. Households are assumed to differ in their job skills and in their preferences for local public goods, housing, and a composite private good. Different job locations offer different (wage, commuting) options. House locations differ in the public goods they provide, and in the price of housing. Each household is assumed to weigh its options before choosing the job-house combination that maximizes its utility. Kuminoff (2010) develops an empirical model of this choice process and calibrates it to data from Northern California.

In this paper, we extend Kuminoff's model to introduce unemployment. When a worker in our model loses his job, he experiences a temporary unemployment spell. Its duration may vary with the worker's skills and with the state of the broader economy (e.g. recession versus expansion). At the end of the unemployment spell, the worker finds a new job. We force the worker to move to his best available job in a different metro area, holding the worker's occupation fixed but allowing him to change industries. Thus, unemployment is treated as a constraint on the worker's labor market mobility. Forcing unemployed workers to migrate allows us to evaluate the *potential* for labor market migration to influence the welfare effects of layoffs. A key feature of our model is its ability to capture the richness of commuting options in a major urban area. Northern California is comprised of eight contiguous metropolitan areas, making it possible to commute between some of them (e.g. live in Oakland, work in San Jose).

Table 1: Wage and Welfare Effects of Layoffs, by Original Job Location

	(1)	(2)	(3)	(4)	(5)	(6)
			Share experiencing an increase in:			
Job Location in 2000	Expected change in real wages	Δ in wages / Δ in welfare	housing price	air quality	school quality	commute time
Northern California	-5,547	76%	0.27	0.42	0.55	0.59
Oakland MSA	-5,452	81%	0.22	0.31	0.59	0.57
Sacramento MSA	-2,604	35%	0.68	0.83	0.28	0.78
San Francisco MSA	-6,603	86%	0.12	0.20	0.63	0.47
San Jose MSA	-7,237	89%	0.13	0.46	0.58	0.52
Santa Cruz MSA	-6,703	119%	0.16	0.61	0.80	0.78
Santa Rosa MSA	-5,621	97%	0.26	0.30	0.68	0.73
Vallejo MSA	-3,347	58%	0.34	0.31	0.48	0.79
Yolo MSA	-3,125	52%	0.55	0.72	0.58	0.79

Note: Column 1 reports the expected change in real wages. It equals the change in annual wages from moving to a new job plus an annualized measure of the wages lost during a spell of temporary unemployment. Column 2 reports the change in wages as a share of equivalent variation (EV). EV reflects the changes in wages, housing prices, local public goods, and commute times experienced by households who lose their jobs. Columns 3 through 6 report the shares of households experiencing increases in housing prices, air quality, school quality, and commute times at their new locations. The underlying calculations and assumptions are explained in the main text.

Table 1 summarizes our main results. The model predicts that the average Northern California worker's wage would decline by $5,547 if he were to lose his job and relocate to a different metro area (column 1). Approximately 70% of this reduction is due to a loss of job-specific human capital. The other 30% comes from wages lost during his unemployment spell. Our layoff simulator predicts that earnings losses account for only 76% of the change in welfare (column 2). The remaining welfare losses come from a novel margin: even after workers find new jobs, they often face a tradeoff between moving to a less desirable community with, for example, lower air quality (column 4) or remaining in their current community and driving a longer commute (column 6).

Our model also predicts that the wedge between the earnings effect and the welfare effect will differ greatly across workers according to their age, experience, education, occupation, job skill, preferences, and geographic location. For example, workers who lose their jobs in the Sacramento metro area experience relatively small reductions in wages when they move to new jobs (row 3). However, most of them end up in more expensive communities with lower quality schools. The reduction in their quality of life accounts for 65% of the welfare effect from losing their job. In contrast, the reduction in earnings experienced by the average worker in Santa Cruz exceeds their reduction in welfare. This is because people who move out of Santa Cruz often end up in communities where they pay less for housing and have access to better performing public schools.

The results in table 1 are based on a "normal" state of the business cycle in which workers who lose their jobs are unemployed for an average of 6 months. We also consider "recession" and "expansion" scenarios, adapting the methodology from Shimer (2005, 2012) to model the distribution of unemployment spells in each scenario. Not surprisingly, we find that the state of the business cycle matters for the welfare effects of layoffs.

Overall, our findings suggest that spatial migration has the potential to be of first order importance for evaluating the welfare effects of layoffs. This conclusion is general. We do not evaluate any specific regulation. In principle, our simulator could be adapted to predict the welfare effects of a specific regulation targeting air pollution or school quality that would also affect the demand for labor. The simulator can also be easily modified to embed any assumption about the share of unemployed workers who will find new jobs in the same metro area.

Of course, we abstract from reality in several ways. We do not estimate the effects of regulations on firm profits or on the deadweight loss from unemployment insurance programs. Moreover, our analysis has a static partial equilibrium perspective. We do not model moving costs, dynamics, or general equilibrium adjustments to housing prices, wages, and endogenous local public goods. For example, high unemployment could cause housing prices to fall. This might benefit renters, while reducing homeowners' assets and increasing their probability of foreclosure. These are important considerations for future research.

The remainder of the paper is organized as follows. Section II outlines the conceptual sorting model from Kuminoff (2010) and then extends it to consider layoffs. Section III explains how we calibrate the model and use it to build our layoff simulator. Section IV presents results, Section V discusses caveats, and Section VI identifies important directions for future research. Finally, section VII provides some concluding remarks.

II. An Intra-Urban Sorting Model with Unemployment

A. The spatial landscape

Consider an urban area containing $k = 1, \ldots, K$ labor markets and $j = 1, \ldots, J$ housing communities. Each (j,k) pair represents a unique house-job combination, and each combination requires a commute time, $t_{j,k}$. Communities differ in the annualized after tax price of housing, p_j, and in a vector of local public goods, g_j. Public goods are defined here to include services produced from tax revenue, such as public school quality, as well as environmental amenities such as air quality.

Households differ in terms of their exogenous nonwage income (*nw*), their relative preferences for different public goods (γ), and their overall preferences for public goods relative to private goods (α). Let $q_j(\gamma)$ represent the composite provision of public goods in community j as perceived by a household with γ-type preferences. Since households differ in their preferences over public goods, they may differ in the way they rank communities by overall public goods provision. Households also differ in their disutility of commuting to work (ϕ).

Workers are assumed to face spatially differentiated job opportunities. Let

$w_k(\theta)$ represent the wage schedule in labor market k. It defines the wages paid to workers as a function of their job skill, θ. One can think of $w_k(\theta)$ as a hedonic wage function. The k subscript on the wage function recognizes that, conditional on skill, a worker may be compensated differently in different labor markets due to spatial variation in regulation, tax rates, agglomeration effects, local cost-of-living adjustments, unionization, and other factors that affect labor demand.

Working households are assumed to be price-takers and to have perfect information about the spatial landscape.[3] They evaluate their feasible job-house locations and select the combination that maximizes their utility from consumption of housing (*h*), a numeraire good (*b*), public goods, and commute time,

$$\text{(1)} \qquad \max_{j,k,h} U\left[q_j(\gamma_i), h_j, b, t_{j,k}, \alpha_i\right] \quad \textit{subject to} \;\; y_{i,k} = p_j h_j + b.$$

Their interrelated choices in both markets will determine their income ($y_{i,k}$) and their annual expenditures on housing ($p_j h_j$). Assuming households are free to choose continuous quantities of housing in each community, the utility maximization problem can be rewritten in indirect terms: $V\left[q_j(\gamma_i), t_{j,k}, \alpha_i, y_{i,k}\right]$.

B. Indirect Utility

Equation (2) provides a parametric expression for the indirect utility obtained by household *i* in community-job *j,k*.[4] The first term in the CES function represents utility from public goods, and the second represents utility from the private good component of housing and the disutility from commuting.

[3] While the model allows some households to be retired, they do not play a direct role in our analysis. Retired households are assumed to ignore the labor market. They select a community, which determines their housing expenditures and their consumption of public goods.

[4] For additional background on the properties of this specification for utility see Epple and Sieg (1999), Sieg et al. (2004), and Kuminoff (2010).

(2) $$V_{i,j,k} = \left\{ \alpha_i \left(q_{i,j}\right)^{\rho} + \left[\exp\left(\frac{y_{i,k}^{\;1-\nu} - 1}{1-\nu} - \phi_i t_{j,k} \right) \exp\left(-\frac{\beta P_j^{\eta+1} - 1}{1+\eta} \right) \right]^{\rho} \right\}^{\frac{1}{\rho}},$$

$$\text{where} \quad q_{i,j} = \gamma_{i,1} g_{1,j} + \ldots + \gamma_{i,N-1} g_{N-1,j} + \gamma_{i,N} \xi_j .$$

All households are assumed to share the same elasticity of substitution between public and private goods (ρ) as well as the same housing demand parameters: price elasticity (η), income elasticity (ν), and demand intercept (β). Applying Roy's Identity yields a Cobb-Douglas demand curve for housing,

(3) $$h_i = \beta p_j^{\eta} y_i^{\nu} .$$

While households are assumed to share a common set of demand parameters, individual demand varies with income.

Households also differ in their preferences over a linear index of public goods provided by each community, $q_{i,j}$. Of the *N* public goods in the index, *N-1* are observable. The N^{th} public good ($g_{N,j} = \xi_j$) is not observed by the econometrician.[5] Households differ in the weights they place on each public good in the index $\left(\gamma_{i,1},\ldots.,\gamma_{i,N}\right)$ and in their overall preferences for public goods relative to private goods $\left(\alpha_i\right)$. The weights are assumed to sum to 1, allowing α_i to be defined separately as a scaling parameter on the strength of preferences.

The primary earner of each household is assumed to possess skills that determine the wages they would earn in each job location. Job skill is divided into observed and unobserved components: $\theta = [x, \varepsilon]$. The worker's age, education, and occupation (e.g. biomedical engineer, locksmith, lawyer) are among the ob-

[5] ξ_j can be interpreted as a composite index of all the *unobserved* public goods under the restriction that they are vertical characteristics; i.e. the weights in the index of unobserved public goods are all constants. This is an example of the "pure characteristics" approach to modeling the utility from a differentiated product (Berry and Pakes 2007).

servable dimensions of skill represented by x. Unobserved features of skill, such as the quality of the worker's education and their "ability", are represented by ε.

Each household's total income is observed at their chosen location $\left(y_{i,k^*}\right)$ along with the primary earner's hourly wage $\left(w_{i,k^*}\right)$ and hours worked $\left(h_{i,k^*}\right)$. Nonwage income (nw_i) is defined as the difference between wage income and total income: $y_{i,k^*} = nw_i + h_{i,k^*} \cdot w_{i,k^*}$. These objects are combined with the observable attributes of job skill to define household income at every possible location:

(4.a) $y_{i,k} = y_{i,k^*}$ at the observed job location, k^*.

(4.b) $y_{i,k} = nw_i + h_{i,k^*} \cdot \left[\overline{w}_k(x_i) \cdot \varepsilon_{i,k}\right]$ at any other job location: $k \neq k^*$.

A household's total income is observed at their chosen location (4.a). Equation (4.b) defines the counterfactual income a working household would receive if its primary earner were to move to a different job. Nonwage income (including the wages of any secondary earners) and hours worked are assumed to remain the same. However, the wage that the primary earner would earn in their new job depends on the local demand for their skills. $\overline{w}_k(x_i)$ represents the average wage paid to observationally equivalent workers in labor market *k*. If $\varepsilon_{i,k}$ is greater (less) than 1, worker *i* would earn more (less) than the average wage. Notice that the *k* subscript on $\varepsilon_{i,k}$ allows for spatial heterogeneity in the market value of a worker's idiosyncratic skills. For example, a lawyer who is highly skilled in agricultural law may have $\varepsilon_{i,k} > 1$ in a job location dominated by farming and $\varepsilon_{i,k} < 1$ in a job location dominated by manufacturing.

The job location decision can present working households with a long-run tradeoff between leisure time and the consumption of private goods. Holding his house location fixed, a worker may be able to increase his wage by commuting to a more distant labor market. His willingness to make this commute depends, in part, on $\phi_i t_{j,k}$, where ϕ_i is a parameter describing his disutility from commuting and $t_{j,k}$ is the commute time between *j* and *k*. For a worker with $\phi_i = 0$, there is no disutility from commuting. As ϕ_i increases, so does the threshold wage needed to induce the worker to lengthen their commute. By influencing a worker's job location, ϕ_i can affect the amount of income his household has to spend on housing and other private goods.

The specification for utility in (2)-(4) generalizes the Epple-Sieg (1999) model of neighborhood sorting that has been used to estimate preferences for air quality in the Los Angeles metro area (Sieg et al. 2004) and to evaluate the welfare implications of the Clean Air Act Amendments (Smith et al. 2004). Specifically, equation (2) reduces to their specification for utility in the special case where wage income is exogenous to location choice, households have vertically differentiated preferences (i.e. $\gamma_i = \gamma$ for all *i*), and the joint distribution of preferences and income is lognormal. We now proceed to extend the model in (2)-(4) to depict job transitions for workers who unexpectedly lose their jobs.

C. Job Transitions

If a worker is laid off, the transition to a new job may take some time. The unemployed worker must prepare a resume, search for vacancies, and go through an interview process. If a prospective job is located far away, the worker may choose to search for housing simultaneously. We denote by ω_{rst} the probability that a worker who loses their job in industry *r* at time *t* will find a job within *s* weeks. We propose to construct ω_{rst} using the actual job-finding experiences of workers who experience unemployment in the data. In practice we consider three temporal scenarios for the incidence of job loss: losing a job during a boom, when jobs are relatively easy to find; losing a job during an "average" period; and losing a job during a severe recession, when jobs are difficult to find. By allowing for temporal variation we can address the question of whether aggregate business cycle conditions are relevant for cost-benefit analyses of environmental regulations that induce layoffs.

Finally, during the interim when a worker is looking for a new job we assume the worker collects unemployment insurance, ui_i. In this case, household income can be rewritten as

$$(5) \qquad y_{i,k} = nw_i + ui_i,$$

where $ui_i = h_{i,k^*} \cdot w_{i,k^*} \cdot \tau$. Unemployment insurance payments are expressed as a constant fraction (τ) of the worker's wage at the job they lost, consistent with current U.S. policy.

D. Welfare Implications of a Regulation with Employment Effects

Consider a policy that reduces pollution, while creating layoffs (or new job vacancies) in the targeted sector. If these changes are small relative to baseline pollution and employment, there may be little or no adjustment to market prices.[6] Equation (6) defines a partial equilibrium measure of annualized equivalent variation for a household that is unaffected by the layoffs or job vacancies.

$$(6) \qquad V\left[q_j^1(\gamma_i), p_j, t_{j,k}, \alpha_i, \phi_i, y_{i,k}\right] = V\left[q_j^0(\gamma_i), p_j, t_{j,k}, \alpha_i, \phi_i, y_{i,k} + EV\right].$$

EV is the amount of money one would have to give household *i* in year 0 (before the regulation) to make them as well off as they are in year 1 (after the regulation), given the change in environmental quality experienced by the household.

[6] In the case of a regulation that produces a "large" shock to the housing and labor markets, a sorting model such as this one can be used to simulate ex post equilibria, taking into account changes in housing prices, wage rates, and commuting patterns. However, fairly strong restrictions on preferences are required to guarantee the equilibrium is unique. Current research is focused on evaluating the external validity of these models. See Kuminoff (2011) and Kuminoff, Smith, and Timmins (2012) for a discussion.

Similar to the welfare measures reported in most empirical applications of sorting models, equation (6) holds job location and income fixed.

Welfare calculation is more complicated for the workers who move to new jobs following the regulation. These workers may have unemployment spells, adjustments to their wages, and adjustments to their job and / or house locations. These factors are reflected in the following, more general, measure of EV,

$$(7) \qquad V\left[q_l^1(\gamma_i), p_l, t_{l,m}, \alpha_i, \phi_i, y_{i,m}^1\right] = V\left[q_j^0(\gamma_i), p_j, t_{j,k}, \alpha_i, \phi_i, y_{i,k}^0 + EV\right].$$

The *l*,*m* subscripts on locations to the left of the equality recognize that when a temporarily unemployed worker moves to a new job, that job may be located in a different metropolitan area; i.e., the worker moves from k to m. This relocation may also induce the worker to move to a new housing community; i.e., from *j* to *l*. Alternatively, the household may choose to adjust one location, while keeping the other fixed: $(j = l, k \neq m)$ or $(j \neq l, k = m)$. For example, a worker who loses his job and finds a lower-paying one in the same metro area may decide to move to a similar house in a less expensive community with fewer public goods.

Because the model is inherently static, it assumes that each worker's next job is their second-best choice, without accounting for any intervening or temporary jobs. Likewise, it assumes that they earn their long-run salary immediately, without accounting for any initial period of lower salary or higher salary growth. The lack of dynamics also complicates the treatment of unemployment spells. As a matter of convenience, we convert the wages lost during the worker's unemployment spell into an annuity, using the worker's expected lifespan and an interest rate set to match the cost of a borrowing on a 30-year fixed rate mortgage. Intuitively, we are assuming the household finances its consumption during the unemployment spell by borrowing against their house, spreading the temporary wage shock across the worker's expected lifespan.

Equation (8) decomposes ex post annual real income into three components.

$$y_{i,m}^{1} = h_{i,k^*} \cdot \left[\overline{w}_m(x_i) \cdot \varepsilon_{i,m}\right] + nw_i - A_i \ . \tag{8}$$

The first component is the wage at the worker's new job: $h_{i,k^*} \cdot \left[\overline{w}_m(x_i) \cdot \varepsilon_{i,m}\right]$. The worker is assumed to work the same number of hours as he did at his old job, h_{i,k^*}.[7] His hourly wage depends on the quality of his match to his new job, determined by the market specific skill parameter ($\varepsilon_{i,m}$). The second component is the household's nonwage income, which is also assumed to be fixed. The final component is our annualized measure of the total wages lost during the worker's period of temporary unemployment:

$$A_i = \left[\frac{d_i}{12} \cdot \left(h_{i,k^*} \cdot w_{i,k^*}\right) \cdot (1-\tau)\right]\left(\frac{e^{\pi}-1}{1-e^{-\pi N}}\right), \tag{9}$$

where d_i indicates the number of months the worker is unemployed and $1-\tau$ measures the share of monthly income lost after the worker collects unemployment insurance. Thus, $\left[\frac{d_i}{12} \cdot \left(h_{i,k^*} \cdot w_{i,k^*}\right) \cdot (1-\tau)\right]$ is the total wage income lost during the period the worker is unemployed. It is annualized over the number of years the worker can expect to live, N, using an interest rate of π.[8]

Equation (9) is consistent with the idea that some workers who find new jobs may be underemployed. Underemployment is modeled here at the extensive margin. That is, the worker's occupation and hours worked are assumed to be fixed, but his second-best job option may be in an industry that does not allow him to fully utilize his occupational skills. The loss of industry-specific or job-specific human capital may cause the worker's wage to decline.

[7] To relax this assumption, one would need to extend the sorting model to include a labor supply decision at the intensive margin.

[8] If a new regulation creates jobs, the additional vacancies will mechanically reduce the average duration of unemployment. The opposite will be true if the regulation produces layoffs. However, these changes will be small as long as aggregate layoffs from the regulation are small relative to current unemployment.

Together, equations (7)-(9) illustrate how the spatial and temporal dimensions of unemployment affect welfare measures generated by a static sorting model. These equations also illustrate why household mobility should prevent us from interpreting observed changes in earnings as measures of the welfare effects from layoffs or newly created jobs. Specifically, equation (9) illustrates how changes in earnings fail to account for the welfare implications of: (i) changes in commute time for households moving from j,k to l,m; (ii) changes in housing expenditures for households moving from j to l; and (iii) changes in the public goods consumed by households moving from j to l.

As an extreme case, consider a worker who, prior to the regulation, chose to work at a low paying job in order to live in a desirable community. If the worker loses his job because of the regulation, his next best alternative may be to move to a less desirable community near a higher paying job. If the worker's unemployment spell is brief, his annualized income could actually increase despite the fact that he is worse off from the move. Our point is simply that changes in earnings may understate or overstate welfare effects. The direction of the bias depends on whether the displaced workers move to neighborhoods with housing options, commuting options, and amenity bundles that they perceive to be more or less desirable.

E. Differences from a Conventional General Equilibrium Model

Compared to a conventional general equilibrium (GE) model of the economy, our sorting framework puts more emphasis on understanding the distribution of wage effects and welfare effects experienced by workers, and less emphasis on placing these effects within the context of social welfare. This allows us to approach the problem at a high level of resolution. For example, we can investigate the extent to which wage effects and welfare effects vary across working households according to demographic characteristics we can observe (e.g. income, occupation, industry) and according to estimated parameters representing unobserved features of their human capital and preferences for public goods. The sorting model also allows us to consider the role of space, recognizing that adjustments to earnings and public goods may be conveyed to households through spatial adjustment. In contrast, most GE models lack a spatial dimension. Finally, unlike most applied GE models, our sorting framework allows utility to be nonseparable in public goods.[9] This is important because it enables us to invoke the logic of revealed preferences to infer households' willingness-to-pay for environmental quality from observed tradeoffs between a complementary private good (housing) and the numeraire.[10] Thus, we can use the sorting model together with the logic of revealed preferences to consistently evaluate policies that improve environmental quality and simultaneously shock the demand for labor.

The flexibility allowed by our sorting model also comes at a cost. While it depicts interrelated behavior in multiple markets, it is a partial equilibrium framework. Unlike most GE models, the price of the numeraire good is assumed to be unaffected by shocks to the housing and labor markets. Furthermore, the lack of an explicit model of the firm or government means that we cannot construct measures of producer surplus, social welfare, or the deadweight loss from unemployment insurance schemes. Finally, unlike the broad class of dynamic stochastic GE models used in macroeconomics, our sorting framework does not allow us to predict the adjustment path to a new equilibrium.

III. Using the Model to Simulate Wage and Welfare Effects of Job Losses

In order to demonstrate how the sorting model could help us evaluate a regulation that is expected to induce layoffs, we use it to construct a "layoff simulator"

[9] The computable general equilibrium model developed by Carbone and Smith (2012) is a notable exception. See their paper for a discussion of the issues involved with building nonseparable preferences into general equilibrium models.

[10] More precisely, nonseparability recognizes that changes in environmental quality may affect marginal rates of substitution between different private goods. Assuming a parametric form for utility that satisfies Mäler's weak complementarity restriction then allows us to infer Hicksian welfare measures from observed behavior.

for Northern California. We begin by summarizing how Kuminoff (2010) calibrated the location choice model in (2)-(4) to data from Northern California. Readers are referred to his paper for econometric details. Then we explain how we adapt the calibrated model to predict the wage effects and welfare effects of layoffs. This involves three steps: (i) a mechanism to mimic job loss; (ii) a mechanism to predict where an unemployed worker will find a new job and how this will affect their choice of house location; and (iii) a mechanism to predict the duration of unemployment.

A. Calibration to Northern California

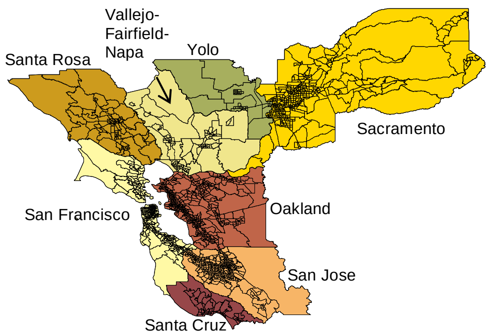
The model is calibrated to Northern California's two main population centers—the San Francisco and Sacramento consolidated metropolitan statistical areas.[11] Housing communities are defined by dividing the region into 122 unified school districts; job locations are defined by the region's 8 primary metropolitan statistical areas (PMSA), shown in figure 1.[12] The population is concentrated around the San Francisco Bay and the city of Sacramento, as seen by the density of census tracts in the map on the left. The set of possible location choices is defined by 268 community-PMSA combinations that, together, account for 99% of the working population.[13]

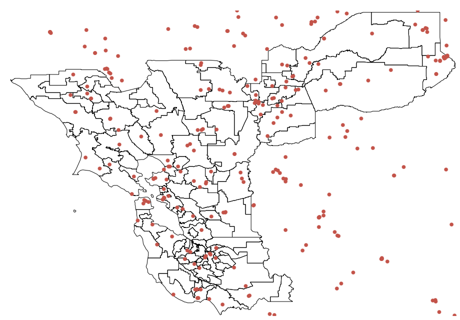
Housing prices were calculated from micro data on approximately half a million housing sales recorded by county assessors between 1995 and 2005. These data were used to calculate an index of community-specific housing prices using the hedonic procedure described in Seig et al. (2002). The index ranges from 1.00 to 6.51. Its distribution is consistent with the conventional wisdom that housing is particularly expensive in the Bay Area. All but one of the 25 most expensive

[11] This region contains approximately 9 million people, or 3% of the U.S. population.
[12] These definitions are standard ones in the empirical literatures on Tiebout sorting and Rosen-Roback sorting.
[13] The criterion used to select locations is that they must account for at least 500 working households (0.02% of the working population). This effectively excluded multiple-hour commutes between distant locations.

communities are located in the San Francisco and San Jose PMSAs.

Figure 1: San Francisco and Sacramento Consolidated Metro Areas





Notes: The map on the left illustrates census tracts overlaid on the eight primary metro areas in the study region. The map on the right illustrates the locations of air quality monitoring stations overlaid on public school districts.

Air quality is measured using concentrations of ground level ozone, one of the main components of urban smog. Northern California has some of the most spatially detailed information on ozone in the United States. The right-side map in figure 1 shows the locations of 210 monitoring stations in school districts. It is not uncommon for a district to have multiple monitoring stations. The exact ozone measure used is the average of the top 30 1-hour daily maximum readings recorded at each monitoring station during the course of a year. Households are assumed to be concerned with air quality near their house, not their job. Under this assumption, community-specific measures were constructed by first assigning to each house the ozone measure recorded at the nearest monitoring station, and then taking an average over all the houses in the community. Then, to control for annual fluctuation in ozone levels, the process was repeated for 1999, 2000, and 2001, and the results averaged. The final measure ranges from 0.031 (parts per million) in the highest air quality community to 0.106 in the lowest.

School quality is defined using California's Academic Performance Index (API), a composite index of standardized test scores, weighted across all subjects and grade levels. For each community, a three-year average API was constructed by weighting the score of each school in the community by its number of students from 1999-2001. The resulting measure ranges from 528 to 941. A set of community-specific fixed effects ($\xi_1,...,\xi_J$) is used to capture the composite effect of all other localized amenities on household location choices.

Finally, micro data on households and their location choices were drawn from the 5% micro data sample of the 2000 Census of Population and Housing. Key variables include house location, household income, and the primary earner's job location, occupation, industry, wage income, commute time, gender, age, race, and years of education.[14] If a worker were to move to a different job-house location, his counterfactual commute time is assumed to be the average commute time observed for that location.

Kuminoff (2010) uses these data to estimate the parameters of (2) for a 1-in-10 sample of Northern California households, randomly drawn using the Census PUMS household weights. Table 2 reports the estimated housing demand parameters used in our simulation. The price and income elasticities ($\eta = -0.39, \nu = 0.65$) are typical for empirical sorting models based on Epple and Sieg (1999). Given the signs of these parameters, the negative sign on ρ implies a downward sloping demand curve for public goods.

Table 2: Housing Demand Parameters Used to Calibrate the Model

β	η	ν	ρ
15.39	-0.39	0.65	-0.13

[14] Occupation is defined using the Standard Occupational Classification system. Industry is defined using the North American Industrial Classification System. Job and house locations are defined in the Census data as public use microdata areas (PUMA). In most cases, there is an exact mapping from PUMAs to PMSAs and unified school districts. In cases where PUMA boundaries overlap school district boundaries, we assigned households to communities based on the assumption that people are uniformly distributed across PUMAs.

Kuminoff partially identifies the heterogeneous parameters representing households' preferences and skills, adapting the logic of Manski (2007) and building on the econometric techniques of Bajari and Benkard (2005). This involves using a system of revealed preference inequalities to recover a separate set of values for $(\alpha_i, \gamma_i, \phi_i, \varepsilon_i)$ that is consistent with the observed behavior of each household. We use these preference sets to calculate measures of expected equivalent variation under the assumption that preferences are uniformly distributed within each set.

B. Mimicking Job Loss

We mimic the experience of losing a job by removing the primary earner's current job location from his choice set. The worker is forced to move to a new job in one of the seven remaining PMSAs. Thus, unemployment is treated as a constraint on the worker's labor market mobility. Forcing unemployed workers to migrate allows us to evaluate the *potential* for spatial migration in the labor market to influence the welfare effects of layoffs.

C. Predicting the Spatial Location of a New Job

After removing a worker's current job location from his choice set, we can determine which of the remaining PMSAs would maximize his utility, conditional on a draw for the heterogeneous parameters. This process works by assigning each worker to a job in his second-best spatial location. When a worker moves to a new PMSA he may find work in a different industry, but his occupation is assumed to be unchanged. We define occupations using 5-digit codes from the Standard Occupational Classification system. This allows us to match each worker to the range of wages paid to other workers with similar training.[15] Whether a

[15] For example, the 5-digit SOC codes distinguish between five types of social scientists: economists, market and survey researchers, psychologists, sociologists, and urban and regional planners.

worker's wage rises or falls at his new job depends on his idiosyncratic skills (ε_{ik}).[16] After moving to a new job location, the worker may choose to remain in the same housing community. If, however, the necessary commute time induces the worker to move to a different community, then his change in utility will also depend on his household's idiosyncratic tastes for amenities $(\alpha_i, \gamma_i, \phi_i)$ in relation to the amenities provided by the new community. Thus, a household may prefer the amenities provided by the new community and the household's income may rise at the primary earner's new job, but both cannot occur simultaneously. Utility must decline when the household's preferred location is removed from their choice set.

There are three caveats to our predictions. First, recall that our model focuses exclusively on the primary earner's contribution to household income. Non-wage income is assumed to be fixed. Thus, we are ignoring any changes in commuting or wages that would be experienced by secondary earners in a household. In order to consistently predict how the incomes of secondary earners would adjust, the sorting model would need to be extended to depict bargaining within the household.[17] Second, we do not allow unemployed workers to move to lower-pay lower-skill jobs in the same metropolitan area (e.g. a machinist working as a cashier).[18] Again, the estimator does not identify skill parameters that would enable us to consistently model this possibility. Finally, since the heterogeneous preferences parameters are set identified, rather than point identified, we must address our uncertainty about the model's predictions for a particular household's ex post utility. We do this by integrating over the preference set recovered for each

[16] Recall that these parameters are recovered during the estimation.
[17] We return to this idea in section IV as a potential area for future research.
[18] The welfare effects of this outcome would lie within the range reported in the last two rows of table 3. We plan to model localized underemployment in future research.

household, assuming a uniform distribution, and then use the result to calculate a measure of expected equivalent variation.[19]

D. Predicting the Duration of Unemployment

Earnings losses and welfare effects will also depend on the duration of unemployment, as shown in (6)-(9). We address this by calibrating our layoff simulator to reflect the duration of unemployment spells observed in the Current Population Survey (CPS) at different stages of the business cycle.

The primary goal of the CPS is to provide monthly data on the labor market status of a sample of approximately 60,000 Americans. We construct from these files the subsample of unemployed workers age 16 or older between January 2002 and February 2012. We focus on this time period because the industry classifications were consistent over time, enabling us to construct industry-specific job finding rates. The CPS asks each unemployed worker how long they have been unemployed. Given the total number of workers unemployed at date t, u_t, and the number unemployed for more than s weeks at date $t+s$, u_{t+s}^{s}, we can construct an approximation to the job finding rate at various durations as:

$$(10) \quad \omega_{s,t} = 1 - u_{t+s}^{s}/u_t \ .$$

The job finding rate ($\omega_{s,t}$) provides a measure for the share of workers who were unemployed at date t but found work within s weeks of that date. This technique follows Shimer (2005, 2012).

Since the CPS provides a wealth of information about unemployed workers, we can in principle calculate $\omega_{s,t}$ by industry of prior employment, geographic region, date of initial unemployment, and so on. In practice we calculate $\omega_{s,t}$ by

[19] This is analogous to the standard practice of reporting measures of expected compensating variation calculated from random utility models that assume the presence of idiosyncratic preference shocks distributed according to a Type I extreme value distribution. Unlike a standard RUM, our model is partially identified. This makes it feasible to systematically evaluate the robustness of our results to the uniform distribution assumption. See Kuminoff (2010) for details.

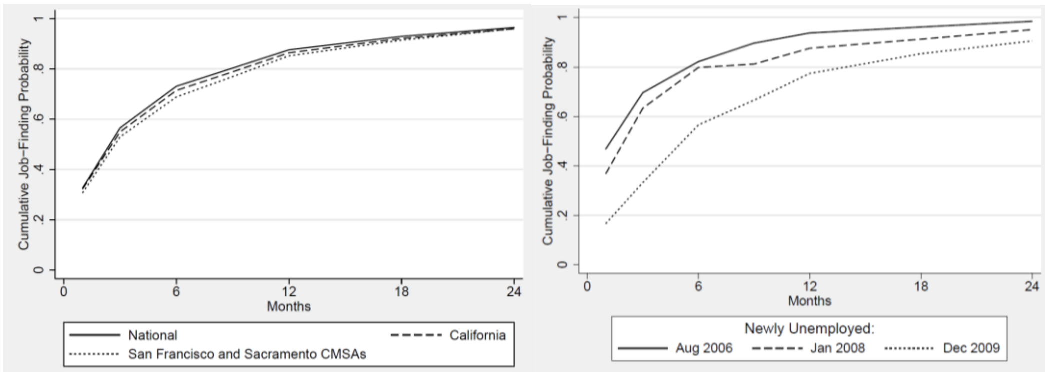
industry nationwide for a few key time periods. That is, we do not exploit the geographic information in the CPS to try to compute job finding rates specific to the San Francisco-Sacramento area. This choice is a conscious decision to focus on the margins of interest (differences in job-finding rates by industry and over the business cycle) in view of limitations on the available sample size.[20]

We abstract from geographic variation because our analysis indicates that job-finding rates for unemployed workers in the San Francisco-Sacramento area are similar to those for the nation as a whole. On the other hand, there are modestly larger differences by industry. Both of these differences are, however, dominated by the variation over the course of the business cycle. The right side graph in figure 2 shows the job-finding rates for workers who became initially unemployed in August 2006, January 2008, and December 2009. These months had the highest, median, and lowest job-finding rates in the first month in our CPS sample. By comparing this with the left side graph of figure 2, and with figure 3, one can see immediately that the differences in job-finding rates over the business cycle are much larger than those for geographic region or industry, and that they persist strongly for at least two years.[21] Our findings are consistent with the prior work of Hall (2006) and Shimer (2012), who document that variation in the job-finding rate over the business cycle explains most of unemployment fluctuations; and with the work of Șahin, Song, Topa, and Violante (2012), who document that cross-sectional mismatch explains little of aggregate unemployment, where mismatch is defined as variation in the vacancy-unemployment rate (e.g., tightness of labor markets) across geographic regions or industries/occupations.

[20] The primary problem is that the CPS is not a very large dataset. The calculation in (10) compares the number of unemployed workers at time t with the number of workers unemployed for at least k weeks during week $t + k$ (with the probability of finding a job during k weeks implicitly computed using the difference). This calculation provides useful results as long as the sizes of these cells are sufficiently large. In practice, cell sizes make it difficult to calculate job-finding rates for cross-tabulations. For example, we can reliably estimate job-finding rates for men or Californians or manufacturing workers, but not male manufacturing workers in California.

[21] Although the CPS documentation indicates that workers should be able to report almost arbitrarily long unemployment spells, we find that almost no workers report spells longer than two years, and that the maximum duration is 124 weeks. We truncate unemployment duration at two years.

Figure 2: Spatiotemporal Variation in the Cumulative Job Finding Probability



Note: The graph on the left displays the job finding probability for (i) the United States; (ii) California; and (iii) our study region. The graph on the right displays the job finding probability for workers who were newly unemployed in (i) August 2006; (ii) January 2008; and (iii) December 2009, our "expansion", "normal" and "recession" scenarios, respectively.

Figure 3: Cumulative Job Finding Probability, by Industry and Business Cycle

Note: These graphs display national cumulative job finding probabilities, by NAICS industry, for workers who were newly unemployed during expansion (Aug 2006), recession (Dec 2009), and normal (Jan 2008) periods. Job finding probabilities were estimated from data on unemployed workers in monthly CPS. In 1.6% of industry/month combinations, the estimated marginal job finding probability is negative due to sampling error. In these cases we use linear interpolation to restrict the job finding probability to be positive. Some 2-digit industries were aggregated to reduce sampling error. Specifically, Agriculture and Natural Resources = 11, 21; Manufacturing = 31-33; Wholesale/Retail Trade = 42, 44, 45; Transportation and Utilities = 22, 48, 49; FIRE = Finance and Insurance (52) and Real Estate and Rental and Leasing (53); Business Services = 54-56; Education and Health = 61-62; Entertainment and Food = 71-72; and Other Services = 51, 81, 92.

Since variation over the business cycle and industry of prior employment seem to be the most important channels, we focus on these. We perform three sets of welfare calculations. In each we assign to unemployed workers the job-finding rates that prevail in the data for workers from their industry at the national level. The calculations differ only in the assumed business cycle conditions. In particular, we feed in the actual job-finding probabilities that prevailed in August 2006, January 2008, and December 2009, which replicate "expansion", "normal", and "severe recession" labor markets. Doing so allows us to address whether aggregate economic conditions are important for the implied welfare costs of job loss from environment regulations.

IV. Results from the Northern California Model

Table 3 presents our aggregate results. All figures in the table are based on iterating over a random 1-in-10 sample of Northern California households, drawn using the Census Bureau's household weights. Panel A summarizes the wages lost due to temporary unemployment. Wages lost per worker during the unemployment spell ranges from an average of $15,224 in our expansion scenario to an average of $30,821 in our recession scenario. Following (9), we convert these figures to annuities:

$$A_i = lost\ wages * \left(\frac{e^{.07}-1}{1-e^{-.07N}}\right),$$

where *N* is the number of life years remaining for the worker, based on Center for Disease Control life tables for the year 2000, and the interest rate is set to 0.07 to match the 1995-2005 average interest rate on a fixed rate 30-year home loan. The annualized wage loss from temporary unemployment ranges from $1,231 to $2,493.

Table 3: Annual Wage and Welfare Effects of Simulated Layoffs, per Household

A. TEMPORARY UNEMPLOYMENT

	expansion	normal	recession
Mean unemployment duration (months)	4.60	6.14	9.41
Net wages lost during unemployment period (mean per worker)	-15,224	-19,978	-30,821
Annualized net wage loss (mean per worker)	-1,231	-1,618	-2,493

B. CHANGE IN ANNUAL SALARY

Assumption about New Job	expansion	normal	recession
Rehired at identical job in original location	0	0	0
Move to 2nd best (job, house) location	-3,929	-3,929	-3,929

C. EXPECTED EQUIVALENT VARIATION

Assumption about New Job	expansion	normal	recession
Rehired at identical job in original location	-1,231	-1,618	-2,493
Move to 2nd best (job, house) location	-6,986	-7,287	-7,936

Notes: The first row of panel A summarizes the mean unemployment duration for the three scenarios shown in figure 3. The second row reports the wages foregone during the unemployment period for the average worker, net of unemployment insurance. Workers are assumed to collect unemployment insurance at 36% of the old wages. Row 3 converts the total loss to an annuity, using the worker's expected life years remaining and an interest rate of 7%. Row 2 of Panel B reports the mean change in wage from moving to the worker's second best job. Panel C reports the expected equivalent variation, taking into account the unemployment spell along with changes in wage and job-house location.

Panel B reports the average difference in annual salary between workers' new utility maximizing jobs and their old jobs. We consider two scenarios for how layoffs affect employment opportunities. In the first row, we depict the best outcome for workers, in which being fired does not diminish their job opportunities. At the end of a worker's unemployment spell, he is simply rehired at his old job (or hired at an identical job in the same location). Thus, there is no change in the worker's salary. The second row reports the change in wages when all workers are forced to move to their second-best job locations. Annual wages decrease by nearly four thousand dollars in this case.

Finally, Panel C reports the expected equivalent variation. Expected EV is calculated by integrating equation (7) over the distribution of unemployment spells for each business cycle scenario. In the normal scenario, for example, the range of predictions for expected EV per household per year ranges from -$1,618 under the scenario where the worker is rehired at an identical job to -$7,287 in the scenario where the worker has to move to their second best job location. In the first case, the state of the business cycle is very important for welfare measurement, with a 100% difference in EV between the recession and expansion scenarios. In contrast, the state of the business cycle is relatively less important when workers have to relocate. In that case, our measures of EV are driven by changes in salary at workers' new jobs and by changes in utility from moving to different housing communities and different commuting options.

Table 4 disaggregates the results by demographic group. For brevity, we just report results for "normal" business cycle conditions. Our qualitative predictions for the changes in earnings are consistent with the stylized facts about demographic variation in the income effects of layoffs. For example, consistent with Mansur and Posner's (2012) summary of the evidence from ex post models of the earnings effects of layoffs, we observe that earnings losses tend to be (i) larger for men relative to women, (ii) increasing in experience, and (iii) increasing in age.[22] Since our intra-urban sorting model is not constrained to reproduce any of these results, the fact that it does provides some preliminary support for the model's validity. The model also predicts that earnings losses will tend to increase in the level of education and will tend to be larger for homeowners relative to renters.

These trends in earnings losses are driven, in part, by differences in ex ante wages. By construction, the demographic groups with higher ex ante wages will experience larger annualized earnings losses due to temporary unemployment (column 1). However, the sorting model predicts the same pattern of relative magnitudes in the component of earnings losses from moving to a different job (column 2). In this case, our predictions for the differences across demographic

[22] Also consistent with Mansur and Posner (2012), we see that the earnings effects vary across space. See table 5.

groups reflect our estimates for the joint distribution of preferences and skills, in addition to ex ante wages.

Table 4: Wage and Welfare Effects of Layoffs, by Demographic Group

	(1) Annual adjustment for temporary unemployment	(2) Change in annual salary	(3) Expected change in real wages	(4) Expected equivalent variation
Population	-1,618	-3,929	-5,547	-7,287
Gender				
women	-1,288	-2,418	-3,706	-5,570
men	-1,815	-4,833	-6,649	-8,313
Age				
under 40	-1,309	-2,828	-4,137	-5,956
40-60	-1,846	-4,892	-6,739	-8,401
over 60	-2,089	-4,431	-6,521	-8,278
Education				
less than 13 years	-980	-2,295	-3,275	-4,609
13-16 years	-1,306	-2,757	-4,063	-5,705
more than 16 years	-2,161	-5,594	-7,755	-9,764
Experience				
less than 10 years	-1,110	-1,698	-2,808	-4,863
10-20 years	-1,610	-4,165	-5,775	-7,489
more than 20 years	-1,795	-4,554	-6,349	-7,995
Homeownership				
renters	-1,167	-1,979	-3,147	-5,023
owners	-1,910	-5,192	-7,102	-8,752

Note: Column 1 reports the wage loss from temporary unemployment, converted to an annuity using each worker's age and life-year tables for the year 2000 from the Center for Disease Control. The annualized loss reflects an expectation over the distribution of unemployment durations corresponding to the job finding probability distribution during "normal" labor market conditions. Column 2 reports the mean change in annual salary when workers move to their second best job locations. Column 3 is the sum of columns 1 and 2. Finally, Column 4 reports the expected equivalent variation.

Comparing columns 3 and 4 reveals that, in general, our measures of expected equivalent variation exceed the total reduction in earnings. This is because the workers' new job locations tend to induce them to consume (housing price, public good, commuting) bundles that they perceive to be inferior to the bundles they originally chose. The magnitude of this effect is substantial. On average, the expected welfare change for a worker who relocates his job to a different PMSA is 31% larger than the expected change in his wages. Variation in the percentage difference across demographic groups arises from differences in their ex ante locations, preferences, skills, and job opportunities.

Table 5 begins to illustrate the mechanisms that underlie the variation in the wedge between earnings losses and EV by reporting both measures broken out by the worker's original job location, along with information on the experiences of movers. For seven of the eight PMSAs, expected EV exceeds the wage loss. The size of the wedge between them depends on the changes in housing prices, commute times, and amenities experienced by households. The average differential is largest for the workers who lose their jobs in Sacramento (186%) because Sacramento households have the lowest ex ante wages, housing prices, and consumption of many amenities. When Sacramento workers move to jobs in different PMSAs, the physical distance between their old and new jobs induces 91% of them to move to housing communities closer to their new jobs. While their earnings reductions are relatively low, they typically have to pay much more for housing in their new communities. Housing prices are higher, in part, because their new communities tend to have less air pollution and greater provision of the unobserved public goods captured by the ξ index. Yet, these amenity improvements are insufficient to compensate the average Sacramento household for the increase in housing prices. The worker's original choice to live in Sacramento revealed that his household has strong preferences for private goods relative to public goods. This specific example illustrates a more general implication of the sorting model. The workers who chose to live in "dirty" areas based on relatively weak preferences for environmental quality may experience disproportionate welfare losses if they are effectively forced by a regulation to move to "clean" areas where housing prices and amenities are both higher. This is especially important for policies establishing minimum standards on environmental quality, since these policies effectively target the dirtiest areas.

Table 5: Wage and Welfare Effects of Layoffs, by Original Job Location

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
				Share experiencing an increase in:				
Job Location in 2000	Expected change in real wages	Expected equivalent variation	Share moving to different community	housing price	air quality	school quality	ξ	commute time
Oakland	-5,452	-6,728	0.94	0.22	0.31	0.59	0.24	0.57
Sacramento	-2,604	-7,443	0.91	0.68	0.83	0.28	0.66	0.78
San Francisco	-6,603	-7,659	0.94	0.12	0.20	0.63	0.15	0.47
San Jose	-7,237	-8,117	0.96	0.13	0.46	0.58	0.08	0.52
Santa Cruz	-6,703	-5,624	1.00	0.16	0.61	0.80	0.11	0.78
Santa Rosa	-5,621	-5,781	1.00	0.26	0.30	0.68	0.27	0.73
Vallejo	-3,347	-5,770	0.93	0.34	0.31	0.48	0.37	0.79
Yolo	-3,125	-5,983	0.90	0.55	0.72	0.58	0.44	0.79

Note: Columns 1 and 2 report the same measures of the expected changes in real wages and EV as in table 4. Column 3 reports the share of workers who are predicted to move to a different housing community after finding a new job in a different PMSA. Columns 4 through 8 report the share of households experiencing increases in housing prices, air quality, school quality, unobserved public goods, and commute times after moving to their new locations.

In contrast, workers in the high wage areas of San Jose and San Francisco tend to experience large earnings losses when they move to new jobs, along with reductions in air quality and ξ when they move to new houses. However, the differences between their earnings losses and EV are relatively small (12% to 16% on average) because most of them pay less for housing in their new communities and many of them experience reductions in commute times.

Finally, it is worth noting that our layoff simulator can be used to investigate the implications of job losses for any subgroup of the population that can be identified on the basis of worker and/or household characteristics reported in the Census PUMS data. For example, potential subgroups of interest might include the worker's specific industry and occupation, the household's income, house location, and the presence of children in the household. Table 6 provides an example of this by summarizing the expected EV for households where the primary earner works in the manufacturing sector, by the worker's age and original work location.[23] In future evaluations of specific regulations, our simulator could be used to focus on a small subset of workers in the particular industries, occupations, and metro areas that are targeted by those regulations.

Table 6: Wage and Welfare Effects of Layoffs in the Manufacturing Sector

		Expected change in real wages	Expected equivalent variation	Share of manufacturing workers
All Manufacturing		-7,674	-8,800	1.00
Job Location in 2000	Age			
Oakland	under 40	-4,882	-6,082	0.09
	over 40	-7,900	-8,915	0.12
Sacramento	under 40	-3,075	-8,451	0.05
	over 40	-5,741	-11,761	0.05
San Francisco	under 40	-5,005	-6,653	0.06
	over 40	-7,899	-8,791	0.06
San Jose	under 40	-6,981	-7,947	0.21
	over 40	-11,676	-11,337	0.25
Santa Cruz	under 40	-7,368	-5,994	0.01
	over 40	-7,689	-6,157	0.01
Santa Rosa	under 40	-4,081	-4,326	0.02
	over 40	-8,031	-7,981	0.02
Vallejo	under 40	-2,727	-4,617	0.01
	over 40	-7,184	-8,623	0.02
Yolo	under 40	-1,618	-4,401	0.01
	over 40	-4,996	-8,145	0.01

Note: The table reports expected changes in real wages and equivalent variation for workers in the manufacturing sector (NAICS 31-33) broken out by the worker's age and original job location. See the text and notes to tables 3-5 for definitions of the variables in each column.

[23] Appendix table A3 provides a second example: the average changes in real wages and EV by industry.

V. Discussion

Previous studies have used models of neighborhood sorting in a major metropolitan region to evaluate spatial variation in the prospective and retrospective benefits of regulations targeting environmental quality and other public goods (Sieg et al. 2004, Smith et al. 2004, Walsh 2007, Tra 2010, Klaiber and Phaneuf 2010, and Kuminoff 2011). Our simulations demonstrate that there is potential to extend the existing models to adjust welfare measures for the reductions in earnings and utility experienced by workers who lose their jobs (or face new job opportunities) as a result of the regulation. It would be straightforward to extend our calibrated partial equilibrium analysis to simulate the welfare effects of a specific regulation targeting air pollution, commute times, or public school test scores, given that the regulation is expected to induce layoffs (or new job opportunities) in specific industries and metro areas in Northern California.

Our results suggest that the net reduction in earnings experienced by a worker who loses his job may significantly understate the reduction in welfare experienced by that worker's household. In our simulations, the workers who remain in the same houses after losing their jobs tend to experience longer commutes after they relocate to new jobs. Moreover, the workers who move to new housing communities, closer to their new jobs, tend to consume (housing, amenity) bundles that they perceive to be inferior to the bundles at their original locations.

The sorting model also predicted that workers who move to new jobs in different metro areas will tend to be paid less due to a loss of job-specific or industry-specific human capital. This prediction is consistent with evidence from ex post studies of mass layoffs in general (Couch and Placzek 2010) and ex post studies of layoffs caused by environmental regulation in particular (Walker 2012). However, we did not allow workers to adjust the number of hours they work, or to look for jobs outside of their SOC 5-digit broad occupation (e.g. education administrator, detective and criminal investigator, cook). Because we ignore these potential dimensions of underemployment, our predictions for earnings losses and welfare losses may be attenuated.

As with all revealed preference models of housing and labor market outcomes, our specific predictions for the welfare costs of job losses depend on assumptions about unobserved sources of heterogeneity in preferences and skills among workers and households. There are, of course, several other limitations of our analysis that serve as caveats to our results and define potential avenues for future research. First, we have ignored moving costs, forward looking behavior, and dynamics. While focusing on a small geographic area at least mitigates the potential bias from ignoring moving costs, emerging research suggests that these issues are likely to be collectively important for welfare measurement in the sorting literature (e.g. Bishop 2011; Bayer et al. 2011).

Second, we did not attempt to simulate general equilibrium effects. If a particular regulation were to induce enough people to move, their migration patterns could lead to adjustments in housing prices, wage rates, commute times, and the provision of local public goods which, in turn, would feed back into welfare measures. While it is possible to solve for a new equilibrium that embeds these adjustments, relatively little is known about the uniqueness of equilibria in such general environments (e.g. Sieg et al. 2004, Timmins 2007, Kuminoff 2011). This is an area where more research is needed.

Third, our Northern California model is obviously limited in its geographic scope, covering only 3% of the U.S. population. Unfortunately, the model does not provide an easy way to predict immigration or emigration outside the study region. Moreover, the basic idea of spatial sorting suggests that unobserved heterogeneity in preferences and skills presents a fundamental problem for "function transfer" or "value transfer" approaches to transferring estimated welfare measures outside the geographic region of an existing study.[24]

Fourth, our focus has been limited to considering the welfare effects experienced by working households. We have not attempted to model the costs borne by employers. Nor have we attempted to model the deadweight loss of unemployment insurance programs. Thus, our model does not allow us to comment on the implications of a regulation for social welfare.

Finally, the basic idea of using a sorting model to simulate the welfare effects of layoffs presupposes that the analyst begins with a range of values in mind for the potential layoffs that could result from a prospective regulation. That is, the current generation of sorting models does not allow us to endogenously predict how a prospective regulation will affect the demand for labor. To do this, one would need to model the demand for heterogeneous labor on the part of differentiated firms. This would be an interesting and challenging direction for future research.

VI. Areas for Future Research

The residential sorting literature is an active area of research that is being pushed forward on many dimensions. In a review of the literature, Kuminoff, Smith, and Timmins (2013) summarize emerging research on: (i) modeling dynamics and forward looking agents; (ii) modeling housing supply, and (iii) model validation. Further advances in these areas will have implications for the way sorting models can be used to model unemployment in a spatial context.

Moving forward, one approach to using sorting models to systematically assess the effects of prospective regulations would be to develop more refined "regulation simulators" for several major metropolitan regions, similar to our Northern California model. Potential refinements could include tailoring the mecha-

[24] Spatial sorting violates one of the necessary conditions for valid benefit transfers (see Boyle et al. 2009).

nisms used to describe job loss, job match, and unemployment duration to the relevant study area and time period. A second approach would be to pursue the development of a national sorting model that integrates unemployment, moving costs (physical, financial, and psychological), dynamics, imperfect information, and heterogeneous skills and preferences for amenities, extending the recent work of Bayer, Kahn, and Timmins (2011), Bayer, McMillan, Murphy, and Timmins (2011), Bieri, Kuminoff, and Pope (2012), Bishop (2011), Kennan and Walker (2011), and Mangum (2012). In the remainder of this section, we discuss a few additional research areas that may be worth consideration.

A. Unitary v. Collective Household

Gemici (2008) models forward looking agents in a sorting framework that ignores housing market equilibrium. However, she recognizes that households may consist of two adults with frequently diverging economic motivations, and that this can lead to intra-household bargaining and conflict. The implications of joint location constraints on migration decisions, labor market outcomes, and divorce rates are therefore included. Gemici finds that family ties deter mobility, limiting the ability of spouses to simultaneously pursue labor market opportunities. In this context she endogenizes divorce, making it more likely when spouses have better career opportunities in different locations. With her estimated model, Gemici can simulate behavior under counterfactuals. Given the possibility for job separation to result in the breakup of marriage and the social costs that may accompany that breakup, this is an important complication to consider in future applications of residential sorting to unemployment.

B. (Dis)equilibrium

An important feature of sorting frameworks is that they describe long run equilibria. As we introduce the idea of unemployment into our model, the question arises of whether it is appropriate to model the world as being in long run equilibrium. If the world is not in long run equilibrium, then the challenge is to model the constraints that prevent instantaneous adjustment (e.g. moving costs, job search costs, information acquisition). Some models have sought to explain short term migration flows as functions of the differences in the net present value of future earnings and differences in amenities (i.e., the gravity model framework) – see Greenwood et al. (1991).

Disequilibrium models raise a practical problem. While we considered only small policies (i.e., that only displaced a single worker at a time), many real-world policies are large. For large policy changes, disequilibrium models are not able to predict what the world would have looked like in the absence of the policy. Without that counterfactual they are unable to generate welfare measures. In general, the concept of long run equilibrium is useful in constructing a theoretically consistent measure of welfare, but raises a number of important questions. How do we know if we are in long run equilibrium? Most applications simply assume it. In the context that we consider (i.e., movements after a disruptive regulation), the world may very well be in an adjustment phase. In our analysis, we focus on "small" policies that avoid this problem to some extent.

C. Spatial Unobservables

There are many factors that drive sorting across labor and housing markets, many of which are not observed by the researcher. How best to control for these? Gyourko and Tracy (1991) propose a random effects model. Bayer, Keohane and Timmins (2009) use panel variation in the index of local amenities derived from a horizontal sorting model based on repeated waves of census data. Other studies have suggested various approaches to developing instruments for endogenous variables (see Kuminoff, Smith, and Timmins 2013 for a review).

Given the current level of concern about omitted variable bias in empirical microeconomics, it would be useful to conduct research on defining a set of "best practices" for handling spatial unobservables in sorting models. Evidence from the extensive literature on reduced form program evaluation models is unlikely to translate directly to the sorting literature because of differences in econometric methods (e.g. partially identified nonlinear models in the sorting literature vs. point identified linear models in the program evaluation literature) and differences in the objects of interest (e.g. well defined welfare measures in the sorting literature vs. "effects" in the program evaluation literature). Explicit tests of the external validity of sorting models could also provide useful feedback (e.g. see Galiani, Murphy, and Pantano 2012).

D. Tracking Migration in Response to Regulatory Shocks

Finally, developing some direct evidence on the migration patterns of workers who lose their jobs could help to inform the most productive direction for future research. While aggregate migration data are widely available, it is not clear whether migration patterns are systematically different for workers who lose their jobs. Walker (2012) provides some initial evidence by tracking the *job locations* of workers who relocated within four states, reporting that more than 40% of job separators moved to new jobs in different counties. However, it is not clear how many of these job migrants moved to new houses. Likewise, Mangum's (2012) work on developing an "islands" model of metropolitan areas with unemployment begs the question of whether unemployed workers move to new metro areas *before* or *after* finding a specific job there. More generally, if the share of unemployed workers who move to new housing communities and labor markets is small, then a Roy-type model of labor market sorting might be more useful than a dual-market model of sorting across the housing and labor markets. If the share is larger but most movers stay within the same metro area, then a regional model of both markets—similar to the one is this paper—may be the most appropriate one to pursue. Lastly, if the share of workers who move cross-country is large, then advancing a national sorting model may be the most productive direction for research.

VII. Conclusion

Over the past decade, full-employment equilibrium models of housing market sorting have increasingly been used to evaluate the benefits of prospective environmental regulations. We demonstrated that the literature can potentially be extended to consider unemployment and some dimensions of underemployment. In a demonstration of the model where workers who lose their jobs were assumed to receive no benefits of improved environmental quality, we observed that the average worker's change in earnings was substantially smaller (in absolute magnitude) than their household's expected equivalent variation. This wedge arises because workers who move to new jobs often move to new housing communities as well. Their new communities often provide bundles of housing, commuting options, and local public goods that the movers perceive to be less desirable. These preferences were revealed by the movers' original location decisions. This non-wage effect on utility dominated welfare measures for workers in some metro areas and was a relatively minor component of welfare in other metro areas. Our analysis also suggests that the state of the business cycle, as reflected through the duration of unemployment spells, has the potential to be of first order importance in assessing the costs and benefits of environmental regulations from the perspective of working households.

Overall, the results from our preliminary analysis and from other recent papers in the literature cause us to be optimistic about the potential for using sorting models to evaluate the benefits and costs of environmental regulations that may result in layoffs. However, the current models should be refined and vetted before using them for “prime time policy analysis”. We made several specific suggestions for further research along these lines.

REFERENCES

Bajari, Patrick and C. Lanier Benkard. 2005. "Demand Estimation with Heterogeneous Consumers and Unobserved Product Characteristics: A Hedonic Approach." *Journal of Political Economy*, 113(6): 1239-76.

Bayer, Patrick, Nathaniel Keohane, and Christopher Timmins. 2009. "Migration and Hedonic Valuation: The Case of Air Quality." *Journal of Environmental Economics and Management*, 58(1).

Bayer, P., S. Khan, and C. Timmins. 2011. “Nonparametric Identification and Estimation in a Roy Model with Common Nonpecuniary Returns.” *Journal of Business and Economic Statistics*, 29(2): 201-215.

Bayer, Patrick, Robert McMillan, Alvin Murphy, and Christopher Timmins. 2011. “A Dynamic Model of Demand for Houses and Neighborhoods.” *NBER Working Paper #17250*.

Berry, Steven and Ariel Pakes. 2007. "The Pure Characteristics Demand Model." *International Economic Review*, 48(4): 1193-225.

Bieri, David, Nicolai V. Kuminoff, and Jaren C. Pope. 2012. “The Role of Local Amenities in the National Economy.” *Working Paper.*

Bishop, Kelly. 2011. “A Dynamic Model of Location Choice and Hedonic Valuation.” *Working Paper*.

Boyle, Kevin J., Nicolai V. Kuminoff, Christopher F. Parmeter, and Jaren C. Pope. 2009. “Necessary Conditions for Valid Benefit Transfers.” *American Journal of Agricultural Economics*, 91 (5), 1328-1334.

Carbone, Jared C. and V. Kerry Smith. 2012. “Valuing Nature in General Equilibrium.” Forthcoming in *Journal of Environmental Economics and Management.*

Couch, Kenneth A. and Dana W. Placzek. 2010. “Earnings Losses of Displaced Workers Revisited.” *American Economic Review*. 100(1): 572-589.

Epple, Dennis and Holger Sieg. 1999. "Estimating Equilibrium Models of Local Jurisdiction." *Journal of Political Economy*, 107(4): 645-81.

Galiani, Sebastian, Alvin Murphy, and Juan Pantano. 2012. "Estimating Neighborhood Choice Models: Lessons from a Housing Assistance Experiment." *Working Paper.*

Gemici, A. 2011. "Family Migration and Labor Market Outcomes" *Working Paper.*

Greenwood, M., G. Hunt, D. Rickman, and G. Treyz. 1991. "Migration, Regional Equilibrium, and the Estimation of Compensating Differentials." *American Economic Review*, 81(5):1382-1390.

Gyourko, J. and J. Tracy. 1991. "The Structure of Local Public Finance and the Quality of Life." *Journal of Political Economy*, 99(1): 774-806.

Hall, Robert E. 2006. "Job Loss, Job Finding and Unemployment in the U.S. Economy Over the Past 50 Years." *NBER Macroeconomics Annual 2005*, edited by Mark Gertler and Kenneth Rogoff. MIT Press.

Kennan, J. and J.R. Walker. 2011. "The Effect of Expected Income on Individual Migration Decisions." *Econometrica*, 79(1): 211-251.

Klaiber, H. Allen and Daniel J. Phaneuf. 2010. "Valuing Open Space in a Residential Sorting Model of the Twin Cities." *Journal of Environmental Economics and Management*, 60(2): 57-77.

Kuminoff, Nicolai V. 2010. "Partial Identification of Preferences from a Dual-Market Sorting Equilibrium." *Working Paper.*

Kuminoff, Nicolai V. 2011. "An Intraregional Model of Housing and Labor Markets for Estimating the Benefits of Changes in Public Goods." *Working Paper.*

Kuminoff, Nicolai V., V. Kerry Smith, and Christopher Timmins. 2013. "The New Economics of Equilibrium Sorting and Policy Evaluation Using Housing Markets." *Forthcoming in Journal of Economic Literature*.

Mangum, Kyle. 2012. "A Dynamic Model of Cities and Labor Market Development." *Working Paper.*

Manski, Charles F. 2007. *Identification for Prediction and Decision*. Harvard University Press, Cambridge.

Mansur , Jonathan S. and Eric A. Posner. 2012. "Regulation, Unemployment, and Cost-Benefit Analysis." *Virginia Law Review*, 98: 579-634.

Noonan, Mary C. and Jennifer L. Glass. 2012. "The Hard Truth about Telecommuting." *Monthly Labor Review*, Bureau of Labor Statistics. June: 38-45.

Roback, J. 1982. “Wages, Rents, and the Quality of Life.” *Journal of Political Economy*, 90(6): 1257-1278.

Rosen, S. 1974. “Hedonic Prices and Implicit Markets: Product Differentiation in Pure Competition.” *Journal of Political Economy*, 82(1): 34-55.

Rosen, S. 1979. “Wage Based Indices of Urban Quality of Life.” In Mieszkowski and Straszheim (eds.), *Current Issues in Urban Economics*.

Roy, A.D. 1954. “Some Thoughts on the Distribution of Earnings.” *Oxford Economic Papers*, 3(2): 135-146.

Șahin, Ayșegül, Joseph Song, Giorgio Topa, and Giovanni L. Violante. 2012. “Mismatch Unemployment.” *Working Paper.*

Sieg, Holger, V. Kerry Smith, H. Spencer Banzhaf, and Randy Walsh. 2002. "Interjurisdictional Housing Prices in Location Equilibrium." *Journal of Urban Economics*, 52(1): 131-53.

Sieg, Holger, V. Kerry Smith, H. Spencer Banzhaf, and Randy Walsh. 2004. "Estimating the General Equilibrium Benefits of Large Changes in Spatially Delineated Public Goods." *International Economic Review*, 45(4): 1047-77.

Shimer, Robert. 2005. “The Cyclical Behavior of Equilibrium Unemployment and Vacancies.” *American Economic Review*. 95(1): 25-49.

Shimer, Robert. 2012. “Reassessing the Ins and Outs of Unemployment.” *Review of Economic Dynamics*. 15(2): 127-148.

Smith, V. Kerry, Holger Sieg, H. Spencer Banzhaf, and Randy Walsh. 2004. "General Equilibrium Benefits for Environmental Improvements: Projected Ozone Reductions under EPA’s Prospective Analysis for the Los Angeles Air Basin." *Journal of Environmental Economics and Management*, 47(3): 559-84.

Tiebout, Charles M. 1956. "A Pure Theory of Local Expenditures." *Journal of Political Economy*, 64(5): 416-24.

Timmins, Christopher. 2007. "If You Cannot Take the Heat, Get Out of the Cerrado...Recovering the Equilibrium Amenity Cost of Nonmarginal Climate Change in Brazil." *Journal of Regional Science*, 47(1): 1-25.

Tra, Constant I., 2010. “A Discrete Choice Equilibirum Approach to Valuing Large Environmental Changes.” *Journal of Public Economics*, 94 (1-2): 183-196.

United States Office of Management and Budget. 2012. “Draft 2012 Report to Congress on the Benefits and Costs of Federal Regulations and Unfunded Mandates on State, Local, and Tribal Entities”.

Walker, W. Reed. 2012. “The Transitional Costs of Sectoral Reallocation: Evidence from the Clean Air Act and the Workforce.” *Working Paper*.

Walsh, Randall L. 2007. "Endogenous Open Space Amenities in a Locational Equilibrium." *Journal of Urban Economics*, 61(2): 319-44.

Part A.I summarizes data on movers from the American Housing Survey. Part A.II reports additional results from the layoff simulator, by industry.

A.I. Reasons for Moving

Tables A1 and A2 summarize results from the "reasons for moving" tables in the biennial American Housing Surveys for 1999, 2001, 2003, 2005, and 2009. In table A1, "new job or job transfer" is consistently the second most frequently cited "main reason for leaving one's previous housing unit". In table A2, "convenient to job" is consistently the most frequently cited "main reson for choice of present neighborhood."

Table A1: Main Reason for Leaving Previous Unit

Main Reason	1999	2001	2003	2005	2007	2009
To establish own household	12%	12%	12%	11%	11%	11%
New job or job transfer	11%	11%	10%	10%	9%	9%
Needed larger house or apartment	10%	11%	10%	10%	9%	9%
To be closer to work/school/other	9%	9%	8%	9%	9%	9%
Other, family/personal related	8%	8%	8%	8%	8%	8%
wanted better home	8%	8%	8%	8%	8%	7%
Married, widowed, divorced, or separated	6%	5%	6%	6%	5%	5%
change from owner to renter or renter to ow	5%	5%	5%	5%	3%	5%
other housing related reasons	5%	4%	5%	5%	5%	4%
wanted lower rent or maintenance	4%	4%	5%	4%	4%	5%
Other, financial/employment related	3%	3%	3%	3%	3%	4%
Private displacement	1%	1%	1%	1%	1%	1%
Disaster loss (fire, flood, etc)	1%	0%	1%	0%	1%	1%
government displacement	0%	0%	0%	0%	0%	0%
Evicted from residence	0%	0%	0%	0%	0%	1%
All reported reasons equal	2%	2%	1%	1%	4%	4%
other	11%	12%	12%	14%	11%	12%
not reported	5%	4%	5%	4%	9%	6%
Number of observations	17,824	17,644	17,866	19,382	18,459	17,464

Table A2: Main Reason for Choice of Present Neighborhood

Main Reason	1999	2001	2003	2005	2007	2009
convenient to job	18%	21%	19%	19%	20%	20%
convenient to friends or relatives	13%	14%	16%	15%	14%	14%
house was most important consideration	14%	15%	15%	15%	10%	10%
looks/design of neighborhood	15%	14%	14%	15%	10%	10%
good schools	6%	7%	6%	7%	6%	6%
Convenient to leisure activities	2%	2%	2%	2%	2%	2%
Convenient to public transportation	1%	1%	1%	1%	1%	2%
other public services	1%	1%	1%	1%	1%	1%
All reported reasons equal	4%	3%	2%	2%	14%	11%
other	16%	18%	20%	21%	15%	19%
not reported	11%	3%	4%	2%	7%	4%
Number of observations	17,826	17,642	17,867	19,384	18,459	17,463

A.II. Additional Results from the Layoff Simulator

Table A3 reports the expected change in real wages and expected equivalent variation, by NAICS industry.

Table A3: Wage and Welfare Effects of Layoffs, by Industry

Industry	Expected change in real wages	Expected equivalent variation
Population	-5,547	-7,287
Industry		
Agriculture, forestry, fishing and hunting (11)	-5,418	-6,279
Mining (21)	-4,915	-7,032
Utilities (22)	-5,413	-7,237
Construction (23)	-4,463	-6,052
Manufacturing (31-33)	-7,674	-8,800
Wholesale Trade (42)	-4,841	-7,028
Retail Trade (44-45)	-4,090	-5,988
Transportation and Warehousing (48-49)	-4,278	-5,619
Information (51)	-6,284	-8,147
Finance and Insurance (52)	-8,684	-9,902
Real Estate and Rental and Leasing (53)	-7,956	-9,810
Professional, Scientific, and Technical Services (54)	-7,238	-9,368
Management of Companies and Enterprises (55)	-5,743	-8,006
Administrative and Support and Waste Management and Remediation Services (56)	-4,109	-5,536
Education Services (61)	-3,511	-5,729
Health Care and Social Assistance (62)	-4,621	-6,806
Arts, Entertainment, and Recreation (71)	-4,805	-6,307
Accomodation and Food Services (72)	-2,536	-3,906
Other Services, except Public Adminstration (81)	-4,277	-5,789
Public Adminstration (92)	-4,012	-6,297