Net Migration and State Labor Market Dynamics

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Abstract

I present a simple model of migration in which the net migration rate into a state depends on the expected present value of labor market conditions and amenities. I show that though this is a common model, existing empirical estimates do not separately identify the underlying parameters. The identification problem can be thought of as an omitted variable bias because no explicit measure of expected future labor market conditions is included. I use state-level data to estimate empirical models in which the underlying parameters are identified. I find that high wages and low unemployment encourage in-migration, but that the omitted variable bias can be large. For example, when I control for future conditions in one model, the strength of the relationship between current wages and net migration is less than half as large. I integrate the migration model into a simple labor supply and demand framework and use my estimates of the migration model to simulate a labor market's response to permanent and transitory demand shocks. In the short run, net migration responds more to permanent shocks and current wages and employment rates respond more to transitory ones.

1 Introduction

National-level measures of economic performance such as aggregate wages and unemployment rates mask much geographic variation. This is not a static phenomenon, with some states permanently doing better and others lagging. State economic fortunes converge, but with substantial short run fluctuations along the way (Barro and Sala-i-Martin, 1991; Blanchard and Katz, 1992). Similarly, a glance at national-level population data gives no hint of the demographic churning that goes on each year as the result of human migration (Greenwood, 1985). These two features of the United States and other national economies are linked in ways that economists have been studying for decades. Two questions appear repeatedly: How sensitive is migration to regional differences in labor market conditions? What role does migration play in eliminating these differences?

Most empirical studies of net migration are based on variations of a simple theoretical model in which net migration to an area depends on the current and expected future value of living there. That is, migration is treated like an investment. Though this has been recognized since Sjaastad (1962), the investment nature of migration has been largely ignored in empirical studies of net migration. To estimate the model, most authors have used state or Census division data to regress net migration on labor market variables such as wages and unemployment (Greenwood et al., 1991; Pissarides and McMaster, 1990). Some authors also include non-market variables such as climate and other amenities (Barro and Sala-i-Martin, 1991). These and other authors acknowledge that as an investment, the migration decision is forward looking. They do not, however, explicitly account for this in their empirical work.[1] In this paper I show that because they ignore this aspect of the theory, existing empirical studies of net migration do not properly identify the underlying parameters of the theoretical model. I propose and implement an alternative empirical strategy to solve this problem.

What is gained by identifying the parameters of the migration model? The theory predicts that migration will respond differently to shocks that differ in their persistence and predictability. These responses will affect local labor markets through labor supply. We should therefore also expect that labor market variables such as wages and employment respond differently to permanent and transitory shocks. Indeed, Topel (1986) found evidence for these types of effects. But we need estimates of all the underlying parameters of the migration model to examine how migration and labor market variables respond to different kinds of shocks. Thus to get the labor market right we need to get migration right.

The rest of this paper is organized as follows. In Section (2) I present a simple model of net migration that is essentially identical to those in Barro and Sala-i-Martin (1995) and Greenwood et al. (1991). I show why previous empirical models such as Greenwood et al. (1991), Barro and Sala-i-Martin (1991), and Pissarides and McMaster (1990) do not separately identify the underlying parameters of the theoretical model. The identification problem can be thought of as an omitted variable bias because a relevant variable, the

[1] In a separate, but related, strand of research, Bartik (1991), Blanchard and Katz (1992), and Eberts and Stone (1992) focus on understanding the joint behavior of local labor market variables such as wages, unemployment rates, and labor force participation rates. They do not study migration directly, but infer its behavior from the level of employment and rates of unemployment and labor force participation.

expected future value of living in an area, is omitted from the estimation. My alternative empirical strategy flows directly from the theory. If migration depends on the value of living in an area, next period's migration depends on next period's value. Thus, the one-year-ahead net migration rate is a measure of the future value. This strategy has been used to examine investment in housing (Topel and Rosen, 1988) and education (Ryoo and Rosen, 1997).

In Section (3) I discuss the data and econometric issues involved in estimating the models. I use state-level data from 1976 to 1996, including measures of state labor demand shifts as instruments, to estimate empirical models of net migration. I use state wages and unemployment rates to measure local labor market conditions. To provide a basis for comparison, I estimated models similar to those found in the literature. My estimates of these unidentified models are similar to existing work. They are quite different, however, from my new, identified, estimates of the migration model. For example, in a model without unemployment, the effect of current wages is more than halved when I control for future conditions. In a model with unemployment, the effect of current wages is larger and the effect of current unemployment is smaller when I control for future conditions.

To illustrate why we need to identify the parameters, I integrate the migration model into a simple labor supply and demand framework in Section (4). The full model is similar to capital accumulation models with adjustment costs (Abel, 1981). Here, the population stock replaces the capital stock and the employment rate replaces the capital utilization rate. The population and employment rate provide the two margins along which a labor market can adjust, and the type of shocks determines the type of adjustment. I use my estimates of the migration parameters to simulate how net migration, wages, and employment rates respond to permanent and transitory shocks. In the short run, net migration responds more to permanent shocks and current wages and employment rates respond more to transitory ones. Of particular interest is that high current wages and low current migration are consistent if a shock is expected to be transitory. Though the theory predicts this, existing empirical studies of net migration do not allow for such a response. I conclude in Section (5).

2 Empirical Models of Net Migration

I start with a simple model in which the net migration rate into a state is proportional to the value of living there relative to outside alternatives. I use states as my unit of observation because of data availability.[2] Let the net migration rate be the ratio of net migration to the base population and s and t index state and time. Then

$$m_{st} = \gamma E_t(\tilde{V}_{st} - \tilde{\mu}_t), \tag{1}$$

where m_{st} is the net migration rate and $\tilde{V}_{st}$ is the value of living in state s at time t. The value of outside alternatives is given by $\tilde{\mu}_t$ and γ is what I call the migration response.[3]

[2] See Hojvat-Gallin (1998) for a description of metropolitan area data and results.

[3] Both theory and empirical work suggest that the migration decision varies by age, education, and other demographic groups (Greenwood, 1985; Topel, 1986; Bound and Holtzer, 1996). I ignore these complications here.

I assume that $\tilde{V}_{st}$ can be written as

$$\tilde{V}_{st} = \sum_{j=0}^{\infty} \beta^j (v_{s,t+j} + \tilde{\phi}_s + \tilde{\eta}_{s,t+j}), \tag{2}$$

where v_{st} is most often a measure of local labor market conditions, β is a discount factor, $\tilde{\phi}_s$ is a state effect that captures the role played by fixed amenities, and $\tilde{\eta}_{st}$ measures other omitted state specific factors, such as tax rates, that can change over time.[4] Most researchers include in v_{st} a measure of real wages or income. Others also include unemployment and housing prices. Still others include explicit measures of a region's amenities (Barro and Sala-i-Martin, 1991 and 1995). High wages, low unemployment, and low housing prices should encourage in migration.[5] Later, I will use wages and the unemployment rate to measure labor market conditions.

My primary goal is to estimate the underlying parameter's of the model, γ and β. Most researchers have considered the following empirical model:

$$m_{st} = a(L)v_{st} + \phi_s + \mu_t + \eta_{st}, \tag{3}$$

where $a(L)$ is a polynomial in the lag operator, ϕ_s captures state effects, μ_t captures year effects, and η_{st} is an error term. This says that net migration depends on current and lagged measures of local labor market and non-market conditions.

[4]This formulation includes the value of future migration if all states maintain non-zero population. This is because the marginal mover is indifferent between staying and moving in any period. Therefore we can just look at the wage stream that accrues to stayers. This simple form also avoids complications that arise from more involved models that include savings or finite lifetimes.

[5]Falling housing prices could inhibit out-migration of home owners.

Estimation issues aside, what do the parameters measure? How are the coefficients in $a(L)$ related to γ and β? To answer this, we must return to the underlying theoretical model. Suppose expected future labor market conditions can be predicted from past values:

$$E_t v_{s,t+j} = c_j(L) v_{st}. \tag{4}$$

Equations 1, 2, and 4 can be combined to yield

$$\begin{aligned} m_{st} &= \gamma[(\sum_{j=0}^{\infty}(\beta^j c_j(L) v_{st} + \tilde{\phi}_s + E_t \tilde{\eta}_{s,t+j}) - \tilde{\mu}_t] \qquad (5) \\ &= \gamma d(L) v_{st} + \frac{\gamma \tilde{\phi}_s}{1-\beta} + \gamma \sum_{j=0}^{\infty} \beta^j E_t \tilde{\eta}_{s,t+j} - \gamma \tilde{\mu}_t, \end{aligned}$$

where

$$d(L) = \sum_{j=0}^{\infty} \beta^j c_j(L).$$

Each coefficient in $d(L)$ is a combination of the coefficients in the $c_j(L)s$ and β. So even if I know the order of $d(L)$, and choose $a(L)$ so that their orders match, the coefficients in $a(L)$ do not measure γ and β. They instead measure combinations of γ, β, and the $c_j(L)s$. Of course, if the orders of $a(L)$ and $d(L)$ differ, the identification problem is worse.

Consider the following simple example. Suppose a region's real wage, given by w_{st}, is a sufficient statistic for local labor market conditions and that it follows an AR(1) with parameter ρ. Then the j-step-ahead forecast of $v_{s,t+j} = w_{s,t+j}$ is

$$E_t w_{s,t+j} = \rho^j w_{st}. \tag{6}$$

This can be substituted into Equations 1 and 2, the migration model, to get current migration in terms of the current wage:

$$m_{st} = \frac{\gamma}{1-\beta\rho} w_{st} + \frac{\gamma\tilde{\phi}_s}{1-\beta} + \gamma \sum_{j=0}^{\infty} \beta^j E_t \tilde{\eta}_{s,t+j} - \gamma\tilde{\mu}_t. \tag{7}$$

Equation 7 makes it clear that the coefficient on current wages does not provide an estimate of γ or β. Rather, it provides a particular combination of γ, β, and ρ. If one is willing to take a stand on how expectations are formed, the $c_j(L)s$ from Equation 4, and the value of β, one could in principle solve for γ.

As an alternative, I can take advantage of the recursive structure of Equation 2. The value of living in a state can be rewritten as

$$\tilde{V}_{st} = v_{st} + \tilde{\phi}_s + \tilde{\eta}_{st} + \beta\tilde{V}_{s,t+1}. \tag{8}$$

This can be substituted into Equation 1 to yield

$$m_{st} = \gamma v_{st} + \beta E_t m_{s,t+1} + \gamma\tilde{\phi}_s + \gamma(\beta\tilde{\mu}_{t+1} - \tilde{\mu}_t) + \gamma\tilde{\eta}_{st}. \tag{9}$$

This suggests that I estimate

$$m_{st} = \gamma v_{st} + \beta E_t m_{s,t+1} + \phi_s + \mu_t + \eta_{st}. \tag{10}$$

To proxy for the expected future net migration rate, I use the fact that

$$\epsilon_{s,t+1} \equiv m_{s,t+1} - E_t m_{s,t+1} \tag{11}$$

defines the one-step-ahead forecast error and assume that people form their expectations rationally. This implies that $\epsilon_{s,t+1}$ is orthogonal to all time t information.

Substituting Equation 11 into 10 yields

$$
\begin{aligned}
m_{st} &= \gamma v_{st} + \beta m_{s,t+1} + \phi_s + \mu_t + \nu_{st} \\
\nu_{st} &= \eta_{st} - \beta \epsilon_{s,t+1}.
\end{aligned} \tag{12}
$$

Thus the net migration rate depends on a state's current labor market conditions, current amenities, and tomorrow's expected net migration, which measures the expected value of living there tomorrow.

Equation 12 helps illustrate the nature of the identification problem in previous studies. If only v_{st} is included, as in Greenwood et al. (1991), then the problem can be thought of as an omitted variable bias. Equation 12 shows that future migration should be included to control for expected future labor market conditions. If it is left out, then the coefficient on v_{st} does not capture just the effect of current conditions. To the extent that current conditions tell us something about future conditions, the coefficient also picks up the effect of expected future conditions on current migration.[6] By estimating Equation 12, we can avoid this identification problem and separately identify the underlying parameters. In the next section I discuss how I estimated Equation 12. In the following section, I show why we need the estimates to examine how migration and labor market variables, such as the wage rate, respond to different kinds of shocks.

[6] If lags of v_{st} are included but future migration is excluded, as in Pissarides and McMaster (1990), then the model is still misspecified and can still be thought of as having an omitted variable bias problem. The coefficient on current conditions will still pick up both the effect of current conditions and the part of future conditions that is correlated with current conditions once we have accounted for the effect of the lags.

3 Data and Estimation

To compare the identified model to those that have been estimated in the past, I estimated the following two empirical models:

$$m_{st} = av_{st} + \quad bm_{s,t+1} + \quad \phi_s + \mu_t + \nu_{st} \tag{13}$$

$$m_{st} = av_{st} + \qquad\qquad \phi_s + \mu_t + \nu_{st} \tag{14}$$

using state data from 1976 to 1996.[7] Note that Equation 14 does not include $m_{s,t+1}$. This provides a comparison to the models that have been estimated in the past and helps highlight the identification problem I mentioned above. I used wages and the unemployment rate to capture state labor market conditions. The March CPS provides data on income, weeks worked, and state of residence for each person in the sample. From these data I calculated each person's log weekly wage. I used the CPI-U series from the Bureau of Labor Statistics (BLS) for the four Census regions of the U.S. This provides a rough correction for state changes in the price level. The BLS reports the civilian unemployment rate for each state.[8] See the Data Appendix for details.

Why should migrants care about unemployment? In a simple labor market clearing model, there is no unemployment at all and the wage is a suffi-

[7] The March CPS does not separately identify each state prior to 1976.

[8] The average wage or unemployment rate in a state may not provide a measure of labor market conditions that are relevant to the average migrant. For instance, shifts in the composition of a state's workforce may affect the average wage even if the wage that is relevant to the average migrant does not change. In Hojvat-Gallin (1998) I constructed alternative measures of wages and the unemployment rate. For instance, I corrected for states' demographic composition. I also allowed wages in "close" states, defined in terms of long-run gross migration, to matter more than those in "far" states. The results are not sensitive to these alternative wage measures.

cient statistic for labor market opportunities. But some studies have found that unemployment plays a role in determining migration even after the effect of wages has been taken into account (Pissarides and McMaster, 1990; Gabriel et al., 1993). There are several possible explanations for this. First, if wages are measured with error, unemployment can help predict migration because it in effect gives us another "observation" of wages. Second, unemployment can play a role in non-market-clearing models. Third, unemployment can signal the probability of finding employment in a search model.[9] Finally, perhaps wages are a sufficient statistic, but unemployment has a statistically significant effect in linear models because of non-linearities in the theoretical relationship.

Since I am interested in the links between labor market conditions and migration, I used net migration rates for people aged 16 to 64; people in this age range will have stronger labor force attachments.[10] I constructed the rates from data on population by age, death rates, and foreign immigration rates. See the Data Appendix for details.

Equation 13 and 14 suffer from a typical endogeneity bias; the right-hand-side variables are correlated with the error term. In addition, when $m_{s,t+1}$ is included in Equation 13, the error term $\nu_{st} = \eta_{st} - \beta\epsilon_{s,t+1}$ will usually be serially correlated even if η_{st} is not because innovations to migration at time t are part of the forecast error of expectations that were formed the period

[9] Labor turnover may be a better measure (Fields, 1979).

[10] This age range may still contain many people with weak ties to the labor force. For example, students and retirees may not respond to state differences in wages in the same way as the average worker. In Hojvat-Gallin (1998) I found that restricting the sample to those aged 24 to 55 did not significantly change the results.

before (Topel and Rosen, 1988; Cumby et al., 1983; Hansen, 1982). To deal with these problems, I estimated the models using GMM with a set of state labor market demand shifters as instruments.

The instruments take advantage of differences across states in industrial composition. They are based on the idea that if national employment in an industry is growing fast, then states in which the industry makes up a large share of total employment should have fast employment growth. I argue that this captures a labor demand shift that is correlated with state-level wages and unemployment rates but uncorrelated with shocks to migration.

I constructed the instruments using a technique similar to Davis et al. (1997). I allowed national level industry employment growth to be driven by two sources: changes in the real price of oil and "everything else," and constructed instruments based on each of these sources of variation. For each of ten industries i, I estimated

$$GE_{it} = \beta_i + \theta_{i0}\,OILPR_t + \theta_{i1}\,OILPR_{t-1} + \zeta_{it} \quad i = 1..10,$$

where GE_{it} is the employment growth rate in industry i from the BLS Employment and Earnings program and $OILPR_t$ is the growth rate of the PPI for crude oil relative to the PPI for all finished products. The industries are Mining, Government, Construction, Primary Metals, Services, Motor Vehicles, Finance, Insurance, and Real Estate, Other Manufacturing, Trade, and Transportation, Communications, and Public Utilities.

Then, to construct my instruments, I weighted each industry's response by its employment share for each state, Λ_{ist}. That is,

$$Oil_{st} \;=\; -\sum_i (\hat{\theta}_{i0}\,OILPR_t + \hat{\theta}_{i1}\,OILPR_{t-1})\Lambda_{ist}$$

$$Growth_{st} = \sum_i \zeta_{it}\Lambda_{ist}.$$

I calculated the shares using a linear interpolation between decennial census years to eliminate cyclical changes in employment shares while retaining their trends. Before using them for estimation, I also deviated the instruments from their state and year means.

Though I expect that *Oil* and *Growth* measure labor demand shifts, they may not. To examine this issue, I ran state-level OLS regressions of the endogenous variables on six lags of *Oil* and four lags of *Growth*. Table 1 contains the results. The reported numbers are the sums of the coefficients on each lag and therefore measure each instrument's cumulative effect (Davis et al., 1997). I also scaled the variables by their standard deviations from Table 2 to help compare magnitudes . The main point to take from the table is that the regressions support the idea that the instruments measure state labor demand shifts. Wages and migration move in the same direction, and opposite unemployment, in response to changes in the instruments. This is just as we would expect if the instruments measured demand shifts.[11]

Estimates of the parameters of the migration model, the main results of the paper, are in presented Table 3. I estimated the equations using iterated GMM (ITGMM) using six lags of *Oil* and four lags of *Growth*. The models include state and year effects. Columns 1 and 2 contain estimates of models in which labor market conditions are measured by each state's average log real wage. Columns 3 and 4 include unemployment. Columns 2 and 4 include

[11] An oil price shock will have different effects in different states. Even the direction of the effect can differ. For example suppose the price of oil increased. Relative wages would rise in "oil states" like Texas and fall in states like Michigan.

Table 1: First Stage Regressions:1976-1996

Cumulative Effect (Five Lags)	Relative Wage	Unemployment Rate	Net Migration Rate	Expected Net Migration Rate
Oil	$-.674^{**}$	$.263^{**}$	$-.472^{**}$	$-.176^{**}$
	(.057)	(.042)	(.055)	(.057)
Growth	$.096^{**}$	$-.172^{**}$	$.143^{**}$	$-.009$
	(.053)	(.039)	(.051)	(.053)
R^2	.885	.726	.575	.535
Partial R^2	.126	.078	.143	.064

Notes: The model is $y_{st} = \sum_{k=1}^{6} \delta_i^1 Oil_{s,t-k} + \sum_{k=1}^{4} \delta_i^2 Growth_{s,t-k} + v_{st}$,with state and year effects. Standard errors are in parentheses. The reported numbers are $\sum_{i=1}^{6} \delta_i^1$ and $\sum_{i=1}^{4} \delta_i^2$. *Oil* and *Growth* measure regional labor demand shifts. See the text for a complete description of the variables. ** - Significant at .05. Partial R^2 is defined net of state and year effects.

Table 2: Within State Standard Deviations

			Instruments	
Log Wage	Unemployment Rate	Net Migration Rate	*Oil* ($\times 10^3$)	*Growth* ($\times 10^3$)
0.034	1.665	.009	2.039	2.290

See text for variable definitions. Estimates are for the 50 states and DC from 1976 to 1995.

a term for future labor market conditions.

The basic predictions of the theoretical model are confirmed by the empirical work: higher wages and lower unemployment rates are generally associated with greater net migration. A second prediction of the model, that expected future wages should be positively related to current net migration, is also borne out. The estimate for β, the coefficient on future net migration, is .946 when the unemployment rate is excluded (Column 2) and .541 when the unemployment rate is included (Column 4).

The lower panel of Table 3 contains information regarding the over-identifying restrictions. Prob is the probability that a random draw from a χ^2 distribution with DF degrees of freedom will be greater than NT times the value of the objective. The over-identifying restrictions are not rejected in any of the models.

A comparison of Column 1 to Column 2 and Column 3 to Column 4 shows that the exclusion of an explicit measure of expected future labor conditions can significantly affect the coefficients on current labor market variables.

Table 3: Net Migration Regressions: 1976-1996

	1	2	3	4
Log Wage	.171**	.065**	.005	.033
	(.054)	(.024)	(.032)	(.026)
Unemployment Rate	—	—	−.008**	−.004**
			(.001)	(.002)
Expected Migration	—	.946**	—	.541**
		(.136)		(.226)
$NT \cdot$ Objective	8.611	11.376	10.492	12.379
DF	9	8	8	7
Prob	.474	.181	.232	.089

Notes: $N = 51$ and $T = 20$. All models include state and year effects. I used six lags of *Oil* and four lags of *Growth* as instruments. Prob is the probability that a random draw from a χ^2 distribution with DF degrees of freedom is larger than $NT \cdot$ Objective. ** - Significant at .05. Asymptotic standard errors are in parentheses.

Consider Columns 1 and 2. Column 1 is exactly the model estimated (with different data) by Greenwood et al. (1991). My estimate of .171 for the coefficient on log wages is within one standard error of their estimate of .215. A common way to interpret this result is to say that a one percent increase in a state's wage induces a .171 percentage point increase in the net migration rate. Alternatively, one can use the data in Table 2 to show that a one standard deviation increase in a state's log wage is associated with about a .7 standard deviation increase in net migration. But the results from Column 2 suggest that this is an upward biased estimate of γ, the migration response. Column 2 says that the response of net migration to current log wages is less than half as large as one might think from looking at Column 1. In the following section I show what the parameter magnitudes imply about how much migration responds to shocks.

Next, consider Columns 3 and 4. These columns include unemployment and are similar to the models estimated by Eichengreen (1992) and Pissarides and McMaster (1990).[12] In Column 3 it appears that low unemployment increases net migration but that high wages do not have any statistically significant effect. When future labor market conditions are held constant in Column 4, the effect of unemployment is halved. The coefficient on the log wage increases by six times but is still not statistically significantly different from zero. As above, a common interpretation of Column 3 is that a one percentage point increase in a state's unemployment rate is associated with a .008 percentage point decrease in the state's net migration rate. Alterna-

[12] I cannot make a direct comparison of the models because Eichengreen and Pissarides and McMaster include lagged net migration.

tively, a one standard deviation increase in a state's unemployment rate is associated with a 1.4 standard deviation decrease in the state's net migration rate. But the results from Column 4 suggest that the effect is half as large as Column 3 might lead one to believe.

There are two striking features of the results in Columns 3 and 4. First, wages do not seem to matter. Second, the estimate of .541 for the discount factor is much lower than the estimate of .946 from Column 2. It has proven difficult in the past to estimate the discount factor. Fleischman (1996) provides evidence that GMM estimation of β in models such as those in Columns 2 and 4 may be biased down in finite samples. Thus many authors simply restrict β to be close to .95 (Topel and Rosen, 1988). I do the same, and reestimate the identified models, Columns 2 and 4, with restrictions on β.

Table 4 displays GMM estimates of the identified models when β is restricted to be .98 and .90. I used the weighting matrix from the final iteration of ITGMM estimation of the unrestricted versions. The lower panel of Table 4 provides information to test the validity of the restrictions. Since I used the same weighting matrix to estimate both the restricted and unrestricted models and I imposed one restriction,

$$NT \cdot \text{Objective(restricted)} - NT \cdot \text{Objective(unrestricted)} \sim \chi^2(1). \quad (15)$$

In this table, Prob is the probability that a random draw from a χ^2 distribution with one degree of freedom will be greater than the test statistic formed by the difference of NT time the objective (Cochrane, 1996). Neither restriction is rejected at a .05 significance level.

Since the unrestricted estimates of β in the wage only model was .946, it is not surprising that the coefficient on the log wage does not change much

Table 4: Restricted Net Migration Regressions: 1976-1996

	$\beta = .98$		$\beta = .90$	
	1	2	3	4
Log Wage	.064**	.051**	.068**	.048**
	(.023)	(.024)	(.023)	(.024)
Unemployment Rate	—	$-.001$	—	$-.0015$
		(.001)		(.001)
$NT \cdot$ Objective	11.440	16.143	11.491	14.896
Prob	.801	.052	.735	.113

Notes: $N = 51$ and $T = 20$. All models include state and year effects. I used six lags of *Oil* and four lags of *Growth* as instruments Prob is the probability that a random draw from a χ^2 distribution with one degree of freedom is larger than NT(Objective(restricted) $-$ Objective(unrestricted)). ** - Significant at .05. Asymptotic standard errors are in parentheses.

in the restricted models. The estimates of Columns 1 and 3 are quite close to the unrestricted estimate of .065 from Column 2 of Table 3.

The restricted estimates of the model that includes unemployment are quite different from the unrestricted estimates. Columns 2 and 4 of Table 4 suggest that wages are statistically significantly related to migration but that unemployment is not. This is exactly the opposite conclusion one would reach from Table 3. The results suggest that though the unemployment rate may be useful in practice for predicting migration, once future migration is explicitly included in a restricted model, the unemployment rate does not add explanatory power to wages. This suggests that the model in Column 2 of Table 3, the specification without unemployment, is preferable.

Other authors have found weak or contradictory evidence for the relationship between unemployment and migration. Fields (1979) noted that many studies have found that unemployment has a statistically insignificant effect on migration. Some early studies found that high unemployment attracts workers (Greenwood, 1969). Later studies, such as Pissarides and McMaster (1990) found that unemployment has a negative and statistically significant effect on net migration after controlling for the wage. Gabriel et al. (1993) found that high unemployment in the state of origin induces out-migration but that high unemployment in the destination state does not inhibit in-migration.

The above results show that by ignoring the role of expected future labor market conditions, previous studies have suffered from an omitted variable bias that can significantly affect parameter estimates. The main point here, then, is not the relative importance of wages or the unemployment rate in explaining migration. Rather, it is that estimates of these effects that ignore the role of expectations can be misleading.

4 Net Migration and State Labor Market Dynamics

Until now, I have discussed the coefficients as they are typically discussed in the literature: how much is migration affected by changes in a state's log wage or unemployment rate? But this type of partial equilibrium statement can be misleading because migration and labor market conditions are jointly determined in equilibrium. Instead, we should examine how migration and market conditions adjust together in response to various types of state labor market shocks. To do this we need a model of a state labor market and, as I show, estimates of the underlying parameters of the migration model.

I model aggregate state labor supply as being determined by the stock of potential workers in a state (the population) and the intensity with which they work (the employment rate). Let n_{st} be log aggregate labor supply, p_{st} be log population, and h_{st} be the log employment rate in state s at time t. Then

$$n_{st} = h_{st} + p_{st}. \tag{16}$$

The log employment rate, h_{st}, is determined by the labor supply decisions of state s residents. I assume that individual labor supply is log linear in wages. That is,

$$h_{st} = \psi_0 + \psi_1 w_{st} + \varphi_{st}, \tag{17}$$

where φ_{st} is a supply shifter. Thus in the short run, defined as the time frame in which p_{st} is fixed, aggregate labor supply can adjust only through changes in individual supply and the short run elasticity of labor supply is equal to the elasticity of individual labor supply.[13]

I ignore capital and write state labor demand as

$$w_{st} = \tilde{\alpha}_0 - \tilde{\alpha}_1 n_{st} + \tilde{\theta}_{st}, \tag{18}$$

where $\tilde{\theta}_{st}$ is a demand shifter.[14]

Equations 16, 17, and 18 can be solved for h_{st}, w_{st}, and n_{st} in terms of p_{st}, θ_{st}, and φ_{st}:

$$\begin{aligned} w_{st} &= \alpha_0 - \alpha_1 p_{st} + \theta_{st} - \alpha_1 \varphi_{st} && (19) \\ h_{st} &= \psi_0 + \psi_1 \alpha_0 - \alpha_1 \psi_1 p_{st} + \psi_1 \theta_{st} + (1 - \alpha_1 \psi_1)\varphi_{st} && (20) \\ n_{st} &= \psi_0 + \psi_1 \alpha_0 + (1 - \alpha_1 \psi_1) p_{st} + \psi_1 \theta_{st} + (1 - \alpha_1 \psi_1)\varphi_{st} && (21) \end{aligned}$$

where

$$\alpha_0 = \frac{\tilde{\alpha}_0 - \tilde{\alpha}_1 \psi_0}{1 + \tilde{\alpha}_1 \psi_1}, \quad \alpha_1 = \frac{\tilde{\alpha}_1}{1 + \tilde{\alpha}_1 \psi_1}, \quad \text{and} \quad \theta_{st} = \frac{\tilde{\theta}_{st}}{1 + \tilde{\alpha}_1 \psi_1}.$$

If p_{st} were fixed, Equations 19 through 21 would be the solution to a simple supply and demand model in terms of the underlying shocks. With p_{st} free to adjust, I need to describe how it is determined.

Population can change for several reasons: natural population growth, foreign migration, and internal migration. Here I ignore population growth and foreign migration to focus on the effects of internal migration. To keep

[13] I ignore whether ψ_1 is the uncompensated or compensated elasticity. The analysis can be extended to explicitly allow for the distinction.

[14] I am implicitly assuming a fixed factor to get negatively sloped demand.

the model simple, I assume that migration depends only on current and expected future wages. This is consistent with the empirical results presented above.

I approximate the growth rate in population with the difference in the logs. This, and the above assumptions, imply that state population evolves according to

$$p_{st} - p_{s,t-1} = m_{st} = \gamma[\sum_{j=o}^{\infty} \beta^j (w_{s,t+j} + \tilde{\phi}_s + \tilde{\eta}_{s,t+j}) - \tilde{\mu}_t]. \tag{22}$$

The second equality is from the migration model from Section (2).

Equation 19 gives the log wage as a function of the population stock and demand and supply shifters. Thus the above equation can be rewritten as a second order linear stochastic difference equation in p_{st}. Let

$$z_{st} = \gamma\alpha_0 + \gamma\theta_{st} - \gamma\alpha_1\varphi_{st} + \gamma\tilde{\phi}_s + \gamma\tilde{\eta}_{st} - (\tilde{\mu}_t - \beta E_t\tilde{\mu}_{t+1}) \tag{23}$$

Then

$$\beta E_t p_{s,t+1} - (1 + \beta + \gamma\alpha_1)p_{st} + p_{s,t-1} = -z_{st}. \tag{24}$$

Let λ_1 and λ_2 solve

$$1 - \frac{1 + \beta + \gamma\alpha_1}{\beta}L + \frac{1}{\beta}L^2 = (1 - \lambda_1 L)(1 - \lambda_2 L) \tag{25}$$

so that

$$\lambda_1 = \frac{2}{1 + \beta + \gamma\alpha_1 + \sqrt{(1 + \beta + \gamma\alpha_1)^2 - 4\beta}} \tag{26}$$

$$\lambda_2 = \frac{2}{1 + \beta + \gamma\alpha_1 - \sqrt{(1 + \beta + \gamma\alpha_1)^2 - 4\beta}}. \tag{27}$$

This implies that $0 < \lambda_1 \leq 1 < \lambda_2$ with strict inequality if $\gamma\alpha_1 > 0$. Then log population can be written as

$$p_{st} = \lambda_1 p_{s,t-1} + \lambda_1 \sum_{j=0}^{\infty} (\frac{1}{\lambda_2})^j E_t\{z_{s,t+j}\}. \tag{28}$$

Equation 28 shows how a state's population responds to shocks. The response is governed by the migration parameters, the elasticity of labor demand, and the elasticity of individual labor supply. The equation can be used in tandem with Equations 19, 20, and 21 to examine state migration and labor market dynamics given estimates of all the underlying parameters.[15] I can choose values for the elasticities of supply and demand from the literatures on these subjects. I cannot do the same for the migration parameters because existing studies do not identify them.

Instead, I can use the migration parameters estimated above from the identified model. In particular, the values from Column 2 of Table 3 provide estimates of γ and β. Hamermesh (1986) surveyed empirical estimates of the elasticity of the demand for labor. Estimates of the own-price elasticity of labor demand are in the range of $-.15$ to $-.75$. This translates into values of $\tilde{\alpha}_1$, the inverse of the elasticity, in the range of 1.33 to 6.67.[16] Pencavel (1986) and Killingsworth and Heckman (1986) surveyed the literature on the elasticity of male and female labor supply. Estimates of the uncompensated elasticity are usually small. Juhn, Murphy, and Topel (1992) concluded that .1 is a reasonable estimate. The uncompensated elasticity for females may

[15] The value of outside alternatives, $\tilde{\mu}_t$, depends on the values of φ_{st}, θ_{st}, η_{st}, and ϕ_{st} for all states. I assume that each state is small enough relative to the nation so that I do not need to solve explicitly for $\tilde{\mu}_t$.

[16] State labor demand may be more elastic because of capital flows.

be quite a bit higher, though some studies show that it is similar to that for males (Killingsworth and Heckman, 1986). Estimates of the compensated elasticity are higher. I choose a value of $\psi_1 = .25$. To summarize, I use the following set of parameters:

$$\begin{aligned} \tilde{\alpha}_1 &= 2 & \psi_1 &= .25 \\ \gamma &= .065 & \beta &= .946. \end{aligned} \tag{29}$$

In Figure 1, I display a simulation of the response of a state labor market to an unexpected permanent demand shock. I scaled the shock so that it results in a long run employment increase of one percent. I have graphed the percent change in population, wages, and the employment rate. Migration is the change in population. The demand shock drives wages up immediately. The market adjusts through an increase in the employment rate and migration. One can see that in the first period, population adjusts more than the employment rate. As more people enter the state, both the wage and employment rate fall. In the long run, all the adjustment comes from migration as wages and the employment rate return to their previous levels. Almost all of the adjustment occurs within ten years.

In Figure 2, I display a simulation of a market's response to an equal sized transitory demand shock. As before, the wage increases sharply when the shock hits. It increases by more than it does in response to a permanent shock because fewer people move in. Little migration and high current wages are consistent with each other because the transitory shock does not increase the value of moving by much. As a result, transitory shocks induce a larger increase in individual labor supply than in population, at least initially. After the shock passes, wages and employment rates fall below their previous levels

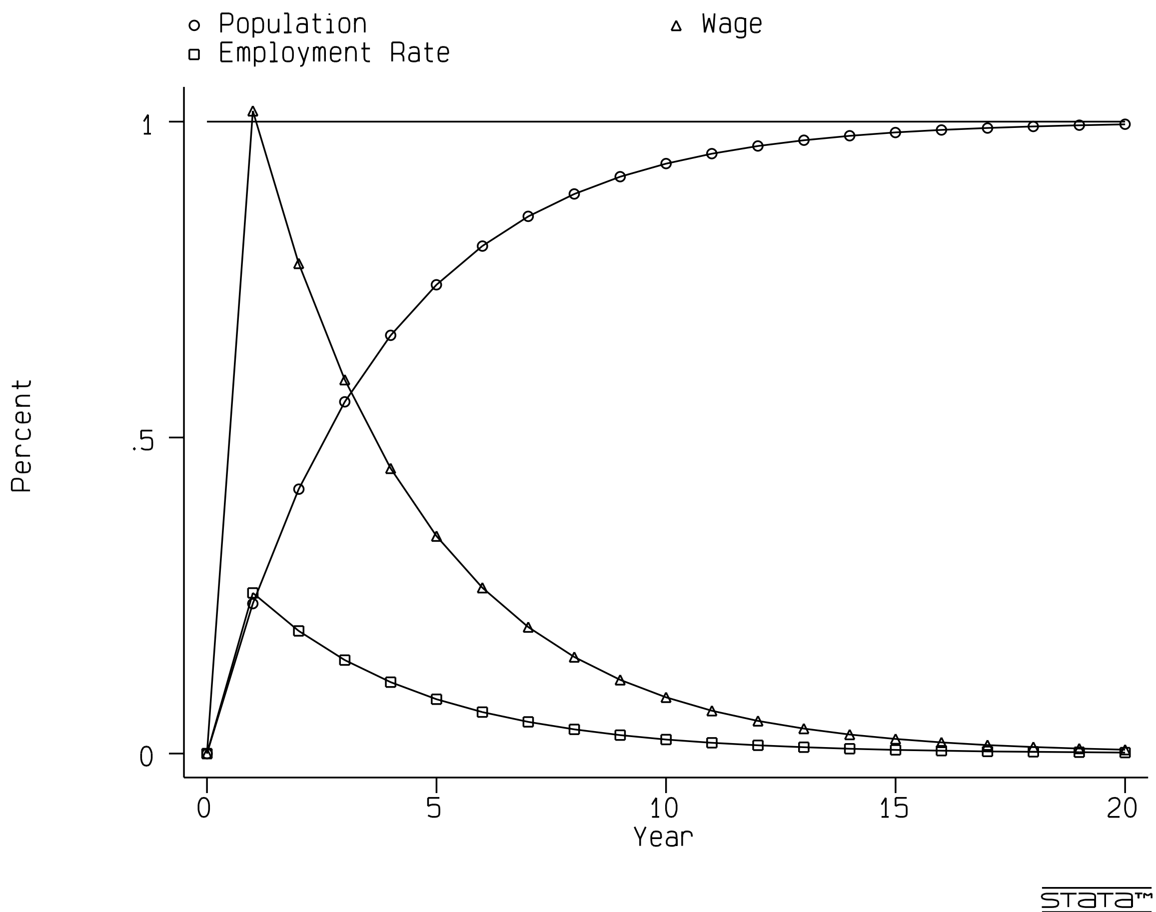

Figure 1: Response to a Permanent Demand Shock

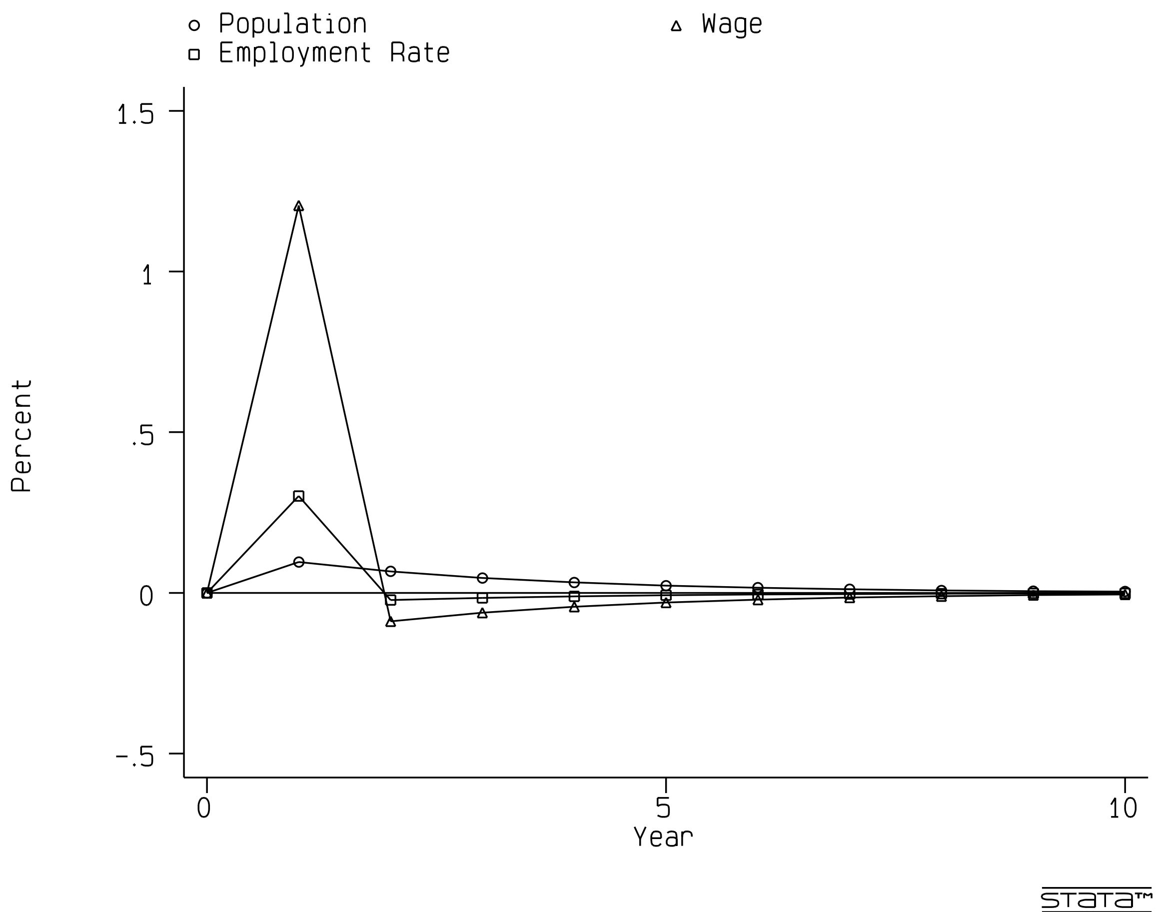

Figure 2: Response to a Transitory Demand Shock

and people begin to leave the state. Notice that although the demand shock is completely transitory, labor market effects are felt for years. The vast majority of the adjustment process occurs within five years.

These two simulations provide an excellent illustration of the identification problems associated with previous empirical studies of net migration. Aggregate labor supply can adjust along two margins, population and the employment rate. This is analogous to adjustment cost models of capital accumulation with variable capital utilization rates (Abel, 1981). The population is the "capital" stock and the employment rate is the capital utilization rate. The type of shock determines the margins along which labor supply will adjust.

The figures show that adjustment occurs along both margins in both cases. But when a shock is expected to be temporary, it does not make sense for many people to engage in costly migration. This means, of course, that wages and employment rates must be higher in the short run. It is this kind of response that cannot be analyzed or understood unless the migration model is identified. The models that have been estimated in the past imply that larger increases in wages always imply larger increases in net migration. But the transitory shock is a case in which high current wages and low migration are perfectly consistent with each other.

5 Conclusions

Migration is an investment. This idea pervades theoretical studies of migration but has been largely ignored in empirical work. This lack of attention has affected the estimation and interpretation of net migration equations. In particular, existing empirical studies of net migration do not separately identify the underlying parameters of the typical theoretical model of net migration. These studies suffer from an identification problem that can be thought of as an omitted variable bias; the models do not include an explicit measure of future labor market conditions even though the theory says they should.

In this paper I addressed this problem by developing and estimating an empirical model of state-level net migration in which the underlying parameters are identified. The new, identified, estimates of the migration model show that biases in the unidentified models can be large. For example, in a model like the one in Greenwood et al. (1991), the estimated relationship between current wages and net migration is biased up by more than two and a half times when I do not control for expected future labor market conditions.

A second advantage of my approach is that it highlights the endogeneity of migration and labor market conditions. Though this is not a new point, many authors talk about how migration responds to wages or unemployment. To be consistent with the theory, we should talk about how migration and local labor market conditions jointly respond to shocks. To do this I integrated the migration model into a simple labor supply and demand framework and used my new, identified estimates of the migration model to simulate to how net migration and labor market conditions jointly respond to permanent and transitory labor demand shocks. I find that wages and employment rates rise sharply in response to transitory demand shocks because few people migrate. The effects of such shocks dissipate within five years. Wages and employment rates rise less in response to equal sized permanent demand shocks because more people migrate. Permanent shocks have permanent effects on employment and population but transitory effects on wages and employment rates that dissipate within ten to twelve years. These results indicate that we need to understand migration as an investment to understand how local labor markets operate.

Data Appendix

I constructed the wage rate series with data from the March Annual Demographic Supplement file of the Current Population Survey (CPS). The CPS is a survey of a random sample of U.S. households. The March files contain information on personal characteristics and retrospective data on labor market activity in the year preceding the survey. The wage subsample includes civilian non-agricultural workers who were between the ages of 16 and 64, reported more than 30 hours of work in a typical week, and did not report self employment income that is negative or greater than $100 (1982 dollars) in the year preceding the survey. I also excluded all those who reported fewer than $67 (1982 dollars) per week in wages and salary. I then calculated the log weekly wage for each person from wage and salary employment. I would have liked to correct the wage measure with a state price deflator. Unfortunately, the common deflators are not calculated separately for divisions and states. Instead, I used the CPI-U series from the Bureau of Labor Statistics (BLS) for the four Census regions of the U.S. This provides a rough correction for state changes in the price level.

I do not have direct data on migration by age. Instead, I used data on population, deaths, and foreign immigration to construct measures of net migration for people aged 16 to 64. Let $P_{st}(l,h)$ be the population, $D_{st}(l,h)$ be the number of deaths, $F_{st}(l,h)$ be the net number of foreign immigrants, and $M_{st}(l,h)$ be the net number of migrants between the ages of l and h in state s at time t. In this paper I let $l = 16$ and $h = 64$.

Adding up of the sources of population change implies

$$P_{st}(l,h) = P_{s,t-1}(l-1,h-1) - D_{s,t}(l-1,h-1) + F_{s,t}(l,h) + M_{s,t}(l,h). \quad (30)$$

This suggests

$$\hat{M}_{st}(l,h) = \hat{P}_{st}(l,h) - \hat{P}_{s,t-1}(l-1,h-1) + \hat{D}_{s,t}(l-1,h-1) - \hat{F}_{s,t}(l,h) \quad (31)$$

as an estimate of net migration, where the hats denote estimated values.

The population and death rate data are from the Bureau of the Census. My death rate data begins in 1982. To get estimates for years prior to that I regressed death rates on a linear time trend for each state. I used the estimates to "predict" the death rate by state for the earlier years. I implicitly assumed that death rates are constant across ages.

The immigration data are from the *Statistical Yearbooks* of the Immigration and Naturalization Service (1978, 1984, 1987, 1993,1996). I lack data on emigration and therefore cannot estimate net foreign immigration. Data for 1979 are missing. I used a linear interpolation between 1978 and 1980 to fill these values. I used the 1960-1990 Censuses to calculate the age distribution of new immigrant arrivals. I used these distributions to estimate the number of working-aged immigrants in each year.

National net migration must be zero. This implies that

$$\sum_i M_{st}(l,h) = 0 \quad \forall \;\; t, l, h. \quad (32)$$

Let

$$R_t(l,h) = \sum_i \hat{M}_{st}(l,h),$$

P_{st} be the total population in state i at time t, and

$$P_t = \sum_i P_{st}.$$

Then let

$$\tilde{M}_{st}(l,h) = \hat{M}_{st}(l,h) - \frac{P_{st}R_t(l,h)}{P_t}$$

so that condition 32 holds for $\tilde{M}_{st}(l,h)$. Then define the net migration rate for an age group by

$$m_{st}(l,h) = \frac{\tilde{M}_{st}(l,h)}{P_{s,t-1}(l-1,h-1)}.$$

The results in the paper are not sensitive to whether I subtracted $R_t(l,h)$.

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