The Dynamics of Immigration and Wages

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Abstract

The number of immigrants in the US economy has been increasing rapidly in recent decades. An extensive literature has investigated the effect of this large influx of immigrants on native workers' labor market opportunities. However, to date this literature has not reached a consensus about the consequences of immigration. In this paper, I present a new approach to the analysis of the relationship between immigration and wages based on a panel vector autoregression (VAR) analysis. I develop a flexible model of the joint dynamics of wages, foreign immigration, and internal migration, allowing for capital mobility. I then implement this model empirically using annual CPS data. The VAR analysis of a 26-year panel of US states shows that immigration does not have a significant effect on wages or internal migration. By contrast, wages do affect immigration. The estimated coefficients imply that a 10 percent increase in wages causes up to a 20 percent increase in the rate of immigrant inflow after 3 years. These estimates hide significant heterogeneity: the effect is strongest for low-skill immigrants while it is small and insignificant for high-skill immigrants.

1 Introduction

The number of immigrants in the US economy has been increasing rapidly in recent decades. Figure 1 shows the immigrant share of the adult population from 1970 to 2007. During this period, immigrant share has almost tripled, increasing from less than 6 percent in 1970 to more than 16 percent in 2007. Moreover, as shown in Figure 2, there exists substantial heterogeneity in both the level and the rate of increase of immigrant share across US states.

The large influx of immigrants raises two natural questions. First, what drives the location decisions of recent immigrants? Second, what are the consequences of the influx of new immigrants to natives and earlier immigrants? I address these questions by looking at the dynamic relation between immigration, wages, and internal migration. Using high frequency

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data, I implement a vector autoregression (VAR) analysis on a 26-year panel of US states. This methodology has several advantages in relation to the existing empirical strategies in the literature.

It is possible to divide the existing papers on the effect of immigration on natives' wages in two groups, according to their empirical strategy: 1) the factor proportions approach and 2) the spatial correlation approach. The factor proportions approach compares a nation's actual supplies of workers in particular skill groups to those it would have had in the absence of immigration. It then uses outside information on the elasticity of substitution among skill groups to compute the relative wage consequences of the supply shock. Borjas, Freeman and Katz (1997) apply this approach using two alternative classifications of skill groups. Aggregating workers into high school dropouts and graduates, they find that immigration can explain 44% of the total decline in the relative wage of high school dropouts between 1980 and 1995. However, when using a high school equivalent and college equivalent aggregation, they estimate a much smaller effect of immigration on wages (immigration would only explain 5% of the decline in the wage gap).

One important limitation of the factor proportion approach is that it relies on outside estimates of relative wage elasticities to simulate the impact of immigration on wages [Di-Nardo(1997)]. As a consequence, the validity of this approach depends on both the theoretical model and the estimated relative wage elasticities to be correct.

The spatial correlation studies, on the other hand, try to recover the effects of immigration by defining the labor market along a geographical dimension - typically metropolitan areas or states in the US. They regress economic outcomes of natives, most commonly wages, in a given locality on the relative quantity of immigrants in that locality. The coefficient on the quantity of immigrants is then interpreted as the "impact" of immigration on native wages. This strategy was first used by Grossman (1982) and since then many papers have adopted it using different time periods, definition of labor markets, and measures of native outcomes and immigrant shocks.[1] However, the results from these studies remain mixed: the sign and

[1]See, for example, Borjas, Freeman and Katz (1997), Schoeni (1997) and Altonji and Card(1991).

magnitudes of the estimated effects of immigration on native wages vary across studies.

A possible explanation for the failure of the spatial correlation literature to yield consistent results is that native workers might migrate to other localities in response to immigration, until native wages are again equalized across areas. If one of the ways that natives respond to immigration is by moving their labor or capital to other localities, the effects of immigration would be diffused throughout the whole economy and spatial correlation studies would not capture the true effect of immigration on wages or other outcomes.

This caveat with the spatial correlation literature has motivated studies that try to answer whether immigrant inflows to a particular labor market lead to offsetting mobility flows by natives. However, as with the wage-impact literature, these papers also offer mixed results, with some studies finding strong effects (Filer (1992), Frey (1995) and Borjas(2006)) while others find no connection (Kritz and Gurak (2001), Card(2001)).

Borjas (2003) argues that given internal migration, the correct way to define the labor market is in terms of the nation as a whole. Using this definition, he finds that a 10 percent increase in labor supply due to immigration reduces native wages by 3 to 4 percent. Moreover, Borjas (2006) finds that immigration is associated with lower in- and net-migration rates, higher out-migration rates, and a decline in the growth rate of the native workforce. He claims that native migration response attenuates the measured impact of immigration on wages in a local labor market by 40 to 60 percent.

On the other hand, Card (2001) finds that intercity mobility rates for natives and earlier immigrants are insensitive to immigrant inflows. Moreover, his estimates imply that an inflow rate of 10 percent for one occupation group would reduce relative wages for that occupation by a maximum of 1.5 percent (less than half the impact found by Borjas (2003)).

This paper presents a new approach to the analysis of the relationship between immigration and wages based on vector autoregression (VAR) analysis. I construct a flexible model of the joint dynamics of wages, foreign immigration, and internal migration, allowing for capital mobility. Wages are determined by current labor supply, but both foreign and internal migration are affected only by lagged wages. This restriction permits a causal interpretation of the coefficients of a VAR for wages and population flows. Given the lagged nature of migration decisions, this is my preferred restriction, but the results are robust to the choice of alternative identifying assumptions.

The VAR is estimated on a 26-year panel of annual data on immigrant inflows, wages, and internal migration for US states. The use of annual data provides several advantages over the decadal Census data that has been used for most past studies of the effects of immigration. First, I am not restricted to assuming that differences in current wages cause current migration, but can allow for more realistic lagged effects. Second, I can be flexible in the timing of these lags, rather than requiring them to occur over the 5- or 10-year windows that can be constructed in Census data. My approach allows the data to identify the timing of the effects of wages on immigration and internal migration and of labor movements on wages.

A second advantage of my VAR approach is that it incorporates the effects of immigration on wages and on internal migration into the same model, rather than treating them separately as in past research. Moreover, I do not require external estimates of key parameters, but I can estimate them all from within my data.

The results show that immigration does not have a significant effect on wages or internal migration. By contrast, wages do affect immigration. The estimated coefficients imply that a 10% increase in wages in a state causes up to a 20% increase in the rate of inflow of new immigrants to that state after 3 years. The effect is strongest for low-skill immigrants, whose rate of inflow increases by 30%. Moreover, the skill group analysis shows that an exogenous increase in the inflow of immigrants with a certain level of skill does not cause skill-specific wages to fall.

The paper proceeds as follows. Section 2 presents a theoretical model that relates wages, immigration, and native migration and which provides a framework for the empirical analysis in this paper. Section 3 presents the methodology used – panel Vector Autoregressions (VAR) – and is followed by section 4 that describes the data and the construction of the variables. Section 5 presents the results from the VAR estimation and the impulse response function analysis. Section 6 concludes.

2 A Dynamic Model of Wages, Immigration and Internal Migration

This section presents a model of the joint determination and evolution of immigration, wages, and internal migration. The theoretical framework is an extension of the model in Blanchard and Katz (1992) and will be used as a guide for the empirical analysis. This model is based on two main ideas: states produce different bundles of goods and both labor and firms are mobile across states. Production takes place under constant returns to labor and the demand for each product is downward sloping. The inverse labor demand for workers with education level i, in state j and time t is specified as

$$w_{ijt} = -dl_{ijt} + z_{ijt}, \tag{1}$$

where w_{ijt} is the wage, l_{ijt} is employment, and z_{ijt} is the labor demand shifter. The parameter d is positive, reflecting the downward sloping demand for each product. The property that the relative wage of a particular skill group depends only on the relative employed population of that group can be derived using the assumption of a CES production function.

The model assumes full employment, such that employment l_{ijt} is given at any point in time and movements in z translate into movements in w. The demand shifter z can be interpreted as capital. Movements in z are modeled as

$$z_{ij,t+1} - z_{ijt} = -aw_{ijt} + x^d_{ij} + e^d_{ij,t+1}, \tag{2}$$

where x^d_{ij} is a constant, $e^d_{ij,t+1}$ is a white noise error and a is a positive parameter. According to this specification, firms that employ a certain kind of labor will be attracted to regions where the wage of this kind of labor is lower. The parameter a captures this – everything else being equal, lower wages make a state more attractive. The term x^d_{ij} captures both the drift in the demand for individual products and the "amenities", that is, elements other than wages – such as public sector infrastructure, natural resources, local taxes, and the regulatory and labor environment – that affect firms' decisions to create or locate their business someplace. I will refer to $e^d_{ij,t+1}$ as the innovation to labor demand. The above formulation implies a short-run elasticity in the movement of capital of a and a long-run elasticity of infinity.

The labor force is composed of both natives and early immigrants, and recent immigrants (immigrants who moved to the country during the past year).[2] The dynamics of total employment is given by

$$l_{ijt+1} = l_{ijt} + n_{ijt+1} + m_{ijt+1} \tag{3}$$

where n_{ijt+1} is net internal migration, that is, the net number of natives and earlier immigrants with education level i who moved into state j from other states in the US sometime between t and t+1. Similarly, m_{ijt+1} is recent immigrant influx, which is equal to the number of immigrants with education level i who moved to state j from abroad between t-1 and t.

These movements in the labor force are modeled by two migration equations. One for natives and early immigrants (that is, internal migration):

$$n_{ijt+1} = b^n w_{ijt} + x^n_{ij} + e^n_{ij,t+1}; \tag{4}$$

and another for recent immigrants (in other words, foreign migration):

$$m_{ijt+1} = b^m w_{ijt} + x^m_{ij} + e^m_{ij,t+1}, \tag{5}$$

where x^n_{ij} and x^m_{ij} are constants, e^n_{ijt} and $e^m_{ij,t+1}$ are white noise errors, and b^n and b^m are positive parameters. Therefore, migration of both natives and immigrants of a given education level depends on three factors: the relative wage for that education level, a drift term, and a stochastic component.

[2] The division of the labor force between recent immigrants, and natives and earlier immigrants is the main departure from Blanchard and Katz (1992).

The parameters b^n and b^m capture the fact that everything else being equal, higher wages increase the in-migration of natives, and recent and earlier immigrants. The drift terms x_{ij}^n and x_{ij}^m capture amenities, those non-wage factors that affect migration. I assume amenities to be education specific – workers of different levels of education might value location characteristics differently, like local public services, for example – and to differ for recent immigrants and natives and early immigrants.[3] I will refer to the term $e_{ij,t+1}^m$ as an innovation in labor supply due to immigration. The above formulation implies short-run elasticities in the movement of labor of b^n and b^m and long-run elasticities of infinity.

Taking the first difference of the labor demand (1), and using equations (2) and (3), it is possible define the change in wages as an explicit function of labor movements

$$w_{ijt+1} = (1-a)w_{ijt} - d\left(n_{ijt+1} + m_{ijt+1}\right) + x_{ij}^d + e_{ij,t+1}^d \tag{6}$$

The system defined by equations (4), (5) and (6) can be written in matrix form as follows

$$\begin{pmatrix} 1 & -d & -d \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{pmatrix} \begin{pmatrix} w_{ijt} \\ n_{ijt} \\ m_{ijt} \end{pmatrix} = \begin{pmatrix} (1-a) & 0 & 0 \\ b^n & 0 & 0 \\ b^m & 0 & 0 \end{pmatrix} \begin{pmatrix} w_{ijt-1} \\ n_{ijt-1} \\ m_{ijt-1} \end{pmatrix} + \begin{pmatrix} x_{ij}^d \\ x_{ij}^n \\ x_{ij}^m \end{pmatrix} + \begin{pmatrix} e_{ijt}^d \\ e_{ijt}^n \\ e_{ijt}^m \end{pmatrix}$$

It is interesting to note from the above system that this simple labor demand and supply model has an autoregressive form. This form suggests the empirical specification adopted in this paper, as explained in the next section.

One important thing to notice in this model is that wages are determined by current labor supply, but both foreign and internal migration are affected only by lagged wages. Migration decisions are usually seen as costly and more lagged than other economic decisions[4]. This

[3]One amenity that might affect recent immigrants and natives and earlier immigrants differently is state legislation regarding illegal immigration. Since recent immigrants are more likely to be illegal, they might respond to differences in such legislation more. One example is how difficult it is for an illegal immigrant to have a driver's license, which varies across states.

[4]Kennan and Walker (2003) estimate that the migration costs for a typical move between US states range between US$176,000 and US$270,000, roughly 4 to 6 times the average annual household income in their sample. These high costs might lead to lagged migration decisions due to liquidity constrains, for example.

assumption will be useful in section 4, because it will help identify the system of estimated equations.

Solving the model for wages yields

$$w_{ij,t+1} = (1-\phi)w_{ijt} + \left(x_{ij}^{d} - d\left(x_{ij}^{n} + x_{ij}^{m}\right)\right) + \left(e_{ij,t+1}^{d} - d\left(e_{ij,t+1}^{n} + e_{ij,t+1}^{m}\right)\right), \tag{7}$$

where $\phi = a + d\left(b^{n} + b^{m}\right)$ is the short-run adjustment in wages due to movements in capital (a) and labor $\left(d\left(b^{n}+b^{m}\right)\right)$. In the analysis below, I will assume that $1 > \phi > 0$, which is plausible given the high persistence of wages.[5] As long as there is either labor or product mobility (a, b^{n} or b^{m} greater than zero), wages follow a stationary process around state-specific means. Thus, starting from any distribution of wages, this distribution will converge to a stationary distribution over time.

From equation (7), the average wage is given by

$$\overline{w_{ij}} = \frac{x_{ij}^{d}}{\phi} - \frac{d\left(x_{ij}^{n} + x_{ji}^{m}\right)}{\phi}. \tag{8}$$

That is, the average wage for labor type i in state j is higher the more attractive this state is to firms that employ labor i and the less attractive the state is to workers (both recent immigrants, and natives and early immigrants) type i.

Solving the model for native migration, yields[6]

$$n_{ij,t+1} = \left(\begin{array}{c} (1-\phi)n_{ijt} + \left(b^{n}x_{ij}^{d} - b^{n}dx_{ji}^{m} + (db^{m}+a)x_{ji}^{n}\right) \\ -b^{n}(de_{ij,t}^{m} - e_{ij,t}^{d}) + e_{ijt+1}^{n} + \left(db^{m}+a-1\right)e_{ijt}^{n} \end{array}\right), \tag{9}$$

so that the average trend in native migration is given by

$$\overline{n_{ij}} = \frac{b^{n}}{\phi}x_{ij}^{d} + \frac{(db^{m}+a)}{\phi}x_{ji}^{n} - \frac{b^{n}d}{\phi}x_{ji}^{m}. \tag{10}$$

Similarly, for recent immigrant influx

[5] In section 5, I show evidence that the series for wages is fairly persistent but does not have a unit root.

[6] For simplicity, from now on I will refer to n_{ijt} as native (or internal) migration even though it includes the location decision of both natives and early immigrants.

$$m_{ij,t+1} = \left(\begin{array}{c} (1-\phi)m_{ij,t} + \left(b^m x_{ij}^d - b^m d x_{ij}^n + (db^n + a)x_{ij}^m\right) \\ -b^m(de_{ij,t}^n - e_{ij,t}^d) + e_{ijt+1}^m + (db^n + a - 1)\, e_{ijt}^m \end{array} \right), \tag{11}$$

so that the trend in recent immigrant influx is given by

$$\overline{m_{ij}} = \frac{b^m}{\phi} x_{ij}^d + \frac{(db^n + a)}{\phi} x_{ij}^m - \frac{b^m d}{\phi} x_{ij}^n. \tag{12}$$

Note that the equations for internal and foreign migration are similar, differing only with respect to the elasticities b^n and b^m, and the errors e^n and e^m (which is expected given the symmetry in the model). The trend in native net in-migration is higher the more attractive the state is to firms (because, everything else constant, the more attractive a state is to firms, the higher the wage level), the more attractive the state is to native and early immigrant workers, and the less attractive the state is to recent immigrants (since they mean competition in the labor market). An equivalent claim can be made with respect to the trend in immigrant influx.

In contrast to the stationary process of wages, the native and immigrant employment grows or declines at an average rate determined by the labor demand and labor supply drifts. That is, the average net-migration rates are different from zero even in the steady state. In states attractive to workers, states where x_{ij}^n and x_{ij}^m are positive, the steady flow of workers (both natives and immigrants) leads to a lower wage, which in turn triggers a steady flow of new jobs and sustains growth. In states attractive to firms, states where x_{ij}^d is positive, the steady flow of firms leads to a higher wage, which in turn triggers an inflow of native and immigrant workers and sustains growth. So, different than for wages, innovations to both labor demand and labor supply (either through immigrant or native shock) permanently affect the level of employment.

The result that wages follow a stationary process while employment grows or declines over time is an intended feature of the Blanchard and Katz (1992) model to mimic the stylized facts observed in the US economy. These facts include a steady convergence of relative wages [Barro and Sala-i-Martin (1991)] and a persistent range of different employment growth rates across states [Blanchard and Katz (1992)].

The theoretical model laid down in this section suggests that immigration, wages, and internal migration are jointly determined variables that interact dynamically. In this case, the use of a panel Vector Autoregression (panel VAR) methodology is appropriate since it explicitly models each variable as a function of all the variables in the system and allows for feedback effects between them. Section 5 presents the estimation of the panel VAR and performs an impulse-response analysis. In the next two subsections, I show what the theoretical model predicts for such impulse-response analysis. More specifically, I derive equations for changes in the variables in the model over time in face of 1) a positive labor supply shock due to recent immigrant inflow and 2) a positive labor demand shock.

2.1 Effect of a labor supply shock due to immigration on recent immigrant inflow, internal migration, and wages

One of the questions this paper addresses is what happens to wages and native migration over time when a region receives a labor supply shock due to immigration. Here, I examine the effects of an innovation in labor supply due to immigration on all the variables in the model. Denote by a hat ($\widehat{\ }$) the deviation of a variable from its base (no-shock) path.[7]

From equation (7) above, the effect of an innovation of +1 in period 0 in e^m_{ij} on wages at time t is given by:

$$\widehat{w}_{ijt} = -d(1-\phi)^t. \tag{13}$$

So, a positive innovation in labor supply due to immigration immediately (at time 0) decreases wages. The size of the initial effect of immigration on wages will depend on the slope of the demand curve, d. Over time, wages return to normal as net out-migration of workers and job creation reestablish the initial equilibrium. The speed at which wages return to normal is an increasing function of short run elasticities a, b^n and b^m (remember, ϕ is a

[7]For simplicity, I assume that total foreign immigration to the country at time t is given, so that the effect of immigration will depend on whether the region j received a larger or smaller fraction of the total immigrant increase. This explains why the long run effect of a shock to immigration on deviation wages is zero.

function of these elasticities). For the reasons explained above, the effect of an innovation in labor supply on wages is transitory: as time goes to infinity, the distribution of wages converges to its no shock path.

The response of native migration to this supply shock is initially zero (in this model, wages only affect migration with a lag). After time zero, this response is given by

$$\widehat{n}_{ijt} = -(1-\phi)^{t-1} b^n d, \forall t > 0. \tag{14}$$

The native migration rate decreases as a result of the immigration shock and, in the long-run, native employment is permanently lower. Note however, that immigration only affects native employment through wages, as can be seen from the role of b^n in equation (14). The initial effect of an innovation to immigration is to decrease wages, which decreases native employment (due to native out-migration). As time passes, firms start to move in, attracted by the lower wages, and wages start to rise. As wages rise, native employment continues to fall, but at a decreasing rate. In the long run, native employment is lower than in the no shock path and native migration rate is back to its no-shock level.

Similarly, the effect of the supply shock on immigrant influx over time is

$$\widehat{m}_{ijt} = -(1-\phi)^{t-1} b^m d, \forall t > 0. \tag{15}$$

That is, the initial rise the immigrant influx decreases wages and as a result it decreases future immigrant influx in the next period. However, note that even though there is no long term effect on the immigrant influx rate, the total effect relative to the no shock path on the number of recent immigrants is still positive. The cumulative effect on recent immigrant influx is given by

$$\sum_{t=0}^{\infty} \widehat{m}_{ijt} = 1 - \sum_{t=1}^{\infty} (1-\phi)^{t-1} \left(b^m d\right) = 1 - \frac{b^m d}{\phi} > 0. \tag{16}$$

At time zero, the effect on immigrant employment is one. However, as explained above, this innovation causes wages to fall, and this will in turn cause the recent immigrant inflow to decrease. As time passes and wages go back to normal, immigrant inflow stops falling (the long run effect on the influx rate is zero) and immigrant employment stabilizes at a higher level relative to its no shock path.

So, we have seen that, as a response to an innovation in labor supply due to recent immigration, native and earlier immigrant employment decreases while recent immigrant employment increases. What happens to the total labor force in the state where such innovation occurred? The equation below shows that in the long run, as long as the wage elasticity of capital is positive ($a > 0$), the size of the total labor force increases (remember that $\phi = a + d\left(b^n + b^m\right)$). In this case, the smaller wages attract firms, which in turn raise wages and offset the net out-migration of natives and immigrants.

$$\widehat{l}_{ijt} = \sum_{t=0}^{\infty} \widehat{n}_{ijt} + \sum_{t=0}^{\infty} \widehat{m}_{ijt} = 1 - \frac{d\left(b^n + b^m\right)}{\phi} > 0. \tag{17}$$

2.2 Effect of a labor demand shock on recent immigrant inflow, internal migration, and wages

Another question that this paper addresses is how wages affect the location decisions of immigrants and natives. Wages change when states face a shock, adverse or favorable, to the demand for their goods. From equation (7) the effect of an innovation to labor demand (e^d_{ij}) of +1 in period 0 on wages at time t is (as in the previous subsection, a hat ($\widehat{\ }$) denotes the deviation of a variable from its base (no-shock) path)

$$\widehat{w}_{ijt} = (1 - \phi)^t, \forall t \tag{18}$$

A positive innovation to labor demand increases wages. Immigrants and natives respond to this increase in wages with increased in-migration and recent immigration influx. On the other hand, capital flows away, eliminating jobs. With time, these three forces reestablish the initial equilibrium. The increase in wages will be completely dissipated, in a speed that depends on the short run elasticities a, b^n, and b^m.

The response of native migration to this demand shock is given by

$$\widehat{n}_{ijt} = b^n (1-\phi)^{t-1}, \forall t > 0. \tag{19}$$

Similarly, the response of the inflow of immigrants is

$$\widehat{m}_{ijt} = b^m (1-\phi)^{t-1}, \forall t > 0. \tag{20}$$

Initially (at time zero), employment remains unchanged as wages absorb the positive shift in demand (by the assumption of full employment). Over time, native and immigrant employment increases relative to its base path to end asymptotically higher. In the long run, the immigrant inflow and the internal migration rates go back to their initial levels. Note that the size of the long run increase in employment depends on the short run elasticities of firms and workers.

The reason for the relation between long run employment and short run mobility elasticities is that the higher wages trigger three adjustment mechanisms: firms leave the state, natives and earlier immigrants have a positive net in-migration rate and recent immigrant influx increases. In the long run, wages must return to the initial level, but the size of native and immigrant employment will depend on the speed at which workers (natives, earlier and recent immigrants) come and firms leave. If, for example, firms leave more quickly than natives move in, then native employment will increase less than if firms move more slowly.

The model in this section suggests that we need to take into account the dynamic interactions between wages, immigration, and internal migration in the empirical analysis. In the next section, I argue that panel vector autoregression is a suitable methodology in this case and I explain the method. The analysis in Subsections 2.1 and 2.2 shows the theoretical predictions for the impulse-response functions. Once the empirical results are presented in Section 5, I will discuss what they imply about the magnitudes of the parameters in the theoretical model.

3 Methodology: Panel Vector Autoregression

The model in the last section suggests that the adjustment of a local economy to a shock in labor demand or supply involves a dynamic system of wages, native employment, and immigrant flow. Three adjustment mechanisms come into play in response to these shocks. In the case of a positive labor demand shock, for example, higher wages increase net-migration of natives and earlier immigrants and the influx of recent immigrants. Besides that, higher wages induce net out-migration of firms and destruction of jobs. To estimate the strengths of these adjustment mechanisms as a response to innovations to labor demand and supply, I run a panel vector autoregression with three equations: one for log wages, another for migration rate of natives and earlier immigrants, and a third one for recent immigrant inflow.[8] The next section defines each of these variables and describes how they are constructed in the data. I estimate[9]

$$\begin{aligned} \log W_{jt} &= \alpha_{10} + \alpha_{11}(L)\log W_{j,t-1} + \alpha_{12}(L)M_{j,t-1} + \alpha_{13}(L)N_{j,t-1} + s_j + y_t + \in^{w}_{jt} \qquad (21) \\ N_{jt} &= \alpha_{20} + \alpha_{21}(L)\log W_{j,t-1} + \alpha_{22}(L)M_{j,t-1} + \alpha_{23}(L)N_{j,t-1} + s_j + y_t + \in^{n}_{jt} \\ M_{jt} &= \alpha_{30} + \alpha_{31}(L)\log W_{j,t-1} + \alpha_{32}(L)M_{j,t-1} + \alpha_{33}(L)N_{j,t-1} + s_j + y_t + \in^{m}_{jt} \end{aligned}$$

where $\log W_{jt}$ is the mean log wage, M_{jt} is the recent immigrant inflow and N_{jt} is a measure of migration rate for natives and earlier immigrants (out-, in- or net-migration) for state j in year t. State fixed effects (s_j) control for the presence of state specific amenities as described in the theoretical model. Time fixed effects y_t are also included to control for macroeconomic shocks that might cause spurious correlation between wages and immigration, for example.

[8] Due to lack of a good measure of capital flow, I do not include it in the empirical analysis. However, we can still learn about this mechanism by considering it to be the residual of the other two adjustment mechanisms. For example, if we observe strong convergence in wages beyond of what can be explained by observed labor movements, this convergence is considered to be the result of capital movements.

[9] One problem with estimating a VAR system using panel data is that the inclusion of fixed effects to control for heterogeneity biases the coefficients. In my case, such bias will cause the estimated system to be less persistent than the truth. However, the bias is smaller the greater the size of the time-series (T) and the smaller the persistency of the system. Two of the three equations in the system above describe the dynamics of rates, which are not very persistent by nature. In the case of wages, the estimated autoregressive coefficient is 0.6. According to Arellano(2003) with T=15 and an autoregressive coefficient equal to 0.5, the bias would be -0.11 (or 22%). Given the above, the bias due to fixed effects and lagged dependent variables should not alter my results significantly (in my case, T=26).

The lag operator (L) specifies how many lags each model has.

A possible worry would be that the variables in the system, especially wages, have a unit root. To test for this, I use a panel unit root test developed by Im, Pesaran and Shin (2003). The test rejects the null hypothesis of the presence of a unit root in all the variables and different specifications. The estimation is done in levels, since this is the specification suggested by the theoretical model.

Another specification choice regards the number of lags to include in each model. The qualitative results presented in Section 5 do not change with the variation in the number of lags but the magnitude of the effects can vary. To choose the number of lags that best fit the data, I use the "General-to-specific sequential rule" described in Hayashi (2000, p. 395).[10] The optimal number of lags varies between 2 and 3 depending on the exact specification.

As mentioned in the previous section, there are theoretical reasons to believe that all the variables in the system affect each other (e.g. immigration affects wages and wages affect immigrant inflow). One important question is in what direction the causality is running, and what is the magnitude of the effect in each direction. In this paper, the timing of the data is used to shed some light on this issue. Once the system in (21) is estimated, I run Granger-causality tests to investigate which variables are good predictors of other variables. For example, one of the most researched questions in the immigration literature is whether immigration has a causal effect on wages of native workers. In system (21), one can examine whether immigration is a significant predictor of wages and internal migration by testing the null hypothesis

$$H_0 : \widehat{\alpha}_{12}^1 = \widehat{\alpha}_{12}^2 = ... = \widehat{\alpha}_{12}^p = \widehat{\alpha}_{22}^1 = \widehat{\alpha}_{22}^2 = ... = \widehat{\alpha}_{22}^p = 0,$$

where p is the number of lags included in the VAR.

Given the estimated coefficients in (21), a straightforward way to learn about the magnitudes of the effects is to graph the impulse-response functions (IRFs) from the system,

[10] This rule basically consists of estimating the model with a large number of lags (in the present case, 4) and testing for the significance of the last lag. If the last lag is significant at some prespecified significance level (5 percent), then the maximum number of lags is optimum. Otherwise, I drop the last lag and repeat the same test until the significance level is reached.

which trace the variables' responses to typical random shocks. One problem of interpreting the implied impulse response functions as causal is that the errors in the different equations in the system will likely be correlated. For example, we would like to know how an innovation to immigrant influx, holding everything else constant, affects wages after a given number periods. However, since the error terms in (21) are contemporaneously correlated, one cannot assume that everything else is constant. In other words, shocks to immigration are likely to be accompanied by shocks in wages. So, we must take this into account if we want to analyze the responses to a shock that occurs in only one variable at a time.[11]

One way to overcome this shortcoming is by making recursive assumptions in order to construct mutually uncorrelated innovations. This is similar to placing identification restrictions on a system of dynamic simultaneous equations. Once these restrictions are imposed, the residuals of the different equations are uncorrelated (or orthogonal), and the IRFs derived from this new system are called orthogonalized impulse response functions (OIRFs) (see Hamilton(1994) and Lutkepohl(1993)).

To see how this works consider the zero mean VAR(p) process process with K equations[12]

$$y_{it} = A_1 y_{it-1} + ... + A_p y_{it-p} + u_{it} \tag{22}$$

This process can be rewritten in such a way that the residuals of different equations are uncorrelated. For this purpose we choose a decomposition of the white noise covariance matrix $\Omega_u = W \Lambda W'$, where Λ is a diagonal matrix with positive diagonal elements and W is a lower triangular matrix with unit diagonal. A popular form in which this is implemented is by using the Cholesky decomposition $\Omega_u = PP'$, defining a diagonal matrix D which has the same diagonal as P and by specifying $W = PD^{-1}$ and $\Lambda = DD'$.

Premultiplying the equation (22) by W^{-1} gives

$$W^{-1} y_{it} = B_1 y_{it-1} + ... + B_p y_{it-p} + v_{it} \tag{23}$$

[11] As noted by Sims (1981) it is dangerous to simulate a model's response to conditions widely different from what occurred in the sample period. If the errors of the different equations have a high contemporaneous correlation, simulation of a shock to one variable while all others are held at zero might be misleading.

[12] This exposition is based on Lutkepohl, chapter 2.

where $B_i = W^{-1}A_i$, $i = 1, ..., p$, and $v_{it} = (v_{1it}, ..., v_{Kit})' = W^{-1}u_{it}$ has diagonal covariance matrix

$$\Omega_v = E\left(v_{it}v_{it}'\right) = W^{-1}E\left(u_t u_t'\right)\left(W^{-1}\right)' = \Lambda \tag{24}$$

Adding $\left(I_K - W^{-1}\right)y_t$ to both sides of (23) gives

$$y_{it} = B_0 y_{it} + B_1 y_{it-1} + ... + B_p y_{it-p} + v_{it} \tag{25}$$

where $B_0 = I_K - W^{-1}$. Since W is lower triangular with unit diagonal the same is true for W^{-1}. Hence,

$$B_0 = I_K - W^{-1} = \begin{bmatrix} 0 & 0 & ... & 0 & 0 \\ \beta_{21} & 0 & ... & 0 & 0 \\ : & : & : & : & : \\ \beta_{K1} & \beta_{K2} & ... & \beta_{K,K-1} & 0 \end{bmatrix} \tag{26}$$

is a lower triangular matrix with zero diagonal. For the system of equations in (25) this implies that the first equation contains no contemporaneous y's on the right-hand side. The second equation may contain y_{1it} and otherwise lagged y's on the right-hand side. More generally, the k-th equation may contain $y_{1it}, ..., y_{k-t,it}$ and not $y_{kit}, ...y_{Kit}$ on the right hand side. In the econometrics literature, such a system is called a recursive model.

Using the Cholesky decomposition to orthogonalize the errors, the OIRFs are calculated by tracing v_{it} innovations of size one standard deviation through the system (25). This is due to the fact that the diagonal elements of D are just standard deviations of the components of v_{it}.

One problem with this kind of impulse response analysis is that the ordering of the variables is important for the results and it cannot be determined with statistical methods. Note that the choice of ordering of the variables is equivalent to the choice of P, since a multitude of P matrices with $\Omega_u = PP'$ exists. This choice must always be taken on the basis of a priori knowledge on the structure of the relationships between the variables of interest.

Here, I will assume that movements of labor affect wages within one year but wages only affect immigrant and native migration decisions with at least one year lag.[13] This assumption was imposed in the construction of the theoretical model presented in the previous section. Since the costs of moving are considered to be high, migration decisions are viewed as taking more time than other economic decisions.

This assumption gives rise to two possible systems of equations:

$$\begin{aligned} N_{jt} &= \alpha_{20} + \alpha_{21}(L)\log W_{j,t-1} + \alpha_{22}(L)M_{j,t-1} + \alpha_{23}(L)N_{j,t-1} + s_j + \in^{n}_{jt} \\ M_{jt} &= \alpha_{30} + \alpha_{31}(L)\log W_{j,t-1} + \alpha_{32}(L)M_{j,t-1} + \alpha_{33}(L)N_{j,t-1} + \theta_{31}N_{jt} + s_j + \in^{m}_{jt} \\ \log W_{jt} &= \alpha_{10} + \alpha_{11}(L)\log W_{j,t-1} + \alpha_{12}(L)M_{j,t-1} + \alpha_{13}(L)N_{j,t-1} + \theta_{11}M_{jt} + \theta_{12}N_{jt} + s_j + \in^{w}_{jt} \end{aligned} \tag{27}$$

and

$$\begin{aligned} M_{jt} &= \alpha_{30} + \alpha_{31}(L)\log W_{j,t-1} + \alpha_{32}(L)M_{j,t-1} + \alpha_{33}(L)N_{j,t-1} + s_j + \in^{m}_{jt} \\ N_{jt} &= \alpha_{20} + \alpha_{21}(L)\log W_{j,t-1} + \alpha_{22}(L)M_{j,t-1} + \alpha_{23}(L)N_{j,t-1} + \theta_{21}M_{jt} + s_j + \in^{n}_{jt} \\ \log W_{jt} &= \alpha_{10} + \alpha_{11}(L)\log W_{j,t-1} + \alpha_{12}(L)M_{j,t-1} + \alpha_{13}(L)N_{j,t-1} + \theta_{11}M_{jt} + \theta_{12}N_{jt} + s_j + \in^{w}_{jt} \end{aligned} \tag{28}$$

In the first system the assumption is that internal migration affects recent immigrant influx contemporaneously, but immigration only affects internal migration with lags.[14] In contrast, in the second system the reverse assumption is made: immigration affects internal migration contemporaneously but internal migration only affects immigration with lags. Since there is no theoretical reason to prefer one over the other, I show both sets of OIRFs and compare the results.

[13] One could argue that migration decisions are based on expectations about future wages instead of past wages. The question would then be how agents form such expectations. In section 5 I will show evidence that the wage series is fairly persistent, so that expectations of future wages must at least in part be formed based on past wages. If this is the case, the parameters in (27) and (28) could be reinterpreted and no significant change in the systems is needed.

[14] One way to think of what is being done is to note that a shock to native migration is assumed to disturb all other variables in the system instantly, according to the strength of the contemporaneously correlation of other residuals with the internal migration residual, while the wage shock is only allowed to affect the wage variable in the initial period.

Since these recursive ordering assumptions are identifying the system, one might ask how important these are for the results that will be presented here. In effect, Sims (1981) suggests trying different orderings to investigate the sensitivity of the conclusions to the ordering of the variables. This analysis is done in section 5 and the main results are robust to the choice of different identifying assumptions.

4 Data

4.1 March CPS data

I use data from the March Current Population Survey (CPS) every year between 1982 and 2007, obtained from the Integrated Public Use Microdata Series, Current Population Survey (King, Ruggles, Alexander, Leicach (2004)). Since the sample size of the CPS is smaller than that of the Census, the analysis is restricted to the 38 most populated states.[15] This only restricts the sample slightly since 95.73 percent of the total population and 96.86 percent of immigrants live in these 38 states during the sample period.

Ideally, I would use the metropolitan area as the definition of a labor market since there is heterogeneity in immigrant influx within states. However, due to the small sample sizes in the CPS, the series constructed at the metropolitan area level were noisy.[16] Even though the state is not a perfect approximation of the labor market, this definition is sometimes used in the immigration literature [Borjas, Freeman and Katz (1996), Borjas(2006)] and the analysis at this level is still informative about the relationship between the variables of interest.[17]

I divide the data into cells by survey year and state. Later, I also divide the cells into two education groups (high school dropouts and high school graduates; some college and college graduates). The division into education groups comes from the assumption that immigrants

[15] The qualitative results do not change when we use the 50 states plus the District of Columbia, but the measure of recent immigration is substantially noisier. Besides that, later in the paper the sample is further divided by education level and the results restricting the sample to the most populated states are more reliable. See table 1 for a list of states used.

[16] As explained below, I use the question on place of residence in the previous year to construct my measure of recent immigrant inflow. I use respondents that say they lived abroad in the previous year to approximate for recent immigrant inflow rate. This rate is on average 0.004 per year, so with small sample sizes of some city-year cells, the constructed variable is noisy and the number of zeros of this variable is large.

[17] Examples of papers that use metropolitan areas as the geographical unit of analysis include Altonji and Card (1991), Card (2001), Card and DiNardo (2000) and Schoeni(1997).

compete more directly with natives with their same level of skill, here approximated by education.

Within the 38 most populated states, the sample is further restricted to men and women age 16-68 with at least 2 years of potential experience (this last restriction is meant to exclude students). Table 2 presents the descriptive statistics of the variables used in the analysis (a precise definition of each one of these variables will be given in the next subsection).

The analysis is based on a panel of 38 states over 26 years, resulting in 988 observations. It is interesting to note in Table 2 the differences in statistics for different education groups. First, the recent immigrant inflow rate is higher for high school dropouts and graduates than for those with some college and college graduates (0.0042 versus 0.0036), meaning that during this period immigration to the US was disproportionately composed of low skilled immigrants. Besides that, one can see that the gross internal migration flows (in- and out-migration rates) are much higher for more educated workers, an established result in the migration literature [Greenwood(1997)].

4.2 Construction of Variables

From individual CPS data, I construct state-year weighted means of the variables of interest – wages, recent immigrant inflow, and native and early immigrant's rates of in-, out- and net-migration. Non-citizens and naturalized citizens are defined to be immigrants[18]. I calculate hourly wages dividing annual earned income from wages, business and farm activities by the product of weeks worked during the year and usual hours worked per week. I inflate wages to 2007 values using the Consumer Price Index (CPI). Observations with hourly wage smaller than 2 or greater than 90 were dropped. The log wage variable used in the analysis is a weighted mean of the logarithms of such individual wages, calculated using survey weights.

I use the question on the state of residence in March of the previous year to calculate in-, out- and net-migration rates of natives and earlier immigrants. This question is available

[18]The results would be the same if I defined immigrants to be all who were born abroad. The only difference between these two definitions are those born abroad from American parents (who are considered citizens), and they are a small fraction of the whole population.

in the survey starting in March 1982. The in-migration rates for state j were calculated as the sum of the weights of all the individuals currently living in j who reported living in a different state in the previous year,[19] divided by the total population in state j, calculated as the weighted sum of all observations in state j and year t. The out-migration rate was calculated in a similar manner and the net-migration rate is defined as the in-migration minus the out-migration rate.

The recent immigrant inflow to state j in year t is defined as the number of immigrants who moved to j (from abroad) during the past year (between t-1 and t) divided by the total population in j at year t. One problem with calculating such series with the available data is that the survey only carries information about the respondent's nativity and citizenship since 1994. To overcome this problem I use once more the question about place of residence one year ago. One of the possible answers to this question is "abroad." Using the post-1994 data, one can show that more than 70% percent of the people who answered that their place of residence a year ago was abroad were indeed recent immigrants (immigrants who first moved to the US sometime during the 12 months previous to the survey).

Given this statistic, I decided to use the sub sample of people who said they lived abroad in the previous year to proxy for immigrant status (I assumed the veterans who lived abroad not to be immigrants, since using post-1994 data, I calculated that more than 96% of them are indeed natives).[20,21] For the surveys in 1985 and 1995 the question about place of residence one year ago is not available, instead, there is a question about place of residence five years ago. So, for these years the proxy is calculated using the 5-year question.[22]

An aggregate measure of recent immigrant inflow can be calculated by summing the

[19]Individuals who reported living abroad in the previous year were not included in this calculation.

[20]The idea of using the subsample of people who lived aborad to approximate for immigrant status in the CPS was used by Butcher and Card (1991) to look at the effects of immigration on wages in the 1980's. However, since the post-1994 CPS data was not available to them, they could not assess how good this proxy was. The best they could do was compare the average characteristics of this subsample in the CPS with the average characteristics of the sample of recent immigrants from the Census.

[21]Another way of constructing a proxy of immigrant status is to fit a model on personal characteristics to predict the probability that each individual is an immigrant, given that he lived abroad in the previous year. When I do this, I find that immigrants are on average younger, less educated, more likely to be Hispanic and married and less likely to be black and female. Such model was run using post-1994 data and used to construct an aggregate measure of the "expected number of immigrants" yearly, for the whole period. The results obtained using this predicted measure of immigrant inflow are similar to the ones reported in the text.

[22]0.51 percent of the sample in 1994 and 1996-2007 lived abroad in the previous year. For 1995 and 2005, 2.37 percent lived abroad five years prior to the survey .

number of non-veterans who lived abroad in the previous year for each year and state. The recent immigrant inflow is defined as the number of immigrants who moved to a given state during the previous year, so the numbers for 1985 and 1995 were divided by five.[23] Since I am considering all the non-veterans who lived abroad to be recent immigrants, this is clearly an upper bound of the real immigrant inflow. Using post-1994 data, I find that 77% of this subsample are indeed immigrants, so I scale down my constructed measure of immigrant inflow to match this figure. The recent immigrant inflow rate is calculated by dividing this measure of recent immigration by the total population for each state-year cell.

One way to verify the accuracy of this approach is to check how well the constructed recent immigrant inflow correlates with a measure calculated using citizenship status for the post-1994 period. Figure 3 shows a scatter plot of the natural logarithm of the two measures for the 532 year-state cells with a 45 degree line for reference.[24] There are a couple of interesting things to note from this figure. First, even after scaling the constructed measure down, it is still clearly an upper bound for the real measure. Second, one can see that the constructed measure closely maps the real measure, except for the few data points where the constructed measure is positive even though the real measure is zero (these points only correspond to 4% of the unweighted sample and 2% of the sample weighted by population size). The correlation between the log of the two measures is 0.90.

Figure 4 shows the national yearly recent immigrant influx rate for 1982-2007 constructed using this strategy. The graph also includes the rate calculated using the immigration variables for the post-1994 data. One can see that, as anticipated by figure 3, the two rates are very similar. The vertical lines in the graph correspond to the business cycle's peak and trough contraction dates published by the NBER's Business Cycle Dating Committee.[25]

This figure shows that the national rate of immigrant influx oscillated between approximately 0.3 and 0.55 percent per year during this period. Besides that, the yearly immigrant

[23]This gives an approximate number for these two years, but it is not perfect since it assumes a uniform rate of immigration during the five year period. Setting the immigrant inflow rate to missing in these two years does not significantly change the results.

[24]Approximately 8% if the constructed measure (4% when weighted by population) and 12% of the real measure (7% when weighted) have zero values. I replace these zeroes with ones (that is, I assume that these state-year cells have one recent immigrant instead of zero) before doing the logarithmic transformation.

[25]For more details see http://www.nber.org/cycles.html.

influx is increasing and very responsive to business cycle contractions. It is also worth noting that this rate decreased sharply after the terrorist attacks of September 11, possibly because of the increased immigration controls established after that.

5 Empirical Results

5.1 Results from the 3 equations VAR: Recent Immigration, Wages, and Internal Migration

This section will discuss the results from the estimation of the system of equations (21). As explained in section 3, the number of lags in each model was determined by a rule that tests for significance. Besides the estimated coefficients, the tables also contain the p-values for the Wald tests of joint significance of the lags of selected variables in each of the equations and for Granger-causality tests. In order to perform binary Granger-causality tests, I group the three variables in all the three possible ways.[26]

Table 3 shows the estimated coefficients from the three equation VAR: log wages, immigrant inflow and net-migration rate (defined as in- minus out-migration). One can see from this table that lagged wages are significant in both the immigrant inflow and the net-migration equations. Besides that, lagged immigrant inflow is significant at the 10 percent confidence level in the wage equation. However, I reject the null hypothesis that wages do not Granger-cause labor movements, but it is not possible to reject that immigration does not Granger-cause wages and net-migration. Taken as a whole, the results from the Granger-causality tests point to the conclusion that wages can predict labor movements, but labor movements cannot predict wages.

I chose net-migration as the measure of internal migration since this measure is the measure suggested by the theoretical model in section 2. However, from appendix tables 1 and 2 it is clear that the results are robust to the use of out- or in-migration as the measure of internal migration. The estimated coefficients of lagged immigration on the wage equation

[26]Granger-causality tests are usually performed in a binary manner, with the division of the variables in two groups in the case of systems with more than two equations. One reason to proceed this way is that if we test for significance of each variable separately, we cannot guarantee transitivity in the causal relation.

and of lagged wages on the immigration equation are very similar to the ones presented in table 3. In both cases, the null hypothesis that wages do not Granger-cause recent immigration and internal migration is rejected. Moreover, at the 5% confidence level, I cannot reject the hypothesis that recent immigration do not Granger-cause wages and internal migration (measured either as in- or out-migration of natives and earlier immigrants). To sum up, the appendix tables show that the estimated relation between wages and immigration is robust to the measure of internal migration used.

The result that immigration does not predict wages or internal migration is consistent with the literature that finds zero or small negative effects of immigration on wages. The results just described suggest that the endogeneity in the location of new immigrants is a real problem, since immigrants seem to choose to locate where wages are higher.

As noted by Sims (1980), it is difficult to make sense of autoregressive systems like the ones in Table 3 by examining the coefficients in the regression equations themselves. The estimated coefficients on successive lags tend to oscillate, and there are complicated cross-equation feedbacks. The best descriptive device and one that has been widely adopted by the literature is the use of impulse response functions (IRFs), which trace the system's response to random shocks.

To interpret the magnitudes of the effects in Table 3, I graph the impulse response functions implied by the estimated coefficients. However, as explained in section 3, there are possible problems caused by the contemporaneous correlation between the errors in the different equations of the system. Here I use the orthogonalization of the errors described in that section to overcome these problems. This orthogonalization will be more important the stronger the correlation between the cross-equation residuals.[27] What the orthogonalized impulse response functions (OIRFs) do is to take this correlation into account such that when a shock to immigration is analyzed, a shock to wages is also allowed instantly, with the the sign and magnitude proportional to the contemporaneous correlation between the

[27] To give an idea, in the three equation VAR with log wages, immigrant inflow and net-migration rate, the correlation between wages' and immigration's equations residuals is equal to 0.0001, which is not strong but it is positive, meaning that positive shocks to wages and immigration are usually observed concurrently in reality.

two equations' residuals.

Since the model has three equations, from each system there are 9 possible impulse response functions: I can give a shock to each one of the three variables and see how all three variables respond to such shock over time. Figure 5 plots the OIRFs for the model in table 3, with the recursive assumption that corresponds to the system in (27).[28][29] Here each of the variables was given a shock equal to one standard deviation of its residual. The y-axis of the graphs show the size of this shock as a fraction of the variable's mean.[30] The size of the y-axis was standardized to be equal to one standard deviation of the residual of each variable across different columns.

It is important to note that one standard deviation shock has very different magnitudes relative to the mean depending on the variable. While such shock corresponds to a 3% increase in wage, it is equal to a 40% increase in immigration and a 30% increase in net-migration. This difference is in part because the last two variables are rates (while wages are in levels), and in part because of the bigger sampling error in them. Since accounting for measurement error in these variables does not alter the results[31] and the one standard deviation shocks are traditional in the VAR literature, I follow this rule. The OIRFs presented in figure 5 trace the effect of these typical random shocks in each of the variables over time.

Figure 5 shows that, as anticipated by the tests in table 3, a positive shock to wages has a large and significant positive effect on the rate of immigrant inflow: a 3 percent shock to wages (or 0.03 increase in log wages) increases immigrant inflow by approximately 6 percent (resulting in a wage elasticity of immigration of approximately 2). Another way to describe this effect is that a one standard deviation shock to wages causes a 0.2 standard deviation response in immigration.

[28] The algorithm to plot the OIRFs of system (27) is equivalent to estimating (21) and then computing the Cholesky factorization of the covariance matrix in (21); see Lutkepohl (1993, chapter2).

[29] The confidence intervals presented in figure 5 were constructed from the variance-convariance matrix of the VAR coefficients, using the delta method.

[30] One exception is the graphs for net-migration, since this variable has, by construction, zero mean. In this case, I used the mean of in-migration rate to transform the scale of the y-axis instead.

[31] To assess how much measurement error each variable has, I did a "split sample" analysis. This analysis consists of randomly splitting the sample in two and calculating two measures for each variable. Under the assumption of classical measurement error, it is possible to use these different measures to calculate the variance of the measurement error. As expected, I find more error in the immigration and net-migration rates than in the wage, but these differences do not significantly affect the shape of the OIRFs.

Note that even though lagged immigration was significant in the wage equation presented in Table 3, the OIRFs show that the effect of immigration on wages is very small in magnitude. A 40% increase in immigrant inflow causes a 0.2% increase in wages. In other words, a one standard deviation shock to immigration causes a 0.05 standard deviation wage response. The effect of wages on net-migration is initially positive but it turns negative over time. The other simulated effects of the model are, as expected, small in magnitude.

Is is also interesting to note that, as predicted by the model, a shock to wages dies out slowly and the wage rate takes approximately 15 years to go back to its original level. Following the slow adjustment of the wage rate, the immigrant inflow rate also moves slowly: the effect of a shock to wages on immigration takes 3 years to reach its maximum and the immigrant inflow rate takes 10 years to go back to its original level.

Figure 6 presents the OIRFs with two different recursive orderings. First, the immigration, net-migration and wages recursive ordering: immigration is assumed to be affected only by lagged values of the variables in the system; net-migration is assumed to be affected by lagged variables of the variables in the system and the current rate of immigration; and log wages are affected by lagged values of the variables of the system plus current values of net-migration and immigration. Second, the net-migration, immigration and wages ordering, which implies a similar structure of recursive assumptions. The effects of these orderings can be seen in the graphs in figure 6: while the contemporaneous net-migration response to a shock to immigration is constrained to be zero in the second ordering, it is positive in the first ordering.[32] The important thing to note from the different orderings is that, other than the instantaneous effects, the shape of the functions and the magnitudes of the implied effects are similar.

One might ask how important it is to assume that wages are determined by current labor supply while both foreign and internal migration are affected only by lagged wages for these results to be true. Does the imposition of other recursive orderings in the OIRFs change the results presented so far? The answer to this question is no, as shown by figures 7 and 8.

[32]Remember that contemporaneous here means within the first year of the shock.

From these figures, one can see that it is mostly the effects on the first few periods after the shock that vary with the different assumptions, and these differences are small. In general, the different recursive orderings yield similarly looking OIRFs and close magnitudes of the estimated effects.[33]

It is important to emphasize that there is a direct relation between the Granger-causality tests presented in the tables above and the OIRFs shown in figures 5 to 8. The impulse responses to a shock in one variable are zero if this variable does not Granger-cause the other variables taken as a group. In other words, an innovation in variable k has no effects on the other variables if the former variable does not Granger-cause the set of the remaining variables [see Lutkepohl (1993), chapter 2]. So, given the results presented in Table 3, I should expect that the only clear pattern to emerge should be that a shock to wages has a substantial effect on labor movements; and that is exactly what is found in Figures 5 to 8.

The results in Table 3 and in Figures 5 to 8 suggest that in the relation between labor and wage movements, the causality is running primarily from wages to labor movements than from labor to wage movements. This conclusion comes not only from the different sets of Granger causality tests run in the models with different measures of internal migration but mostly from the magnitudes of the effects estimated and graphed in the orthogonalized impulse response functions. I find no evidence that immigration leads to native net out-migration, neither directly nor through wages. Given this result, and since my interest lies in the relation between wages and immigration, I present in table 4 the results of a 2 equation VAR that includes only immigrant inflow and log wages.

The estimates in the first panel of table 4 includes the entire sample and are very close to estimates in the 3-equation VAR. The Wald tests (that are equivalent to Granger-causality tests in a 2-equation VAR) show once more that wages are a good predictor of immigrant inflow, but immigration is not a good predictor of wages. The orthogonalized impulse response functions (OIRFs) from the model in panel 1 of table 4 are plotted in figure 9. Once again, they are very similar to the OIRFs in the bigger model, and they imply approximately the

[33]This robustness of the results also applies to the models that use out- and in-migration, but due to space constraints, I do not include the graphs for these models here.

same magnitudes of the effects. A 10 percent shock to wages is associated to a 20 percent increase in recent immigrant inflow, and a 10 percent shock to immigration is associated with a 0.05 percent increase in wages. The fact that these results are so close to the results in the 3 equations model is additional evidence that internal migration does not play an important role in the relation between immigration and wages.

5.2 Skill Group Analysis

One possible reason why the estimated effect of immigration on wages is insignificant is that immigrants may only compete for jobs with workers with similar skill level. Since the analysis until here did not break the immigrants into skill groups, this effect could be hidden by the fact that different "types" of immigrants might be moving to places where the returns to education are varying in different ways. Panels 2 and 3 in Table 4 show the analysis for two different education levels (high school dropouts and graduates, and some college and college graduates). Given the results presented above, it seems that internal migration and immigration do not interact in any relevant way, so I restrict the analysis to 2-equation VARs, with log wage and recent immigrant inflow.

The results in panels 2 and 3 of table 4 are different from the ones in panel 1. In neither panel there is a significant effect of immigration on wages. However, the effect of wages on immigration is large and significant for high school dropouts and graduates. By contrast, no effect of wages on immigration is found for more skilled workers.[34] Figure 10 shows the OIRFs for these models in table 4 using the immigration and wages recursive ordering. From these pictures, one can see that the effect of wages on immigration for high school dropouts and graduates is significantly stronger than the effect estimated for the whole sample. A 3 percent increase in low skill wages increase the influx of low skilled immigrants by more than 8 percent. Moreover, this effect is much larger than the estimated effect on the subsample of workers with some college and college graduates: a 3 percent increase in high skill wages is associated with less than 1 percent increase in high skill immigration,

[34] Note that this result goes in contrast with the results in the migration literature that shows that more educated people are more mobile (see Greenwood(1997)).

which is not significantly different from zero. It seems that the strong effects of wages on immigration estimated from the whole sample come mostly from the subsample of less skilled immigrants.[35]

Contrary to what could be expected from the "skill specific" competition hypothesis, I find no significant effects of skill specific immigration on skill specific wages. The effect for high school dropouts and graduates is small and positive, and the effect for those with some college and college graduates is negative but small in magnitude (a 40% increase in immigration is associated with a 0.4% reduction in wages).

Figure 11 graphs the orthogonalized impulse-response functions for high school dropouts and graduates only, including 95% confidence intervals. As anticipated by the tests in table 4, an exogenous shock to low-skill wages has a large and significant effect on low-skill immigration. By contrast, an exogenous shock to low-skill immigration does not have a significant effect on wages of less educated workers.

We can make several conclusions from the analysis in the two previous subsections. First, immigration does not have significant effects on wages or internal migration as previously found by some papers in this literature. Second, wages are an important factor in the location decision of recent immigrants. Besides that, recent immigrants are more responsive to a positive shock in wages than natives and earlier immigrants. Third, higher wages attract mostly low skilled immigrants; more educated immigrants do not seem to be as responsive to higher wages.

5.3 Back to the Theory

What do the conclusions from the empirical analysis imply about the parameters in the theoretical model presented in section 2? It was shown that a supply shock due to immigration was supposed to decrease wages by:

$$\widehat{w}_{ijt} = -d(1 - d\,(b^n + b^m) - a)^t, \forall t. \tag{29}$$

[35] The skill level results are also robust to the recursive ordering imposed.

Since no significant effect of immigration on wages is found, it could be that d is very small, that is, the demand for labor is very elastic. Another possibility would be that $(1 - d\,(b^n + b^m) - a)$ is small, that is, the adjustment of wages due to labor and capital movements is very quick (perhaps this adjustment occurs in a period smaller than one year). However, wages do not seem to adjust so fast: one can see from the impulse response functions presented in figures 5 to 9 that after a demand shock, wages take approximately 15 years to go back to their initial level. Given this evidence, the fast adjustment hypothesis does not seem to hold.

Moreover, as mentioned in section 2.2, a labor demand shock should affect wages, recent immigrant influx and the migration rate of natives and earlier immigrants over time according to

$$\widehat{w}_{ijt} = (1 - d\,(b^n + b^m) - a)^t, \forall t, \tag{30}$$

$$\widehat{n}_{ijt} = b^n(1 - d\,(b^n + b^m) - a)^{t-1}, \forall t > 0, \tag{31}$$

and

$$\widehat{m}_{ijt} = b^m(1 - d\,(b^n + b^m) - a)^{t-1}, \forall t > 0. \tag{32}$$

The strong effect of wages on the recent immigrant inflow suggests that the short run elasticity b^m is large. Besides that, the results suggest that the elasticity for recent immigrants seem to be bigger than that of natives and earlier immigrants. This might be explained by the fact that the mobility decision of immigrants can be divided in two decisions: one about moving to a given country and the other about where to locate in this new country. The first part of this decision is the most costly one, so once immigrants decided to come to this country they already paid most of their moving costs and they are more flexible about their decision to locate in one state or the other (that is, their cost of locating in state j instead of state i is probably smaller than a native worker's cost of moving from j to i).

The results from the analysis by education group showed that low skill immigrants respond much more to wages than high skill immigrants. This suggests that the short run wage elasticity of low skill immigrants is higher than that of high skill immigrants (b^m). This could be explained by the fact that many high skill immigrants might already have a job when they first move to this country while low skill immigrants are less likely to be in this situation.[36] Given that low skill immigrants will need to search for a job they might be more attracted by places that best reward their kind of labor.

6 Conclusions

In this study I proposed a new way to analyze the relationship between immigration and wages using a time series approach. My main contributions are the modeling of the joint dynamics of wages, internal migration and immigration, and the use of yearly data, which allows timing assumptions to identify the parameters.

The vector autoregression analysis of a 26-year panel of US states did not show any significant effect of immigration on wages or internal migration. In contrast, wages have a large and significant effect on immigration. The estimated coefficients imply that a 10 percent increase in wages causes up to a 20 percent increase in the rate of immigrant inflow after 3 years. The effect is strongest for low-skill immigrants, while it is small and insignificant for high-skill immigrants. The results are robust to the exclusion of internal migration from the system and to the use of alternative recursive identification assumptions.

These results suggest that the demand for labor is very elastic and that the short run elasticity of low skilled immigration to wages is high. Besides that, the wage elasticity seems to be heterogeneous across immigrants of different skill levels, which could be explained by differences in job searching behavior between these groups.

My results suggest that the concerns about immigration lowering native workers' wages are misplaced. I find no evidence that the influx of immigrants decreases wages, neither for

[36]For example, many high skill immigrants come in the country with H-1B visas, which are employer-sponsored visas for college graduates who work in "specialty" occupations. Borjas and Friedberg (2007) estimate that 5-8% of all immigrants that moved to the country between 1995 and 1999 held H-1B visas.

the economy as a whole nor for workers who possess the same level of skill.

This paper also sheds light on two possible explanations for the failure of spatial correlation analysis to recover the true effect of immigration on wages: the endogeneity of the location of new immigrants and the fact that native workers might migrate as a response to immigration. My results show that there is no impact, direct or through wages, of immigration on internal migration. As a result, it does not seem that the effects of immigration are diffused across the economy due to migration and spatial correlation results would not be biased because of this effect. However, I do find a strong effect of wages on the location decision of recent immigrants which would bias upward the effect of immigration on wages estimated using less frequent data.

Two other channels that could spread the effects of immigration throughout the economy and bias the results of spatial correlation analysis are movements of capital and inter-state trade. Movements of capital are modeled in the theoretical framework, but they are excluded from the empirical analysis due to a lack of an appropriate measure. Trade is not allowed in the theoretical or empirical model.

Although movements of capital and inter-state trade could in theory diffuse the effects of immigration across the economy, they would have to equalize wages across states very fast (e.g., faster than one year) to explain the lack of a negative estimated effect of immigration on wages. However, evidence in this paper shows that wages do not adjust so fast: after a shock, wages take 10 to 15 years to go back to their initial path. Given these results, it must be that states' economies are adjusting to the large influx of immigrants with mechanisms that do not involve lower wages.

References

[1] Altonji, Joseph G. and David Card. 1991. "The Effects of Immigration on the Labor Market Outcomes of Less-Skilled Natives." In *Immigration, Trade and the Labor Market*, ed. John M. Abowd and Richard B. Freeman, 201-34. Chicago: University of Chicago Press.

[2] Arellano, Manuel. 2003. "Panel Data Econometrics." Oxford: Oxford University Press.

[3] Barro, Robert J. and Xavier Sala-I-Martin. 1991. "Convergence across States and Regions." *Brookings Papers on Economic Activity* 1: 107 - 158.

[4] Blanchard, Olivier and Lawrence F. Katz. 1992. "Regional Evolutions." *Brookings Papers on Economic Activity* 1: 1-75.

[5] Borjas, George J. 2003. "The Labor Demand *Is* Downward Sloping: Reexamining the Impact of Immigration on the Labor Market." *Quarterly Journal of Economics* 118(4):1335-74.

[6] Borjas, George J. 2006. "Native Internal Migration and the Labor Market Impact of Immigration." *Journal of Human Resources* 41(2):221-258.

[7] Borjas, George J., Richard B. Freeman, and Lawrence F. Katz. 1996. "Searching for the Effect of Immigration on the Labor Market." *American Economic Review* 86(2):246-251.

[8] Borjas, George J., Richard B. Freeman, and Lawrence F. Katz. 1997. "How much do Immigration and Trade Affect Labor Market Outcomes?" *Brookings Papers on Economic Activity* 1: 1-67.

[9] Borjas, George J. and Rachel M. Friedberg. 2007. "The Immigrant Earnings Turnaround of the 1990s." Unpublished manuscript, Harvard University.

[10] Butcher, Kristin and David Card. 1991. "Immigration and Wages: Evidence from the 1980s." *American Economic Review* 81(2): 292-296.

[11] Card, David. 2001. "Immigrant Inflows, Native Outflows, and the Local Labor Market Impacts of Higher Immigration." *Journal of Labor Economics* 19(1):22-64.

[12] Card, David and John DiNardo. 2000. "Do Immigrant Inflows Lead to Native Outflows?" *American Economic Review* 90(2): 360-67.

[13] DiNardo, John. 1997. "Comments and Discussion." *Brookings Papers on Economic Activity* 1: 68-76.

[14] Filer, Randall K. 1992. "The Impact of Immigrant Arrivals in Migratory Patterns of Native Workers." In *Immigration and the Workforce: Economic Consequences for the United States and Source Areas*, ed. George J. Borjas and Richard B. Freeman. 245-69. Chicago: University of Chicago Press.

[15] Frey, William H. 1995. "Immigration and Internal Migration 'Flight' from US Metro Areas: Toward a New Demographic Balkanization." *Urban Studies* 32(4-5):733-57.

[16] Greenwood, Michael J. 1997. "Internal Migration in Developed Countries." In *Handbook of Population and Family Economics*, ed. M. R. Rosenzweig and O. Stark, 647-720. New York: Elsevier.

[17] Grossman, Jean Baldwin. 1982. "The Substitutability of Natives and Immigrants in Production." *Review of Economics and Statistics* 54(4): 596-603.

[18] Hamilton, James D. 1994. "Time series analysis." Princeton: Princeton University Press.

[19] Hayashi, Fumio. 2000. "Econometrics." Princeton: Princeton University Press.

[20] Im, Kyung S., M. Hashem Pesaran and Yongcheol Shin. 2003. "Testing for unit roots in heterogeneous panels." *Journal of Econometrics* 115: 53-74.

[21] Kennan, John and James R. Walker. 2003. "The Effect of Expected Income on Individual Migration Decisions." NBER Working Paper No. 9585.

[22] King, Mirian, Steven Ruggles, Trent Alexander, Donna Leicach, and Matthew Sobek.

2004 Integrated Public Use Microdata Series, Current Population Survey: Version 2.0. [Machine-readable database]. Minneapolis, MN: Minnesota Population Center [producer and distributor].

[23] Kritz, Mary M. and Douglas T. Gurak. 2001. "The Impact of Immigration on the Internal Migration of Natives and Immigrants." *Demography* 38(1): 133-45.

[24] Lutkepohl, Helmut. 1993. "Introduction to Multiple Time Series Analysis". Berlin: Springer-Verlag.

[25] Schoeni, Robert F. 1997. "The Effect of Immigrants on the Employment and Wages of Native Workers: Evidence from the 1970s and 1980s." Santa Monica, Calif.:The RAND Corporation.

[26] Sims, C. A. 1980. "Macroeconomics and Reality." *Econometrica* 48(1): 1-48.

[27] Sims, C. A. 1981. "An Autoregressive Index Model for the US 1948-1975." In *Large-Scale Macro-econometric Models*, ed. J. Kmenta and J. B. Ramsey, 238-372. Amsterdam: North-Holland.

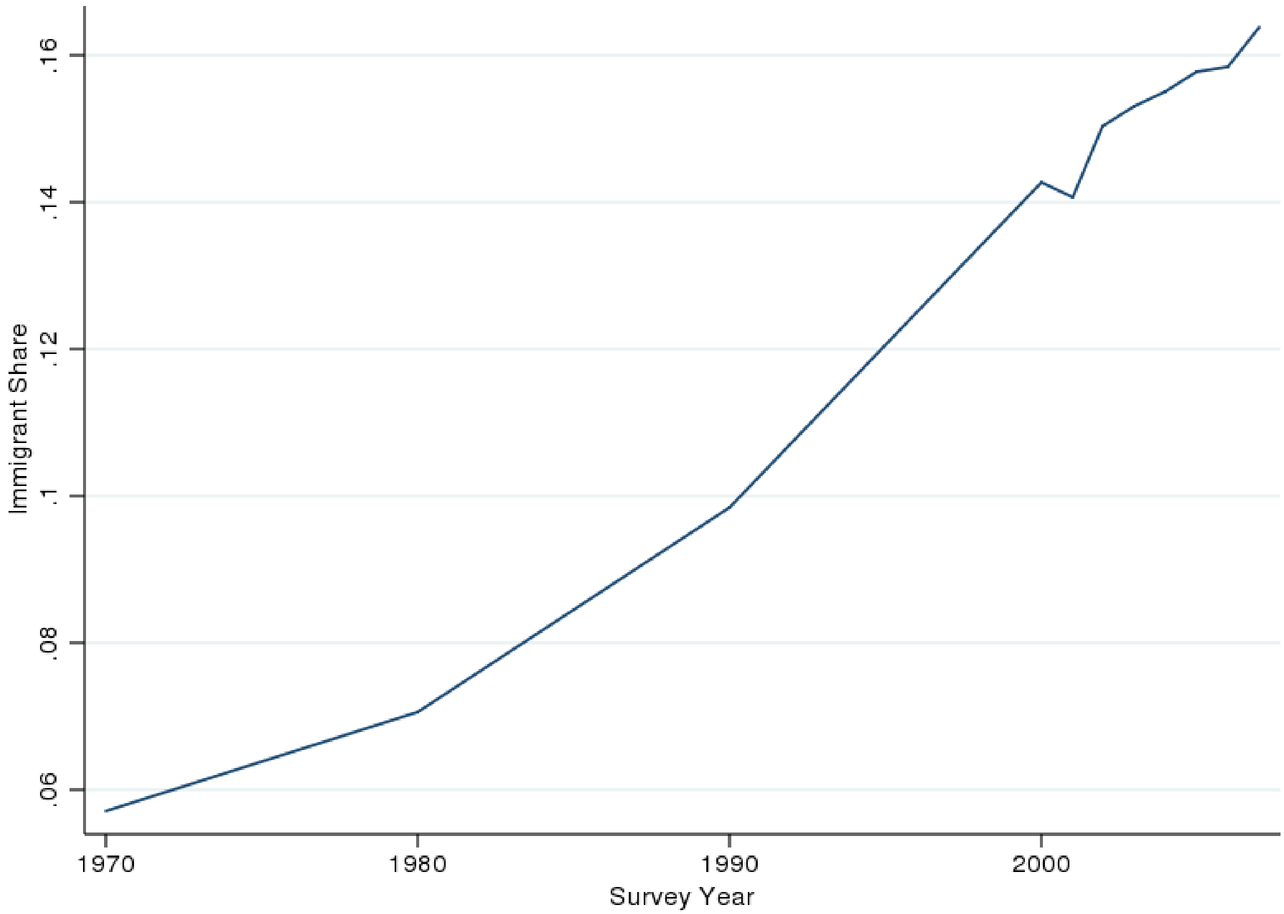

Figure 1: Immigrant Share in Adult Population

Notes: immigrants are non-citizens and naturalized citizens. Sample is restricted to men and women ages 16-68 with at least 2 years of potential experience. Immigrant share is the total stock of immigrants divided by the total population in the restricted sample each year.
Source: author's calculations using Census (1970, 1980, 1990 and 2000) and March CPS data (2000-2007).

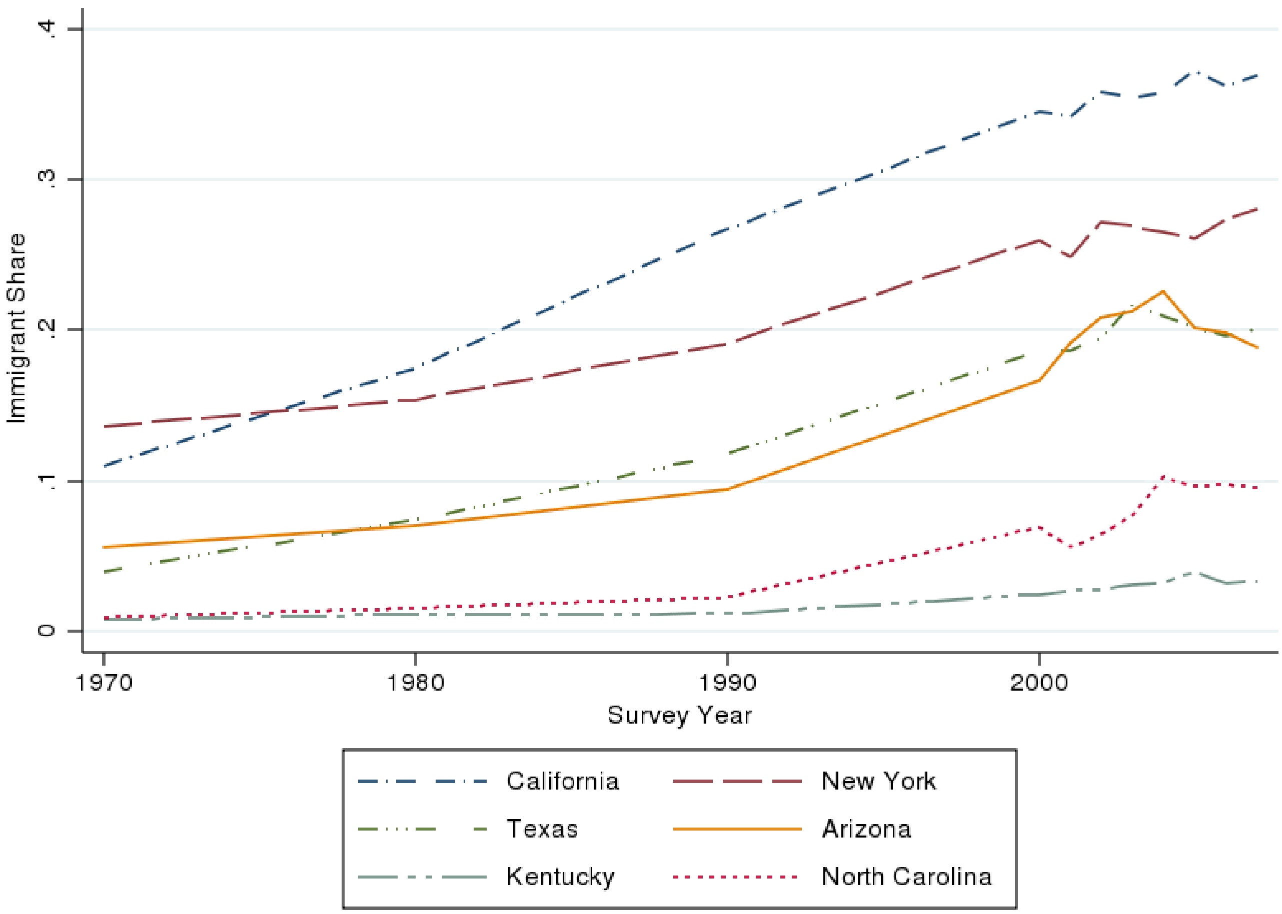

Figure 2: Immigrant Share in Adult Population for Selected States

Notes: immigrants are non-citizens and naturalized citizens. Sample is restricted to men and women ages 16-68 with at least 2 years of potential experience. Immigrant share is the total stock of immigrants divided by the total population in the restricted sample each year.
Source: author's calculations using Census (1970, 1980, 1990 and 2000) and March CPS data (2000-2007).

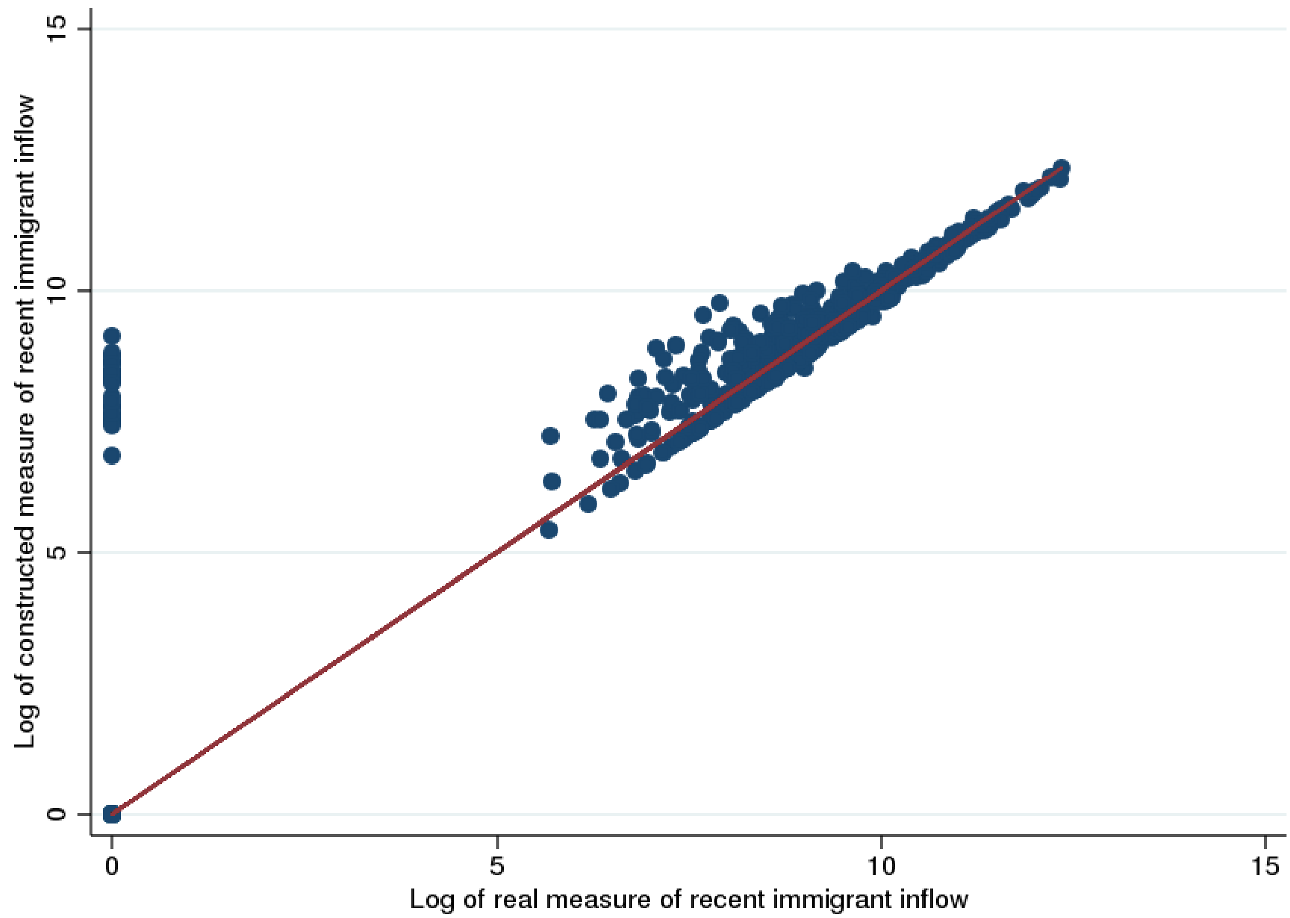

Figure 3: Comparison of Log of Real and Constructed Measures of Recent Immigrant Inflow, 1994-2007

Notes: the constructed measure considers all non-veterans who lived abroad in the previous year to be recent immigrants (see section 4.2). Real measure uses citizenship information available in the CPS beginning in 1994. 45 degree line added for reference.

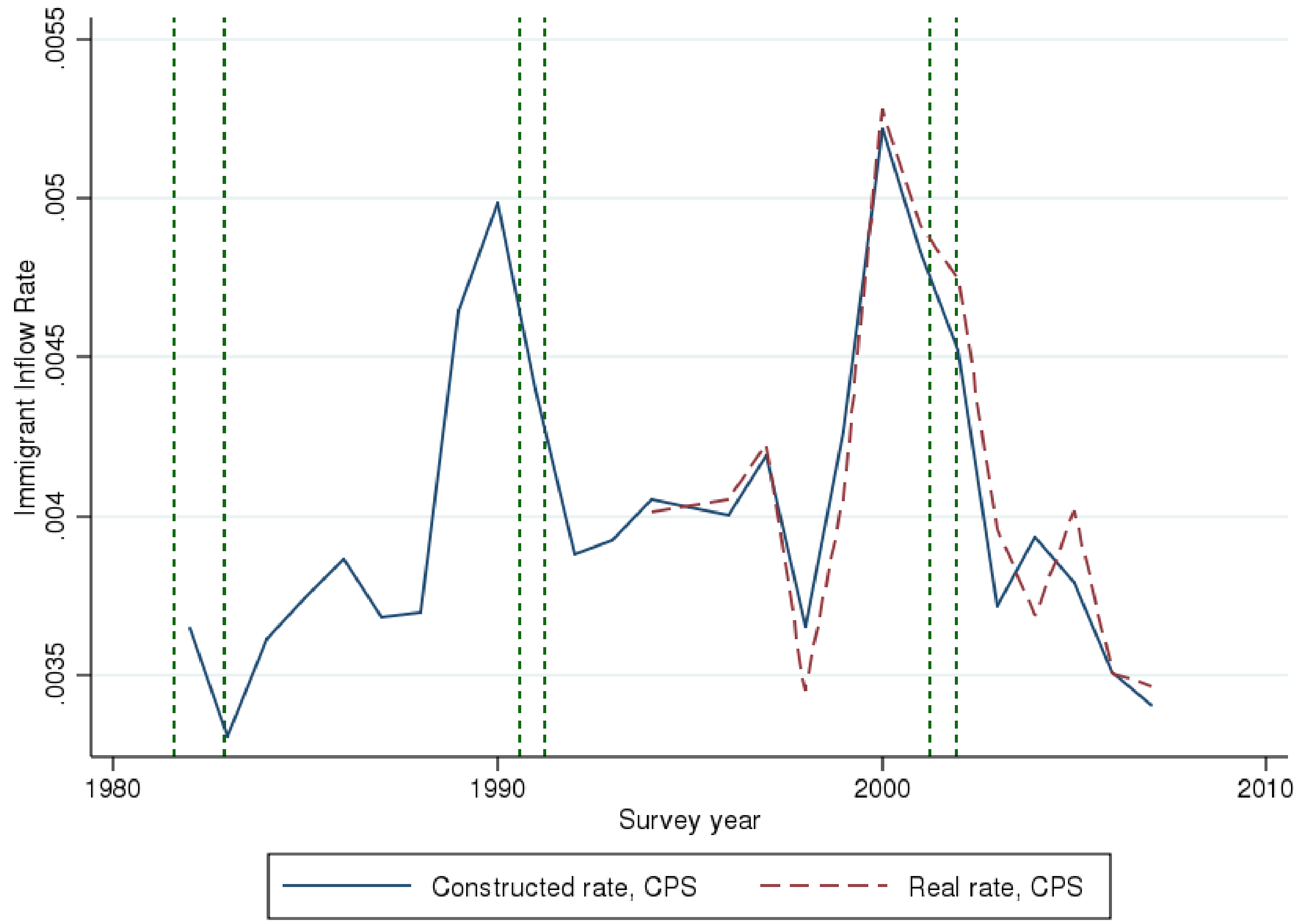

Figure 4: Yearly Immigrant Influx Rate, 1982-2007

Notes: yearly immigrant influx rate calculated using non-veterans who lived abroad as a proxy for recent immigrants (see section 4.2). Real rate calculated using citizenship status available in the CPS since 1994. The vertical lines correspond to the business cycle's peak and trough contraction dates published by the NBER's Business Cycle Dating Committee.

Figure 5: Orthogonalized Impulse Response Functions
Model in Table 3: Net-Migration Rate, Recent Immigrant Inflow and Log Wage (recursive restriction). 95% Confidence Interval.

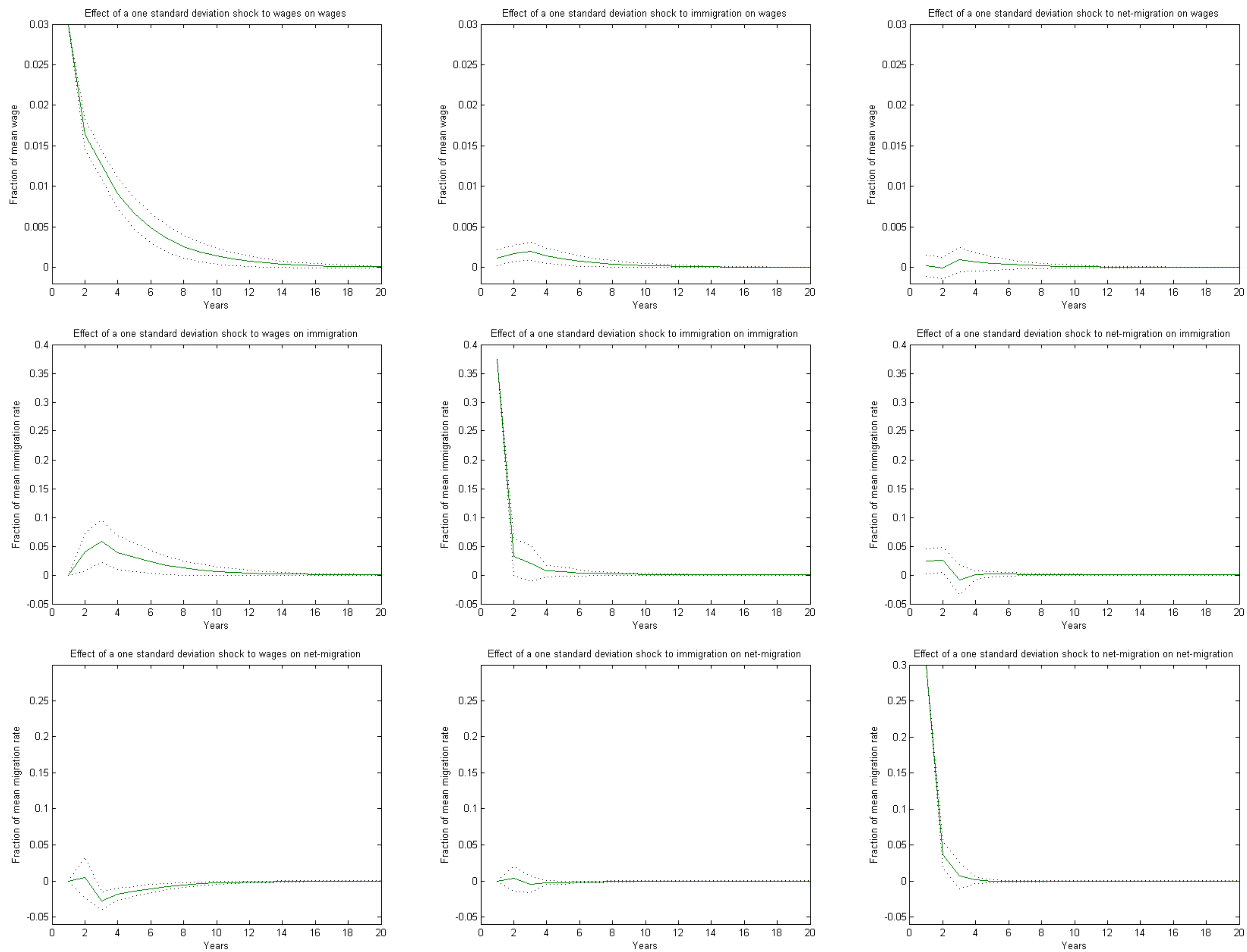

Figure 6: Orthogonalized Impulse Response Functions
Model in Table 3: Log Wage, Recent Immigrant Inflow and Net-Migration Rate. Different recursive orderings (legend).

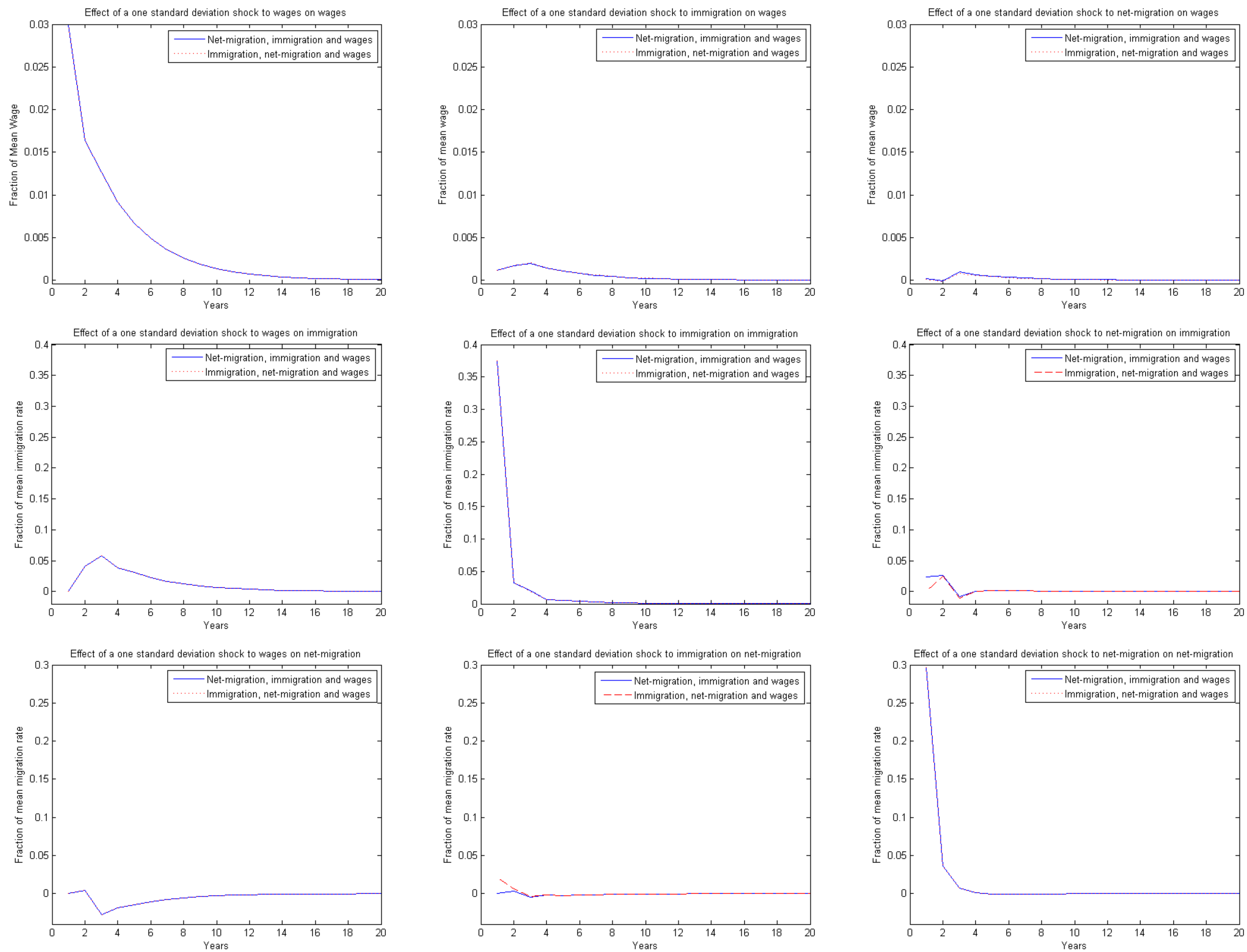

Figure 7: Orthogonalized Impulse Response Functions
Model in Table 3: Log Wage, Recent Immigrant Inflow and Net-Migration Rate. Different recursive orderings (legend).

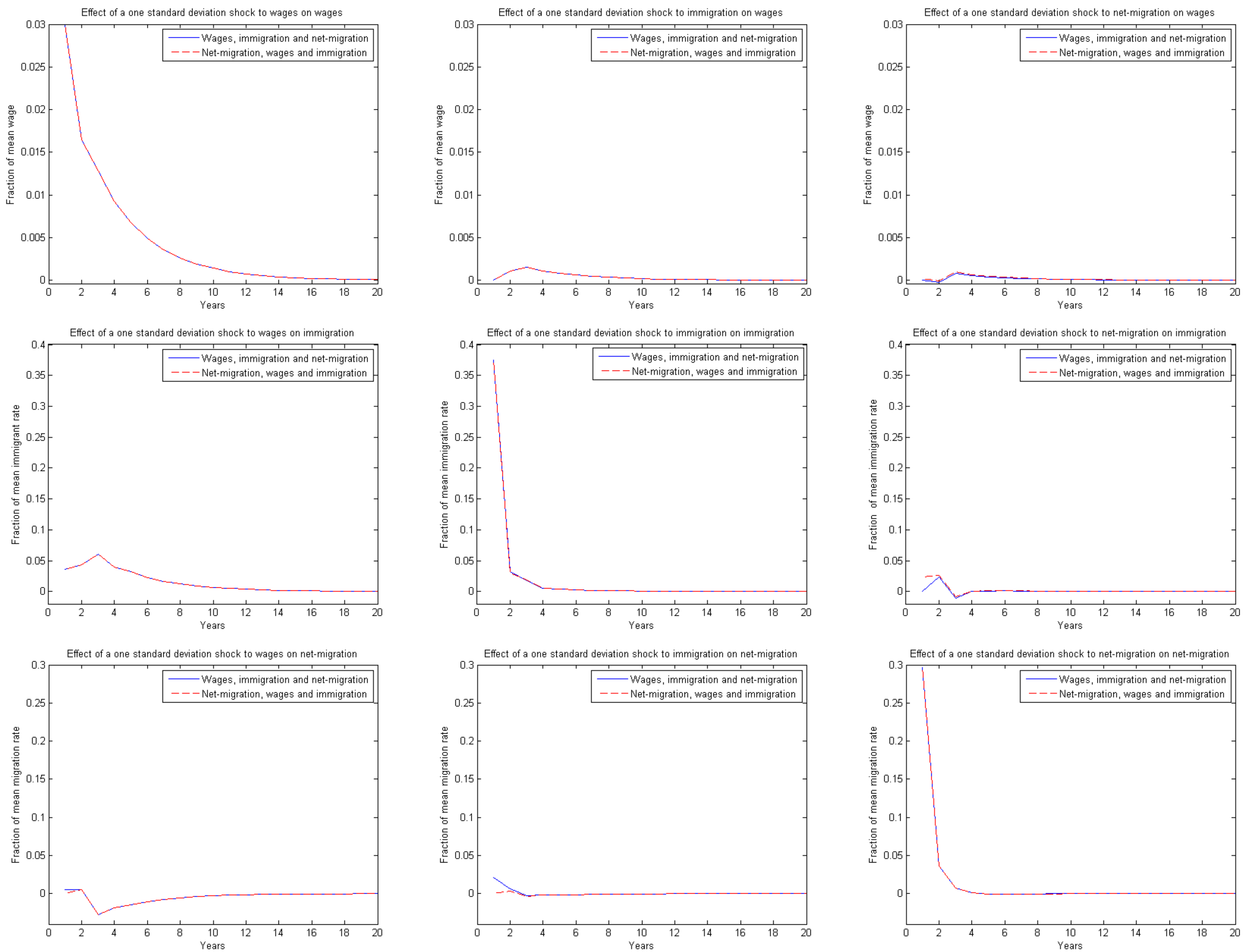

Figure 8: Orthogonalized Impulse Response Functions
Model in Table 3: Log Wage, Recent Immigrant Inflow and Net-Migration Rate. Different recursive orderings (legend).

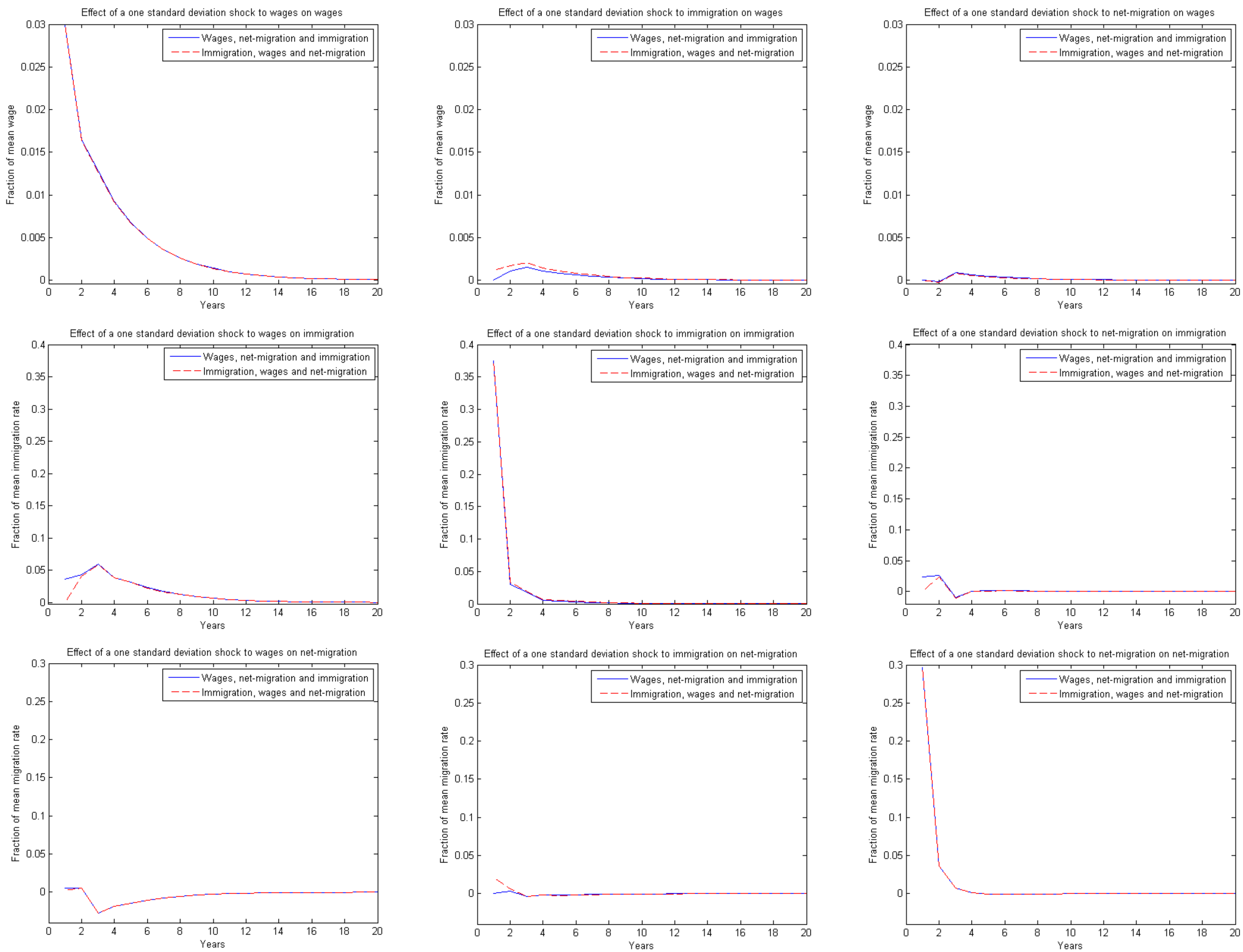

Figure 9: Orthogonalized Impulse Response Functions
Model in Table 4, Panel 1: Log Wage and Recent Immigrant Inflow. Different recursive orderings (legend).

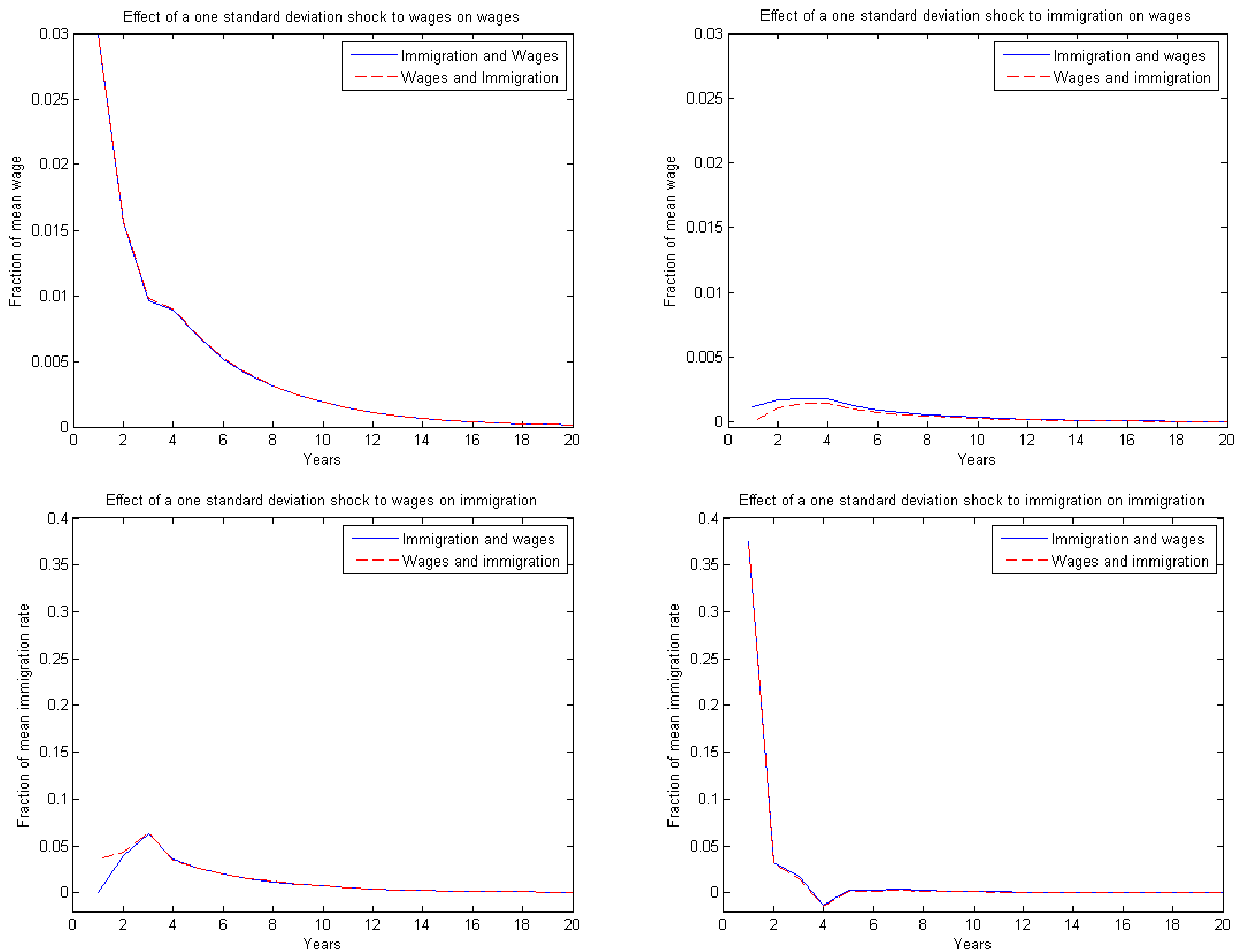

Figure 10: Orthogonalized Impulse Response Functions
Model in Table 4, Panels 2 and 3: Log Wage and Recent Immigrant Inflow, by education. Recursive Ordering: Immigration and Wages

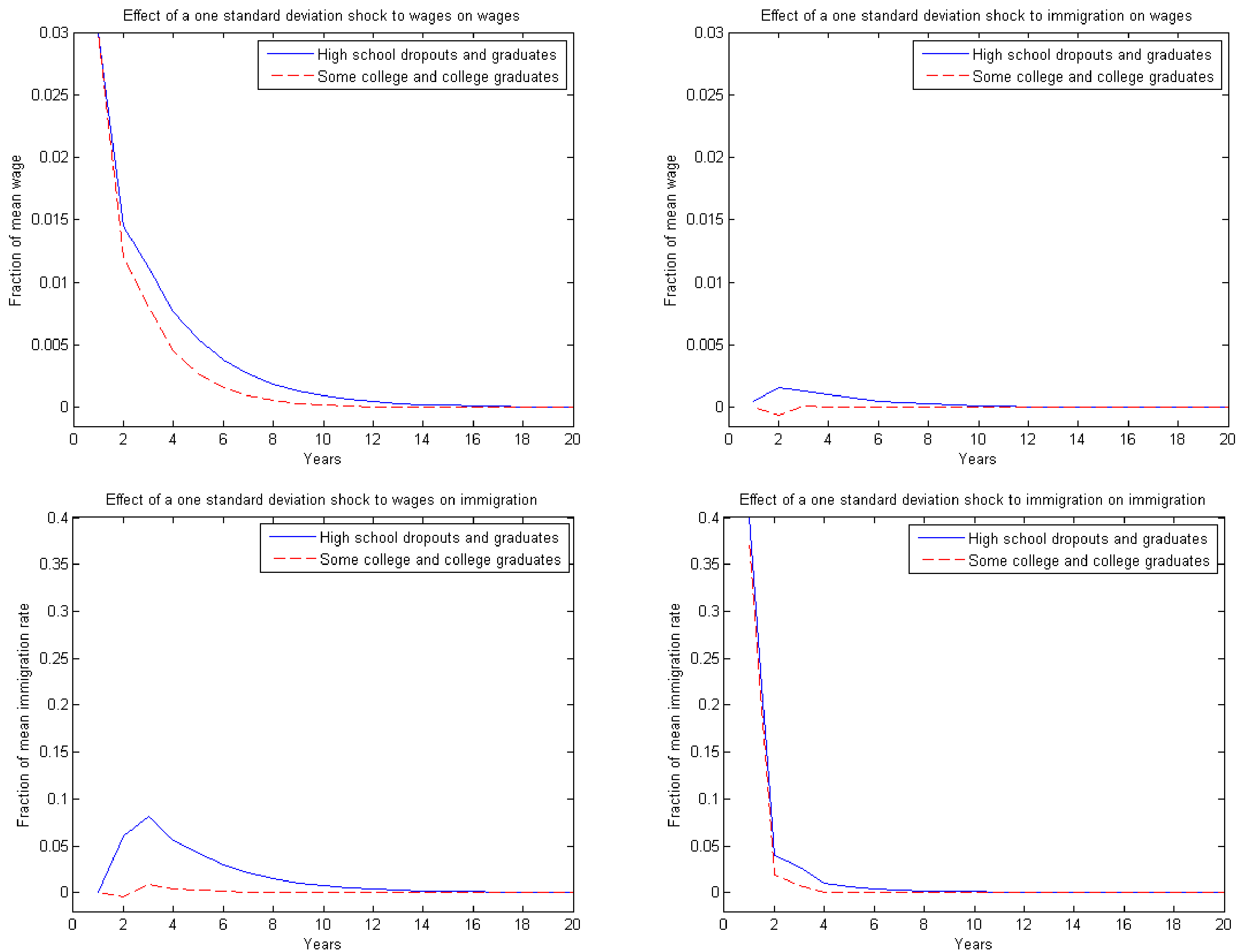

Figure 11: Orthogonalized Impulse Response Functions
Model in Table 4, Panels 2 and 3: Log Wage and Recent Immigrant Inflow, High School Dropouts and Graduates Only. Recursive Ordering: Immigration and Wages. 95% Confidence Interval.

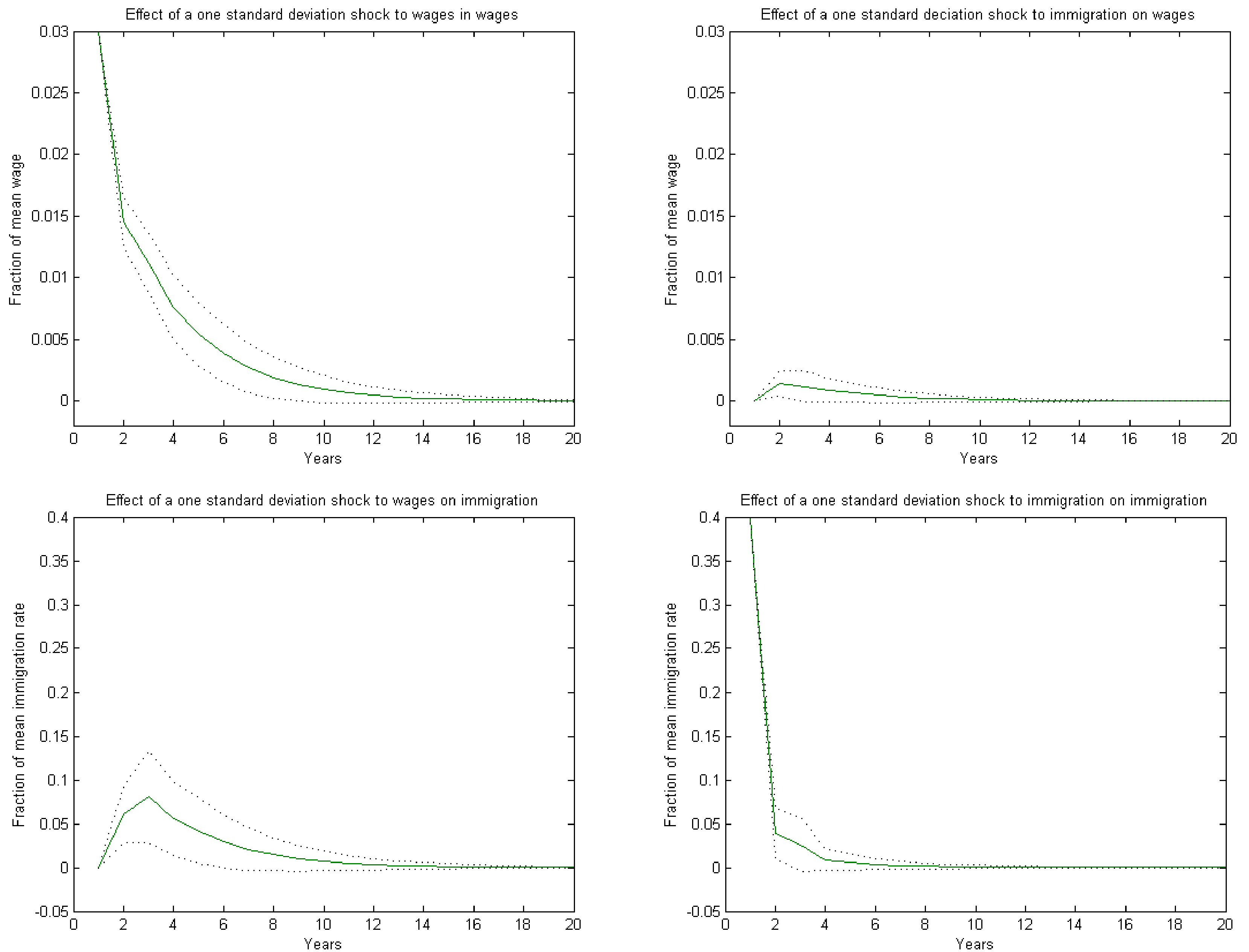

Table 1: US States in the sample

Alabama	Mississippi
Arizona	Missouri
Arkansas	Nebraska
California	New Jersey
Colorado	New Mexico
Connecticut	New York
Florida	North Carolina
Georgia	Ohio
Illinois	Oklahoma
Indiana	Oregon
Iowa	Pennsylvania
Kansas	South Carolina
Kentucky	Tennessee
Louisiana	Texas
Maine	Utah
Maryland	Virginia
Massachusetts	Washington
Michigan	West Virginia
Minnesota	Wisconsin

Notes: the analysis is restricted to the 38 states which had more than a million residents in March of 1982.

Table 2: Summary Statistics

	Mean	St. Deviation	Minimum	Maximum
Recent Immigrant inflow rate	0.0040	0.0029	0.0000	0.0149
Log wage	2.6980	0.1031	2.3806	2.9686
In-migration rate	0.0269	0.0128	0.0059	0.0852
Out-migration rate	0.0266	0.0098	0.0010	0.0955
Net-migration rate (in-out)	0.0003	0.0105	-0.0731	0.0588
High School Dropouts and Graduates Only				
Recent Immigrant inflow rate	0.0042	0.0040	0.0000	0.0283
Log wage	2.4901	0.0843	2.2278	2.7428
In-migration rate	0.0232	0.0132	0.0026	0.0895
Out-migration rate	0.0228	0.0105	0.0000	0.1068
Net-migration rate (in-out)	0.0004	0.0116	-0.0770	0.0503
Some College and College Graduates Only				
Recent Immigrant inflow rate	0.0036	0.0024	0.0000	0.0153
Log wage	2.9034	0.0991	2.5770	3.1670
In-migration rate	0.0313	0.0150	0.0059	0.0999
Out-migration rate	0.0310	0.0126	0.0025	0.1212
Net-migration rate (in-out)	0.0003	0.0136	-0.0746	0.0721

Notes: statistics for the 26 years and 38 US states used in the analysis. Series where constructed using a sample of men and women aged 16-68 and with at least 2 years of potential experience. Survey weights were used when constructing the series and the statistics were calculated for the 988 cells, using the cell population as weight. Recent immigrant inflow is constructed from the sample of people who lived abroad in the year previous to the survey and are not veterans, as explained in section 4.2.

Table 3: Vector Autoregression Results
Log Wage, Recent Immigrant Inflow and Net-Migration Rate

	Log wage	Immigrant inflow	Net-migration rate
Immigrant inflow lag 1	0.073	0.081	0.006
	(0.042)	(0.054)	(0.020)
Immigrant inflow lag 2	0.054	0.037	-0.008
	(0.035)	(0.045)	(0.014)
Net-migration lag 1	-0.032	0.121	0.120
	(0.103)	(0.068)	(0.039)
Net-migration lag 2	0.111	-0.074	0.010
	(0.101)	(0.078)	(0.041)
Log wage lag 1	0.546	0.054	0.004
	(0.039)	(0.028)	(0.016)
Log wage lag 2	0.119	0.044	-0.028
	(0.027)	(0.031)	(0.014)
R^2	0.96	0.62	0.35
Wald Tests P-values (joint test of all lags of the indicated variable)			
Log Wage = 0	–	0.0164	0.0021
Recent immigrant inflow = 0	0.0763	–	0.8575
Net-migration rate = 0	0.5418	0.1346	–
Granger Causality Tests P-values			
H_0: Wages do not Granger-cause immigration and net-migration			0.0000
H_0: Immigration and net-migration do not Granger-cause wages			0.1029
H_0: Immigration does not Granger-cause wages and net-migration			0.1884
H_0: Wages and net-migration do not Granger-cause immigration			0.0132
H_0: Net-migration does not Granger-cause wages and immigration			0.2086
H_0: Wages and immigration do not Granger-cause net-migration			0.0030

Notes: variables constructed using CPS data as explained in section 4.2. Each column shows the coefficients of one equation in a panel vector autoregression system like (21). Each regression has 912 observations. All regressions include state and year fixed effects and are weighted using cell size. For better exposition of the coefficients, immigrant inflow was multiplied by 10. The standard errors (shown in parentheses) are clustered at the state level.

Table 4: Vector Autoregression Results
Log Wage and Recent Immigrant Inflow

	Log wage	Recent immigrant inflow
Panel 1: All Sample		
	Log wage	Recent immigrant inflow
Immigrant inflow lag 1	0.073	0.082
	(0.042)	(0.056)
Immigrant inflow lag 2	0.053	0.030
	(0.038)	(0.048)
Immigrant inflow lag 3	0.036	-0.053
	(0.032)	(0.065)
Log wage lag 1	0.518	0.053
	(0.046)	(0.029)
Log wage lag 2	0.049	0.052
	(0.035)	(0.030)
Log wage lag 3	0.096	-0.004
	(0.034)	(0.030)
R^2	0.96	0.62
Wald Tests P-values (joint test of all lags of the indicated variable)		
Log Wage = 0	–	0.0115
Recent immigrant inflow = 0	0.1351	–
Panel 2: High School Drop-Outs and Graduates Only		
	Log wage	Recent immigrant inflow
Immigrant inflow lag 1	0.088	0.097
	(0.041)	(0.046)
Immigrant inflow lag 2	0.022	0.048
	(0.039)	(0.043)
Log wage lag 1	0.482	0.081
	(0.042)	(0.027)
Log wage lag 2	0.132	0.062
	(0.042)	(0.036)
R^2	0.90	0.63
Wald Tests P-values (joint test of all lags of the indicated variable)		
Log Wage = 0	–	0.0082
Recent immigrant inflow = 0	0.1023	–
Panel 3: Some College and College Graduates Only		
	Log wage	Recent immigrant inflow
Immigrant inflow lag 1	-0.039	0.051
	(0.045)	(0.043)
Immigrant inflow lag 2	0.025	0.017
	(0.044)	(0.044)
Log wage lag 1	0.400	-0.007
	(0.036)	(0.035)
Log wage lag 2	0.109	0.015
	(0.025)	(0.026)
R^2	0.93	0.32
Wald Tests P-values (joint test of all lags of the indicated variable)		
Log Wage = 0	–	0.8430
Recent immigrant inflow = 0	0.5114	–

Notes: variables constructed using CPS data as explained in section 4.2. Each column shows the coefficients of one equation in a panel vector autoregression system like (21). The regressions in panel 1 contain 874 observations, the ones in panels 2 and 3 contain 912 observations each. All regressions include state and year fixed effects and are weighted using cell size. For better exposition of the coefficients, immigrant inflow was multiplied by 10. The standard errors (shown in parentheses) are clustered at the state level.

Appendix Table 1: Vector Autoregression Results

Log Wage, Recent Immigrant Inflow and Out-Migration Rate

	Log wage	Immigrant inflow	Out-migration rate
Immigrant inflow lag 1	0.073	0.082	-0.008
	(0.042)	(0.055)	(0.012)
Immigrant inflow lag 2	0.058	0.035	-0.007
	(0.035)	(0.046)	(0.009)
Out-migration lag 1	0.152	-0.100	0.172
	(0.133)	(0.083)	(0.047)
Out-migration lag 2	-0.106	-0.017	0.010
	(0.124)	(0.098)	(0.037)
Log wage lag 1	0.549	0.052	0.001
	(0.039)	(0.028)	(0.009)
Log wage lag 2	0.116	0.046	0.012
	(0.027)	(0.031)	(0.010)
R^2	0.96	0.62	0.59
Wald Tests P-values (joint test of all lags of the indicated variable)			
Log Wage = 0	–	0.0156	0.3781
Recent immigrant inflow = 0	0.0717	–	0.6382
Out-migration rate = 0	0.5158	0.4791	–
Granger Causality Tests P-values			
H_0: Wages do not Granger-cause immigration and out-migration			0.0115
H_0: Immigration and out-migration do not Granger-cause wages			0.1266
H_0: Immigration does not Granger-cause wages and out-migration			0.0780
H_0: Wages and out-migration do not Granger-cause immigration			0.0139
H_0: Out-migration does not Granger-cause wages and immigration			0.4784
H_0: Wages and immigration do not Granger-cause out-migration			0.5043

Notes: variables constructed using CPS data as explained in section 4.2. Each column shows the coefficients of one equation in a panel vector autoregression system like (21). Each regression contains 912 observations. All regressions include state and year fixed effects and are weighted using cell size. For better exposition of the coefficients, immigrant inflow was multiplied by 10. The standard errors (shown in parentheses) are clustered at the state level.

Appendix Table 2: Vector Autoregression Results

Log Wage, Recent Immigrant Inflow and In-Migration Rate

	Log wage	Immigrant inflow	In-migration rate
Immigrant inflow lag 1	0.071	0.080	-0.004
	(0.042)	(0.055)	(0.015)
Immigrant inflow lag 2	0.054	0.041	-0.017
	(0.036)	(0.045)	(0.015)
In-migration lag 1	0.087	0.137	0.177
	(0.173)	(0.092)	(0.043)
In-migration lag 2	0.102	-0.168	0.092
	(0.140)	(0.116)	(0.052)
Log wage lag 1	0.546	0.057	0.005
	(0.040)	(0.029)	(0.013)
Log wage lag 2	0.118	0.041	-0.015
	(0.028)	(0.030)	(0.012)
R^2	0.96	0.62	0.77
Wald Tests P-values (joint test of all lags of the indicated variable)			
Log Wage = 0	–	0.0146	0.3183
Recent immigrant inflow = 0	0.0784	–	0.3238
In-migration rate = 0	0.7139	0.1582	–
Granger Causality Tests P-values			
H_0: Wages do not Granger-cause immigration and in-migration			0.0040
H_0: Immigration and in-migration do not Granger-cause wages			0.1575
H_0: Immigration does not Granger-cause wages and in-migration			0.0984
H_0: Wages and in-migration do not Granger-cause immigration			0.0077
H_0: In-migration does not Granger-cause wages and immigration			0.3688
H_0: Wages and immigration do not Granger-cause in-migration			0.2996

Notes: variables constructed using CPS data as explained in section 4.2. Each column shows the coefficients of one equation in a panel vector autoregression system like (21). Each regression contains 912 observations. All regressions include state and year fixed effects and are weighted using cell size. For better exposition of the coefficients, immigrant inflow was multiplied by 10. The standard errors (shown in parentheses) are clustered at the state level.