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An examination of the effect of immigration on income inequality: A Gini index approach

Brian Hibbs
Indiana University South Bend

Gihoon Hong
Indiana University South Bend

Abstract

This paper examines the impact of immigration on income inequality. Using data from 1990 and 2000 US Censuses, we link the changes in income inequality as measured by the Gini index with immigrant flows into each metropolitan area in the U.S. We address endogeneity of immigrant inflows by relying on variation in historical distribution of earlier immigrants from each source country. The results suggest that using the Gini index as a measure of income inequality results in immigration having stronger effects on inequality than the findings of other studies based on changes in skill-related wage premiums. Interestingly, low-skilled immigration as proxied by Mexican immigration is found to have little effect on income inequality. However, the estimates are subject to a downward bias if native workers respond to an increase in low-skilled immigration by moving away from the affected locations.

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Contact: Brian Hibbs - bhibbs@iusb.edu, Gihoon Hong - honggi@iusb.edu.
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1. Introduction

Due to the consistent increases in income inequality and immigrant population in the U.S. since the 1980s, economists have speculated if there is any causal relationship between the two distinct trends.[1] For example, Card (2009) uses city level wage data and shows that immigration explains about 5% of the rise in income inequality between 1980 and 2000. A number of other studies using city-level data consistently find small effects of immigration on native wages (see Card 2001, and Friedberg 2001, and Card and Lewis 2007, and Card 2007). One common approach with the existing studies is that the empirical analysis on the distributional impacts of immigration is mostly focused on between-group inequality, where groups are identified based on observable characteristics such as age, education, experience, etc. As a result, inequality is measured by the differences between the wages of certain skill groups or *relative* wages (see Borjas 2003, and Manacorda, Manning and Wadsworth 2012, and Ottaviano and Peri 2012).

However, one potential issue with these studies is that the estimates can be sensitive to alternative definitions of the group categories. For example, using national census data, Aydemir and Borjas (2007) show that immigration reduces real wages among low skilled workers and increases income inequality in the United States. The differences in findings between Card and Borjas seem to be attributable to differences in the education groups specified. Card (2009) notes that this is because among immigrants to the U.S., there is a higher share of high school dropouts among immigrants than natives but a similar share of high school equivalent workers. In addition, the recent literature on income inequality provides evidence that the rise in inequality in the U.S. has been coincided with the rapid increases in within-group inequality in more recent years (see Lemieux 2008), which calls for a new empirical approach to account for the changes in inequality along the distribution of income.

In this paper, rather than determining the effects of immigration in inequality using the wages of two different skill groups, we use changes in the Gini index between 1990 and 2000 correlated with changes in the share of immigrants in each U.S. metropolitan area. While this method may have less theoretical explanatory power, it should offer a more accurate and complete measure of income inequality by including residual inequality not included in wage premiums between different skill groups. This implies that the use of the Gini index should better capture changes in within-group inequality as well as between-group inequality. The results show that after correcting for endogeneity associated with immigrant location decisions, immigration explains about 24% of changes in inequality, with a 1% increase in immigrant population being associated with about a 0.66 point increase in Gini coefficients between 1990 and 2000 for a given metropolitan area. We also find that low skilled immigration, with Mexican immigration used as a proxy for it, is not statistically significant in explaining the changes in inequality. Although the estimates may be subject to biases due to native out-migrations, the results still indicate a need for alternative theories that better capture how immigration influences inequality.

The rest of the paper is structured as follows. Section 2 presents the empirical model. Section 3 discusses the data. The results are presented in Section 4. We conclude in Section 5.

2. Empirical Specification

In order to examine the effects of immigration on income inequality, we consider the following regression equation:

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[1] According to the OECD Database (http://stats.oecd.org/), the before-tax Gini coefficient has increased from 0.43 in 1980 to 0.49 in 2010. At the same time, U.S. Census reports that the number of immigrants in the U.S. grew from 14.1 million to 40 million over the three decades.

$$\Delta GINI_m = \alpha + \beta I_m + \varepsilon_m, \quad (1)$$

where the dependent variable $\Delta GINI_m$ is the change in the Gini index for a metropolitan area *m* from 1990 to 2000; I_m is the number of immigrants who arrived in *m* between 1990 and 2000[2]; ε_m captures city-specific random shocks to income inequality over the same period. However, one potential concern is that the tendency of immigrants to cluster in larger cities may produce spurious correlation with the dependent variable, if the size of the city happens to be correlated with income inequality as a result of factors other than immigration. For example, a larger city may be capable of supporting a wider variety of industries and more firms within an industry which could create external economies of scale by generating learning effects between people from these different industries and firms. In this case, high-skilled workers are more likely to be complements to one another in larger cities. If high-skilled workers are also more likely to cluster in larger cities similar to immigrants, perhaps due to the larger variety of goods and services that would be available to them in these areas, then this clustering combined with the complementary nature between immigrant and high-skilled native labor would result in higher inequality. Therefore, it is expected that these scale effects would bias the coefficient β for the immigrant inflow I_m upward, if not controlled properly. Following Card (2001) and Peri and Sparber (2011), we address the issue by normalizing the immigrant population by the city's initial population at the beginning of the period observed, 1990.[3] Therefore, (1) is modified as:

$$\Delta GINI_m = \alpha + \beta\left(\frac{I_m}{P_m^{1990}}\right) + \varepsilon_m, \quad (2)$$

where P_m^{1990} represents the 1990 population in metropolitan area *m*. The model would then measure the correlation between the changes in the Gini index of a metropolitan area between 1990 and 2000 with the ratio of new immigrants to citizens in that area.

Another issue with the specification in (1) concerns endogenous location decisions of immigrants. When immigrants locate within the U.S., they consider differences in relative wages between cities. This implies that immigrants are more likely to place in cities that offer higher wages in the occupations they are most likely to be employed in. To the extent that these differences in relative wages also influence the inequality within those metropolitan areas, (1) is subject to omitted variable biases. To assess the causal effect of immigration on inequality, we adopt an instrumental variable from the literature (see Card 2001, and Wozniak and Murray 2012) that predicts current immigration in a city as a proportion of total immigration using the geographic distribution of earlier immigrants from the same source country across the U.S. Specifically, we compute the predicted immigrant flows into location *m* as:

$$SP_m = \sum_s M_s \, \lambda_{sm}, \quad (3)$$

where SP_m is the supply-push immigrant flows into location *m*, as developed in Card (2001); M_s is the total number of new immigrants from source country *s* arriving in the U.S. between 1990 and 2000; λ_{sm} is the fraction of immigrants from source country *s* who were observed to locate in *m* as of 1990. Then under the assumptions that newly arriving immigrants are allocated within the U.S. following the same pattern as the earlier immigrant cohorts and the historical geographic distribution of immigrants are independent of local economic conditions,

[2] Although existing immigrants may influence income inequality as well, the first difference specification in (1) does not allow existing or all immigrants to enter the regression equation as independent variables.

[3] An alternative way to addressing the scale effects is to control directly for the size of the city. However, Wright et al. (1997) show that the strong correlation between the city size and immigrant population may lead to multicollinearity.

the instrumental variable provides arguably exogenous variation to identify the causality between immigration and inequality.

3. Data

At the national, state, and local level, previous research have indicated that immigration to the US has a positive, but relatively small, impact on native wages and income inequality (see Card 2001, and Friedberg 2001, and Card and Lewis 2007). However, one consistent problem with these studies is that the measure of inequality used is incomplete. Rather than using the Gini index, inequality in the literature is measured by the differences between the wages of certain skill groups, which does not include changes in residual inequality, or as the difference between the median and the mean income in Martin (2013). In this paper, to determine more accurately the impact of immigration on inequality, we construct Gini indices for 237 metropolitan areas, consistently defined from 1990 to 2000, using a sample of about 10 million people using census data.[4] In constructing the final sample included in the estimation, we focus on working age population (20<age<65) with positive reported income.[5] In addition, we drop observations with missing information on metropolitan area. New immigrants are defined as those who have immigrated to a given metropolitan area between 1990 and 2000. Data are also collected for the sensitivity analysis on the share of manufacturing workers and the share of college graduates in the labor force in 1990 for each metropolitan area. The city level data include the information on the metropolitan area, local immigrant inflows as predicted by the supply-push instrument, and the Gini indices for the metropolitan area in 1990 and 2000. The individual-level data contain information on the year of survey, the metropolitan area in which the respondent resides, age, educational attainment, marital status, occupation, immigration status including the year in which they immigrated to the US if they are immigrants as well as labor income. The data on annual income are used to calculate the Gini index at the city level.

Table I: Descriptive Statistics

Variable	Mean	Std. Dev.	Min	Max	Nobs.
Metropolitan area	456	275	4	936	237
Immigrant inflows	494	1650	46	17403	237
Gini index in 1990	0.432	0.025	0.345	0.518	237
Gini index in 2000	0.440	0.028	0.371	0.565	237
College-graduate share in 1990	0.228	0.063	0.111	0.436	237
Manufacturing share in 1990	0.193	0.080	0.039	0.463	237

Table I presents descriptive statistics for the main variables used in the regression. It shows that there is significant variation in immigration as calculated with the supply-push instrument, and that immigration is concentrated among a relatively small number of cities. This is because there is a clear skew towards the upper end based on the mean being larger than the median, which confirms our prediction that immigrants tend to cluster. At the same time, both the mean and variance of Gini index are shown to have increased from 1990 to 2000. Insofar as the higher standard deviation in Gini indices in 2000 is the result of

[4] We employ a decomposition method to estimate Gini coefficients at the city level as described in Jenkins (1999). Microdata used in this study are acquired from the IPUMS-USA database (Ruggles et al, 2010).
[5] Observations with implausibly high labor income (annual labor income>$1 million) are dropped.

immigrant clustering in certain areas, this seems to indicate before running any specific regression that immigration does have at least a small positive effect on inequality.

4. Results

Table II: The impacts of immigration on income inequality (instrumental variables estimates)

	[1]	[2]	[3]	[4]
Immigrant share	.660***	.629***		
	(.084)	(.087)		
Mexican share			.155	.235
			(.140)	(.145)
Non-Mexican immigrant share			1.015***	.923***
			(.096)	(.112)
Manufacturing share, 1990		.017		.006
		(.014)		(.014)
College-graduate share, 1990		.074***		.041**
		(.018)		(.020)
Constant	-.003*	-.023***	-.004**	-.014**
	(.001)	(.006)	(.001)	(.006)
Adjusted R^2	.243	.292	.313	.323
Observations	237	237	237	237

Notes: Standard errors are in parentheses. *** , **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

The instrumental variables (IV) regression results are presented in Table II. Overall, we find that immigration results in a significant increase in local inequality. Specifically, a 1% increase in immigrant population relative to the population in 1990 within a metropolitan area is predicted to result in a 0.66 point increase in the Gini index of that metropolitan area. The adjusted R^2 is 0.243, suggesting that immigration alone explains about one-fourth of the change in inequality at the local level, substantially more than the existing literature found.[6] This could be explained by the use of the Gini index which captures more of the effects in the changes in residual inequality within a skill group.

As a sensitivity analysis, cross-sectional variations in the sectoral and educational composition of the labor force are examined using the following model:

$$\Delta GINI_m = \alpha + \beta_1(\frac{I_m}{P_m^{1990}}) + \beta_2 MANU1990_m + \beta_3 COL1990_m + \varepsilon_m, \qquad (4)$$

where $MANU1990_m$ and $COL1990_m$ refer to the share of manufacturing workers and the share of college graduates in the labor force in the metropolitan area *m* in 1990, respectively. The use of these variables is based on the premise that, in the long run, these metropolitan areas' manufacturing and college graduate shares indicate systematic differences between these areas that may influence both inequality and immigration patterns simultaneously. For example, it is conceivable that immigrants are attracted to areas with a higher manufacturing share due to better employment prospects. To the degree that these city characteristics also influence income inequality in the region, the IV regression results are subject to omitted variable biases. By including these control variables in the regression, we can reasonably verify whether the correlation in the previous model falsely identifies the cause of the correlation. Column [2] in Table II indicates that the impact of immigration on income inequality is fairly robust, although the magnitude of the immigration effect is reduced. The

[6] For example, Card (2009) finds that immigration explains between 4% and 6% of the variation in income inequality.

results support the claim that the statistical correlation is a result of a direct causal relationship between changes immigration and changes in income inequality.

Although the empirical model used above better measures the overall effects of inequality by using the Gini index, it is not useful for a theoretical explanation of how and/or why immigration increases inequality. For example, existing theories on immigration and income inequality explain the correlation by linking the changes in inequality to the skill distribution of immigrants, usually with educational attainment used as a proxy (see Aydemir and Borjas 2007, and Card 2009). One way to incorporate immigrant skill heterogeneity into the current model is to split the immigration variable into different groups that are also proxies for different skill groups. For this, we propose the following model:

$$\Delta GINI_m = \alpha + \beta_1(\frac{I_m^{MX}}{P_m^{1990}}) + \beta_2(\frac{I_m^{OTHER}}{P_m^{1990}}) + \varepsilon_m, \tag{5}$$

where $\frac{I_m^{MX}}{P_m^{1990}}$ is the population of Mexican immigrants and divided by the metropolitan area's 1990 population; $\frac{I_m^{OTHER}}{P_m^{1990}}$ is the corresponding ratio for the all other immigrant group excluding the Mexican population. Mexican immigrants make up by far the largest immigrant population in the U.S., and it is generally understood that they are a relatively low-skilled group (see Borjas and Katz 2007, and Hanson 2006).[7] Therefore, equation (5) allows us to investigate the differential effects of immigration, if any, on inequality by immigrant skill level. A significantly positive estimate of β_2 would imply that the increase in inequality comes from the greater supply of low-skilled labor reducing the wages of low-skilled workers relative to high-skilled workers. However, Column [3] in Table II shows that the effect of Mexican immigration on inequality is small and is not statistically significant. Taking Mexican immigration as a proxy for low-skilled immigration in general, and consequently the other immigrant group as a proxy for relatively high-skilled immigration, the results seem to suggest that inequality only increases as a result of high-skilled immigration, while low-skilled immigration does not have a significant effect on income inequality. The small effect and statistical insignificance of Mexican immigration may be because the model does not control for the endogenous movement of natives in response to immigration between metropolitan areas. Increased immigration in an area may result in native out-migration from the affected area, thereby dampening the effects of immigration on native labor supply where the immigration is measured. If this is the case, the out-migration would result in a stronger relationship between immigration and inequality as the area measured is widened as discussed in Borjas (2006). Because the current analysis of Gini indices does not control for native out-migration, this implies that the estimates yielded here may understate the effects of immigration on income inequality. However, it is still not clear as to why only Mexican immigration rendered insignificant when it is by far the largest immigrant group. One possible explantion is that natives may be more sensitive to the arrival of Mexican immigrants than other groups. Column [4] in Table II shows that the same effect remains when the two variables, $MANU1990_m$ and $COL1990_m$, are added to control for metropolitan area. Interestingly, the adjusted R^2 rises to 0.313 with the separate control for Mexican immigration (without the sensitivity analysis, and 0.323 with it), suggesting that immigration in this model can explain nearly a third of the change in inequality. This indicates that Mexican immigration possesses substantial explanatory power for inequality despite the statistical insignificance and the theoretical problems associated with the out-migration which the model does not account for.

[7] While it is the convention in the literature that skill groups are defined by educational attainment, it is not compatible with our preferred instrumentation strategy.

5. Conclusion

In this study, we show that when a more complete measure of inequality is used, the effects of immigration on inequality are larger and immigration explains a greater portion of the variation in inequality. This suggests that other studies using the wage premiums of different skill groups have not been capturing the total impact of immigration on income inequality. Despite the large and statistically significant effects of immigration on inequality found, it is important to point out that the empirical specification used here still may underestimate the total impact of immigration in income inequality insofar as it doesn't account for native out-migration in response to immigration.

It should also be noted that the discussions about the channel through which immigration affects income inequality are exclusively focused on the changes in labor supply due to immigration, while implicitly assuming that labor demand in a metropolitan area is fixed. However, this is not a realistic assumption because immigrants presumably spend at least some of their income in the market to which they have moved. To the extent that immigration-induced increase in labor demand is not balanced across different skill groups or industries, failing to account for the changes in product demand may lead to an incomplete analysis of immigration and inequality. This suggests that an examination of immigrant spending patterns and their consequent influence on relative labor demand may also be useful in explaining the influence of immigration on inequality.

References

Aydemir, A., & Borjas, G. J. (2007). Cross Country Variation in the Impact of International Migration: Canada, Mexico, and the United States. *Journal of the European Economic Association, 5*(4), 663-708.

Borjas, G. J. (2003). The Labor Demand Curve Is Downward Sloping: Reexamining The Impact Of Immigration On The Labor Market. *The Quarterly Journal of Economics, 118*(4), 1335–1374.

Borjas, G. J. (2006). Native internal migration and the labor market impact of immigration. *Journal of Human Resources, 41*, 221–258.

Borjas, G. J., Freeman, R. B., & Katz, L. F. (1996). Searching for the Effects of Immigration on the Labor Market. *American Economic Review, 86*(2), 246-251.

Borjas, G. J., & Katz, L. F. (2007). The Evolution of the Mexican-Born Workforce in the United States. NBER Chapters, in: Mexican Immigration to the United States, 13-56, National Bureau of Economic Research, Inc.

Card, D. (2001). Immigrant Inflows, Native Outflows, and the Local Labor Market Impacts of Higher Immigration. *Journal of Labor Economics, 19*(1), 22–64.

Card, D. (2007). How Immigration Affects US Cities. CReAM Discussion Paper No. 11/07.

Card, D. (2009). Immigration and Inequality. *American Economic Review, 99*(2), 1-21.

Card, D., & Lewis, E. G. (2007). The Diffusion of Mexican Immigrants During the 1990s: Explanations and Impacts. In G. Borjas, *Mexican Immigration.* University of Chicago Press.

Friedberg, R. M. (2001). The impact of mass migration on the Israeli labor market. *The Quarterly Journal of Economics, 116*(4), 1373–1408.

Hanson, G. (2006). Illegal Migration from Mexico to the United States. *Journal of Economic Literature*, American Economic Association, 44(4), 869-924.

Jenkins, S. (1999). INEQDECO: Stata module to calculate inequality indices with decomposition by subgroup. Boston College Department of Economics. Retrieved from http://ideas.repec.org/c/boc/bocode/s366007.html

Lemieux, T. (2008). The changing nature of wage inequality. *Journal of Population Economics, 21*(1), 21-48.

Manacorda, M., Manning, A., & Wadsworth, J. (2012). The Impact Of Immigration On The Structure Of Wages: Theory And Evidence From Britain. *Journal of the European Economic Association, 10*(1), 120-151.

Martin, J. (2013). *Immigration: Fueling US Income Inequality.* Federation for American immigration Reform.

Ottaviano, G. I., & Peri, G. (2012). Rethinking the effect of immigration on wages. *Journal of the European Economic Association, 10*(1), 152–197.

Peri, G., & Sparber, C. (2011). Assessing inherent model bias: an application to native displacement in response to immigration. *Journal Urban Economics, 69(1), 82–91*.

Ruggles, S., Alexander, J. T., Genadek, K., & Goeke, R. (2010). *Integrated Public Use Microdata Series: Version 5.0.* University of Minnesota, Minnesota Population Center.

Wright, R. I., Ellis, M., and Reibel M. (1997). The Linkage Between Immigration and Internal Migration in Large Metropolitan Areas in the United States. *Economic Geography, 73(2), 234-254.*