Inequality Attributable to Housing Value and Immigration

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February 16, 2016

CATO WORKING PAPER
No. 37

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ABSTRACT: This paper examines the effects immigrants have on economic inequality in the United States via their bidding up of real-estate rental prices. Rognlie (2015) has argued that the net-capital share of aggregate income is rising entirely from an increase in the value of housing, not from other sources. We estimate how much immigration has contributed to the increase in rental prices based on the elasticity of demand for rentals. We then build counterfactuals to estimate what rents in certain American counties would be without immigrants. About 30.1% of housing value in 2010 is attributable to immigrants in urban areas bidding up their value. Immigration thus has a modest impact on rents and economic inequality within the United States consistent with the lower-end estimates of the immigrant-inequality literature.

Keywords: Immigration, Inequality, Housing, Piketty, Rognlie

JEL Codes: F22, R21, D30
I. Introduction

Piketty (2014) argues that capitalism is increasing the share of earning from capital share while shrinking that of wages, thus exacerbating income inequality. Rognlie (2015) criticizes and extends Piketty, showing that the increases in capital share and inequality tie in directly with long run increases in housing values. There is much scholarly work on how immigration affects earning inequality and the housing market but none that combines the two using the recent Piketty-Rognlie findings that real-estate prices drive inequality.

We seek to bridge this gap by using the findings from Saiz (2007) that show a one percentage point increase in foreign born individuals as a percentage of the total population corresponds to a one percentage point increase in housing rents. Following the result that the observed increase in inequality is caused by increases in housing prices, we use this to indirectly determine what proportion of the total change in wealth inequality observed by Piketty-Rognlie is attributable to immigrants bidding up housing prices. To make our estimation in the spirit of Saiz’ results, we estimate this for a small cross section of urban counties in America. Doing so restricts the richness of the data available, but extrapolating beyond these types of counties is not externally valid. Our results are consistent with Card (2009), who attributes little of the increase in inequality to immigration.

We started with the county-level data associated with the fifteen largest Metropolitan Statistical Areas in the United States. Because this data was unavailable for the state of Texas in 1970, we then dropped Houston and Dallas. This left us with New York City, Los Angeles, Miami, San Francisco, Philadelphia, Washington, DC, Atlanta, Boston, Phoenix, Riverside, Detroit, and Seattle. Excepting New York City and San Francisco, a single county sufficed to represent the city. We used population-weighted averages of the counties for each of the boroughs to represent New York City and the population-weighted average of San Francisco and San Mateo counties for San Francisco. We calculate the
percentage of foreign born in the county population in 1970 and the percentage of foreign born in the county population in 2010 according to the U.S. Census. Our primary variable of interest is the forty year long-difference of foreign born from 1970 to 2010.

II. Preliminaries

Immigration’s impact on inequality is a hotly debated question. Although international economic inequality could drive immigration (Lee et al. 2014), much of the past work has sought the effect on destination countries. Borjas et al. (1997) found that immigration from 1980 to 1995, combined with trade, had only a small affect on earnings inequality in the United States and could only explain a tiny portion of the growing compensation gap between skilled and less-skilled workers. Borjas et al. attribute most of the increase in earnings inequality to skills biased technological change (SBTC). The Council of Economic Advisors (1997, p. 175) and a colloquium at the Federal Reserve Bank of New York also analyzed growth in earnings inequality in the 1980s and 1990s, largely concurring with Borjas that SBTC accounted for roughly half of the increase in earnings inequality while increased immigration explained about five percent of the increase.

Reed (1999) focused on earnings inequality in California, a state whose low-skilled immigrant population has expanded rapidly in recent decades. Reed attributed 17 to 40 percent of the increase in income inequality during that time to immigration from the late 1960s to 1997. Her finding is driven by the surge of lower-skilled Hispanic immigration to California during that time period. The addition of so many millions of lower-skilled immigrants increased earnings inequality in the state.

David Card (2009) found a substantially causal relationship between increased immigration and wage inequality. Card pointed out that wage inequality should be viewed through two different lenses. The first lens is the wage distribution of all workers, natives and immigrants, in the labor market. Since immigrants tend to have either higher or lower wages than natives do, more of them in the labor market
would tend to increase wage inequality for all workers. Through this view, Card found that increased immigration explains about 5 percent of the rise in overall wage inequality between 1980 and 2000. The second view is how immigrants affect the wage distributions of native workers only or, in other words, how immigration affected the wage inequality of natives. Card found negligible economic effects of immigration on native wages.

Hibbs and Hong (2015) used the Gini index as their measure of inequality. Comparing U.S. metropolitan areas from 1990 to 2000, they found that immigration can explain about 24 percent of the increase in inequality. For every 1 percent increase in immigrants relative to the population of a metropolitan area, the Gini coefficient increases by 0.66 points.

Lerman’s (1999) paper approached the subject differently than the rest surveyed here. He tried to take account of the rapid immigrant wage gains after working in the United States over a few years through two different methods. The first was by excluding recent immigrants from the base and end years of his analysis because their wages are temporarily very low. Lerman’s first method eliminated 20 to 25 percent of the standard estimates of growth in wage inequality. His second method was to include immigrant wages in their home countries prior to immigration, thus taking in to account their large economic gains upon arrival. This second method eliminated virtually the entire estimated rise in income inequality. By tracking immigrant income from before they entered the United States, Lerman was able to measure the earnings inequality for the entire workforce during the course of their work-lives.

None of the researchers above have tried to estimate how immigration affects economic inequality through the Piketty-Rognlie housing price effect. The novelty of this paper is our attempt to put these results in context of one another. Our findings suggest that if housing is the primary channel by which immigration affects inequality, it does so only modestly.

Immigration likely has a larger impact on rental and housing prices than any other market, including that for labor. Albert Saiz (2003) finds that immigrants from the Mariel Boatlift, which boosted
Miami’s worker population by about 7 percent, increased rental prices in the Miami area from between 8 and 11 percent between 1979 and 1981 when compared to control cities. By 1983, the rent differential was still 7 percent despite increased construction. Greulich et al (2004) finds that nominal rent prices in American cities with more immigrants are higher than in similar cities without many immigrants. However, the rent-to-income ratio is the same across all cities because the concurrent increase in income keeps rental burdens unchanged. A metropolitan area where the proportion of rents paid by immigrants is 0.3 has rents that are 0.18 log points, or 18 percent, higher than in a metropolitan area where immigrants’ proportion of rents is zero.

Ottaviano and Peri’s (2006) examination of housing prices across U.S. states and Metropolitan Statistical Areas (MSAs) from 1970 to 2010 found that an increase of the foreign-born population by 1 percent of the employed population increased housing prices by 1.1 percent. Similarly, Saiz (2007) found that an increase in immigration inflow to MSAs that accounts for 1 percent of the initial MSA population is associated with a 1 percent increase in rents and a 1 percent increase in housing values.

Sharpe (2015) argues that previous estimates of the impact of immigration on housing prices are biased upwards due to a lack of controls for city-specific characteristics that attract immigrants and predispose them toward higher rent growth. He uses Core Based Statistical Areas (CBSA) to study the impact of immigration on rents, a geographical area distinct from the MSAs studied by the others. When he controls for those initial economic conditions, immigration’s impact loses statistical significance. Sharpe’s use of CBSAs rather than MSAs, despite other researchers using the latter, explains his different findings. For our purposes here, we employ Sharpe’s statistically insignificant point estimate of 0.45 to complement the findings of Saiz.

Data limitations force us to use proxy variables instead of our true variables of interest. Piketty-Rognlie is ultimately about the capital share and the “upper 1%.” In its place we employ the more
conventional Gini coefficient, which is a relatively new piece of data estimated by Census.\textsuperscript{1} The estimates of Saiz and Sharpe are about cities, which may be contingent on the presence of regulatory or hard physical land constraints. Because of this we focus on counties in metropolitan areas that anecdotally have been most impacted by immigration, high housing prices, or both. Additionally data limitations require us to use average rent from the Census of Housing as a proxy for housing value. On the one hand, all of this introduces several concerns about whether these imperfect measures and debatable interpretations are “close enough” to work. On the other, we have selected the most extreme examples of growing immigrant populations on the county level; if the effects are large, they should be readily evident, even given many imperfections.

III. Model and Results

Let the population that is foreign born be denoted as \( FB_{it} \), the average rent (2010 dollars) in the county be denoted as \( AR_{it} \), and \( PPP_{it} \) the total population, all in in year \( t \) and county \( i \). We define \( a \) as the percentage point change in housing values which results from the percentage point change in foreign born percentage (it is the variable which corresponds to the Saiz and Sharpe estimates). Our estimated counterfactual average rent in county \( i \) in year 2010, \( CAR_i \), is

\[
CAR_i = \frac{AR_{2010i}}{\frac{FB_{2010i} + PPP_{2010i}}{PPP_{2010i}}} \tag{2}
\]

From this we can strip out \( \mathcal{S}_i \), the percentage of the total rent attributable to the increase in immigration

\[
\mathcal{S}_i = \frac{AR_{2010i} - CAR_i}{CAR_i} \tag{3}
\]

\textsuperscript{1} See Bee (2012).
Initially, we assume that $a$ is equal to 1.0, as in Saiz (2007). The results from that parameterization can be found in Table 1. The effects are generally modest, with the exception of Miami and Riverside. The increase in foreign born population in Miami and Riverside from 1970 to 2010 are 78.5% and 93.0%, respectively. The average of the thirteen county-cities is 30.1% while it is only 20% if Miami is excluded. Detroit has had net negative outflow of their foreign born population (our calculation is relative to no inflow or outflow and we provide estimates given that). The magnitudes of these effects are large enough to be casually observable but also not so large that they are the primary factor explaining the nationwide rise in housing values. Table 2 provides alternative estimates using the work of Sharpe (2015), instead of Saiz, where $a$ is set to 0.45. Assuming Sharpe’s findings, 13.1% of the increase in rents is attributable to immigration, on average.

Data from 1970 for the Gini coefficient by county do not exist. For the lack of a better alternative, we are forced to guess each county’s Gini coefficient using the change in national averages. In this case, we look at 2012 data. Let the county Gini coefficient in year $t$ and county $i$ be denoted as $C_{C_t,i}$ and the Gini coefficient for the US as a whole in year $t$ be denoted as $US_{C_t}$. Then,

$$C_{C_{1970},t} = \frac{C_{C_{2012},t}}{US_{2012} / US_{1970}}$$  \hspace{1cm} (4)

Finally, we estimate the counterfactual Gini coefficient in county $i$ ($C_{CG_t}$) as the actual less, in percentage terms, the rent attributable to the increase in the county’s foreign born.

$$C_{CG_t} = C_{C_{1970},t} + (1 - a)(C_{C_{2012},t} - C_{C_{1970},t})$$  \hspace{1cm} (5)

These results are provided in Figure 1. The interpretation of Figure 1 is limited because of the assumptions made regarding each county’s Gini coefficient in 1970. In reality, it does nothing but “scale” the numbers for each county. However, when placed in this context, those numbers are small. The average county’s Gini coefficient increased by 0.023 due to immigration. The largest estimate, again with Riverside, is a 0.065 greater Gini coefficient caused by immigrants. The actual 2012 Gini coefficient was
at 0.439 with the no-net immigrant counterfactual at 0.374. With the exception of Riverside and Miami, our result is in line with Card (2009), who approached the issue entirely differently.

IV. Conclusion

About 30.1% of housing value in 2010 is attributable to immigrants in urban areas bidding up their value. Large increases in immigration significantly increased housing values and inequality in Miami while it was a modest contributor to increased inequality elsewhere. Rognlie (2015) has shown, plausibly, that the measured increase in inequality is simply the result of the increased value of housing. Immigration increases the demand for housing. This raises the question of to what degree higher numbers of immigrants lead to more inequality. While we are unable to directly access county-level data on economic inequality or data on housing value, we employed proxy variables to approximate the possible size of these effects. Improved data may allow a more precise estimate of immigration’s effect on inequality through the Piketty-Rognlie channel. The effect is at least an order of magnitude too small for immigration to be the key catalyst driving economic inequality based on Piketty-Rognlie. Contra Borjas (2013), there are likely far superior policy avenues for addressing rising inequality than further restricting immigration.
Works Cited


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<th>City</th>
<th>Imm. Increase, % of 1970 Pop.</th>
<th>Rent, 1970</th>
<th>Rent, 2010</th>
<th>Rent % Increase</th>
<th>Counterfactual Rent</th>
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Figure 1. Effects of Immigration on Gini Coefficient
Table 2. Housing Counterfactual Using Sharpe’s (2015) Estimates

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