Abstract

We exploit the bilateral and skill dimensions from recent data sets of international migration to test for the existence of Zipf’s and Gibrat’s Laws in the context of aggregate and high-skilled international immigration and emigration using graphical, parametric and non-parametric analysis. The top tails of the distributions of aggregate and high-skilled immigrants and emigrants adhere to a Pareto distribution with an exponent of unity i.e. Zipf’s Law holds. We find some evidence in favour of Gibrat’s Law holding for immigration stocks, i.e. that the growth in stocks is independent of their initial values and stronger evidence that immigration densities are diverging over time. Conversely, emigrant stocks are converging in the sense that countries with smaller emigrant stocks are growing faster than their larger sovereign counterparts. These findings are consistent with relatively few destinations, with low birth rates, continuing to attract the vast majority of emigrants whom face lower migration costs from evermore origin countries, whose birth rates are higher. We also document within immigration stocks, immigrant densities and emigrant densities and to a lesser extent within emigrant stocks, convergence in the high skill composition, consistent with an increasing global supply of high-skilled workers and the imposition of selective immigration policies.

JEL classification: F22, J61

Keywords: Zipf’s Law, Gibrat’s Law, International Migration
1 Introduction

In urban economics, Zipf’s Law and Gibrat’s Law occupy a special place in explaining the relationships between cities in terms of their relative sizes and growth rates. In this paper, we link the literature on international migration to urban economics, especially the literature on population growth and distributions. More specifically, we draw upon two of the most recent advances in the development of bilateral migration data, Özden et al. (2011) and Artuc et al. (2013), to examine the existence of Gibrat’s and Zipf’s Laws for immigrant and emigrant levels and densities in aggregate levels as well as examining high-skilled migration patterns.

Zipf’s law for cities states that the city size distribution within a country can be approximated by a power law distribution. More specifically, if we were to rank the cities in terms of their sizes, the $n$th largest city is $1/n$ of the size of the largest city. Another way to state this regularity is running a regression with $\ln(\text{city size rank})$ as the dependent variable and $\ln(\text{city size})$ as the main explanatory variable. The coefficient typically is equal to around 1 with a high level of precision, especially when larger cities are considered.

Gibrat’s law, on the other hand, is about growth rates and was initially noted for the French firms Gibrat (1931). When applied to cities, it states that growth processes have a common mean and are independent of initial sizes. The seminal paper of Gabaix (1999) establishes that, when cities grow according to Gibrat’s law, then, in steady state, their size distribution will follow a pareto distribution with a power exponent of 1. This, as well as numerous results from across the urban economics literature, which also show that Zipf’s Law holds, provides some evidence against the existence of Gibrat’s Law, which instead predicts that the resulting distribution is log-normal. Eeckhout (2004) manages to accommodate both ‘laws’ by showing that Pareto distribution best fits the observed pattern if upper tail of the distribution of city sizes is considered. Conversely, a log-normal distribution provides the best fit if the entire distribution were to be considered. These patterns are observed across the world and are discussed in great detail in many other places (such as Gabaix and Ioannides (2004)).
The natural question then is to ask what mechanisms exist that might link Gibrat’s and Zipf’s laws. This question is especially important when divergent rates of population growth across locations are the norm. Among the causes that would lead to differing growth rates are climate, natural disasters and resource endowments. There are numerous examples of cities that disappear from history or boom after a discovery of a natural resource for example. People however, have the ability to move from one location to another, especially as some locations become overcrowded and resources are restrained due to higher natural growth rates. Under these circumstances, the convergence of growth rates via migration would naturally take place within a larger geographic area (such as a country) without internal barriers to population mobility.

There had been few studies that take the analysis outside of national boundaries since the theoretical models used to explain Zipf’s and Gibrat’s laws are not truly applicable when the unit of observation is a sovereign country. Governments exercise considerable power over their international (as opposed to internal) borders and can dictate who can enter and, to a certain extent, exit the country. The most prominent study is Rose (2005) who tests these theories using countries as the relevant geographical entities. He concludes that the ‘hypothesis of no effect of size on growth usually cannot be rejected.’ When testing the Zipf’s law for countries, Rose (2005) shows that it also strongly holds in the upper tail of the distribution of country sizes, as is the case with city sizes. The only study that links Gibrat’s and Zipf’s laws to international immigration is the work by Clemente et al. (2011) who uses aggregate immigration numbers and densities. They test for the existence of Zipf’s Law specifically in the context of immigrant levels and densities and find for the top 50 countries that Zipf’s Law holds only for immigrant levels.

In this paper, we draw upon two recent bilateral migration databases, Özden et al. (2011) and Artuc et al. (2013). These yield two advantages. Firstly, global bilateral migration data allow us to calculate country level emigrant stocks, as opposed to simply

\footnote{Offering a critique of Rose (2005), Gonzlez-Val and Sanso-Navarro (2010) apply more up-to-date empirical strategies to test the application of Gibrat’s Law to countries and find mixed results, some evidence in favour of population growth being independent of initial country size but conclude on the whole that the results from across their range of empirical strategies that some evidence of convergence is found.}
immigrant stocks. Secondly, the latter database, which reports bilateral migration stocks by education levels, allows us to further delineate between patterns of migrants with low and high education levels.

Zipf’s law implies a concentrated distribution of the total population among a few large cities. We observe similar patterns in immigration patterns but the converse over time in emigration patterns. In 2000, the top ten receiving countries accounted for no less than 57% of the world migrant stock, which is approximately equivalent to the total emigrant stocks of the top 25 emigration countries in the same decade. In 1960, the equivalent figure for the top ten receiving nations was 54%, which is equivalent to less than the total emigrant stock of the top 9 sending countries in 1960. A similar concentration is observed for individual corridors. In 2000, of all bilateral corridors (over 40,000 in total) comprised fewer than 50 migrants each. Together, they accounted for only 0.1 percent of total migrant stock. On the other hand, in the same year, just 505 corridors accounted for over 80 percent of the global migrant stock of over 160 million people.

Whether the sum of these bilateral trends holds across countries is the subject of our paper. We delve deeper into the observed patterns of international migration over the period 1960-2000, by examining the existence of Zipf’s and Gibrat’s Laws, two empirical regularities that are ubiquitous in the urban economics literature. We therefore adopt an alternative perspective in analyzing to what extent the underlying trends in global migration patterns are converging or diverging.

The results in the paper are both interesting and encouraging. In regards to Zipf’s law, we find that it holds very strongly in the upper tail of the distribution with the Pareto coefficient very close to unity for both immigration and emigration for all time periods. The results are less precise for high skilled migration but we cannot reject the coefficient being unity. When the whole sample is included, we find a log-normal distribution in terms of immigrant sizes which are very similar to the results found for cities and countries in the literature. With respect to Gibrat’s law, our results are somewhat less uniform. We find evidence of convergence with the growth rates being linked negatively to initial levels
for both aggregate and high-skilled immigration and emigration levels and densities. In our non-parametric analysis, we find some evidence in favour of Gibrat’s Law holding for immigration stocks, i.e. that the growth in stocks is independent of their initial values and stronger evidence that immigration densities are diverging over time. Conversely, emigrant stocks are converging in the sense that countries with smaller emigrant stocks are growing faster than their larger sovereign counterparts. These are all surprising regularities given that government policies and other physical and cultural barriers impose strong restrictions on international migration patterns.

The following Section offers a brief overview of the bilateral data sets that we use in the paper. Section 3 introduces an analysis of Zipf’s Law while in Section 4 we analyse the extent to which the underlying distributions of our variables of interest approximate to log-normal distributions. Section 5 presents an examination of Gibrat’s Law in international migration patterns, before we finally conclude.

2 Basics of Migration Data

This section aims to outline the broad patterns observed in the global migration databases. Özden et al. (2011) show that while the global migrant stock increased from 92 million to 165 million between 1960 and 2000, immigrants as a share of the world population actually decreased from 3.05 percent to 2.71 percent during the same period. Özden et al. (2011) provide bilateral migrant stocks for 226 origins and destinations globally at decennial intervals between 1960 and 2000, which correspond to the last five completed census rounds. While South-South migration dominates the global stock, mainly due to the millions of migrants created during the partition of India and the collapse of the Soviet Union, the most significant trend between 1960 and 2000 has been the surge in South-North migration. Over the period, two-thirds of the total growth in migration stocks was due to migrant flows to Western Europe and the United States from developing countries. Other notable patterns were the emergence of the oil-rich Persian Gulf countries.

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2The data from the 2010 census round is currently being collated since these data are typically published with a significant lag.
as key destinations, greater intra-Africa migration flows and migration to the “migrant-friendly” countries of the New World, namely, Australia, New Zealand, and Canada.

The analysis of international migration patterns faces many challenges and these studies aim to overcome them in various ways. For example, no census round has ever been completed in the sense that all countries have participated. Even when censuses are conducted, not all countries are willing to make the data publicly available. International borders have changed over time, most notably following the dissolution of the Soviet Union and Yugoslavia. Various countries adhere to different methodologies, national standards and classifications when conducting their censuses and recording the results. Özden et al. (2011) strive to present as full and as harmonious a matrix of aggregate bilateral migration stocks over the period, breaking down the numbers in accordance with the international borders currently in existence. migrant stock, respectively.

Table 1 presents summary statistics of the frequency and the total numbers of migrants comprising bilateral migrant corridors of various sizes (zero corridors, 1-50 migrants, 51-500 migrants, 501-5,000 migrants, 5,001-50,000 migrants and corridors containing more than 50,000 migrants) over the period 1960-2000. Several stark patterns are evident. Over time, the number of empty bilateral migrant corridors has fallen substantially as the globe has become more interconnected through international migration. While smaller corridors are far more common, these comprise far fewer international migrants as when compared to larger corridors. As discussed earlier, around half of all bilateral corridors (over 40 thousand) are basically empty and have less than fifty migrants in each. These micro corridors account around 0.1 percent of global migrant stocks.

The basic numbers suggest an agglomeration of human capital in the upper tail of the distribution as shown in Figure 1. This pattern might be indicative of Zipf’s Law holding; and concurrently a diversification in terms of the increasing numbers of origins from which these migrants hail. Figure 2 plots the growth in bilateral migration corridors over the period 1960 and 2000 against their initial values, a graphical examination of whether Gibrat’s Law holds or not. The two lines correspond to lines of best fits should zero values be included or excluded. Should they be included, by adding one to the log, the
figure suggests that Gibrat’s Law holds. If they were to be excluded, signs of convergence across the entire distribution of bilateral migration corridors are evident.

3 Zipf’s Law in International Migration

We begin our analysis with an examination of the existence of Zipf’s Law, the so-called rank-size rule, which can be viewed as an empirical regularity that describes the (upper tail) of the population distribution of the geographical entity under investigation. This distribution may result from a growth process that may or may not be governed by Gibrat’s law. Typically the existence of Zipf’s Law is analysed graphically and using regression techniques. Both approaches first rank the (population) size variable of interest $S$, from highest to lowest ($S_1 > S_2 > S_3 > ... S_N$). Then the natural logarithm of the rank variable is analysed with respect to the natural logarithm of the (population) size variable.

The top two panels in Figure 3 show the graphical scatter plots of the natural logarithms of the rank of total immigrant and emigrant levels for the 50 countries in the top tail of the various distributions contained in Özden et al. (2011). Although we plot these only for the year 2000, these graphs are representative of other decades as well. The bottom two panels instead draw on the data from Artuc et al. (2013). These data instead refer to high-skilled migrants, defined as having completed at least one year of tertiary education. Clear linear trends are evident, but the line imposed demonstrates that some deviations from Zipf’s Law clearly exist in the data. For a more robust analysis we turn to simple regression analysis, following the norms in the literature. Zipf’s Law can be expressed as:

$$P(\text{Size} > S) = \alpha S^{(-\beta)}$$


4 We do not report estimates using the Hill estimator since Gabaix and Ioannides (2004) argue that in finite samples the properties of this estimator are ‘worrisome’.

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where $\alpha$ is a constant and $\beta = 1$ if Zipf’s law holds. For the basis of our regression analysis we denote $m$ to be the stock of immigrants or emigrants, expressed either in levels or in terms of densities, high-skilled or otherwise. Next, $r$ is the rank of $m$, when ordered from highest to lowest. Equation (1) expressed in logarithmic form can be written as:

$$\log r = \alpha + \beta \log m + \epsilon$$

(2)

where $\epsilon$ is an error term and $\beta$ is the Pareto exponent, which equals unity if Zipf’s Law holds. Equation (2) is typically estimated using OLS, which leads to strongly biased results in small samples (Gabaix and Ibragimov, 2007). These authors propose a simple and efficient remedy to overcome these biases, namely to subtract one-half from the rank. The regression to be estimated therefore becomes:

$$\log (r - 0.5) = \alpha + \beta \log m + \epsilon$$

(3)

Despite this adjustment, the standard error of $\beta$ is not equal to that obtained from OLS, but instead can be approximated as $\beta \sqrt{\frac{2}{n}}$ (Gabaix and Ioannides (2004), Gabaix and Ibragimov (2007)). Table 2 presents the regression results from across our various specifications together with with corrected standard errors for each decade from 1960 to 2000.

Beginning with the total migrant measures, the Pareto coefficient is remarkably close to unity (at 1.03 for 2000) for the 50 largest countries in the upper tail of the size distribution, although Zipf’s Law is resolutely rejected across the entire distribution where the coefficient is 0.385 for 2000. This is consistent with the results presented in Eeckhout (2004) which argues that the Pareto distribution best describes the upper tail but a log-normal distribution provides a better fit over the entire distribution. The estimates of the Zipf coefficient have remained fairly stable over time for both immigrant and emigrant levels. In contrast, the estimates on immigrant densities have risen in the upper tail of the distribution, demonstrating some convergence across these countries, but have fallen across the entire distribution, i.e. providing evidence of divergence. The estimates
on emigrant densities however show some signs of convergence between 1960 and 2000.

Turning to the High Skill migration numbers in the bottom eight rows of Table 2, although the point estimates on the Zipf coefficient are substantively different from unity, they are nevertheless within the confidence intervals. Both immigrant and emigrant levels are similar in both 1990 and 2000 and if anything exhibit marginal convergence. Turning to high skilled immigrant and emigrant densities, both have increased significantly across the entire distribution, which again is indicative of a process of convergence across the globe.

4 An examination of log-normality

The previous section showed that we cannot reject the existence of Zipf’s Law in the upper tails of the distributions of total and high skilled immigrants and emigrants in levels. On the other hand, if we were to consider the entire distribution, we easily reject Zipf’s Law. With these results in hand, we next empirically test whether or not the underlying distributions of our variables approximate to log normal. If this is the case, it might be the case that Gibrat’s law holds i.e. that these distributions could have resulted from an independent growth process.

Figures 1 and 4, show the (Epanechnikov) kernel density plots, in 1960 and 2000 for total emigrant levels and densities and total immigrant levels and densities and then similarly in 1990 and 2000 for the highly skilled. We implement a series of Kolmogorov-Smirnov equality-of-distributions tests where the null hypothesis is that the relevant variable is distributed log-normally. Table 3 presents the corrected p-values from the Kolmogorov-Smirnov tests for each migration variable in 1960 and 2000 and in 1990 and 2000 for the highly skilled. In just over half of the total cases, we fail to reject the null hypothesis of (log) normality. Cases where we can reject the null are highlighted in bold. Both immigrant levels and densities are log-normally distributed as was the case in Clemente et al. (2011).\footnote{Note that the scale of our density figures differ from Clemente et al. (2011) since we calculate our density measure differently and we further omit refugees, i.e. forced migrants from our analysis.}

Since if Gibrat’s Law were to hold, the resulting distributions of the relevant variables
will be log-normal, we proceed by examining whether Gibrat’s Law holds for our various measures of international migration.

5 Gibrat’s Law in International Migration

As opposed to the static analysis presented when discussing Zipf’s Law, an examination of Gibrat’s Law with growth rates requires a dynamic analysis of global migration movements. Gibrat (1931) postulated that “The Law of proportionate effect will therefore imply that the logarithms will be distributed following the (normal distribution)” (as quoted in Eeckhout (2004)). In other words, should the growth of geographical entities be independent of their size, their growth will subsequently result in a log-normal distribution. Of course, this does not mean that a log-normal distribution implies that Gibrat’s Law necessarily holds. Both immigration and emigration are determined by government policies and limited to the extent by which individuals are willing and able to move. Internal mobility, on the other hand, is far less restricted and is typically thought to lead to Zipf’s and Gibrat’s laws. Thus, it is difficult to argue that some natural underlying law of nature would determine the underlying growth and distribution processes of populations over national boundaries and across the globe.

We estimate parametric and non-parametric kernel regressions to test for the existence of Gibrat’s Law. These regress the size of migrant populations (or in our case densities) on their growth.\(^6\) In logarithmic form, parametric regressions take the following form:

\[
\log m_{it} - \log m_{it-1} = \gamma + \delta \log m_{it} + \mu_{it}
\]

where \(\gamma\) is a constant and \(\mu\) is a stochastic error term, such that if \(\delta = 0\) then Gibrat’s Law holds. Following the analysis of Eaton and Eckstein (1997), we distinguish between the aforementioned case of (i) parallel growth, when \(\delta = 0\), i.e. when growth does not depend on initial size, (ii) convergent growth, when \(\delta < 0\) when smaller initial populations

\(^6\)While Panel Unit Root tests have been suggested as appropriate in the literature, it is not feasible to conduct such an analysis in the current work due to the frequency of our data (decennial) and the low number of observations in our underlying data (five points in time or four growth rates).
grow faster than their larger counterparts so that there is long-run convergence to the median value and (iii) divergent growth when $\beta > 1$, meaning that growth is a positive monotonic function of initial size. Evidence of either convergent or divergent growth can therefore be taken as evidence against the existence of Gibrat’s Law.

Table 4 presents the results from this first round of analysis, where Equation (4) is estimated with OLS with robust standard errors, due to typical heteroskedasticity of these types of results Gonzlez-Val and Sanso-Navarro (2010). Although Gibrat’s Law is fundamentally a long run concept, we estimate Equation (4) across each decade for each of our different measures of immigration and emigration.

The simplest and most intuitive way to test for the existence of Gibrat’s Law is by plotting geographical entities’ growth on their initial values, which for the sake of brevity are not included here but are available on request. Such an analysis is strongly reflected in the results in Table 4.\textsuperscript{7} Across all decades and across all measures, the parametric regression results are negative and statistically significant or else statistically insignificant. These results are indicative of convergence over time or indeed of Gibrat’s Law holding. Fundamentally however, Gibrat’s Law is a long-run concept and it might therefore be more appropriate to have more faith in the final column of results from over the period 1960-2000. In each case the results are strongly negative and statistically significant, providing some evidence of convergence in immigrant and emigrant levels and densities over time.

Our OLS estimates yield total or aggregate effects of initial size on subsequent growth, while conversely non-parametric estimates facilitate an analysis of the effects of initial size across the entire distribution. We follow Eeckhout (2004) for our non-parametric analysis of Gibrat’s Law and adopt the following specification:

$$g_i = m(S_i) + \epsilon_i$$  \hspace{1cm} (5)

where $g_i$ is the decadal growth of one of our migration measures normalised between two

\textsuperscript{7}We do not report the $R^2$ from these regressions although these are very low for our decadal regressions and substantially higher for those regressions run over forty years.
consecutive periods by subtracting the mean growth and dividing through by the standard deviation. Maintaining our notation from earlier, \( m_i \) is the corresponding logarithm of the relevant migration measure. Since such estimators are sensitive to atypical values, we follow Clemente et al. (2011) and drop the bottom 5% of observations. Figures 5 and 6 plot the results from these regressions and we would expect these values to be flat and concentrated around zero if Gibrat’s Law were to hold.

In keeping with the findings of Clemente et al. (2011), we find, at least across most of the distribution of the stock of immigrants, that Gibrat’s Law holds. The major exceptions are those countries in the lower end of the distribution, which tend to grow faster than the other countries in the distribution. We find much stronger evidence of the divergence in immigrant densities across the globe. The underlying distributions for both of these variables are log-normal however, demonstrating that log-normality can result, despite Gibrat’s Law not holding. Emigrant stocks exhibit strong signs of convergence with smaller emigrant stocks growing far more strongly than larger emigrant stocks. The results from the kernel regression for emigrant densities are far mixed however, no doubt in part reflecting the role played by Small Island Developing States (see for example de la Croix et al. (2013).

All of the kernel regression plots pertaining to the highly skilled, reflect patterns of convergence since they slope down from left to right. Our estimates for emigrant levels are never statistically different from zero, providing some evidence that Gibrat’s Law holds in this context, although the confidence intervals are very wide. The same is true for the middle and the very upper tail of the distribution of immigrants in levels. These findings are consistent with the fact that a relatively small number of destinations with low birth rates, continue to attract a growing number of emigrants from origin countries where birth rates are higher. In this respect our conclusions are consistent with Clemente et al. (2011), only we provide further evidence as to the other side of the migration coin. The convergence in emigration levels are indicative of destination countries drawing on a greater number of origin countries to meet their human capital needs. Arguably the mechanics of this process have be lubricated by falling global migration costs.
The composition of high skilled immigrant and emigrant levels and densities exhibit signs of convergence, albeit to differing degrees. These patterns are consistent with the onset of the global competition for international talent, an increasing global supply of high-skilled workers across all origins, limited supplies per origin as well as the imposition of selective immigration policies by an increasing number of destination countries.

6 Conclusion

Gibrat’s and Zipf’s laws are among the most studied and well established phenomenon in various contexts including linguistics, firm sizes and urban agglomorations. The linkages between population growth and the distribution across geographic space are key to all economic analysis since economic activity cannot be analyzed in isolation from location. Thus, it is important to study and identify the underlying processes that determine the growth rates of populations over time and their allocation across various locations. Even though Zipf’s and Gibrat’s laws have been extensively analyzed in the literature, there are fewer studies on the role of population movements and there are even fewer studies that focus on mobility across national boundaries. It is therefore natural to search for a relationship between such population laws and migration patterns.

New data sets on bilateral migration stocks enable us to carry out these analysis. Özden et al. (2011) reports bilateral stocks for all migrants for each decade between 1960 and 2000 for 226 countries. Similarly, Artuc et al. (2013) analyzes migrant stocks by education categories for 1990 and 2000. The current analysis demonstrates interesting patterns. In terms of comparison to Zipf’s law, we see that the migration patterns are very similar to what is observed with respect to cities. In the upper end of the distribution, Zipf’s law holds since the Pareto coefficient is very close to unity. On the other hand, when the whole distribution is included, we often fail to reject the log-normality assumption, especially in the case of immigration. High-skilled levels satisfy (although less well) to Zipf’s Law but more often fail to adhere to log-normality.

While the tests regarding Zipf’s law and the size distribution analysis are static, the
tests on the Gibrat’s law and the growth rates require dynamic analysis. The results in this area are also promising. We find evidence of convergence in the relatively simpler parametric analysis. In the case of non-parametric regressions, we find some evidence in favour of Gibrat’s Law holding for immigration stocks, i.e. that the growth in stocks is independent of their initial values and stronger evidence that immigration densities are diverging over time. Conversely, emigrant stocks are converging in the sense that countries with smaller emigrant stocks are growing faster than their larger sovereign counterparts.

Our goal in this paper is to extend the insights from the urban economics literature to international migration. Zipf’s and Gibrat’s laws provide natural avenues to do so since they are linked via population movements. We find various support for these laws in international migration which is surprising given the policies and many other barriers that limit international migration patterns.
References


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... aux statistiques des familles, etc. d’une loi nouvelle, la loi de l’effet proportionnel, Librairie du Recueil Sirey.


Figure 1: Kernel Density Plots Aggregate Immigrants and emigrants levels and densities, 1960-2000
Figure 2: Graphical Examination of Gibrat’s Law across Bilateral Corridors, 1960-2000
Figure 3: Zipf Plots for Aggregate and High-skilled Immigrants and Emigrants, 2000
Figure 4: Kernel Density Plots High-Skilled Immigrants and emigrants levels and densities, 1990-2000
Figure 5: Non-parametric estimation of Gibrat's Law, aggregate immigrant and emigrant levels and densities, 1960-2000
Figure 6: Non-parametric estimation of Gibrat’s Law, high-skilled immigrant and emigrant levels and densities, 1990-2000
Table 1: The Evolution of Bilateral Migration by Corridor Size

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<th></th>
<th>Empty corridors</th>
<th>1-50 migrants</th>
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<th>501-5000 migrants</th>
<th>5001-50000 migrants</th>
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<td>34,591</td>
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<td>10,470</td>
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<td>1970</td>
<td>32,966</td>
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<td>120,585</td>
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<td>1980</td>
<td>31,758</td>
<td>-</td>
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<td>125,792</td>
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<td>12,897</td>
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Immigrant Levels: 1.009 0.912 0.748 0.351 0.988 0.904 0.765 0.372 1.028 0.92 0.79 0.383 0.989 0.946 0.842 0.394 1.03 0.95 0.882 0.385

Immigrant Densities: 2.247 1.921 1.582 0.62 2.138 1.729 1.54 0.607 2.033 1.732 1.41 0.549 2.465 1.75 1.375 0.532 2.57 1.81 1.424 0.532

Emigrant Levels: 0.925 0.891 0.868 0.337 1.031 0.98 0.934 0.328 1.125 1.069 1.026 0.38 1.254 1.17 1.1 0.362 1.392 1.316 1.22 0.375

Emigrant Densities: 2.455 2.071 1.74 0.595 2.081 1.857 1.643 0.651 2.71 2.033 1.683 0.7 2.401 1.842 1.506 0.719 2.696 1.996 1.703 0.718

HS Immigrant Levels: 0.82 0.758 0.68 0.387 0.828 0.777 0.687 0.396

HS Immigrant Densities: 3.235 2.832 2.556 0.656 4.166 3.196 2.752 0.798

HS Emigrant Levels: 1.354 1.254 1.097 0.435 1.336 1.257 1.117 0.442

HS Emigrant Densities: 4.675 3.915 3.056 0.758 5.7 4.818 3.652 0.861

Note: Gabaix and Ioannides (2004) Standard errors are reported in parenthesis. All variables are highly significant at the 1% level.
Table 3: P-values from Kolmogorov-Smirnov equality-of-distributions tests

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<td><strong>0.001</strong></td>
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Table 4: Parametric Tests of Gibrat’s Law

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