Cities, Institutions, and Growth: The Emergence of Zipf’s Law

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Abstract

Zipf’s Law characterizes city populations as obeying a distributional power law and is supposedly one of the most robust regularities in all of economics. This paper shows, to the contrary, that Zipf’s Law only emerged in Europe between 1500 and 1800. It documents how Zipf’s Law emerged with the development of markets in the centuries preceding the onset of modern economic growth. It shows that the long-run historical evidence is consistent with random growth theories of Zipf’s Law. Because land and land-intensive intermediates entered city production as quasi-fixed factors, big cities grew relatively slowly and were “too small” before 1500. Then, as trade and rising agricultural productivity relaxed the land constraint, it became possible for growth to become random, for big cities to appear, and for Zipf’s Law to emerge. Random growth and Zipf’s Law emerged early to Western Europe. However, the institutions of the “second serfdom” in Eastern Europe were associated with delayed emergence. I find that laws limiting labor mobility and sectoral reallocation were associated with two factors that generate persistent deviations from Zipf’s Law: relatively low variation in growth rates and a negative association between city sizes and growth rates. These legal institutions were also associated with a 1/3 reduction in city growth in Eastern Europe 1500-1800.

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1 Introduction

Economists have identified an underlying order in urban hierarchies: Zipf’s Law characterizes city populations as obeying a distributional power law (a Pareto distribution) and is supposedly one of the most robust regularities in all of economics. Krugman (1996a: 39) observes that this distributional regularity is so exact and so “suspiciously like a universal law” as to be “spooky.” Gabaix (1999a: 129) notes that it appears to hold in all economies and periods for which there are data. This paper shows, to the contrary, that Zipf’s Law only emerged in Western Europe between 1500 and 1800. It documents how Zipf’s Law emerged with the development of markets in relatively advanced economies in the centuries immediately preceding the onset of modern, capitalist economic growth.

The leading theories tie Zipf’s Law to either (1) random growth or (2) the underlying distribution of geographic advantages or “locational fundamentals” (Krugman 1996a, Davis and Weinstein 2002, Gabaix 2008). The random growth theory provides a benchmark for thinking about city population dynamics. The locational fundamentals theory carries important predictions about the way geography shapes economic life. Zipf’s Law is thus more than a mathematical curiosiry and examining its emergence leads us to ask important questions about cities and the determinants of growth.

This paper exploits data on the populations of European cities since 800 AD to examine and test the random growth and locational fundamentals theories. I document that Zipf’s Law did not hold before 1500 and only emerged after city growth became random. Similarly, I find significant churning in the distribution of European city populations – evidence that geography matters but is not destiny.

In addition to testing the random growth and locational fundamentals theories, I document that significant deviations from Zipf’s Law reflected big impediments to trade and limits on the operation of markets. Historically, a land constraint limited the growth of big cities, which grew relatively slowly and were far smaller than Zipf’s Law would lead us to expect until at least 1500. As developments in trade and rising agricultural productivity relaxed the land constraint, it became possible for large cities to grow as fast as small cities. Zipf’s Law emerged with this “modern” pattern of size independent growth 1500-1800, before the industrial revolution.

The paper also documents how institutional distortions shaped the pattern of city growth in Eastern Europe. In Eastern Europe, the legal institutions of the “second serfdom” placed severe restrictions on labor mobility and sectoral reallocation 1500-1800. These institutions were associated with persistent deviations from Zipf’s Law and with a 1/3 reduction in city growth 1500-1800.
2 Literature

2.1 Zipf’s Law

Zipf’s Law for cities can be characterized in two ways\(^1\). The first is in terms of the probability distribution of city populations in the upper tail. Where Zipf’s Law holds, city populations are distributed according to a power law such that the probability of drawing a city with population size \(S\) greater than some threshold \(N\) is:

\[
Pr(S > N) = \alpha N^{-\beta}
\]  

Equation (1) is consistent with a power law distribution where the size ranking of a city (denoted \(R\)) is inversely proportional to its population size\(^2\):

\[
R = \alpha S^{-\beta}
\]  

Equation (2) implies a tidy, second characterization of Zipf’s Law:

\[
\log R = \log \alpha - \beta \log S
\]  

In the literature, Zipf’s Law is often illustrated by plotting city rank \((R)\) against city size \((S)\). Figure 1 shows how Zipf’s Law is apparent in data on city populations in three high income, three lower income, and three historical economies. In some cases, the literature associates Zipf’s Law with the case where \(\beta \approx 1\). However, estimates of \(\beta\) vary across time and economies. This paper focuses on the log-linear (power law type) relationship, but takes an agnostic position on the range of acceptable \(\beta\)’s\(^3\).

2.2 Theories

Two types of theories have been advanced to explain Zipf’s Law. Random growth theories explain Zipf’s Law as the outcome of a growth process in which all cities – big and small – draw growth rates from some common distribution. Geographic theories explain Zipf’s Law as reflecting the distribution of natural advantages across locations.

\(^1\)The proper entities are urban agglomerations, which are what this paper analyzes.

\(^2\)Even if the data generating process conforms to equation (1), equation (2) only holds approximately. Gabaix (1999b, 2008) provides discussion and derivations.

\(^3\)Gabaix and Ioannides (2004: 2350) observe: “the debate on Zipf’s Law should be cast in terms of how well, or poorly, it fits, rather than whether it can be rejected or not...if the empirical research establishes that the data are well described by a power law with exponent \(\beta \in [0.8,1.2]\), then this is a useful result.” NB: For consistency, notation changed to \(\beta\).
Gabaix (1999b, 2008) has shown that Zipf’s Law may emerge as the limiting distribution of a process in which cities draw random growth rates from a common distribution. Beyond random growth, the key assumption in Gabaix (1999b) is that there is an arbitrarily small reflecting barrier that prevents cities from getting “too small.”

Earlier contributions tying Zipf’s Law to random growth include Krugman (1996a) and Simon (1955) and are reviewed in Gabaix (1999b, 2008).

Recent theoretical work has explored how random growth may deliver Zipf’s Law. Cordoba (2004) provides a model in which either tastes or technologies follow a reflected Brownian motion. Rossi-Hansberg and Wright (2007) develop a model in which there are increasing returns at the local level and constant returns in the aggregate, and Zipf’s Law emerges under special circumstances. In Cordoba (2004) and Rossi-Hansberg and Wright (2007), cities specialize in particular final (or tradable) goods, and Zipf’s Law emerges as cities reach efficient size given their specialization.

Against theories that center on random growth, Krugman has suggested a geographic explanation. Krugman (1996b) observes that the physical landscape is not homogeneous, and that the distribution of propitious locations may follow a power law and thus account for the size distribution of cities. Davis and Weinstein (2002: 1269-1270) similarly argue

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4 This assumption is consistent with the historical evidence. Livi-Bacci (1999) observes that while certain cities have experienced relative decline, since 1000 AD cities have rarely disappeared in European history. Without this assumption, random growth delivers a lognormal distribution, not a power law.

5 It emerges when (i) capital does not enter production and permanent productivity shocks are the only shocks, or (ii) production is linear in capital and shocks are transitory.

6 As discussed on p. [12], the fact that Zipf’s Law emerged over time, and that there was substantial “churning” in Europe’s urban hierarchies, indicates that a purely geographic theory will be insufficient. It also suggests that pre-modern growth was non-random.
that city size hierarchies are determined by locational fundamentals that are essentially fixed over time. Davis and Weinstein observe that, “crucial characteristics for locations have changed little over time...for example, there are advantages of being near a river, on the coast, on a plain instead of a mountain.” In their view, “Instead of city growth itself being random, it is fundamental economic characteristics of locations that are random.”

2.3 Evidence

In recent work, Ioannides and Overman (2004) show that contemporary city growth in the USA appears to be random. But Soo (2005) examines cross-country data and finds that they are inconsistent with a $\beta = 1$ Zipf’s Law in many economies, a finding also emphasised in Ioannides et al. (2008). Rossi-Hansberg and Wright (2007) observe that contemporary data are marked by a mild case of what this paper shows was a glaring historical fact: from the perspective of Zipf’s Law, small cities are under-represented and big cities are too small. They argue that this results when small cities grow quickly and large cities grow slowly. Gabaix (1999b) observes a further anomaly: capital cities typically do not conform to Zipf’s Law. I return to these points below.

Davis and Weinstein (2002) provide evidence in support of the locational fundamentals view. Davis and Weinstein find that a regional analogue to Zipf’s Law holds across time periods stretching back thousands of years and that the hierarchy of regional population densities in Japan has been relatively stable over many centuries. They also observe that the Japanese city size hierarchy has been stable even in the face of massive shocks due to the firebombing of select Japanese cities during the World War II. Based on these findings they argue that fixed locational fundamentals are key determinants of the distribution of populations and that random growth theories are flawed.

The economic history literature has examined Zipf’s Law in a number of settings, but to my knowledge has not examined its emergence in Western Europe. Russell (1972) provides data revealing that, from the perspective of Zipf’s Law, the largest cities in the urban systems of medieval Europe were relatively small. Similarly, de Vries (1984, 1990: 52) observes that urban systems may not always conform to Zipf’s Law and that rank-size distributions, “can summarize effectively the process of urbanization and identify gross differences in the design of urban systems over time [and] in different societies.”

8In de Vries (1984), analysis is restricted cities with population of 10,000 or more and the period 1500-1800. This paper examines a panel of cities with population of 5,000 or more over the period 800-1800. In addition, this paper examines data on all European cities while the de Vries data excludes much of Eastern Europe.
Archaeological data confirm departures from Zipf’s Law across a range of pre-modern or non-capitalist economies (Johnson 1980, Drennan and Peterson 2004, and Savage 1997).[^9]

3 Data

In this section I present the city population data and the regional classification of cities. Additional data are discussed as introduced and in Appendix A.

3.1 Data on City Populations

This paper employs data on European city populations from Bairoch et al. (1988). Their approach is to identify the set of cities that ever reached 5,000 inhabitants between 1000 and 1800, and then to search for population data for these cities in all periods. The data are intended to record (in thousands) the populations of urban agglomerations, not simply populations within administratively defined boundaries.[^10] These data – henceforth the “Bairoch data” – are recorded every 100 years 800-1700, and then every 50 years to 1850.

This paper only examines cities with population of at least 5,000. It further restricts the principal analysis to the period from 1300 forward, when data on a relatively large set of cities are available. Table 1 summarizes the Bairoch data for Western Europe.

I test for measurement error in several ways. In Appendix B I compare the Bairoch data to the most comprehensive independent source for city population data, the database in de Vries (1984).[^11] I document that the Bairoch and de Vries population figures are on average within 7 percentage points of each other and that there is no evidence of systematic shortfalls in the populations that the Bairoch data record for large cities.[^12] However, it is possible that there is non-classical measurement error in both the Bairoch

[^9]: Zipf’s Law has also been examined by anthropologists. Smith (1982) observes that pre-capitalist economies typically do not exhibit Zipf’s Law. Smith suggests deviations from Zipf’s Law may be due to limited “commercial interchange” or to low agricultural productivity, but does not identify the negative correlation between size and growth as the key source of historical deviations from Zipf’s Law.

[^10]: Bairoch et al. (1988: 289) make a special effort to include, “the ‘fauborgs’, the ‘suburbs’, ‘communes’, ‘hamlets’, ‘quarters’, etc. that are directly adjacent” to historic city centers. Bairoch et al. draw data from primary and secondary sources. Prior to publication the data was reviewed by 6 research institutes and 31 regional specialists in urban history.

[^11]: The Bairoch data covers all European cities that reached 5,000 inhabitants by or before 1800, has rich data from 1300 to 1850, and contains observations on 2,204 cities. The data in de Vries (1984) covers cities that reached a population of 10,000 between 1500 and 1800 and covers 379 cities.

[^12]: Classical measurement error is not a plausible explanation for the observed deviations from Zipf’s Law. Gabaix (2008) observes that: power laws are preserved under addition, multiplication and polynomial combination; multiplying by normal variables or adding non-fat tail noise does not change the exponent; and while noise will effect variances in empirical settings, it does not distort the exponent.
Table 1: City Growth in Western Europe

<table>
<thead>
<tr>
<th>Period</th>
<th>Cities</th>
<th>Mean</th>
<th>St. Dev.</th>
</tr>
</thead>
<tbody>
<tr>
<td>800 - 900</td>
<td>31</td>
<td>0.09%</td>
<td>0.52%</td>
</tr>
<tr>
<td>900 - 1000</td>
<td>13</td>
<td>0.30%</td>
<td>0.77%</td>
</tr>
<tr>
<td>1000 - 1200</td>
<td>74</td>
<td>0.16%</td>
<td>0.30%</td>
</tr>
<tr>
<td>1200 - 1300</td>
<td>99</td>
<td>0.14%</td>
<td>0.58%</td>
</tr>
<tr>
<td>1300 - 1400</td>
<td>255</td>
<td>-0.22%</td>
<td>0.58%</td>
</tr>
<tr>
<td>1400 - 1500</td>
<td>187</td>
<td>0.06%</td>
<td>0.52%</td>
</tr>
<tr>
<td>1500 - 1600</td>
<td>321</td>
<td>0.18%</td>
<td>0.46%</td>
</tr>
<tr>
<td>1600 - 1700</td>
<td>514</td>
<td>-0.13%</td>
<td>0.55%</td>
</tr>
<tr>
<td>1700 - 1750</td>
<td>539</td>
<td>0.28%</td>
<td>0.60%</td>
</tr>
<tr>
<td>1750 - 1800</td>
<td>686</td>
<td>0.29%</td>
<td>0.63%</td>
</tr>
<tr>
<td>1800 - 1850</td>
<td>1,311</td>
<td>0.68%</td>
<td>0.78%</td>
</tr>
</tbody>
</table>

Note: Growth rates and standard deviations computed on an annualized basis.

data and de Vries (1984). In section 4.1, I show that the data would have to embody implausibly large non-classical measurement error for Zipf’s Law to have actually held. In section 5, I show that the observed deviations from Zipf’s Law are consistent with the narrative evidence collected by social historians.

3.2 Regional Classification of Cities

This section explains why it makes sense to examine the Zipf’s Law in Western Europe as a whole and how differences in the institutional environment distinguished cities in Western Europe from cities in Eastern and Ottoman Europe.

The unit of analysis in contemporary research on Zipf’s Law is typically the national economy. However, a transnational perspective is appropriate for an analysis of city growth in European history. Between 1000 and 1800, political fragmentation allowed cross-border economic linkages to organize urbanization and for European cities to begin to develop a single urban system. Significantly, the deviations from Zipf’s Law documented in this paper are not figments of the aggregation. The emergence of Zipf’s Law in Western Europe 1500-1800 was mirrored by its emergence over the same period at the local and national levels. These facts are documented in Appendix C.

Cities West of the Elbe River, which cuts through Eastern Germany, developed in a distinct institutional environment. The distinction between Western and non-Western

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14Cities in Western Germany, the Netherlands, Italy, Belgium, Iberia, Switzerland, and England are
cities was determined by two key aspects of economic institutions: first, the presence of institutions securing municipal autonomy for cities; second, the nature of the institutions determining the possibilities for mobility between the rural and urban sectors. Town charters in the West typically guaranteed townspeople the right to legal proceedings in town courts, the right to sell their homes and to move, and freedom from most obligations associated with serfdom (e.g. arbitrary taxation, the provision of labor services, the head tax, and most forms of military service). These legal institutions fostered relatively secure property rights and the growth of urban commerce. In Eastern and Ottoman-controlled Europe, cities developed in a different institutional environment. Under the Ottomans, cities were not granted municipal autonomy, allocations were more heavily influenced by administrative means, and city growth was shaped by the “ruralization” of Christian populations. In Eastern Europe, where German city law (Deutsches Städtrecht) had previously secured freedoms for townspeople and villagers, institutions limiting labor mobility and city autonomy were installed after 1500. These laws forbade seasonal migration, tied tenant farmers to rural estates, provided for the return of fugitive serfs, and limited the activities of merchants. An extensive literature documents the importance of the Elbe River as an institutional boundary distinguishing Western Europe from a central Eastern Europe in which the legal institutions of serfdom were strengthened after 1500. Section 8 (below) examines the institutional geography, the nature of these laws, and their impact on city growth in greater detail.

4 How Zipf’s Law Emerged

4.1 Documenting the Facts

In this section I use graphs, OLS, quantile, and robust regression to document the paper’s key motivating fact: that Zipf’s Law emerged over time.

Figure 2 provides the motivating picture for this paper. It describes the evolution of city size distributions between 1300 and 1800 in Western Europe. It shows that prior to

\textsuperscript{16}See Pirenne (1927), Braudel (1979a, 1979b), Friedrichs (1995), Nicholas (2003), Scott (2005), Bideleux and Jeffries (2007), and van Zanden et al. (2010).


1600 the large cities were “too small,” and how Zipf’s Law emerged over time, by plotting observed populations against fitted values associated with the robust non-parametric regression estimator proposed by Theil (1950). Table 2 measures the historical deviations from Zipf’s Law. It provides quantitative evidence that deviations from Zipf’s Law went from being large in 1300 to small in 1800.

Figure 2: The Emergence of Zipf’s Law in Western Europe

Note: This figure plots (1) raw data on city populations ($S_i$) and their corresponding size rankings ($R_i$), and (2) fitted values estimated using robust non-parametric Theil regression and the model: \( \ln(R_i) = \alpha - \beta \ln(S_i) + \epsilon_i \).

Populations in thousands are from Bairoch et al. (1988).

A formal test rejects the null hypothesis that the data follow a power law distribution up through 1500. Indexing cities with $i$ and denoting city size $S$ and city rank $R$, the test developed in Gabaix (2008) relies on an OLS regression:

\[
\ln(R_i - 1/2) = \delta_0 + \delta_1 \ln S_i + \delta_2 (\ln S_i - S^*)^2 + \epsilon_i
\]

where $S^* = \text{cov}[(\ln S_i)^2, \ln S_i]/2\text{var}[\ln S_i]$ and the shift of -1/2 provides the optimal reduction in small sample bias in the OLS setting. Under the Gabaix test, we reject the null hypothesis that the data follow a power law distribution up through 1500.

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19 The way robust regression can be used to gauge departures from power laws is discussed below in section 4.3. Appendix D discusses the Theil estimator and shows that for estimating power law exponents it is superior to OLS and competitive with the adjusted-OLS estimator proposed by Gabaix and Ibragimov (2007) in terms of both small sample properties and precision.

20 An earlier literature examined Zipf’s Law with regressions: \( \ln(R_i) = \beta_0 + \beta_1 \ln S_i + \beta_2 \ln S_i^2 + \nu_i \). As
Table 2: Mean Square Deviations from Zipf’s Law

<table>
<thead>
<tr>
<th>Year</th>
<th>Deviation</th>
</tr>
</thead>
<tbody>
<tr>
<td>1300</td>
<td>6.27%</td>
</tr>
<tr>
<td>1400</td>
<td>4.21%</td>
</tr>
<tr>
<td>1500</td>
<td>1.51%</td>
</tr>
<tr>
<td>1600</td>
<td>0.58%</td>
</tr>
<tr>
<td>1700</td>
<td>0.50%</td>
</tr>
<tr>
<td>1800</td>
<td>0.18%</td>
</tr>
</tbody>
</table>

Note: For cities indexed with \( i = 1, \ldots, N \), actual (observed) population \( S^i_a \), and Zipf-consistent population \( S^i_z \) computed from Theil regression estimates, mean square deviation is: 
\[
MSD = N^{-1} \sum_{i=1}^{N} \left( \frac{S^i_a}{S^i_z} - 1 \right)^2.
\]

hypothesis of a power law with 95 percent confidence if and only if \( |\hat{\delta}_2/\hat{\delta}_1^2| > 1.95(2n)^{-0.5} \). Table 3 presents parameter estimates from [4]. It shows that we can reject Zipf’s Law in Western Europe up through 1500, but that we can not reject Zipf’s Law in Western Europe from 1600 forwards.

Table 3: A Regression-Based Test of Deviations from Zipf’s Law

<table>
<thead>
<tr>
<th>Year</th>
<th>Observations</th>
<th>( \delta_1 )</th>
<th>( \delta_2 )</th>
<th>Reject ZL</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>(1)</td>
<td>(2)</td>
<td>(3)</td>
<td>(4)</td>
</tr>
<tr>
<td>1300</td>
<td>255</td>
<td>-1.31</td>
<td>-0.33</td>
<td>Yes</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(0.02)</td>
<td>(0.03)</td>
<td></td>
</tr>
<tr>
<td>1400</td>
<td>187</td>
<td>-1.15</td>
<td>-0.26</td>
<td>Yes</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(0.12)</td>
<td>(0.03)</td>
<td></td>
</tr>
<tr>
<td>1500</td>
<td>321</td>
<td>-1.35</td>
<td>-0.24</td>
<td>Yes</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(0.11)</td>
<td>(0.02)</td>
<td></td>
</tr>
<tr>
<td>1600</td>
<td>514</td>
<td>-1.33</td>
<td>-0.11</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>(0.08)</td>
<td>(0.01)</td>
<td></td>
</tr>
<tr>
<td>1700</td>
<td>539</td>
<td>-1.22</td>
<td>-0.06</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>(0.07)</td>
<td>(0.00)</td>
<td></td>
</tr>
<tr>
<td>1800</td>
<td>1,311</td>
<td>-1.40</td>
<td>-0.02</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>(0.05)</td>
<td>(0.00)</td>
<td></td>
</tr>
</tbody>
</table>

Note: The regression is: 
\[
\ln(R_i - 1/2) = \delta_0 + \delta_1 \ln S_i + \delta_2 (\ln S_i - S^*)^2 + \epsilon_i,
\]
where \( R_i \) is city rank, \( S_i \) is city population, and \( S^* \equiv \text{cov}[(\ln S_i)^2, \ln S_i] / \text{var}[(\ln S_i)] \). We reject the null hypothesis of a power law with 95 percent confidence if and only if \(|\hat{\delta}_2/\hat{\delta}_1|^2 > 1.95(2n)^{-0.5} \). Standard errors adjusted to correct for the positive autocorrelation of residuals induced by ranking.

discussed in Gabaix (2008), heteroskedasticity-robust standard errors will be biased down in this specification and the statistical significance of \( \hat{\beta}_2 \) is not a robust criterion for a test of Zipf’s Law. However, to facilitate comparison with existing studies, Appendix E presents results from this specification which support the conclusion that Zipf’s Law emerged in Western Europe 1500-1800.
Quantile regression identifies more precisely where over the range of city sizes the curvature in the rank-size relation emerges. Table 4 presents historical estimates of local, quantile slope parameters associated with equation (3). It shows that the big non-linearities were at the upper end of the city size distributions. In Table 4, as $\tau$ declines the estimates describe the local Zipf exponents (slopes) associated with progressively larger cities. That the big non-linearities are located at the upper end of the city size distribution is evident in the fact that local slopes change modestly as $\tau$ falls from 0.9 to 0.25 and sharply as $\tau$ falls from 0.25 to 0.1. By 1800 the local Zipf exponents of Western European cities are relatively stable in the upper tail (i.e. as $\tau$ declines).

<table>
<thead>
<tr>
<th>Year</th>
<th>$\tau = 0.9$</th>
<th>$\tau = 0.75$</th>
<th>$\tau = 0.5$</th>
<th>$\tau = 0.25$</th>
<th>$\tau = 0.1$</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>(1)</td>
<td>(2)</td>
<td>(3)</td>
<td>(4)</td>
<td>(5)</td>
</tr>
<tr>
<td>1500</td>
<td>1.12</td>
<td>1.17</td>
<td>1.19</td>
<td>1.16</td>
<td>1.42</td>
</tr>
<tr>
<td></td>
<td>(0.04)</td>
<td>(0.01)</td>
<td>(0.01)</td>
<td>(0.04)</td>
<td>(0.09)</td>
</tr>
<tr>
<td>1600</td>
<td>1.26</td>
<td>1.28</td>
<td>1.24</td>
<td>1.25</td>
<td>1.32</td>
</tr>
<tr>
<td></td>
<td>(0.01)</td>
<td>(0.01)</td>
<td>(0.02)</td>
<td>(0.04)</td>
<td>(0.01)</td>
</tr>
<tr>
<td>1700</td>
<td>1.12</td>
<td>1.12</td>
<td>1.13</td>
<td>1.19</td>
<td>1.24</td>
</tr>
<tr>
<td></td>
<td>(0.01)</td>
<td>(0.00)</td>
<td>(0.02)</td>
<td>(0.01)</td>
<td>(0.01)</td>
</tr>
<tr>
<td>1800</td>
<td>1.33</td>
<td>1.37</td>
<td>1.39</td>
<td>1.39</td>
<td>1.41</td>
</tr>
<tr>
<td></td>
<td>(0.01)</td>
<td>(0.01)</td>
<td>(0.00)</td>
<td>(0.00)</td>
<td>(0.00)</td>
</tr>
</tbody>
</table>

Note: Quantile slope parameter $\beta(\tau)$ estimated with regression: $\ln R_i = \alpha - \beta(\tau)\ln S_i + \epsilon_i$. As $\tau$ declines, quantile regression estimates describe the local slope associated with progressively larger cities. Bootstrapped standard errors in parentheses.

It is, however, conceivable that non-classical measurement error accounts for the pronounced deviations from Zipf’s Law in the upper tail – that historical records undercount populations in big cities. It is also possible that historical data undercount populations of small cities.

To gauge the possibility that the data undercount populations in the largest cities, I estimate hypothetical Zipf’s Laws and calculate deviations from these benchmarks. The exercise amounts to asking: How much larger (smaller) would outlier cities need to be to generate a pure log-linear relation? There are several reasons to use a robust regression

\[ \text{Quantile regression relaxes an assumption the OLS estimator embodies: that, given independent covariates, conditional quantile functions of the response variable have a common slope. Quantile regression estimates assume a piecewise linear loss function and minimizing the (asymmetric except in the case where } \tau = 0.5 \text{) sum of absolute residuals. See Koenker (2005).} \]

\[ \text{The parameter } \tau \text{ defines quantiles in the response variable, city rank. The } \tau \text{ quantile in the city rank distribution corresponds to the } (1 - \tau) \text{ quantile in the city size distribution.} \]

21 Quantile regression relaxes an assumption the OLS estimator embodies: that, given independent covariates, conditional quantile functions of the response variable have a common slope. Quantile regression estimates assume a piecewise linear loss function and minimizing the (asymmetric except in the case where $\tau = 0.5$) sum of absolute residuals. See Koenker (2005).

22 The parameter $\tau$ defines quantiles in the response variable, city rank. The $\tau$ quantile in the city rank distribution corresponds to the $(1 - \tau)$ quantile in the city size distribution.
estimator in this exercise. As shown in Appendix D, when data are generated by a stochastic power law, OLS estimators exhibit pronounced small sample bias. Moreover, there appear to be outliers and the performance of OLS estimators is poor when there are heavy-tailed error distributions or when leverage points are present. Further, examination of the residuals from a robust regression can identify outliers, which examination of OLS residuals typically cannot do (Koenker 2005, He et al. 1990).

Table 5 uses the Theil estimator to construct a measure of deviations from Zipf’s Law. It uses the Theil regression predictions displayed in Figure 2 to compare observed population to “Zipf-consistent” population for the biggest cities in Western Europe. It shows that between 1500 and 1700 the biggest cities were far smaller than they needed to be to satisfy a rank-size rule. For instance, the ten largest cities were on average less than 1/2 the size of the counter-factual Zipf-consistent populations in 1500. The magnitudes of the big city population shortfalls are so big that non-classical measurement error is not a plausible explanation for the observed deviations from Zipf’s Law. The fact that the divergences are all shortfalls is consistent with the narrative evidence presented in the next section.

Table 5: The Ratio of Actual to Zipf-Consistent Population

<table>
<thead>
<tr>
<th>Top 10 Cities</th>
<th>1500</th>
<th>1600</th>
<th>1700</th>
<th>1800</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>(1)</td>
<td>(2)</td>
<td>(3)</td>
<td>(4)</td>
</tr>
<tr>
<td>1</td>
<td>0.3</td>
<td>0.4</td>
<td>0.5</td>
<td>1.1</td>
</tr>
<tr>
<td>2</td>
<td>0.3</td>
<td>0.7</td>
<td>0.8</td>
<td>1.1</td>
</tr>
<tr>
<td>3</td>
<td>0.4</td>
<td>0.7</td>
<td>0.7</td>
<td>1.2</td>
</tr>
<tr>
<td>4</td>
<td>0.4</td>
<td>0.6</td>
<td>0.6</td>
<td>0.7</td>
</tr>
<tr>
<td>5</td>
<td>0.4</td>
<td>0.7</td>
<td>0.7</td>
<td>0.8</td>
</tr>
<tr>
<td>6</td>
<td>0.4</td>
<td>0.8</td>
<td>0.6</td>
<td>0.9</td>
</tr>
<tr>
<td>7</td>
<td>0.5</td>
<td>0.8</td>
<td>0.7</td>
<td>0.8</td>
</tr>
<tr>
<td>8</td>
<td>0.5</td>
<td>0.8</td>
<td>0.8</td>
<td>0.8</td>
</tr>
<tr>
<td>9</td>
<td>0.5</td>
<td>0.8</td>
<td>0.8</td>
<td>0.8</td>
</tr>
<tr>
<td>10</td>
<td>0.5</td>
<td>0.7</td>
<td>0.7</td>
<td>0.9</td>
</tr>
</tbody>
</table>

Note: This table shows the ratio of actual population \( S_i^a \) to Zipf-consistent population \( S_i^z \). Zipf-consistent population is estimated using the predicted values from the Theil regressions in Figure 2.

### 4.2 Implications

The observed deviations from Zipf’s Law have three key implications. First, because the principal geographic features of the European landscape – e.g. the location of navigable rivers and bays suitable for ports – remained essentially unaltered before 1800, the fact
that Zipf’s Law emerged between 1500 and 1800 suggests that it is due to something beyond a power law distribution of propitious locations.

Second, if random growth is the explanation for the rank-size regularity, the fact that this regularity emerged relatively recently implies that there was persistent non-randomness in urban growth in the pre-modern era.

Third, something other than specialization in goods production accounts for Zipf’s Law. Models of urban hierarchies, from Henderson (1974) to Black and Henderson (1999), Cordoba (2004), and Rossi-Hansberg and Wright (2007), assume industrial specialization accounts for city size distributions. In these models, industry-specific externalities combine with diseconomies that increase in city size, driving cities to specialize in specific tradable industries and to optimal size for their particular activities. But Figure 2 shows that “modern” patterns of urban hierarchy emerged before the widespread adoption of the factory system, when industrial specialization, inter-city trade, and even the non-industrial functional specialization of cities was relatively limited.

5 Explaining the Emergence of Zipf’s Law: History

In this section I discuss why land was a quasi-fixed factor for pre-modern cities, how this limited the growth of large cities prior to 1500, and how this changed after 1500. I also discuss the demography of pre- and early modern cities.

Historically, transport costs and the risks associated with long distance trade in food constrained cities to rely on local sources for land-intensive wage goods. Contemporaries recognized that this constraint prevented the proportionate growth (size-independent growth rates) associated with Zipf’s Law. In 1602, Giovanni Botero noted that, “cities once grown to a greatness increase not onward according to that proportion.” Botero considered and rejected explanations centered on wars, plagues, and chance. He observed that the absence of proportionate growth was explained by the difficulty large cities had in feeding themselves given prevailing transport costs (Botero 1602, Book 2, Pt. 9).

In early modern Europe, agricultural surpluses were limited, poor harvests brought famine, and secure access to food supplies was a precondition of the growth of large cities. The security of supplies was often dependent on the degree of control cities could exert on the surrounding countryside. For Paris, the largest city in 17th century Europe, the problem of securing foodstuffs was especially acute, and is repeatedly stressed by

23Nicholas (2003: 7) observes that, “Probably no pre-modern city was as functionally specialised as modern industrial cities tend to be.”
contemporary commentators. In 1591, Pope Gregory XIV issued an edict designed to
facilitate the provisioning of Rome from its countryside. In Northern Italy, great cities –
like Milan and Florence – conquered and dominated dependent territories that included
smaller cities and agricultural hinterlands. Cities on the Istrian and Dalmatian coast
similarly controlled territories that stretched inland to the mountains. However, while
a city’s ability to control a rural district was typically contingent on the absence of a
strong regional prince, urban territorial expansion was most often the result of purchases,
foreclosed mortgages, and piecemeal treaty acquisitions – and not military conquest. In
Germany, Nürnberg, Ulm, and Schwäbisch Hall acquired hinterlands of 1,200, 830, and
330 km², respectively. The balance of political and economic influence might differ, but
similar struggles emerged: Lübeck and Hamburg experienced a series of conflicts with the
counts of Schleswig-Holstein and kings of Denmark over rival claims on land, waterways,
and resources.\textsuperscript{24}

If control over the countryside was important, transportation costs were the other
central constraint. Transportation costs – especially for heavier products and overland
transport – were exceedingly high. Grain transported 200 kilometers overland could
see its price rise by nearly 100 percent. While the early modern period saw major
developments in the international trade in grain, most cities remained heavily reliant on
the provision of foodstuffs from a within a circle of 20 to 30 kilometers which avoided
heavy transport costs and the risks of reliance on foreign supplies.\textsuperscript{25} As a result, cities
preserved substantial forms of land-intensive production. There were gardens, fields, and
areas devoted to livestock within cities themselves.\textsuperscript{26} Costs associated with the transport
of fuel generated similar bottlenecks (Ballaux and Blondé 2004).

The fact that land – or a land-intensive intermediate – was a quasi-fixed factor in
urban production, is reflected in price data. Kriedte (1979: 27) notes that in the late 16th
century grain and oxen prices were, respectively, 89 and 270 percent higher in Antwerp
(commercial hub of relatively urbanized Low Countries) than in Danzig (principal port
of rural Poland). Pounds (1979: 61) observes that prices of agricultural products were
increasing in town size. The data support these observations. Figure 6 plots consumer
prices and bread prices from Allen (2001) against city population, along with the fitted
values from a median regression of consumer prices on city size.\textsuperscript{27} It shows that (1)
consumer prices tracked bread prices, (2) prices were correlated with city size, and (3)


suggest transport over land was four times more expensive than on navigable rivers. I discuss water-borne
transport and estimate the growth advantage enjoyed by ports and cities on navigable rivers below.

\textsuperscript{26}Braudel (1979a), Nicholas (2003), Scott (2004), and Friedrichs (1995).

\textsuperscript{27}Basic land-intensive products account for 2/3’s of spending in Allen’s (2001) consumer price index.

14
that the correlation declined over time\textsuperscript{28}. The data thus support the argument that while food prices were increasing in city size, the land constraint softened over time\textsuperscript{29}.

Figure 6: Consumer Prices and City Sizes

Note: Price data are from Allen (2001). Bread prices scaled by multiplying by 100.

Two factors relaxed the land constraint on city growth: the development of the international grain trade and increases in agricultural productivity. The grain trade was known to the Dutch as the \textit{moedernegotie}: the “mother of all trades.” In the Northern Netherlands, where city growth was unusually rapid, the bread and beer supply of city populations depended on grain imports. Grain came to be imported in quantities sufficient to feed 1 in 4 inhabitants of the Dutch Republic (van Tielhof 2002: 1). As shown in Table 6, Dutch grain imports were sufficient to feed the entire urban population of the Netherlands by 1600. Moreover, as de Vries and van der Woude (1997: 414-5) observe, “grain was the commodity that gave Dutch merchants entrée to the Iberian and Mediterranean ports from the 1590s on.” These developments were made possible by innovations in shipping technology (notably the introduction of the \textit{fluyt} vessel) and an associated decline in freight shipping costs on maritime routes in the 16th century (van Zanden and Tielhof 2009). In the 1510’s, the cost of shipping rye from the Baltic to Amsterdam represented over 20 percent of its price when sold in Holland. By the 1580’s and 1590’s, ratio of shipping costs to sale prices fell to an average of 10 percent (see van Tielhof 2002: 198).

Increases in agricultural productivity also relaxed the land constraint, and were a key factor in the growth of cities in Northwest Europe (Maddalena 1977, Pounds 1990, \textsuperscript{28}\textsuperscript{28}OLS estimates confirm the decline in correlation between prices and city size. The OLS estimate (standard errors in parentheses) declines from 0.21 (0.08) in 1600 to 0.19 (0.07) in 1700 and 0.17 (0.07) in 1800.\textsuperscript{29}\textsuperscript{29}Historical evidence suggests that the price differentials associated with city size are not accounted for by the higher rents paid by bakers and other retail establishments selling basic wage goods. See Kriedte (1979) and Pounds (1979, 1990).
Table 6: Dutch Imports of Baltic Grain

<table>
<thead>
<tr>
<th>Period</th>
<th>Hectolitres/Year</th>
<th>Enough to Feed</th>
</tr>
</thead>
<tbody>
<tr>
<td>1550s</td>
<td>1,053,500</td>
<td>263,375</td>
</tr>
<tr>
<td>1590s</td>
<td>1,745,800</td>
<td>436,450</td>
</tr>
<tr>
<td>1640s</td>
<td>2,859,500</td>
<td>714,875</td>
</tr>
</tbody>
</table>

Note: Data from van Tielhof (2002). Calculations assume consumption of 4 hectolitres per person per year. In 1600, the 24 largest Dutch cities had 421 thousand inhabitants.

Kriedte 1979). Agricultural productivity was positively associated with urbanization, and economies where city growth was concentrated experienced relatively high productivity growth in agriculture. Figure 7 shows how urbanization rates were correlated with estimates of agricultural total factor productivity in nine macroeconomies.

Figure 7: Agricultural TFP and Urbanization in European History


While the period 1500-1800 saw marked increases in agricultural productivity and in the trade in food, the public health environment in cities did not improve substantially. An extensive literature on the demography of early modern cities finds that urban death rates exceeded urban birth rates and rural death rates. In general, mortality was increasing in city size. Other things equal, this limited the growth of large cities. However, the big revolutions in public health came after 1800 and mortality in large cities remained relatively high throughout the early modern period. The plague stopped striking the cities of Western Europe only well into the 1700s. It was only in the wake of the work by John Snow in the mid-1850s that germ theories of disease transmission began to be accepted. Previously, the dominant view was the miasma theory – which held that diseases such as cholera or the Black Death were caused by a form of “bad air.” These facts support the conclusion that the key changes were not in the domain of public health.

6 Explaining the Emergence of Zipf’s Law: Model

6.1 Motivation

The leading theories explain Zipf’s Law as the outcome of a random growth process. Rossi-Hansberg and Wright (2007) have shown that the slight curvature observed in log rank-log size plots of contemporary city population data may reflect a negative correlation between city sizes and city growth rates. Intuitively, this curvature emerges when small cities tend to grow quickly and “escape” to become mid-sized, and when larger cities tend to grow slowly, leaving the largest cities smaller in size and the small cities fewer in number than they “should be.” A similar, but more pronounced curvature characterizes the historical data. As shown below, this curvature is observed when and where growth rates were negatively correlated with city size over long periods.

I incorporate Rossi-Hansberg and Wright’s insight in a simple model of city growth. The model contains a feature that may deliver non-random growth: land may be a fixed argument in production, generating decreasing returns to scale. When this feature is “shut off,” the model reduces to the random growth model in Gabaix (1999b).

6.2 Environment

The model has overlapping generations. At any time $t$, cities indexed with $i$ have old residents $N_{o}^{i}$ and young residents $N_{y}^{i}$, with old people dying at some rate $\delta$. The overlapping generations structure has a first period in which potential workers are born young and decide if and where to migrate (paying some fixed migration cost $x$). In subsequent periods workers are old and live out their days without further migration. There are city-specific amenity shocks $a_{it}$ due to some combination of policy and nature. In particular:

$$a_{it} = \epsilon_{it}(1 - \tau_{it}) \quad (5)$$

$\epsilon_{it}$ is an iid city-specific shock and $\tau_{it} \in (0, 1)$ is a city-specific distortion. Without loss of generality, the amenity shocks $a_{it}$ enter utility multiplicatively:

$$u(c) = a_{it}c \quad (6)$$

31In Rossi-Hansberg and Wright’s model, industrial specialization accounts for urban hierarchies. However, Zipf’s Law emerged when industrial and functional specialization was very limited, suggesting that another mechanism may have been at work.

32Workers are young once and typically old for multiple periods.
Production is Cobb-Douglas in technology \((A)\), labor (young \(N^y\) and old \(N^o\)), and land \((L)\):

\[
Y_{it} = A_{it}(N^y_{it})^\alpha(N^o_{it})^\beta(L_{it})^{1-\alpha-\beta}
\]

Assume that \(\alpha, \beta \in (0,1)\) and that \(\alpha + \beta \leq 1\). Where \(\alpha + \beta = 1\), production is CRS in labor. By assumption, city residents own labor but not land. The wage is the marginal product of labor and is consumed in each period:

\[
c_{it} = w_{it} = \frac{\partial Y_{it}}{\partial N^j_{it}} \quad j \in \{y, o\}
\]

The aggregate number of young potential migrants is determined by a “birth rate” \(n_t\) and the total number of mature agents. The birth rate can equally be taken as a description of the migration rate from the non-urban sector. The number of young agents arriving in each city is endogenous.

### 6.3 Analysis of City Growth – The General Case

Individuals choose a city \(i\) subject to city-specific migration taxes \(\tau_{it}\) and given the existing distribution of populations (wages). The individual maximization problem reduces to:

\[
\max_i a_{it}w_{it}
\]

In equilibrium with free mobility: \(u_{it} = u_t\). It follows that:

\[
w_{it} = \frac{u_t}{a_{it}}
\]

Because young people earn wages equal to their marginal product, and wages equalize across age groups, we have that:

\[
w_{it} = \alpha A_{it}(N^y_{it})^{\alpha-1}(N^o_{it})^\beta(L_{it})^{1-\alpha-\beta}
\]

---

33Production is modelled without a capital argument in the interest of parsimony. NB: In the pre- and early modern era, fixed capital was important in the rural economy but less critical in the cities. See Cipolla (1982).

34This assumption raises the question: who receives rents on urban land? One can assume following Henderson (1974, 2005) that each city is owned by a single private land developer. This was the situation in many Eastern European cities, which were owned by feudal lords. Alternately, assuming that a (small) class of urban landowners receive and consume the marginal product of urban land, would not change the basic story. Historically, the evolution of city populations was largely driven by the evolution of non-landowning populations. In the interest of parsimony, the model focuses on these agents.

35For simplicity, agents make a calculation based on utility in the current period, completely discounting future periods (and potential tax changes). A tax on wages leads to the same results.
Combining (5), (9), and (10), we get an expression for the number of new-comers in the representative city:

\[ N^y_{it} = \left( N^0_{it} \right)^{1-\sigma} (A_{it})^{1-\alpha} (L_{it})^{1-\alpha-\beta} (1 - \tau_{it})^{1-\alpha} \left( \frac{\alpha \epsilon_{it}}{u_t} \right)^{1-\alpha} \]  

(11)

The representative city growth rate is:

\[ g^N_{it} \equiv \frac{\Delta N_{it}}{N_{it}} = \frac{N^y_{it} - \delta N^0_{it}}{N^0_{it}} \]  

(12)

Substituting with equation (11) gives:

\[ g^N_{it} = \left( N^0_{it} \right)^{\beta + \alpha - 1} (A_{it})^{1-\alpha} (L_{it})^{1-\alpha-\beta} (1 - \tau_{it})^{1-\alpha} \left( \frac{\alpha \epsilon_{it}}{u_t} \right)^{1-\alpha} - \delta \]  

(13)

A distortion hitting productivity would have an identical growth rate impact.

### 6.4 Case 1: Random Growth with No Distortions

The conventional argument in the Zipf’s Law literature is that growth rates are independent of city size. This argument typically embodies three assumptions: fixed factors are not important in urban production; productivity does not vary with population across cities; and distortions are independent of city size. When land does not enter production \( \alpha + \beta = 1 \). The idea that productivity and distortions (e.g. migration costs) do not vary with city size can be captured by assuming: \( \tau_{it} = \tau_t \) and \( A_{it} = A_t \). To consider the case without distortions let \( \tau_t = 0 \). Substituting into equation (13) gives:

\[ g^N_{it} = \left( A_t \right)^{1-\alpha} \left( \frac{\alpha \epsilon_{it}}{u_t} \right)^{1-\alpha} - \delta \]  

(14)

Since the only city-specific argument on the right-hand side of (14) is the iid random shock \( \epsilon_{it} \), the rate of population growth is independent of city size. Provided we have some (arbitrarily small) reflecting barrier that keeps cities from getting “too small,” random growth delivers Zipf’s Law. This is the model in Gabaix (1999b).\(^{36}\)

\(^{36}\)Gabaix assumes technology is fixed \( (A_t = 1) \).
6.5 Case 2: Non-Random Growth Due to Fixed Land

Assume that migration costs are constant across cities, but land has some positive income share. For simplicity, normalize $L_{it} = L_i = 1$ and assume that $A_{it} = A_t$. We now have the following variant of equation (13):

$$g^N_{it} = \left( N^0_{it} \right)^{\beta+\alpha-1} (A_t)^{\frac{1}{1-\alpha}} \left( 1 - \tau_t \right)^{\frac{1}{1-\alpha}} \left( \frac{\alpha \epsilon_{it}}{u_t} \right)^{\frac{1}{1-\alpha}} - \delta$$  \hspace{1cm} (15)

Here land has a positive income share because $\alpha + \beta < 1$. This fact secures the key feature of (15): city growth rates decline in population when land is fixed. Broadly, one can imagine the long pre-modern era as one in which land entered production and land was more or less fixed. Under a fixed-land regime, growth rates are negatively correlated with city populations. Small cities will tend to draw high growth rates and become mid-sized. Similarly, big cities will tend to draw low growth rates and remain relatively small. Thus a fixed factor can deliver a distribution of growth rates in keeping with the curvature we see in European city size distributions between 1300 and 1600. (See Appendix for a simple simulation.)

6.6 Case 3: Taxes and Distorted Growth

Prospective migrants face utilities that embody a tax $\tau_{it}$. The tax $\tau_{it}$ generates non-random growth when (and if) it falls hardest on larger cities. When the tax is constant across cities, it lowers the variance of city growth rates.

Assume land is absent from production and all cities have the same level of productivity (normalized to unity). Migration into the representative city is:

$$N^y_{it} = N^0_{it} (1 - \tau_{it})^{\frac{1}{1-\alpha}} \left( \frac{\alpha \epsilon_{it}}{u_t} \right)^{\frac{1}{1-\alpha}}$$  \hspace{1cm} (16)

The associated growth rate is:

$$g^N_{it} = (1 - \tau_{it})^{\frac{1}{1-\alpha}} \left( \frac{\alpha \epsilon_{it}}{u_t} \right)^{\frac{1}{1-\alpha}} - \delta$$  \hspace{1cm} (17)

\[37\text{This model is sketched in reduced form. The model as sketched has distinct regimes. A more detailed treatment could incorporate a transition that allows the share of income going to the fixed factor to decay.}\]

\[38\text{It is assumed in equations (5) and (6) that $\tau_{it}$ enters utility through the multiplicative amenity shock, but an additive structure would not change the story.}\]
\(\tau_{it}\) captures the serfdom distortion. It can be thought of as embodying the effects of migration restrictions and legislation imposing higher effective taxes on larger cities (via a productivity distortion) – as generating a negative correlation between size and growth.

The institutions of the second serfdom had such biases. Historically, the share of economic activity accounted for by merchants and capitalists involved in the coordination and financing of longer-distance trade was increasing in city size. An institutional set-up biased against these activities is one with higher effective taxes on big cities. In Poland, merchants were in 1565 forbidden from owning land, travelling abroad, and engaging in international trade. In Prussia and Poland-Lithuania, land owners won the right to export their produce directly, circumventing local cities and merchants, and without paying otherwise required export taxes. In Poland, Prussia, and Bohemia price maxima were also placed on urban goods tilting the terms of trade towards agricultural landowners, lowering city incomes and the incentive to migration. In Hungary, the legislation passed after the defeated peasant uprising of 1514 limited the mobility of tenant farmers and eliminated the legal autonomy of towns. Migration restrictions also appear to have hit larger towns hardest. Larger cities typically had to draw migrants from relatively far afield. However, peasant migrants fleeing serfdom were not able to safely travel great distances. In the late 1600s the Austrians sent an emissary to Krakow to press the Polish authorities to implement their treaty agreement and return fugitive Silesian serfs. While this suggests instances of remarkable mobility, Wright (1961) observes that for most Bohemian serfs Poland was too distant to be an attainable asylum.

It is important observe that even a tax that does not vary with city size will delay the emergence of Zipf’s Law by lowering the variance of the city growth rate. Assume that \(\tau\) is constant across cities and for simplicity denote the variance of \(\epsilon_{it}^{1/(1-\alpha)}\) with \(\sigma_{\tilde{\epsilon}_t}^2\). From equation (17), the variance of the growth rate is declining in \(\tau\):

\[
\sigma_{gN}^2 = (1 - \tau_t)^{4/\alpha} \left( \frac{\alpha}{u_t} \right)^{2-\alpha} \sigma_{\tilde{\epsilon}_t}^2
\]

Moreover, these results hold when there is no distortion in amenities, but discriminatory institutions operate such that productivity is directly deflated by \(\tau_{it}\). In this case, the city growth rate \(g_{it}^N\) suffers from a distortion identical to the one generated by a direct tax on migration. City growth is again negatively correlated with city population when distortions rise in city size, and the variance of the growth rate is depressed even when they do not.

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39 See Blum (1957), Carsten (1954), and Kula (1962).
40 Gabaix (1999b) discusses how a growth process with a higher variance leads to relatively speedy emergence of Zipf’s Law.
7 Explaining the Emergence of Zipf’s Law: Empirics

This section examines random growth and locational fundamentals theories of Zipf’s Law.

7.1 Random Growth

The leading theories that account for Zipf’s Law posit random growth. This section establishes when and how random growth emerged in Western Europe.

Table 7 shows that random growth emerged only after 1500. Before 1500, there was a significant negative correlation between size and subsequent growth in every period except 1300-1400, the century of the Black Death. From 1500 forwards there is no significant correlation between size and growth.

<table>
<thead>
<tr>
<th>Period</th>
<th>Correlation</th>
</tr>
</thead>
<tbody>
<tr>
<td>1000 to 1200</td>
<td>-0.69 **</td>
</tr>
<tr>
<td>1200 to 1300</td>
<td>-0.23 **</td>
</tr>
<tr>
<td>1300 to 1400</td>
<td>-0.09</td>
</tr>
<tr>
<td>1400 to 1500</td>
<td>-0.27 **</td>
</tr>
<tr>
<td>1500 to 1600</td>
<td>-0.05</td>
</tr>
<tr>
<td>1600 to 1700</td>
<td>0.00</td>
</tr>
<tr>
<td>1700 to 1800</td>
<td>-0.07</td>
</tr>
</tbody>
</table>

Table 7: Correlations Between City Size and City Growth

Note: This table presents correlations between normalized city sizes and growth rates. If the growth rate of city $i$ in period $t$, and the mean and standard deviation across cities are $\bar{g}_t$ and $\sigma_t$, then normalized growth is $\hat{g}_{it} = (g_{it} - \bar{g}_t)/\sigma_t$. Significance at the 95 and 90 percent confidence levels denoted “**” and “*”, respectively.

Next I group cities into size quantiles and examine the distribution of growth rates within each quantiles. Figure 8 presents box-plots of city growth by size quintile (quintile 1 comprises the smallest cities and quintile 5 the largest). It confirms that large cities were at a pronounced growth disadvantage 800-1200. Figure 9 presents data for 1200-1800 and shows how random growth emerged from 1500 forward. Figure 10 compares the distribution of growth rates for the top 10 percent and bottom 90 percent of cities using nonparametric kernel densities. It shows that up through the period 1500-1600, the largest cities consistently grew more slowly than smaller cities, and that by 1700-1800 large and small cities were drawing growth rates from approximately identical
distributions.

Figure 8: City Growth Rates By Population Quintile 800-1200

Note: This figure documents how normalized growth rates varied with city size. The smallest cities are in quintile 1, the largest in quintile 5. The boxes describe the interquartile range. The line within each box is the decile’s median growth rate. The “whiskers” mark the adjacent values.

Figure 9: City Growth Rates By Population Decile 1200-1800

Note: The smallest cities are in decile 1, the largest in decile 10. The boxes describe the interquartile range. The line within each box is the decile’s median.
Note: This figure presents kernel densities of the distribution of growth rates for the largest 10 percent (Hi 10%) and smallest 90 percent (Lo 90%) of cities.

7.2 Locational Fundamentals

Geographic theories of Zipf’s Law hold that the distribution of natural advantages across locations is the underlying determinant of city population distributions. This paper documents that European city populations have not always obeyed a power law distribution. If the distribution of city populations is determined by locational fundamentals, this finding suggests that the fundamentals may be dynamic. For instance, the advantages of port locations may be magnified in an era of relatively cheap ocean-going transport or when new trade routes are opened. In other instances, locational advantages may be quite literally constructed (harbors may be dredged, important canals dug, etc.).

Two key findings have been used to support a geographic theory of Zipf’s Law. The first is Davis and Weinstein’s (2002) observation that a regional analogue of Zipf’s Law holds over many centuries in the Japanese data and that Japanese regional population densities in the past are highly correlated with contemporary population densities. As Davis and Weinstein (2002) note, the observed high level of persistence raises the question of whether Japan was special. Figure 11 shows that the high correlations Davis and Weinstein find in the Japanese regional data are not matched in the European data on city populations, but are matched in the European data on national population densities. This suggests that a distinction should be drawn between regional and city-level population densities.
data and that discussions of Zipf’s Law should (data permitting) focus on cities.

Figure 11: Correlation Between Historic and Contemporary Populations

City population data are from Brinkhoff (2008) and Bairoch et al. (1988). National population data are from Eurostat and Acemoglu et al. (2005). Correlations for regional and national data are calculated using population densities. Correlations for Japanese regions are from Davis and Weinstein (2002).

The second key finding for geographic theories is that city size hierarchies have been stable in the face of large temporary shocks in the 20th century. Davis and Weinstein (2002) and Brakman et al. (2004) document that extensive and selective bombing of German and Japanese city cities during the second war had little long run impact on the distribution of city populations in these countries. Evidence on such quasi-natural experiments in the more distant past is very fragmentary. However, the long run evidence suggests that European city size hierarchies were relatively dynamic.

The historical data reveal significant churning in European city hierarchies over the course of centuries. The data thus support the conclusion that geography was not destiny in any direct sense. It is not just that in 1500 the largest cities were concentrated in Southern Europe, while in 1800 the largest cities were concentrated in Northwestern Europe. There were also sharp shifts in urban populations at local levels. In 1400, Madrid was a village while Cordoba and Granada had populations of 60 and 150 thousand. In 1800, Madrid had a population of 160 thousand, where Cordoba and Granada had populations of 40 and 70 thousand. Cologne was the largest German city between 1200 and 1500; today it is the 7th largest. Augsburg went from being the largest German city in 1600 to 8th largest in 1800 and 24th in 2006. In 1000 AD, Laon was the largest city in France with a population of 25 thousand, while Caen, Tours, Lyon, and Paris all

<table>
<thead>
<tr>
<th>Year</th>
<th>Regions Japan</th>
<th>Countries West Europe</th>
<th>Cities West Europe</th>
</tr>
</thead>
<tbody>
<tr>
<td>800</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>1000</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>1200</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>1400</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>1600</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>1800</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>
had approximately 20 thousand inhabitants. In 2006, Laon had 27 thousand inhabitants, Caen had 186 thousand, Tours 307 thousand, Lyon 1.4 million, and Paris over 10 million. Ostia (population 50 thousand in the 2nd century), Pozzuoli (65 thousand in the 2nd century), and Brindisi were great port cities in the Roman era, but fell into disuse and remained small population centers over the early modern era. In 200 AD Rome was Europe’s largest city with a population of nearly one million. Between 800 and 900 AD, Rome had a population of approximately 50 thousand and was Western Europe’s second largest city. In 1300, Rome was the 32nd largest city in Western Europe. Between 1500 and 1800, Rome was among the 10 largest cities. By 1850 it was 17th. 

8 Big Distortions: The Case of Eastern Europe

In this subsection I explain how the institutions of the second serfdom distorted city growth in Eastern Europe and were associated with deviations from Zipf’s Law.

The central institutions of the second serfdom restricted the free circulation of labor (Makkai 1979: 235). Bideleux and Jeffries (2007: 161) observe that that, “the legislative strengthening of eastern European serfdom had begun during the 1490s” and that the new laws reflected, “concerted action to restrict the rights and mobility of the peasantry.”

The laws passed in the economies East of the Elbe River typically required peasants entering towns to carry proof that they had obtained their landlord’s permission to travel and formalized systems of adscription that legally bound tenant farmers to rural estates. The laws provided for the cross-border return of fugitive serfs, limited the activities of merchants and restricted the privileges of towns. The new institutions rolled back previously guaranteed legal freedoms and ended institutional convergence between Eastern and Western Europe.

41 For historical populations see Bairoch et al. (1988), Meigs (1973), and Stillwell et al. (1976). Contemporary French populations are for urban agglomerations and are from Brinkhoff (2008).


44 These laws were instituted in economies where cities were walled and entered only through guarded gates (Friedrichs 1995: 21-22). Feudal lords often maintained control over the gates and employed the gatekeepers (Nicholas 2003). See also Miller (2008: 37) and Mols (1955: 347-348). The penalties associated with illegal movement were severe. The Prussian legal ordinances of 1494 stipulated that runaway peasants could be hanged by their masters without trial or arbitration. Carsten (1954: 108).
Table 8 shows that city growth was not relatively low in Eastern Europe. However, Figure 12 shows that there were persistent deviations from Zipf’s Law in Eastern Europe. It also shows that Berlin, Vienna, St. Petersberg, and Moscow (the four upper tail outliers) were unusual in being substantially larger than predicted by robust regression in 1800. Table 9 documents that negative correlations between size and growth and deviations from Zipf’s Law were relatively persistent in the East.

Table 8: City Growth in Western, Eastern, and Ottoman Europe

<table>
<thead>
<tr>
<th>Period</th>
<th>Western Europe</th>
<th></th>
<th></th>
<th>Eastern Europe</th>
<th></th>
<th></th>
<th>Ottoman Europe</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Cities (1)</td>
<td>Mean (2)</td>
<td>St. Dev. (3)</td>
<td>Cities (5)</td>
<td>Mean (6)</td>
<td>St. Dev. (7)</td>
<td>Cities (8)</td>
<td>Mean (9)</td>
</tr>
<tr>
<td>1300</td>
<td>255</td>
<td>-0.22%</td>
<td>0.58%</td>
<td>45</td>
<td>0.14%</td>
<td>0.48%</td>
<td>23</td>
<td>0.25%</td>
</tr>
<tr>
<td>1400</td>
<td>187</td>
<td>0.06%</td>
<td>0.52%</td>
<td>33</td>
<td>0.08%</td>
<td>0.46%</td>
<td>8</td>
<td>-0.05%</td>
</tr>
<tr>
<td>1500</td>
<td>321</td>
<td>0.18%</td>
<td>0.46%</td>
<td>56</td>
<td>0.14%</td>
<td>0.62%</td>
<td>13</td>
<td>0.53%</td>
</tr>
<tr>
<td>1600</td>
<td>514</td>
<td>-0.13%</td>
<td>0.55%</td>
<td>91</td>
<td>-0.09%</td>
<td>0.70%</td>
<td>15</td>
<td>-0.02%</td>
</tr>
<tr>
<td>1700</td>
<td>539</td>
<td>0.28%</td>
<td>0.60%</td>
<td>62</td>
<td>0.27%</td>
<td>0.98%</td>
<td>16</td>
<td>-0.06%</td>
</tr>
<tr>
<td>1750</td>
<td>686</td>
<td>0.29%</td>
<td>0.63%</td>
<td>166</td>
<td>0.37%</td>
<td>0.95%</td>
<td>19</td>
<td>0.30%</td>
</tr>
<tr>
<td>1800</td>
<td>1,311</td>
<td>0.68%</td>
<td>0.78%</td>
<td>361</td>
<td>0.92%</td>
<td>0.73%</td>
<td>72</td>
<td>0.22%</td>
</tr>
</tbody>
</table>

Figure 12: The Emergence of Zipf’s Law in Eastern Europe

Note: This figure plots raw data on city populations \(S_i\) and size rankings \(R_i\), and fitted values estimated using robust non-parametric Theil regression and the model: \(\ln(R_i) = \alpha - \beta \ln(S_i) + \epsilon_i\). See note to Figure 2.
Table 9: Comparison of City Growth & Deviations from Zipf’s Law

<table>
<thead>
<tr>
<th>Period Starting</th>
<th>Correlation Between Size &amp; Growth</th>
<th>Deviation from Zipf’s Law</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Western Europe</td>
<td>Eastern Europe</td>
</tr>
<tr>
<td>(1)</td>
<td>(2)</td>
<td>(3)</td>
</tr>
<tr>
<td>1400</td>
<td>-0.27 **</td>
<td>-0.38 *</td>
</tr>
<tr>
<td>1500</td>
<td>-0.05</td>
<td>-0.39 **</td>
</tr>
<tr>
<td>1600</td>
<td>0.00</td>
<td>-0.29 *</td>
</tr>
<tr>
<td>1700</td>
<td>-0.07</td>
<td>-0.03</td>
</tr>
<tr>
<td>1800</td>
<td>--</td>
<td>--</td>
</tr>
</tbody>
</table>

Note: Deviations from Zipf’s Law calculated as described for Western Europe.

To examine the impact on cities of legal restrictions on migration in more detail I construct an index of second serfdom laws. The index determines in each period whether a given city was located in a polity with the legal restrictions on peasant mobility that were the institutional heart of the second serfdom. Table 10 records the dates of passage of the principal laws limiting the mobility of tenant farmers. For a given city, the serfdom index captures the presence of local laws limiting labor mobility, from the dates given in Table 10 until the date of the first emancipation decree issued in the territory. Table 11 provides a complete list of emancipation decrees.

Table 10: Dates of Principal Legal Restrictions on Free Migration

<table>
<thead>
<tr>
<th>Historic Territory</th>
<th>Contemporary Location</th>
<th>Date</th>
</tr>
</thead>
<tbody>
<tr>
<td>Austria</td>
<td>Austria</td>
<td>1539</td>
</tr>
<tr>
<td>Bohemia</td>
<td>Czech Republic</td>
<td>1487</td>
</tr>
<tr>
<td>Brandenburg</td>
<td>Eastern Germany</td>
<td>1528</td>
</tr>
<tr>
<td>Hungary</td>
<td>Hungary</td>
<td>1514</td>
</tr>
<tr>
<td>Livonia</td>
<td>Estonia &amp; Latvia</td>
<td>1561</td>
</tr>
<tr>
<td>Mecklenberg</td>
<td>Northeastern Germany</td>
<td>1654</td>
</tr>
<tr>
<td>Poland</td>
<td>Poland</td>
<td>1495</td>
</tr>
<tr>
<td>Pomerania</td>
<td>Northeastern Germany</td>
<td>1616</td>
</tr>
<tr>
<td>Prussia</td>
<td>Eastern Germany, Poland</td>
<td>1526</td>
</tr>
<tr>
<td>Romanian Wallachia</td>
<td>Romania</td>
<td>late 1500s</td>
</tr>
<tr>
<td>Russia</td>
<td>Russia</td>
<td>1640s/1700s</td>
</tr>
<tr>
<td>Saxony</td>
<td>Eastern Central Germany</td>
<td>--</td>
</tr>
<tr>
<td>Schleswig-Holstein</td>
<td>Northern Germany</td>
<td>1617</td>
</tr>
<tr>
<td>Silesia</td>
<td>Czech Rep., Poland, East Germany</td>
<td>1528</td>
</tr>
</tbody>
</table>

Note: See Appendix for sources.

Regression analysis confirms that the institutions of the second serfdom were associ-
Table 11: Dates of Emancipation Decrees in Eastern Europe

<table>
<thead>
<tr>
<th>Historic Territory</th>
<th>Year</th>
</tr>
</thead>
<tbody>
<tr>
<td>(1)</td>
<td>(2)</td>
</tr>
<tr>
<td>Poland (Grand Duchy of Warsaw), Prussia</td>
<td>1807</td>
</tr>
<tr>
<td>Estonia</td>
<td>1816</td>
</tr>
<tr>
<td>Courland</td>
<td>1817</td>
</tr>
<tr>
<td>Livonia</td>
<td>1819</td>
</tr>
<tr>
<td>Mecklenberg</td>
<td>1820</td>
</tr>
<tr>
<td>Saxe-Altenberg</td>
<td>1831</td>
</tr>
<tr>
<td>Saxony</td>
<td>1832</td>
</tr>
<tr>
<td>Schwarzburg-Sonderhausen, Reuss (older), Saxe-Weimar, Austria, Saxe-Gotha, Anhalt-Dessau-Köthen</td>
<td>1848</td>
</tr>
<tr>
<td>Schwarzburg-Rudolstat,Anhalt-Bernberg</td>
<td>1849</td>
</tr>
<tr>
<td>Saxe-Meiningen</td>
<td>1850</td>
</tr>
<tr>
<td>Reuss (younger)</td>
<td>1852</td>
</tr>
<tr>
<td>Hungary</td>
<td>1853</td>
</tr>
</tbody>
</table>

Note: See Appendix for sources.

ated with large variations in city growth. In this section I present results from a baseline model that includes controls for initial population, regional fixed effects, and period fixed effects.\(^{46}\) I present results with and without controlling for the growth effects associated with political primacy. The key finding is that the institutions of the second serfdom were associated with a 1/3 cut in city growth.

The baseline estimating equation examines the association between growth and the laws of the second serfdom:

\[
\log \text{growth}_{i,t} = \alpha + \beta(\log \text{size})_{i,t} + \sum_j \gamma_j \text{region}_j + \sum_k \eta_k \text{year}_k + \theta(\text{second serfdom})_{i,t} + \epsilon_{i,t} \tag{19}
\]

Table 12 presents results for several geographic samples.\(^{47}\) Table 11 begins with a sample of non-Russian cities. However, given the emphasis Acemoglu et al. (2005) place on the role Atlantic trade played in early modern city growth, it makes sense to also examine samples that exclude Atlantic cities and focus on the impact of serfdom on city growth within central Europe. Across geographic samples two parameter estimates stand out. First, there is a strong positive association between city growth and location in Eastern Europe: an Eastern location is associated with an increase of over 0.1 log points of growth.

\(^{46}\) Adding country fixed effects has no substantive impact on the estimated associations between growth and the institutions of the second serfdom.

\(^{47}\) The non-Russian sample includes Kaliningrad (Königsberg) and cities in the Baltics. The Broad Central Europe sample comprises the cities in contemporary Germany, Austria, Poland, Hungary, the former Czechoslovakia, and France. The Central Eastern Europe sample is limited to cities in Germany, Austria, Poland, Hungary, and the former Czechoslovakia.
Table 12: Baseline Regression Analysis of Log City Growth 1300-1850

<table>
<thead>
<tr>
<th>Independent Variable</th>
<th>Non-Russian (1)</th>
<th>Broad Central (2)</th>
<th>Central Eastern (3)</th>
<th>Non-Russian (4)</th>
<th>Broad Central (5)</th>
<th>Central Eastern (6)</th>
<th>Central Eastern (7)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Log Size</td>
<td>-0.01 (0.01)</td>
<td>0.01 (0.01)</td>
<td>0.02 (0.02)</td>
<td>-0.03 ** (0.01)</td>
<td>-0.01 (0.01)</td>
<td>-0.02 (0.02)</td>
<td></td>
</tr>
<tr>
<td>Serf</td>
<td>-0.10 ** (0.04)</td>
<td>-0.17 ** (0.05)</td>
<td>-0.14 ** (0.05)</td>
<td>-0.10 ** (0.03)</td>
<td>-0.15 ** (0.04)</td>
<td>-0.10 ** (0.04)</td>
<td></td>
</tr>
<tr>
<td>West</td>
<td>0.05 (0.05)</td>
<td>-0.16 ** (0.03)</td>
<td>-0.13 ** (0.03)</td>
<td>0.04 (0.05)</td>
<td>-0.17 ** (0.02)</td>
<td>-0.12 ** (0.03)</td>
<td></td>
</tr>
<tr>
<td>East</td>
<td>0.19 ** (0.05)</td>
<td>0.19 ** (0.05)</td>
<td></td>
<td>0.42 ** (0.05)</td>
<td>0.41 ** (0.06)</td>
<td>0.49 ** (0.05)</td>
<td></td>
</tr>
<tr>
<td>Capital</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Observations</td>
<td>4,069</td>
<td>1,523</td>
<td>773</td>
<td>4,069</td>
<td>1,523</td>
<td>773</td>
<td></td>
</tr>
<tr>
<td>F Statistic</td>
<td>65.06</td>
<td>28.60</td>
<td>20.97</td>
<td>65.32</td>
<td>30.74</td>
<td>35.85</td>
<td></td>
</tr>
<tr>
<td>R Squared</td>
<td>0.14</td>
<td>0.16</td>
<td>0.23</td>
<td>0.16</td>
<td>0.17</td>
<td>0.25</td>
<td></td>
</tr>
<tr>
<td>SE Clustered</td>
<td>On City</td>
<td>On City</td>
<td>On City</td>
<td>On City</td>
<td>On City</td>
<td>On City</td>
<td>On City</td>
</tr>
</tbody>
</table>

Note: Non-Russian Europe includes cities in Ottoman Europe and the Baltics. Significance with 90 and 95 percent confidence denoted with ** and *** respectively.

As shown below, this association is robust and appears to reflect the catch-up growth advantage held by the relatively small cities of the East. Second, there is a significant negative association between serfdom and growth roughly equal to the positive association between Eastern location and growth. Among Central Eastern European cities, serfdom is associated with a decline in growth of 0.14 log points. Among non-Russian cities the estimated decline is 0.10 log points.

These magnitudes are economically significant. Over 100 years, a decline of 15 percentage points implies a decline of 0.0016 in the annual growth rate. But mean growth in the East from 1300 to 1850 was 0.0054 and mean annual growth in the East was not more than 0.0027 before 1750. For illustration: (0.0016)/(0.0016 + 0.0054) ≈ 23 percent, and (0.0016)/(0.0016 + 0.0027) ≈ 38 percent. Parameter estimates of these magnitudes suggest that the imposition of laws restricting labor mobility may have cut Eastern city growth by two fifths over several centuries.

In every sample, the positive association between an Eastern location and growth...
and the negative association between serfdom and growth essentially cancel each other out. As discussed above, overall growth rates in Western and Eastern cities are roughly comparable. The fact that Eastern cities grew relatively quickly, but that serfdom was associated with slow growth suggests that the institutional framework may have prevented or delayed a catch-up process otherwise under way. (See Appendix [F] for robustness checks.)

As observed above (section 6.6), we expect a tax that depresses growth to reduce the variance of city growth rates. This matters because Zipf’s Law emerges relatively slowly where the variance of growth rates is low. Table 13 compares similarly sized cities and shows that the institutions of the second serfdom were associated with relatively low variance in city growth between 1500 and 1700. It further shows that from 1500 to 1800 the coefficients of variation for the largest cities (population at least 50,000) were lower in cities exposed to serfdom than in their Western counterparts.

Table 13: Serfdom and the Variance of City Growth Rates

<table>
<thead>
<tr>
<th>Period Starting</th>
<th>Institutional Regime</th>
<th>Coefficients of Variation for Cities Grouped by Population</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>5k - 6k</td>
</tr>
<tr>
<td>(1)</td>
<td>(2)</td>
<td>(3)</td>
</tr>
<tr>
<td>1500 Serfdom</td>
<td></td>
<td>0.6</td>
</tr>
<tr>
<td>No Serfdom</td>
<td></td>
<td>1.2</td>
</tr>
<tr>
<td>Ratio</td>
<td></td>
<td>0.5</td>
</tr>
<tr>
<td>1600 Serfdom</td>
<td></td>
<td>2.2</td>
</tr>
<tr>
<td>No Serfdom</td>
<td></td>
<td>4.7</td>
</tr>
<tr>
<td>Ratio</td>
<td></td>
<td>0.5</td>
</tr>
<tr>
<td>1700 Serfdom</td>
<td></td>
<td>1.8</td>
</tr>
<tr>
<td>No Serfdom</td>
<td></td>
<td>1.8</td>
</tr>
<tr>
<td>Ratio</td>
<td></td>
<td>1.0</td>
</tr>
</tbody>
</table>

Note: This table presents coefficients of variation for cities grouped by population. For instance, cities in column (3) had populations between 5 and 6 thousand, inclusive.

The institutions of the second serfdom may also have delayed the emergence of Zipf’s Law by generating non-random growth. As discussed above, political capitals were unusual in being large and fast growing cities. When they are excluded from the analysis, we observe (i) a negative correlation between growth and size across institutional regimes, and (ii) that the negative correlation is both substantially stronger and more imprecisely estimated for cities exposed to serfdom. Figure 13f illustrates this by pooling normalized
data and plotting normalized growth rates against normalized city sizes.

Figure 13: Growth and City Size

![Non-Serfdom and Serfdom plots]

Note: This graph shows the relationship between growth and size in pooled, normalized data. The data includes all cities that were not political capitals.

9 Conclusion

Zipf’s Law is supposedly one of the most robust empirical regularities in economics. This paper has shown that, to the contrary, Zipf’s Law emerged over time in European history. In particular, Zipf’s Law emerged over the transition to modern economic growth as city production became less reliant on quasi-fixed local land endowments and city growth rates became random, in the sense of being independent of city population.

The historical emergence of Zipf’s Law also has implications for economic theory. The fact that Zipf’s Law emerged over time – while the principal features of the landscape were invariant – suggests that narrowly geographic explanations will be insufficient. Propitious locations are non-homogeneous and distributed unevenly, but the historical emergence of Zipf’s Law suggests that locational advantages may emerge with economic development, and hence be endogenous along important dimensions. In addition, the fact that Zipf’s Law emerged in an era when the industrial specialization of urban activity was relatively limited suggests that explanations emphasizing cities specialized in the production of particular goods and reaching optimal size for their activity may not capture the root
process. The historical evidence is, however, consistent with theories emphasizing random growth in the emergence of Zipf’s Law.

Random growth and Zipf’s Law emerged relatively early in Western Europe. Non-random growth and deviations from Zipf’s Law were relatively persistent in Eastern Europe. In Eastern Europe, laws limiting the mobility of labor employed in the agricultural sector distorted the pattern of city growth and were associated with a 1/3 overall reduction in city growth 1500-1800.

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A Appendix: Data


Data on the dates and nature of the laws restricting labor mobility and limiting the rights of urban groups under the second serfdom is from Makkai (1975), Topolski (1982), Blum (1957), Carsten (1954), Szélenyi (2006), Davies (1981), Pach (1994), Hellie (1971), Kahan (1973), Kamiński (1975), Bogucka (1984), Melton (1988), Maddalena (1977), and Bideleux and Jeffries (2007). Data on the dates of emancipation decrees is from Blum (1978). The historical coding of the Polity-IV index of constraints on arbitrary executive authority is from Acemoglu et al. (2002, 2005). DeLong and Shleifer (1993) class regional institutions as either promoting relatively unrestrained and autocratic rule (“prince”) or as securing relative freedom (“free”). I extend this coding to Poland and Ottoman Europe, neither of which meet the criteria for classification as “free” between 1300 and 1850 (this is confirmed by DeLong).

Data on the historical location of universities are from Darby (1970), Jedin (1970), and Bideleux and Jeffries (2007). Data on the historical location of religious institutions are from Magosci (1993) and Jedin (1970). Data on Roman settlements are from Stillwell et al. (1976).

Data on the historical location of ports are from Acemoglu et al. (2005), supplemented by data in Magosci (1993) and Stillwell et al. (1976). The data in this paper supplements Acemoglu et al. (2005) by coding for cities that were historically ports on the Baltic. These cities include: St. Petersburg, Gdańsk, Kaliningrad, Szczecin, Rostock, and Lübeck. In addition, the coding in this paper accounts for Mediterranean and Black Sea ports omitted in Acemoglu et al. (2005): Gaeta, Fano, Kerch, Korinthos, Pozzuoli, and Trapani.

Data on the location of navigable rivers are drawn from Magosci (1993), Pounds (1979, 1990), Livet (2003), Cook and Stevenson (1978), Graham (1979), Stillwell et al. (1976), and de Vries and van der Woude (1997). The coding captures the principal historically navigable waterways, and does not class as “navigable” waterways that required substantial improvements (dredging, re-channeling, etc.) and became navigable only over the early modern era.

B Appendix: Measurement Error

I test for measurement error in the historical population data several ways. I first compare the Bairoch data to the most comprehensive independent source for city population data, the database in de Vries (1984). The Bairoch data covers all European cities that reached 5,000 inhabitants by or before 1800, has rich data from 1300 to 1850, and contains observations on 2,204 cities. The data in de Vries (1984) covers cities that reached a population of 10,000 between 1500 and 1800. It contains observations on 379 cities.

Table B1 compares data for cities in both databases. It shows that, on average, the sources give figures that are within 7 percentage points of each other. In keeping with the notion that measurement error increases as we reach back in the historical record, the deviations between the de Vries and Bairoch data decline over time: the correlation rises from 0.89 in 1500 to 1.00 in 1800; the ratio of recorded values approaches 1 and its standard deviation falls.

Table B1: Comparison of Source Data on City Populations

<table>
<thead>
<tr>
<th></th>
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<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>1500</td>
<td>117</td>
<td>0.88</td>
<td>1.07</td>
<td>0.30</td>
<td>0.50</td>
<td>2.50</td>
<td>2.92</td>
</tr>
<tr>
<td>1600</td>
<td>207</td>
<td>0.95</td>
<td>1.07</td>
<td>0.44</td>
<td>0.40</td>
<td>5.00</td>
<td>5.60</td>
</tr>
<tr>
<td>1700</td>
<td>250</td>
<td>0.99</td>
<td>1.02</td>
<td>0.22</td>
<td>0.42</td>
<td>2.31</td>
<td>2.83</td>
</tr>
<tr>
<td>1800</td>
<td>367</td>
<td>0.99</td>
<td>1.02</td>
<td>0.18</td>
<td>0.12</td>
<td>2.00</td>
<td>0.60</td>
</tr>
</tbody>
</table>

Note: This table compares population data from Bairoch et al. (1988) and de Vries (1984). Column (3) presents the correlation between recorded values. Columns (4) to (8) examine the ratio of these values.

Given the deviations from Zipf’s Law in the upper tail of the Bairoch data, it is natural to ask whether discrepancies are associated with city size. Figure B1 plots the de Vries data against the Bairoch data. It shows no evidence of systematic shortfalls in the populations that the Bairoch data record for large cities. In the main body of

50 Classical measurement error is not a plausible explanation for the observed deviations from Zipf’s Law. See Gabaix (2008), who observes that: power laws are preserved under addition, multiplication and
the paper (section 4.1), I show that the data would have to embody implausibly large 
non-classical measurement error for Zipf’s Law to have actually held and (section 5) that 
the observed deviations are consistent with the narrative evidence.

Figure B1: Comparison of Source Data on City Populations

Note: This figure plots city populations recorded in de Vries (1984) against corresponding values in Bairoch et al. (1988). The 45 degree line is shown to clarify where the Bairoch data provide larger (smaller) values.

C Appendix: Emergence of Zipf’s Law at the National Level

Data in Russell (1972) on urban systems in the high middle ages shows that Zipf’s Law did not hold at the local level. Figure C1 shows how Zipf’s Law emerged between 1400 and 1800 in the six leading national economies of Western Europe.

D Appendix: Small-Sample Estimators for Zipf Exponents

This appendix discusses the estimation of Zipf exponents and some properties of the Theil estimator.

Classically, Zipf’s exponents have been estimated with standard OLS regressions of the form:

$$\ln R_i = \alpha - \beta \ln S_i + \epsilon_i$$  \hspace{1cm} (20)

There are two problems with a standard OLS estimator. The first is that, even if the data generating process conforms strictly to a power law, the estimated coefficient $\hat{\beta}_{OLS}$ polynomial combination; multiplying by normal variables or adding non-fat tail noise does not change the exponent; and while noise will effect variances in empirical settings, it does not distort the exponent.
Figure C1: The Emergence of Zipf’s Law at the National Level

will be biased down in small samples. (As noted below, OLS standard errors are also biased down.) Gabaix and Ibragimov (2007) have proposed a remedy that reduces the bias in OLS coefficients to a leading order: adding a shift of -1/2 to the city rank data.

\[ \ln(R_i - 1/2) = \alpha - \beta \ln S_i + \epsilon_i \] (21)

For many applications this adjusted OLS approach may eliminate small sample bias.

However, the second problem with least squares is that any OLS estimator may be subject to gross errors in contexts marked by significant outliers. This is because the OLS estimator suffers from sensitivity to tail behavior. As He et al. (1990: 1196) note, “the tail performance of the least-squares estimator is found to be extremely poor in the case of heavy-tailed error distributions, or when leverage points are present in the design.” Given the shape of the rank-size relation for European cities in the early modern era, this is a particular concern here.

The literature has discussed the Hill maximum likelihood estimator (MLE) as an alternative to OLS\(^{51}\). However, as Gabaix and Ioannides (2004) observe, the small sample biases associated with the Hill estimator can be quite high and very worrisome. Moreover, the Hill estimator is the MLE under the null hypothesis that the data generating process

\(^{51}\)For a sample of \( n \) cities with sizes \( S_i \) ordered so that \( S_{(1)} \geq \ldots \geq S_{(n)} \), the Hill estimator is:

\[ \hat{\beta}_H = (n - 1)/ \sum_{i=1}^{n} [\ln(S_{(i)}) - \ln(S_{(i+1)})]. \]
is a distributional (and specifically Pareto) power law, but is not the MLE if the empirical distribution is not Pareto. For these reasons, this paper does not present estimates using the Hill estimator.

Robust regression techniques have been designed for situations where sample sizes are small and/or outliers may have an undue impact on OLS estimates. A number of robust regression estimators use the framework provided by the median. In particular, the nonparametric estimator derived from Theil (1950) is intuitive, asymptotically unbiased, robust with small samples, allows us to go some distance in addressing the problem posed by outliers, and has not been exploited in the Zipf’s Law literature. The Theil slope parameter is calculated as the median of the set of slopes that connect the complete set of pairwise combinations of the observed data points. Given observations \((Y_k, x_k)\) for \(k = 1, \ldots, n\), one computes the \(N = n(n-1)/2\) sample slopes \(S_{ij} = (Y_j - Y_i)/(x_j - x_i), 1 \leq i < j \leq n\). The Theil slope estimator is then: \(\beta_T = \text{median}\{S_{ij}\}\). The corresponding constant term is: \(\alpha_T = \text{median}_k\{Y_k - \beta_T x_k\}\). Hollander and Wolfe (1999) provide a generalization of the Theil estimator for cases where – as in the Bairoch data – the \(x_k\) are not all distinct.

The Theil estimator is competitive with the rank-adjusted OLS estimator suggested in Gabaix and Ibragimov (2007) in eliminating small sample bias. This is evident in Figure D1, which uses simulated data (generated by a process with Zipf exponent equal to 1) to compare small sample biases in estimated \(\beta\)’s across OLS, rank-adjusted OLS, and Theil estimators. Figure D1 reports mean estimates of the Zipf coefficient calculated over 1,000 simulations, each of which generates \(n\) synthetic observations from a distributional power law. To illustrate how estimates change with the sample size, Figure D1 reports the results as the number of observations in the simulations (\(n\)) rises from 20 to 300. While biased in small samples (\(n < 80\)), the small-sample bias in Theil estimates is relatively small. Moreover, the Theil estimate converges faster than OLS and as fast as the rank-adjusted OLS estimate.

The Theil estimator also generates relatively precise estimates. Gabaix and Ibragimov (2007) show that, when we estimate power law exponents in small samples, OLS standard errors are biased down. The confidence interval associated with Theil regression estimates similarly overstates the estimator’s precision when data are drawn from

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52 The repeated median regression suggested by Siegel (1982) and the least median of squares estimator suggested by Rousseeuw and Leroy (1987) are alternatives. But in the empirical context of this paper, they produce estimates that are virtually identical to the somewhat more elegant and parsimonious Theil (1950) estimator.

53 Data are constructed as follows. Sample \(n\) times from a uniform distribution on the unit interval to obtain \(x_i, i = 1, \ldots, n\). Construct sizes \(S_i = 1/x_i\) and rank the \(S_i\)’s.

54 The true standard error of \(\hat{\beta}\) in equation (21) is asymptotically \((2/n)^{0.5}\hat{\beta}\).
To gauge and compare the true precision of these estimators, we can use Monte Carlo simulations. Figure D2 shows that the Theil estimates are more precise than the adjusted-OLS estimates. Future research may establish other empirical strategies, but Theil estimator effectively limits small sample bias as well as the estimators employed in the literature, while in addition being both robust to outliers and relatively precise.

Given that the most widely used regression estimator is OLS, and that the Theil estimator is constructed as the median of the observed pairwise slopes, it is worth noting that OLS estimator is itself a weighted average of pairwise slopes. Using $h$ to index the set of paired data points, define:

$$
h \equiv (i,j) \quad X(h) \equiv \begin{bmatrix} 1 & x_i \\ 1 & x_j \end{bmatrix} \quad y(h) \equiv \begin{bmatrix} y_i \\ y_j \end{bmatrix} \quad b(h) \equiv X(h)^{-1} y(h)$$

Under this notation, the OLS estimator is: $\beta_{OLS} = \sum_{h=1}^{N} w(h)b(h)$, where the weights are defined as: $w(h) = |X(h)|^2 / \sum_{h=1}^{N} |X(h)|^2$. These weights are proportional to the distance between design points. As Koenker (2005: 4) observes this is a fact that, “in itself, portends the fragility of least squares to outliers.”

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55See Hollander and Wolfe (1999) for calculation of confidence intervals on Theil slope parameter.
E Appendix: Conventional OLS Regression Test

Indexing cities with \( i \) and denoting city size \( S \) and city rank \( R \), Zipf’s exponents have classically been estimated with OLS regressions of the form:

\[
\ln R_i = \alpha - \beta \ln S_i + \epsilon_i
\]  

(22)

A number of studies suggest employing a regression augmented with a quadratic term to detect non-linearities and deviations from distributional power laws:\(^{56}\)

\[
\ln R_i = \beta_0 - \beta_1 \ln S_i + \beta_2 (\ln S_i)^2 + \nu_i
\]  

(23)

As discussed below, the standard errors associated with this model are biased down. However, I present historical estimates of equation (23) to facilitate comparison with existing studies using non-historical data. Table 4 shows that between 1500 and 1700, and certainly by 1800, a “modern” city size distribution emerged in Western Europe. In contemporary data on a large sample of countries, Soo (2005) finds estimates of Zipf exponents ranging from 0.7 to 1.5. From 1700, Western European cities have a Zipf

---

\(^{56}\) As Soo (2005) notes, this regression may be viewed as a weak form of the Ramsey RESET test.
exponent $\hat{\beta}_1 \in (0.7, 1.5)$ and modest non-linearity in the logarithmic rank-size relation: $\hat{\beta}_2$ is “small” and by 1800 vanishes.

Table E1: OLS Regression Analysis of Deviations from Zipf’s Law

<table>
<thead>
<tr>
<th>Year</th>
<th>Observations</th>
<th>Parameter $\beta_1$</th>
<th>Parameter $\beta_2$</th>
</tr>
</thead>
<tbody>
<tr>
<td>(1)</td>
<td>(2)</td>
<td>(3)</td>
<td>(4)</td>
</tr>
<tr>
<td>1300</td>
<td>255</td>
<td>0.30</td>
<td>-0.28 (0.08)</td>
</tr>
<tr>
<td>1400</td>
<td>187</td>
<td>-0.13</td>
<td>-0.22 (0.20)</td>
</tr>
<tr>
<td>1500</td>
<td>321</td>
<td>0.20</td>
<td>-0.20 (0.11)</td>
</tr>
<tr>
<td>1600</td>
<td>514</td>
<td>0.82</td>
<td>-0.08 (0.04)</td>
</tr>
<tr>
<td>1700</td>
<td>539</td>
<td>0.95</td>
<td>-0.04 (0.05)</td>
</tr>
<tr>
<td>1800</td>
<td>1,311</td>
<td>1.36</td>
<td>0.00 (0.04)</td>
</tr>
</tbody>
</table>

Note: The estimated regression is: $\ln R_i = \beta_0 - \beta_1 \ln S_i + \beta_2 (\ln S_i)^2 + \nu_i$, where $R_i$ is city rank and $S_i$ is city population. Heteroskedasticity-robust standard errors in parentheses.

However, the estimates in Table E1 should be treated with caution. It can be shown using synthetic data from a pure power law distribution that heteroskedasticity-robust standard errors associated with equation (23) exhibit downward bias in finite samples. It follows that the statistical significance of $\hat{\beta}_2$ is not a robust criterion on which to base rejection of Zipf’s Law. Hence Table E1 should be read as indicating the existence (or absence) of gross departures from Zipf’s Law, not as a precise test.

### F Appendix: Serfdom

This paper distinguishes between Western, Eastern, and Ottoman cities. Eastern cities are those exposed to the institutions of the second serfdom 1500-1800. The geography of this distinction is illustrated in Figure F1, which shows the locations of Europe’s historic cities. The consistency of the negative association between size and growth under serfdom is also evident when we examine the data on a period-by-period basis.

$^57$ Ranking induces a positive correlation between residuals which escapes conventional estimation. See Gabaix and Ioannides (2004: 2348).
Figure F1: The Historic Cities of Europe

Note: This map shows cities with historic population data recorded in Bairoch et al. (1988) and classifies cities as Western (○), Eastern (△), and Ottoman (□) as discussed in the main body of the paper.

To show this, I present predictions from a regression where variations in the log of city growth are explained by the log of city size and political primacy (i.e. an indicator capturing whether or not a given city was a capital). Figure F2 presents predicted values from this regression and shows that the negative correlations between city populations and city growth rates were pronounced and persistent in Eastern Europe over the second serfdom.

However, the estimated relationship between size and growth under serfdom is not significant at conventional levels. This may be explained in two ways. First, it may be that the relationship is simply not statistically significant. Second, it may be that measurement error is attenuating the parameter estimates and masking a relatively strong underlying association. As suggested in the Measurement Error Appendix above, the data on city size is noisy. Since I calculate city growth based on observed size, observed city growth is likely very noisy.
Note: This figure shows the persistent and pronounced negative relationship between size and growth for cities exposed to the second serfdom. The regression model is: \( \log S_{i,t+1} - \log S_{i,t} = \alpha_0 + \alpha_1 \log S_{i,t} + \alpha_2 \text{CAPITAL}_i + \epsilon_i \). The figure presents predicted values setting the capital indicator to zero.

**G Appendix: Simulation of Model**

A simple – and provisional – simulation illustrates how the model can generate deviations from Zipf’s Law. Figure G1 shows the city-size distributions that result when one takes an arbitrary, fixed set of cities and runs them through the model assuming that the fixed land \((L)\) has a positive income share and that productivity is static and common across cities. The simulation is run over 250 periods. It is assumed that \(\alpha = 0.6, \beta = 0.2, \delta = 0.1\). The scaling factor \(u\) is chosen to lend plausible final sizes, but has no impact on the shape of the distribution. With no technological change, the model tends to a state with no growth in population (or per capita income) aside from ephemeral variations induced by stochastic shocks. Simulating the model with taxes \(\tau_{it} > 0\) and increasing in city size gives equivalent results.
Figure G1: Simulation of Model

Two Representative Simulations Based on City Growth Model

Simulation 1

Simulation 2