Why Are Big Banks Getting Bigger?

Ricardo T. Fernholz [1] Christoffer Koch [2]

[1]Claremont McKenna College

[2]Federal Reserve Bank of Dallas

April 22, 2016

The views expressed in this presentation are those of the authors and are not necessarily reflective of views at the Federal Reserve Bank of Dallas or the Federal Reserve System. Any errors or omissions are the sole responsibility of the authors.

The Changing U.S. Bank Size Distribution

- Growing concentration of U.S. banking assets starting in the 1990s
  - Bank-holding companies (BHCs)
  - Commercial banks
  - Savings and loan associations (thrifts)

- These changes raise two important questions:
  1. Why did big banks get bigger?
  2. Are larger, less traditional banks also riskier banks?

The Changing U.S. Bank Size Distribution

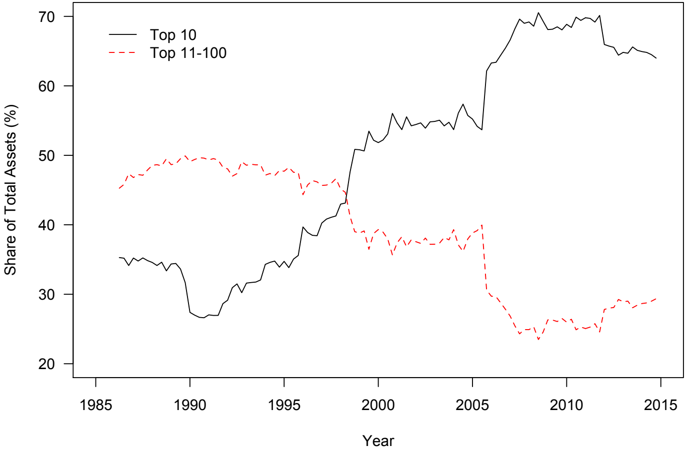


Figure: The share of total assets held by the largest bank-holding companies.

The Changing U.S. Bank Size Distribution

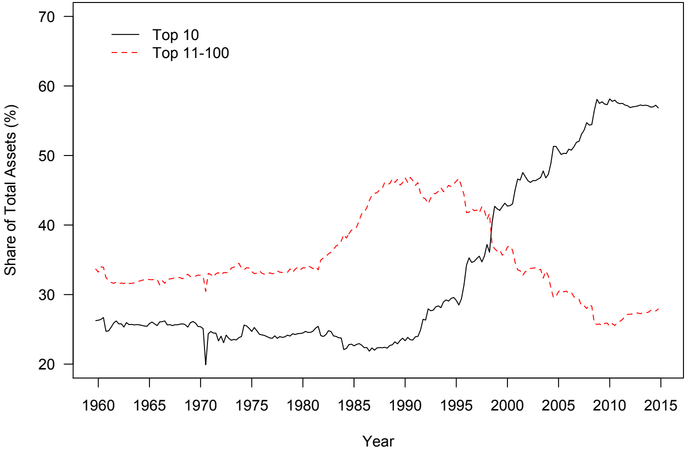


Figure: The share of total assets held by the largest commercial banks.

The Changing U.S. Bank Size Distribution

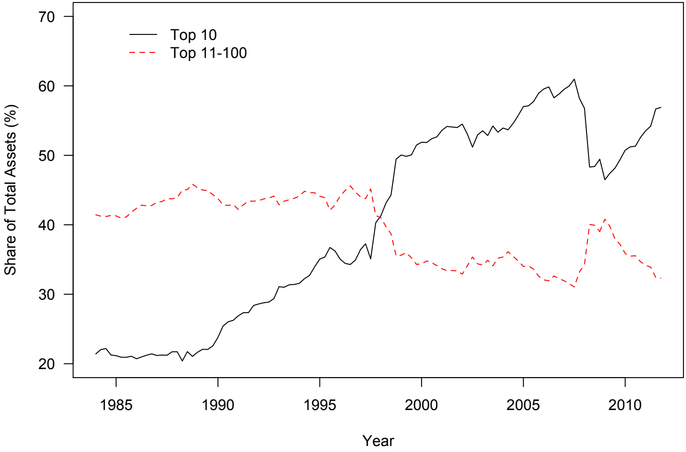


Figure: The share of total assets held by the largest thrifts.

Three Literatures

1. Changes in the banking industry and in bank size
(Janicki and Prescott, 2006; Wheelock and Wilson, 2012; Lucas, 2013)

2. Idiosyncratic risk/random growth and power laws (Gabaix, 1999, 2009)

3. Idiosyncratic risk as a potential source of aggregate volatility, especially when combined with complex and opaque interlinkages
(Gabaix, 2011; Acemoglu et al., 2012; Caballero and Simsek, 2013)

One of the main contributions is to unify and extend these literatures via a purely empirical investigation of the changing U.S. bank size distribution

- Idiosyncratic volatility as a shaping force of power law distributions

Three Literatures

1. Changes in the banking industry and in bank size
   (Janicki and Prescott, 2006; Wheelock and Wilson, 2012; Lucas, 2013)

2. Idiosyncratic risk/random growth and power laws (Gabaix, 1999, 2009)

3. Idiosyncratic risk as a potential source of aggregate volatility, especially when combined with complex and opaque interlinkages
   (Gabaix, 2011; Acemoglu et al., 2012; Caballero and Simsek, 2013)

One of the main contributions is to unify and extend these literatures via a purely empirical investigation of the changing U.S. bank size distribution

- Idiosyncratic volatility as a shaping force of power law distributions

Empirical Methods for Dynamic Power Law Distributions

- Nonparametric approach applied to distribution of bank assets
- Provides simple description of stationary distribution:

$$\text{bank asset concentration} = \frac{\text{idiosyncratic asset volatilities}}{\text{reversion rates of assets}}$$

  - Reversion rates measure cross-sectional mean reversion

- By estimating the changing values of the idiosyncratic volatilities and reversion rates, can address the two questions:
  1. Why did big banks get bigger?
  2. Are larger, less traditional banks also riskier banks?

BHCs vs. Commercial Banks vs. Thrifts

- BHCs: increased asset concentration a result of lower reversion rates
  - Idiosyncratic volatilities are actually lower for BHCs
- Commercial banks and thrifts: increased asset concentration a result of higher idiosyncratic volatility
  - Surprising contrast between BHCs and commercial banks/thrifts
  - BHCs own commercial banks/thrifts, so diversification likely a factor
- Bigger banks are not necessarily riskier banks
  - Even though BHCs are bigger, one source of risk has declined
  - Acemoglu et al. (2012), Carvalho and Gabaix (2013)

Basics

- Economy is populated by N banks, time $t \in [0, \infty)$ is continuous
- Total assets of each bank given by process a_i:

$$d \log a_i(t) = \mu_i(t)\, dt + \sum_{z=1}^{M} \delta_{iz}(t)\, dB_z(t)$$

  - $B_1, \ldots, B_M$ are independent Brownian motions ($M \geq N$)
  - Nonparametric approach with little structure imposed on μ_i and δ_{iz}
  - More general than previous random growth literature based on equal growth rates and volatilities of Gibrat's Law (Gabaix, 1999, 2009)

Rank-Based Asset Dynamics and Local Times

Let $a_{(k)}(t)$ be the total assets of the k-th largest bank:

$$d \log a_{(k)}(t) = \mu_{p_t(k)}(t)\, dt + \sum_{z=1}^{M} \delta_{p_t(k)z}(t)\, dB_z(t) + \frac{1}{2} d\Lambda_{\log a_{(k)} - \log a_{(k+1)}}(t) - \frac{1}{2} d\Lambda_{\log a_{(k-1)} - \log a_{(k)}}(t)$$

- $p_t(k) = i$ when bank i is the k-th largest bank
- Λ_x is the *local time* at 0 for the process x
    - Measures amount of time x spends near 0 (Karatzas and Shreve, 1991)

Let $\theta_{(k)}(t)$ be share of total assets held by k-th largest bank:

$$\theta_{(k)}(t) = \frac{a_{(k)}(t)}{a(t)} = \frac{a_{(k)}(t)}{a_1(t) + \cdots + a_N(t)}$$

Rank-Based Asset Dynamics and Local Times

Let $a_{(k)}(t)$ be the total assets of the k-th largest bank:

$$d\log a_{(k)}(t) = \mu_{p_t(k)}(t)\,dt + \sum_{z=1}^{M} \delta_{p_t(k)z}(t)\,dB_z(t) + \frac{1}{2}d\Lambda_{\log a_{(k)} - \log a_{(k+1)}}(t) - \frac{1}{2}d\Lambda_{\log a_{(k-1)} - \log a_{(k)}}(t)$$

- $p_t(k) = i$ when bank i is the k-th largest bank
- Λ_x is the *local time* at 0 for the process x
  - Measures amount of time x spends near 0 (Karatzas and Shreve, 1991)

Let $\theta_{(k)}(t)$ be share of total assets held by k-th largest bank:

$$\theta_{(k)}(t) = \frac{a_{(k)}(t)}{a(t)} = \frac{a_{(k)}(t)}{a_1(t) + \cdots + a_N(t)}$$

Relative Growth Rates and Volatilities

$$d \log a_{(k)}(t) = \mu_{p_t(k)}(t)\,dt + \sum_{z=1}^{M} \delta_{p_t(k)z}(t)\,dB_z(t) \; + \text{ local time terms}$$

Let α_k be the relative growth rate of the k-th largest bank,

$$\alpha_k = \lim_{T\to\infty} \frac{1}{T}\int_0^T \left(\mu_{p_t(k)}(t) - \mu(t)\right)\, dt,$$

where $\mu(t)$ is growth rate of total assets $a(t) = a_1(t) + \cdots + a_N(t)$.

Let σ_k be the volatility of relative asset holdings $\log \theta_{(k)} - \log \theta_{(k+1)}$,

$$\sigma_k^2 = \lim_{T\to\infty} \frac{1}{T}\int_0^T \sum_{z=1}^{M} \left(\delta_{p_t(k)z}(t) - \delta_{p_t(k+1)z}(t)\right)^2\, dt.$$

Reversion Rates and Idiosyncratic Volatilities

- Refer to $-\alpha_k$ as reversion rates of asset holdings
  - Equal to minus the growth rate of assets for rank k bank relative to growth rate of total assets of all banks (cross-sectional mean reversion)
  - Regulatory and competition policy, mergers and acquisitions (Kroszner and Strahan, 1999, 2014), and the preferences, constraints, and strategic choices that drive asset growth (Corbae and D'Erasmo, 2013)

- Parameters σ_k measure idiosyncratic bank asset volatility
  - Unanticipated changes in liabilities and defaults caused by shocks to borrowers' production technologies (Corbae and D'Erasmo, 2013)
  - One potential source of contagion (Acemoglu et al., 2012)

Theorem (Bank Size Distribution)

There is a stationary distribution of bank assets in this economy if and only if $\alpha_1 + \cdots + \alpha_k < 0$, for $k = 1, \ldots, N-1$. Furthermore, if there is a stationary distribution, then for $k = 1, \ldots, N-1$, this distribution satisfies

$$E\left[\log \hat{\theta}_{(k)}(t) - \log \hat{\theta}_{(k+1)}(t)\right] = \frac{\sigma_k^2}{-4(\alpha_1 + \cdots + \alpha_k)}.$$

- Distribution shaped entirely by two factors
  1. Idiosyncratic asset volatilities: σ_k
  2. Reversion rates of asset holdings: $-\alpha_k$
- Theorem describes behavior of stable versions of asset shares, $\hat{\theta}_{(k)}$

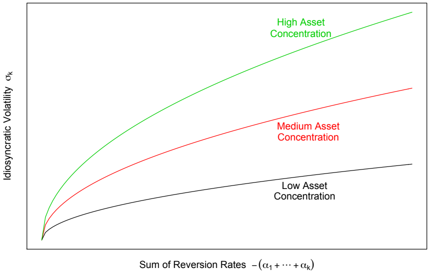
Theorem (Bank Size Distribution)

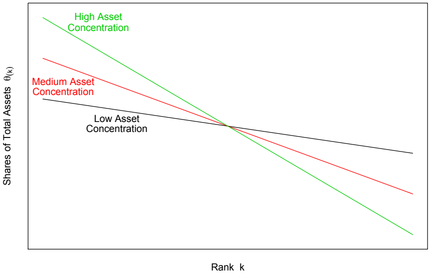
There is a stationary distribution of bank assets in this economy if and only if $\alpha_1 + \cdots + \alpha_k < 0$, for $k = 1, \ldots, N-1$. Furthermore, if there is a stationary distribution, then for $k = 1, \ldots, N-1$, this distribution satisfies

$$E\left[\log \hat{\theta}_{(k)}(t) - \log \hat{\theta}_{(k+1)}(t)\right] = \frac{\sigma_k^2}{-4(\alpha_1 + \cdots + \alpha_k)}.$$

- Distribution shaped entirely by two factors
  1. Idiosyncratic asset volatilities: σ_k
  2. Reversion rates of asset holdings: $-\alpha_k$
- Only a change in these factors can alter the distribution
  - Consider a transition from one stationary distribution to another

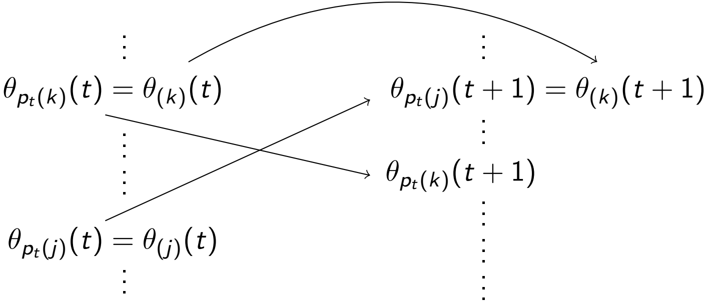
Idiosyncratic Volatility, Reversion Rates, and Concentration

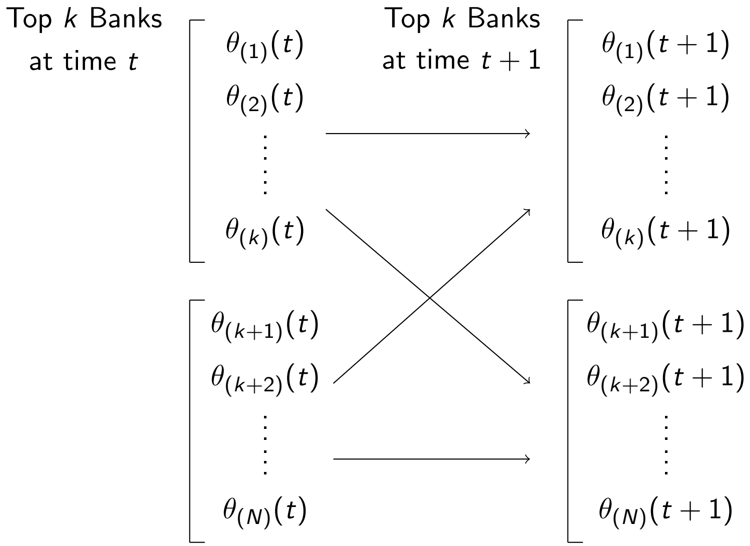




$$E\left[\log \hat{\theta}_{(k)}(t) - \log \hat{\theta}_{(k+1)}(t)\right] = \frac{\sigma_k^2}{-4(\alpha_1 + \cdots + \alpha_k)}$$

$$\begin{array}{ccc} \vdots & & \vdots \\ \theta_{(k)}(t) & \longrightarrow & \theta_{(k)}(t+1) \\ \vdots & & \vdots \\ \vdots & & \vdots \end{array}$$


$\theta_{p_t(k)}(t) = \theta_{(k)}(t)$
$\theta_{p_t(j)}(t) = \theta_{(j)}(t)$
$\theta_{p_t(j)}(t+1) = \theta_{(k)}(t+1)$
$\theta_{p_t(k)}(t+1)$


Top k Banks at time t
$\theta_{(1)}(t)$
$\theta_{(2)}(t)$
$\theta_{(k)}(t)$
$\theta_{(k+1)}(t)$
$\theta_{(k+2)}(t)$
$\theta_{(N)}(t)$
Top k Banks at time $t+1$
$\theta_{(1)}(t+1)$
$\theta_{(2)}(t+1)$
$\theta_{(k)}(t+1)$
$\theta_{(k+1)}(t+1)$
$\theta_{(k+2)}(t+1)$
$\theta_{(N)}(t+1)$

Data: BHCs, Commercial Banks, and Thrifts

Estimate volatility and reversion rates on three different data sets:

1. Bank-holding companies (1986-2014)
   - 500 largest included
   - BHCs own commercial banks and thrifts
2. Commercial banks (1960-2014)
   - 3000 largest included
   - Commercial banks owned by same BHC are counted as one bank
3. Thrifts (1984-2011)
   - 400 largest included

Estimation: Reversion Rates

It can be shown that for all $k = 1, \ldots, N-1$, the reversion rates $-\alpha_k$ are increasing in the quantity

$$\log\left[\theta_{p_{t+1}(1)}(t+1) + \cdots + \theta_{p_{t+1}(k)}(t+1)\right] - \log\left[\theta_{p_t(1)}(t+1) + \cdots + \theta_{p_t(k)}(t+1)\right].$$

Reversion rates measure the intensity of mean reversion, since they are increasing in the difference between the time $t+1$ assets of the largest banks at $t+1$ and the time $t+1$ assets of the largest banks at t.

Estimation: Idiosyncratic Volatilities

- Idiosyncratic volatilities measure variance of relative asset holdings for adjacent ranked banks, $\log\theta_{(k)} - \log\theta_{(k+1)}$

- Discrete-time approximation yields

$$\sigma_k^2 = \frac{1}{T}\sum_{t=1}^{T}\Big[\big(\log\theta_{p_t(k)}(t+1) - \log\theta_{p_t(k+1)}(t+1)\big) - \big(\log\theta_{p_t(k)}(t) - \log\theta_{p_t(k+1)}(t)\big)\Big]^2$$

When Did the Bank Size Distribution Start Transitioning?

- No standard techniques for determining when a transition starts
- Estimate parameters α_k and σ_k for different transition start dates
  - Find date that minimizes the distance between predicted shares (before and after the transition) and those observed in the data
  - For each date, smooth estimated parameters α_k and σ_k to achieve best possible fit

Idiosyncratic Volatilities: Bank-Holding Companies

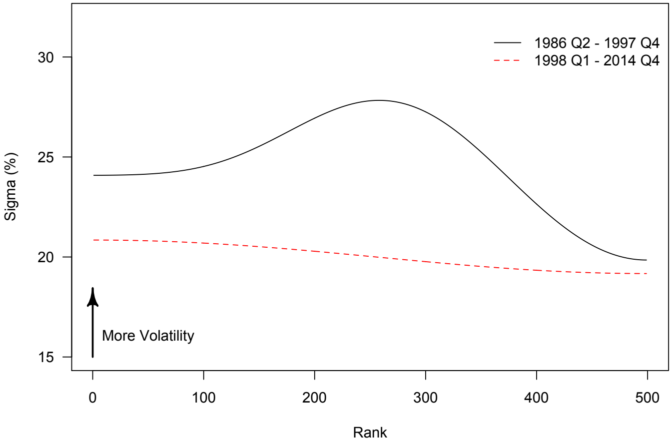


Figure: Standard deviations of idiosyncratic asset volatilities (σ_k) for different ranked BHCs.

Idiosyncratic Volatilities: Commercial Banks

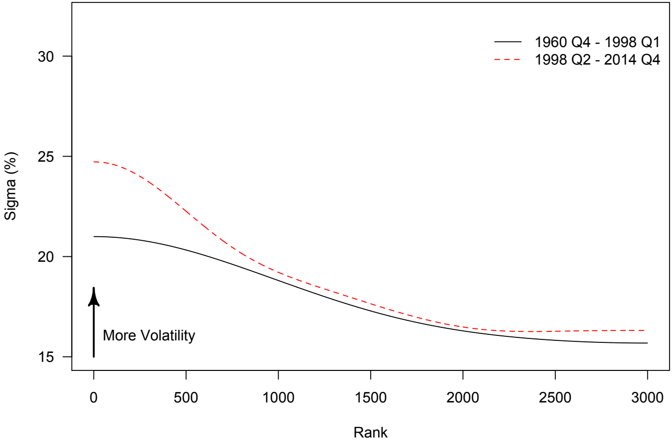


Figure: Standard deviations of idiosyncratic asset volatilities (σ_k) for different ranked commercial banks.

Idiosyncratic Volatilities: Thrifts

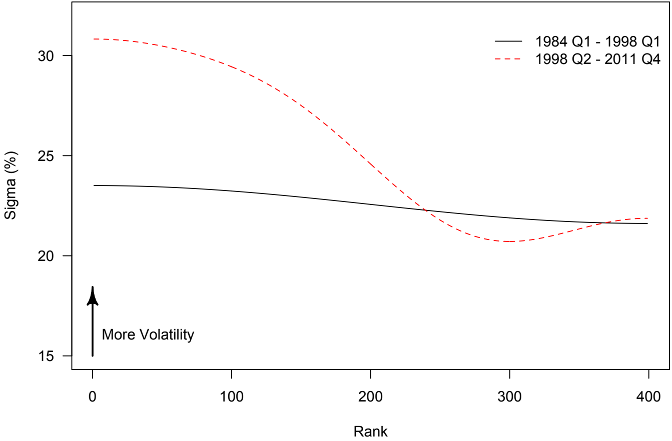


Figure: Standard deviations of idiosyncratic asset volatilities (σ_k) for different ranked thrifts.

Reversion Rates: Bank-Holding Companies

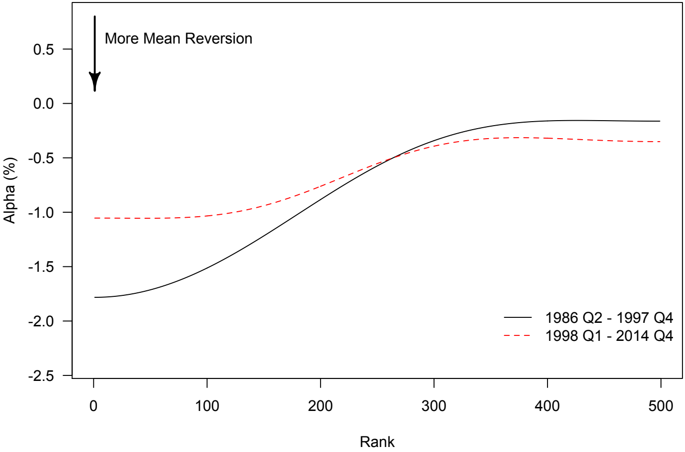


Figure: Minus the reversion rates (α_k) for different ranked BHCs.

Reversion Rates: Commercial Banks

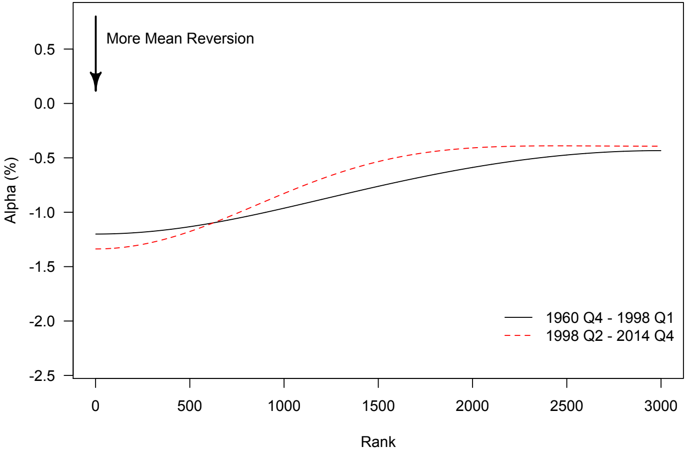


Figure: Minus the reversion rates (α_k) for different ranked commercial banks.

Reversion Rates: Thrifts

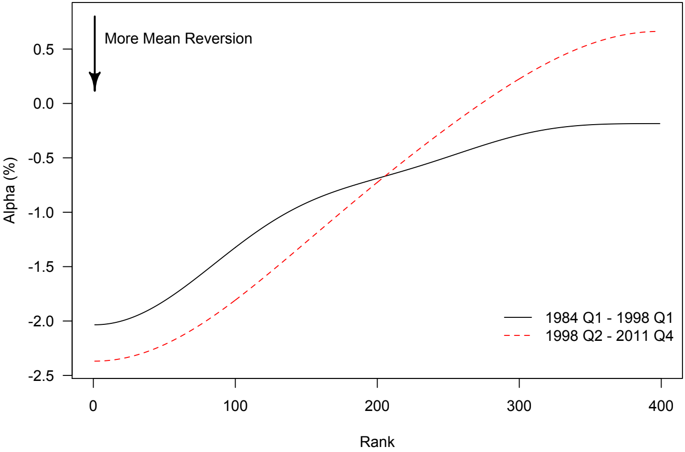


Figure: Minus the reversion rates (α_k) for different ranked thrifts.

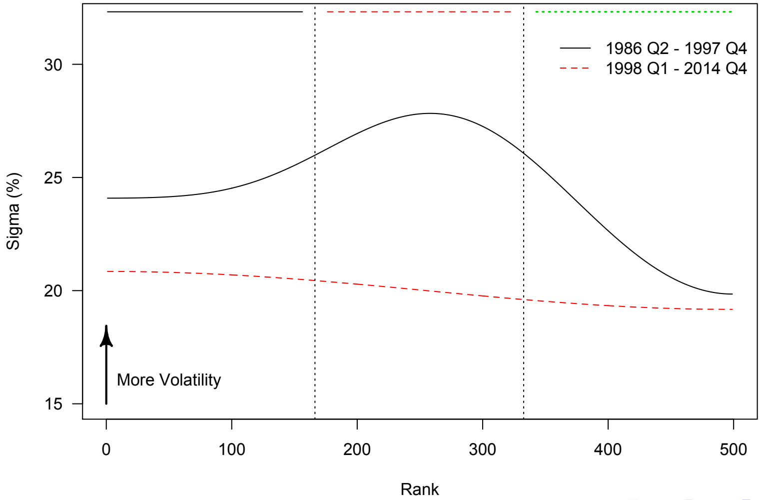
Interpreting the Results

- Idiosyncratic asset volatilities increased for commercial banks/thrifts
- Idiosyncratic asset volatilities decreased for bank-holding companies
  - Cross-sectional mean reversion also decreased, and this is why BHC assets still grew more concentrated
- Contrasting changes in volatility are surprising, especially since bank-holding companies own commercial banks and thrifts
  - Commercial banks owned by same BHC are counted as just one bank
  - Diversification through non-banking activities likely part of explanation

Interpreting the Results

- Why did idiosyncratic volatility increase for commercial banks/thrifts?
- Why did mean reversion decrease for bank-holding companies?
  - Repeal of Glass-Steagall Act (Lucas, 2013), changes in scale economies (Wheelock & Wilson, 2012), end of inter-state branching restrictions
- Industry concentration, interlinkages, contagion, and aggregate risk
  - Gabaix (2011), Acemoglu et al. (2012), Caballero and Simsek (2013)
- Bigger banks are not necessarily riskier banks
  - One source of contagion—idiosyncratic risk—has diminished, even as another more obvious source—concentration—has intensified

Volatilities Over Time: Bank-Holding Companies



Volatilities Over Time: Bank-Holding Companies

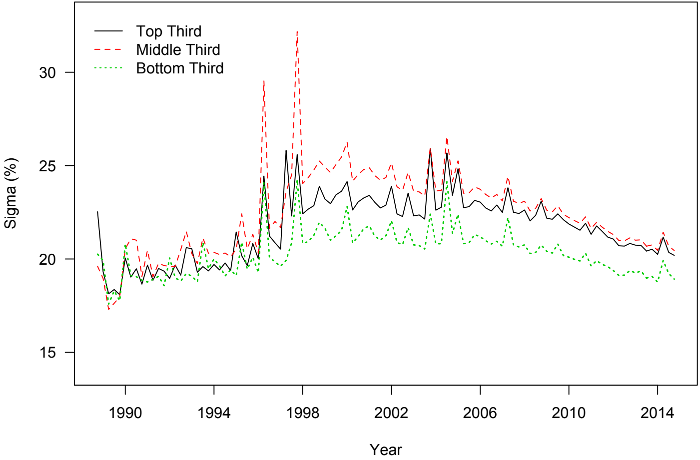
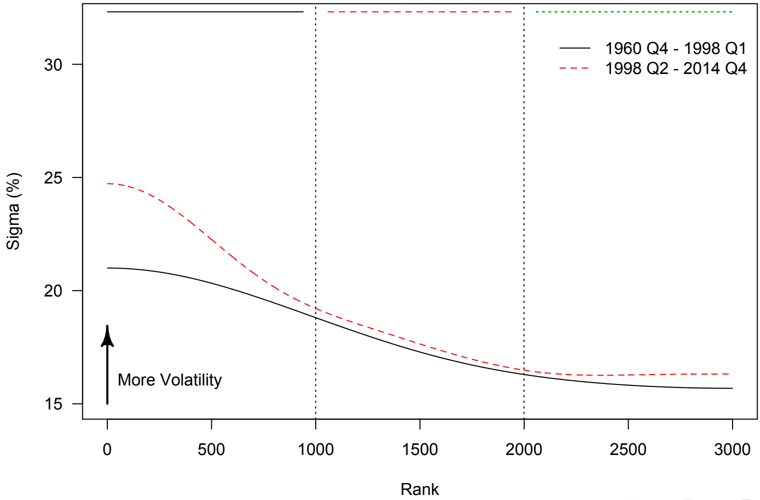


Figure: Ten-quarter moving averages of σ_k for different ranked BHCs.

Volatilities Over Time: Commercial Banks



Volatilities Over Time: Commercial Banks

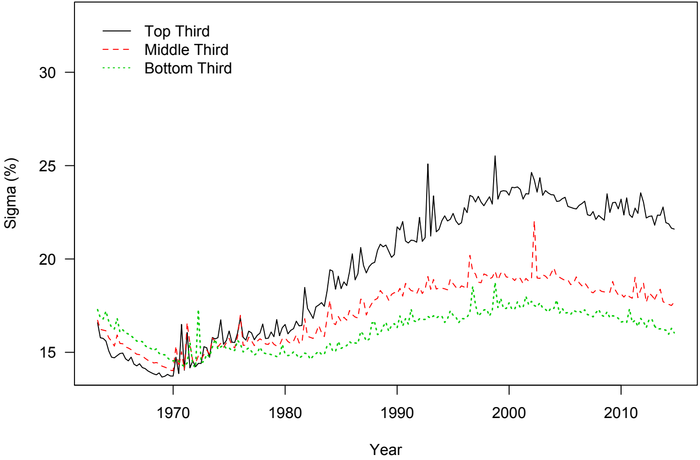


Figure: Ten-quarter moving averages of σ_k for different ranked commercial banks.

Idiosyncratic Volatilities: Beyond Gibrat's Law

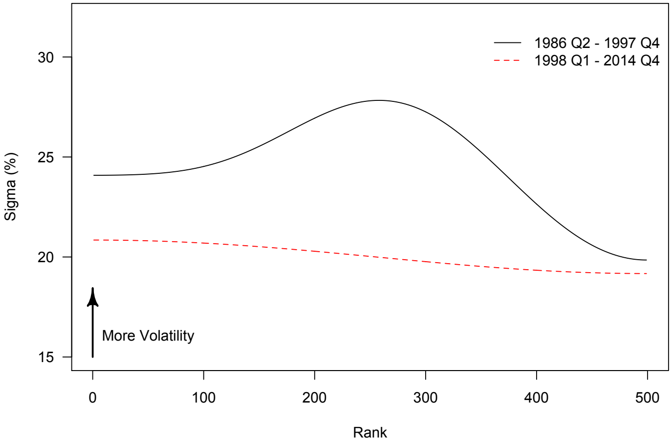


Figure: Standard deviations of idiosyncratic asset volatilities (σ_k) for different ranked BHCs.

Idiosyncratic Volatilities: Beyond Gibrat's Law

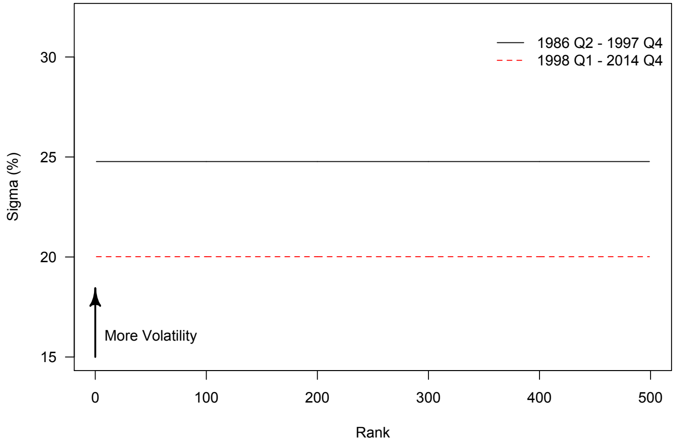


Figure: Standard deviations of idiosyncratic asset volatilities (σ_k) when imposing Gibrat's Law.

Bootstrap Resampling

- Previous figures suggest that at least some of these changes are statistically significant, especially for the volatilities σ_k
- Underlying distribution of parameters α_k and σ_k is unknown
- Bootstrap resampling generates confidence intervals and estimates of probability that σ_k is smaller in one time period versus another
  - 10,000 replicate samples randomly generated with replacement
  - Confidence intervals based on range of estimates in these resamples
  - How often is σ_k in time period one greater than in time period two?

Idiosyncratic Volatilities: Bank-Holding Companies

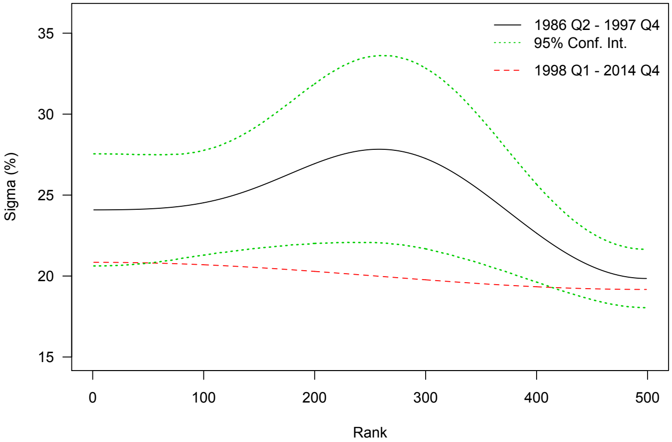


Figure: Standard deviations of idiosyncratic asset volatilities (σ_k) for different ranked BHCs.

Idiosyncratic Volatilities: Bank-Holding Companies

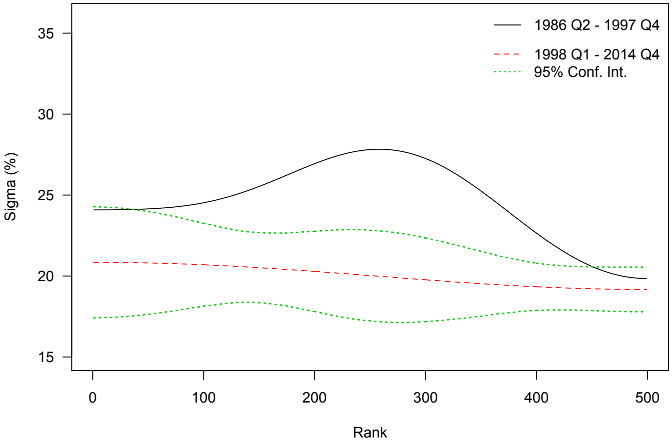


Figure: Standard deviations of idiosyncratic asset volatilities (σ_k) for different ranked BHCs.

Idiosyncratic Volatilities: Commercial Banks

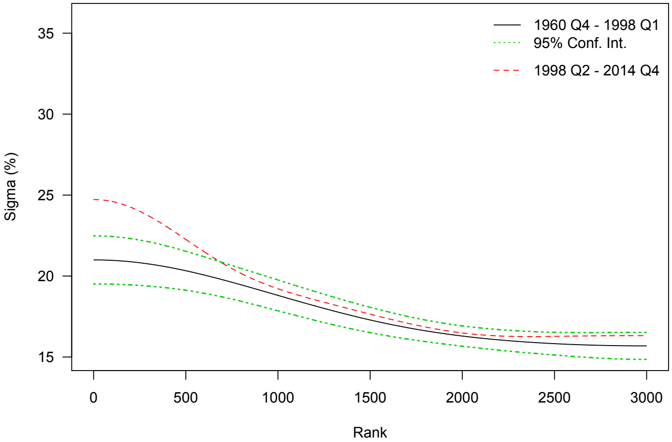


Figure: Standard deviations of idiosyncratic asset volatilities (σ_k) for different ranked commercial banks.

Idiosyncratic Volatilities: Commercial Banks

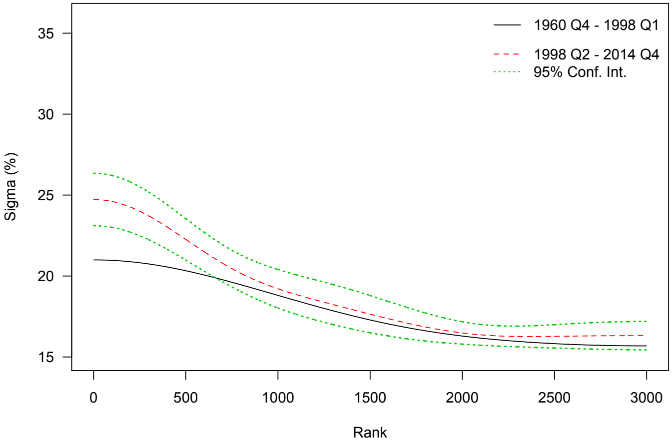


Figure: Standard deviations of idiosyncratic asset volatilities (σ_k) for different ranked commercial banks.

Idiosyncratic Volatilities: Thrifts

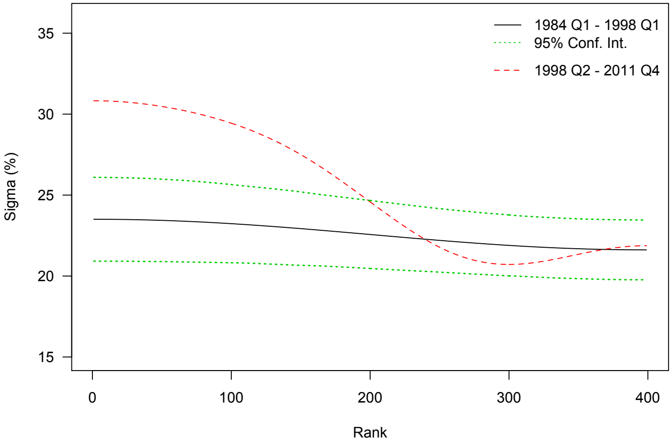


Figure: Standard deviations of idiosyncratic asset volatilities (σ_k) for different ranked thrifts.

Idiosyncratic Volatilities: Thrifts

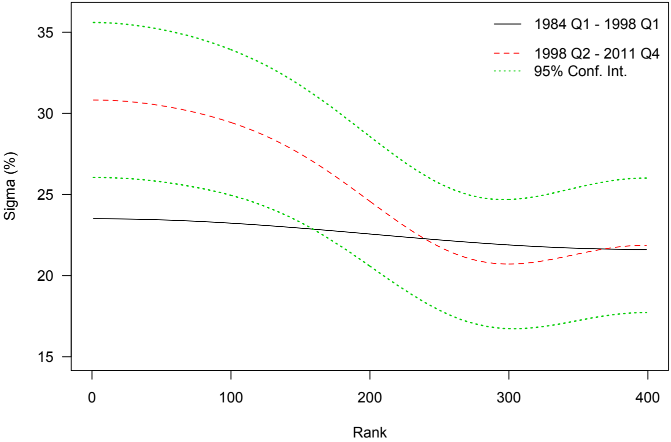


Figure: Standard deviations of idiosyncratic asset volatilities (σ_k) for different ranked thrifts.

P-Values

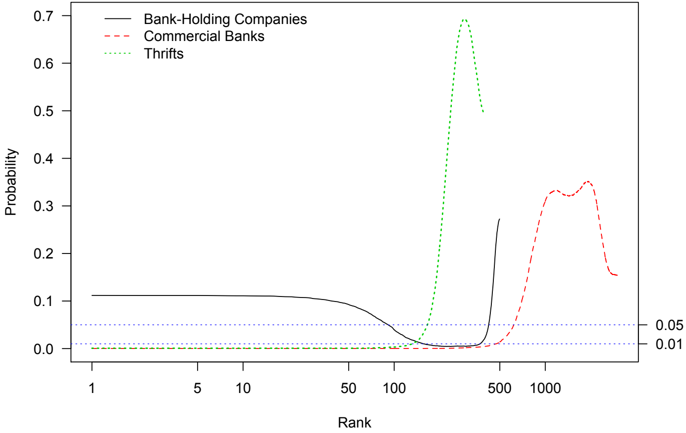


Figure: Probability that σ_k in time period 1 is greater (less) than or equal to σ_k in time period 2 for different ranked U.S. commercial banks and thrifts (BHCs).

Prediction vs. Data

- How well do these nonparametric empirical methods match the data?
  - Log-log plots in which straight lines correspond to Pareto distributions
  - Compare predicted bank asset shares to those observed in the data

- Plots of predicted vs. observed bank asset shares also provide information about the future U.S. bank size distribution
  - If predicted shares match observed, then transition to higher concentration is likely complete

Prediction vs. Data: Bank-Holding Companies

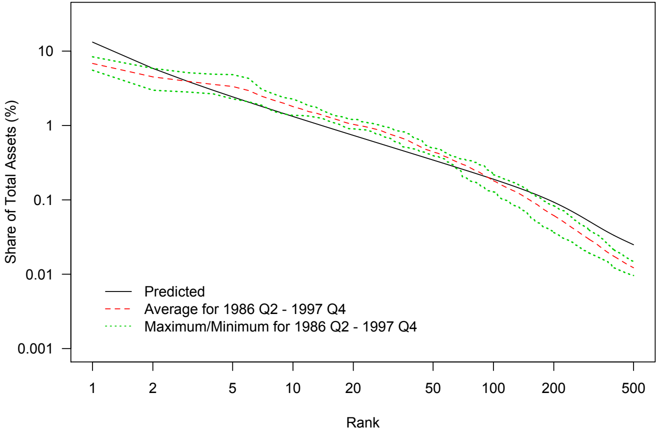


Figure: Shares of total assets held by the 500 largest U.S. BHCs for 1986 Q2 - 1997 Q4 as compared to the predicted shares.

Prediction vs. Data: Bank-Holding Companies

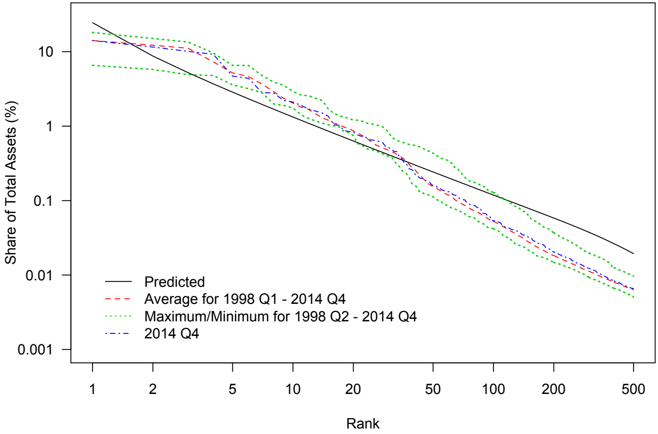


Figure: Shares of total assets held by the 500 largest U.S. BHCs for 1998 Q1 - 2014 Q4 as compared to the predicted shares.

Prediction vs. Data: Commercial Banks

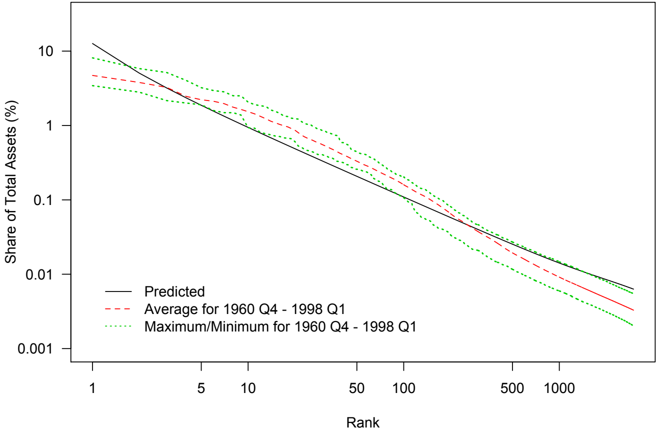


Figure: Shares of total assets held by the 3000 largest U.S. commercial banks for 1960 Q4 - 1998 Q1 as compared to the predicted shares.

Prediction vs. Data: Commercial Banks

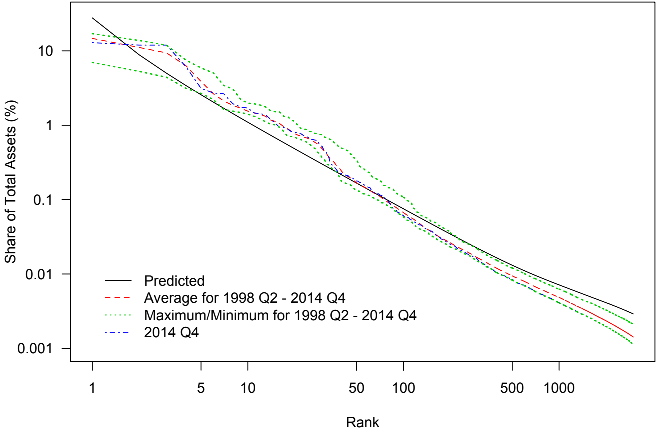


Figure: Shares of total assets held by the 3000 largest U.S. commercial banks for 1998 Q2 - 2014 Q4 as compared to the predicted shares.

Prediction vs. Data: Thrifts

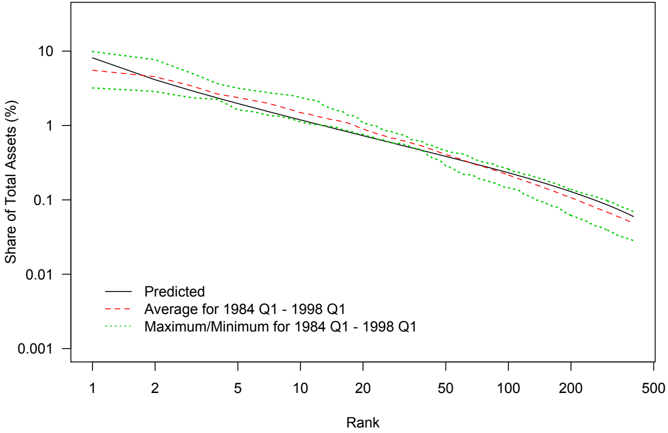


Figure: Shares of total assets held by the 400 largest U.S. thrifts for 1984 Q1 - 1998 Q1 as compared to the predicted shares.

Prediction vs. Data: Thrifts

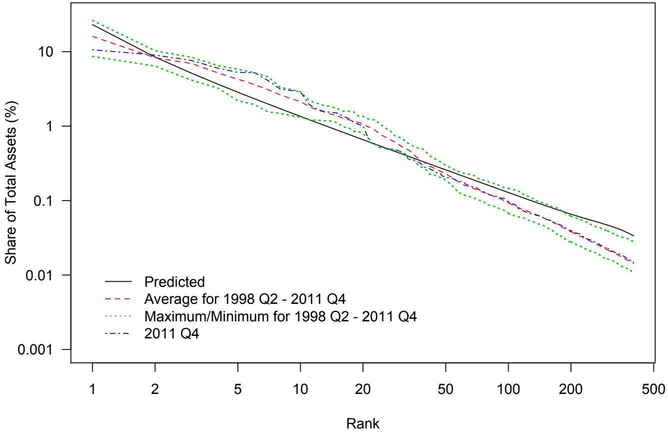


Figure: Shares of total assets held by the 400 largest U.S. thrifts for 1998 Q2 - 2011 Q4 as compared to the predicted shares.

Prediction vs. Data: Beyond Gibrat's Law

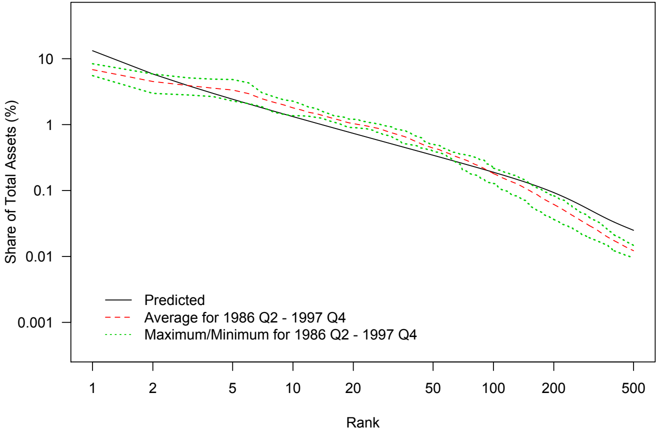


Figure: Shares of total assets held by the 500 largest U.S. BHCs for 1986 Q2 - 1997 Q4 as compared to the predicted shares.

Prediction vs. Data: Beyond Gibrat's Law

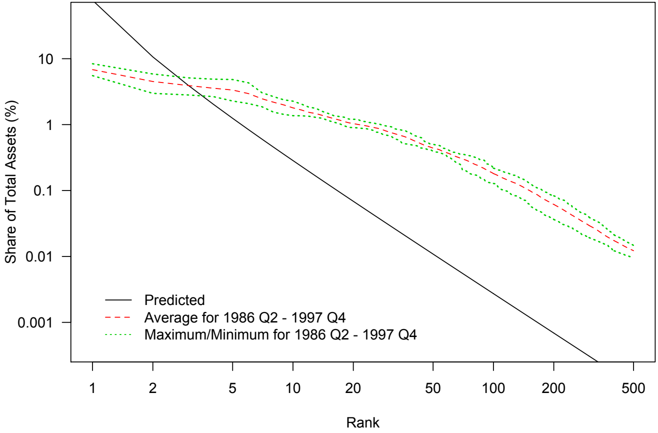


Figure: Shares of total assets held by the 500 largest U.S. BHCs for 1986 Q2 - 1997 Q4 as compared to the predicted shares when imposing Gibrat's Law.

Prediction vs. Data: Beyond Gibrat's Law

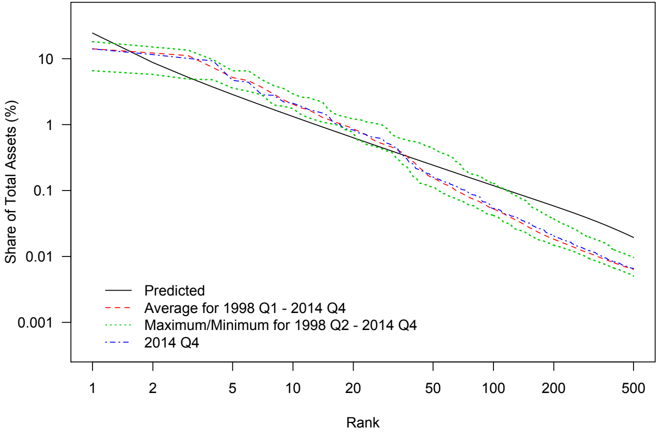


Figure: Shares of total assets held by the 500 largest U.S. BHCs for 1998 Q1 - 2014 Q4 as compared to the predicted shares.

Prediction vs. Data: Beyond Gibrat's Law

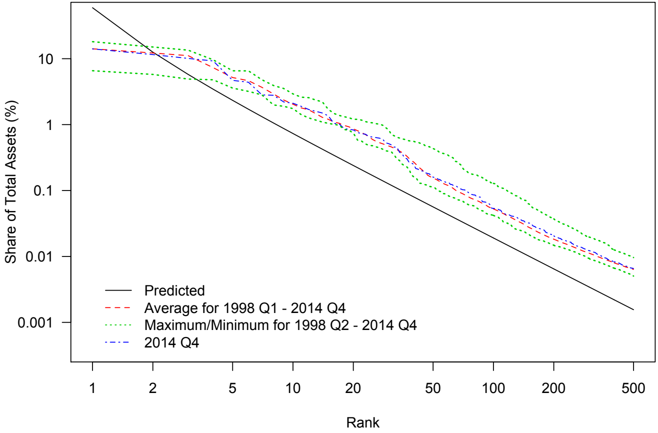


Figure: Shares of total assets held by the 500 largest U.S. BHCs for 1998 Q1 - 2014 Q4 as compared to the predicted shares when imposing Gibrat's Law.

Extensions and Applications

- Empirical methods for dynamic power law distributions
  - Methods can be applied to power law distributions other than bank size
  - Nonparametric techniques are flexible and robust
- Some possible applications
  - Wealth and income: Fernholz (2016a)
  - Firm size: smaller firms generate faster employment growth
  - Distribution of relative commodity prices: Fernholz (2016b)
  - World income distribution: are we converging, and if so, to what?
  - City size: similar to Gabaix (1999), but with more flexibility

The End

Thank You