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Big Banks, Idiosyncratic Volatility, and Systemic Risk†

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The Great Recession and Financial Crisis, characterized by the spectacular failures of large financial institutions such as Lehman Brothers and Bear Stearns, raise a number of concerns about the rise in US bank asset concentration that started in the 1990s (Kroszner and Strahan 1999). These concerns have renewed interest in right-skewed firm size distributions, granularities, and the implications of firm-specific shocks for aggregate macroeconomic volatility (Luttmer 2007; Gabaix 2011).

We explore the changing role of idiosyncratic volatility as a shaping force of the US bank size distribution. This is accomplished using nonparametric empirical methods for dynamic power law distributions to describe the changing bank asset distribution. Our general methods follow the approach of Fernholz (2016) and characterize the entire stationary distribution in terms of only two econometric factors—the cross-sectional mean reversion and idiosyncratic volatilities of bank assets. This first factor reduces asset concentration, while the second factor increases concentration.

Using quarterly data on the total assets of US bank-holding companies, we estimate cross-sectional mean reversion and idiosyncratic volatility of assets for different size-ranked banks over a period of rising bank asset concentration (Figure 1). We show that idiosyncratic asset volatilities decreased after the rise of big banks in the mid-1990s. In contrast, cross-sectional mean reversion fell over this same time period, a change that explains, in an econometric sense, the rising concentration of US bank assets.

Our results both contrast with some recent research and raise questions for future research. Summers and Sarin (2016), for example, find that many market measures of risk for large financial institutions have actually risen after the 2008 financial crisis. We take a different approach and structurally link changes in idiosyncratic balance sheet volatility to the rise in bank asset concentration among a few large and systemically important institutions.

A growing literature has emphasized the potential for idiosyncratic, firm-level shocks to have significant macroeconomic consequences (Gabaix 2011), especially in industries such as banking where interlinkages and contagion between entities are common (Acemoglu et al. 2012; Caballero and Simsek 2013). In the context of this literature, our results imply that one important source of contagion—idiosyncratic volatility—has diminished, even as another more obvious source—bank asset concentration—has increased. Future research that more fully examines the changing relationship between idiosyncratic volatility, networks, and systemic risk in the financial sector should yield useful insight.

I. Dynamic Power Laws

Several papers have documented that firm size distributions around the world follow Zipf's law (Axtell 2001; Gabaix 2009). This is true for various different measures of firm size such as total sales, market capitalization, and employment. For the banking sector, Janicki and Prescott (2006) show that Zipf's law also approximately describes the distribution of assets of US financial intermediaries in certain years.

There are both static and dynamic mechanisms that give rise to Zipf's law and more general power laws in different applications (Newman 2005; Gabaix 2009). The most common way to model dynamic power law distributions is as the result of random growth processes. This

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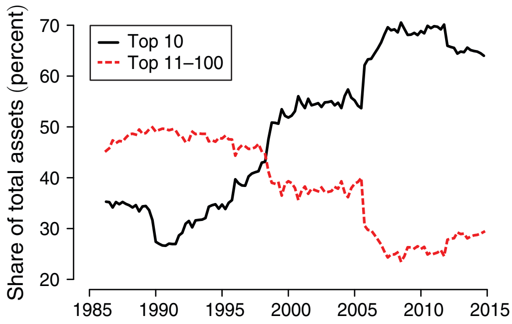

Figure 1. US Bank Asset Concentration

approach was pioneered by Gabaix (1999) in an application to city size distributions, and has since been used in many other applications including firm size distributions (Luttmer 2007) and wealth distributions (Benhabib, Bisin, and Zhu 2011). Most of these applications follow Gibrat's law and impose uniform growth rates and uniform idiosyncratic volatilities throughout the distribution. Our econometric framework goes beyond this approach in several important ways.

The dominant approach to random growth and power laws solves a single stochastic differential equation for a specific parametric distribution that represents a continuum of agents. In contrast, our approach involves solving multiple stochastic differential equations, each of which corresponds to a different rank in the distribution of bank assets. This granularity is essential as it allows us to characterize the assets held by every bank in the distribution.

In addition to this granularity, our empirical framework extends previous work by describing a general power law distribution in which the power law exponent can vary across ranks in any way. This generality is essential for many applications, since many empirical distributions do not conform to any single power law (Axtell 2001; Ioannides and Skouras 2013). Bank size, for example, follows a different power law at high versus low ranks (Figure 2).

Furthermore, our econometric methods impose no parametric structure on the underlying bank asset dynamics. These asset dynamics are represented as general Itô processes, which allow for a rich structure of growth rates and volatilities that can vary both across individual banks and over time. In this sense, our approach nests previous analyses based on Gibrat's law and its extensions.

II. Methods and Data

We follow the empirical approach of Fernholz (2016) and estimate the two shaping factors of the changing US bank asset distribution. At each rank, this distribution is described by the asymptotic statistical identity (1):

$$\text{(1)} \quad \text{bank asset concentration} = \frac{\text{idiosyncratic volatility of bank assets}}{\text{reversion rates of bank assets}}.$$

This econometric identity motivates our empirical strategy. In particular, identity (1) implies that any increase in bank asset concentration must be caused, in an econometric sense, by either an increase in idiosyncratic asset volatility or a decrease in reversion rates.

In order to investigate the rise in concentration of bank assets at a few large institutions, we collect quarterly balance sheet data on total assets, call report item BHCK2170, of US bank-holding companies from the Federal Reserve's FR Y-9C forms from 1986:II to 2014:IV. Our empirical strategy endogenously splits our sample into two periods and two distinct bank size distributions—one from 1986:II to 1997:IV, and one after the rise of big banks from 1998:I to 2014:IV.

Identity (1) highlights the dual role of idiosyncratic bank asset volatility as both a shaping force of the bank size distribution and a determinant of financial stability. Thus, by applying these methods to bank-level data, we connect three distinct and disparate literatures—power laws, bank size distributions, and the importance of idiosyncratic shocks for aggregate outcomes.

III. Idiosyncratic Volatility

Figure 3 shows the estimated idiosyncratic bank asset volatilities from 1986 to 1997 and 1998 to 2014 for the entire bank size distribution. These estimates follow the procedure described by Fernholz (2016) and allow for different asset volatilities at all 500 different bank ranks. This figure shows substantial rank heterogeneity, and thus highlights the methods' flexibility. Indeed, the asset volatilities of middle-ranked, medium-sized banks fell the most after the 1990s, and this asymmetric change altered the relationship between bank size and volatility.

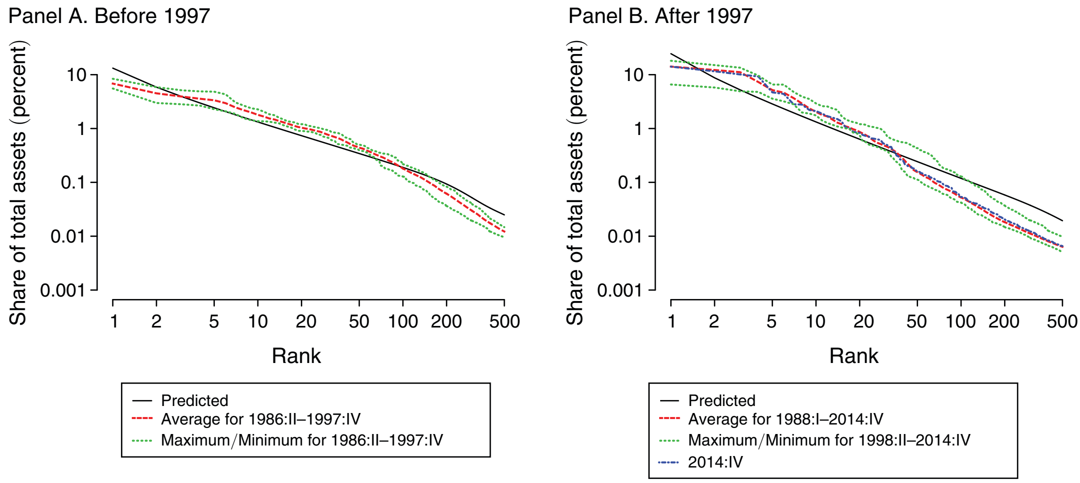

Figure 2. Prediction versus Data

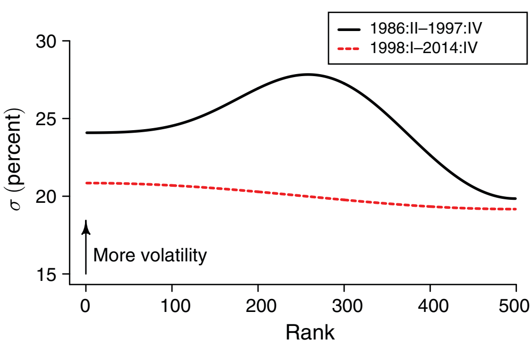

Figure 3. Idiosyncratic Volatilities

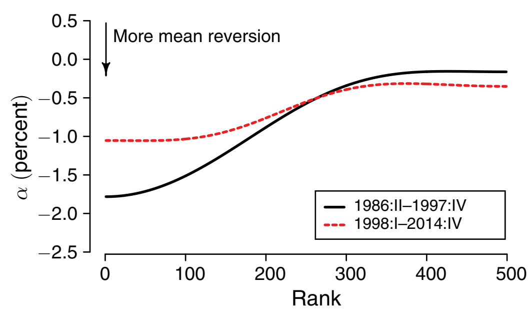

Figure 4. Cross-Sectional Mean Reversion

The most striking feature of Figure 3 is the estimated decline in idiosyncratic bank asset volatility after 1997. This result is surprising for several reasons. First, a fall in idiosyncratic volatility implies a less concentrated distribution, as shown in identity (1). Because bank assets in fact became more concentrated after 1997 (Figure 1), this volatility decline must have coincided with an even larger fall in cross-sectional mean reversion. Figure 4, which plots the intensity of cross-sectional mean reversion for different sized banks, confirms that this is the case.

Second, our results in Figure 3 suggest that the naïve view that a more concentrated banking sector is always a riskier banking sector need not hold. Gabaix (2011); Acemoglu et al. (2012); and Caballero and Simsek (2013), among others, have emphasized the potential for idiosyncratic, firm-specific shocks to affect macroeconomic outcomes, especially in industries with opaque and complex interlinkages. Therefore, to the extent that idiosyncratic volatility might be a source of systemic risk in the financial sector, our results in Figure 3 show that this source of risk has decreased over the last few decades. This is true despite the concurrent rise in asset concentration.

To be clear, we do not directly measure systemic risk in the financial sector. Thus, while we cannot conclude that the overall threat of contagion in this sector has decreased, we can conclude that one potential source of contagion—idiosyncratic volatility—has diminished, even as another more obvious source—concentration—has grown. Future work that attempts to measure the net effect of these contrasting changes on systemic risk should yield useful policy insight.

Figure 4 plots the intensity of cross-sectional mean reversion of assets before and after 1997. Note that more negative values of this measure imply more cross-sectional mean reversion. The figure shows that mean reversion declined after the rise of big banks in the 1990s, a change that caused rising bank asset concentration despite lower idiosyncratic volatility (see identity (1)).

A number of economic explanations can account for these observed changes in cross-sectional mean reversion. Legislative changes in the mid-1990s, such as the repeal of the Glass-Steagall Act (Lucas 2013) and the repeal of interstate branching restrictions (Kroszner and Strahan 1999), are consistent with relatively faster asset growth for the largest banks and hence less cross-sectional mean reversion (Fernholz and Koch 2016). The results in Figure 4 highlight the importance of future empirical work that attempts to link this shift in mean reversion to changes in policy and the economic environment.

IV. Prediction and Data

How well do our rank-based empirical methods match the US bank data? Figure 2 shows the average share of total assets of different ranked banks before (left panel) and after (right panel) 1997 together with the shares predicted using our econometric methods. This is a log-log plot of shares versus rank, so a straight line corresponds to a Pareto distribution (Gabaix 2009). As the two panels show, our estimates of cross-sectional mean reversion and idiosyncratic asset volatility generate an approximate match of the US bank size distribution over these two different time periods.

Figure 2 also demonstrates that the distribution of US bank assets follows different power laws at different ranks. This is where our new rank-based methods are essential. By allowing for a distribution with a power law exponent that varies across ranks, our methods are able to reproduce some of the empirical distribution's concavity displayed in Figure 2.

The changing power law exponent is a consequence of the rank-dependent variation in idiosyncratic volatilities and cross-sectional mean reversion displayed in Figures 3 and 4. Indeed, identity (1) describes how these two econometric factors shape the bank size distribution at every rank. Taken together, therefore, Figures 2, 3, and 4 demonstrate how deviations from Gibrat's law are essential to accurately describe the US bank size distribution both before and after the rise of big banks in the 1990s.

V. Conclusion

Our results present important new facts about the structure of the US financial sector. The fall in idiosyncratic bank asset volatilities after the 1990s, for example, is a surprising finding, and one that raises questions about the underlying structural changes that led to this decline. A deeper understanding of these changes should help to untangle the complex relationship between the rise of big banks and systemic risk.

Perhaps our most notable contribution is to provide an integrated econometric framework that reveals and describes the relationship between idiosyncratic risk and firm size distributions. After all, a growing number of influential studies highlight the importance of heterogeneity and size for aggregate macroeconomic outcomes. Alongside this literature, our framework highlights the two-layered relationship between big banks, idiosyncratic volatility, and systemic risk—volatility affects both concentration and systemic risk, while concentration itself further affects systemic risk.

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