What Drives Bank Performance?

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Abstract

Changes in macroeconomic conditions explain the preponderance of the fluctuations in bank charge-off rates. By contrast, idiosyncratic factors account for a sizable share of the variation in bank revenues, which points to the importance of bank-specific business models as drivers of performance.

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Key words: Pre-provision net revenues, charge-off rates, macroeconomic factors, banking factors, principal components, backcasting.

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1 Introduction

Economic theory teaches us to expect a link between macroeconomic fluctuations and the performance of financial intermediaries. We set out to investigate this link empirically. Focusing on some key metrics of bank performance, such as revenues and loan charge-off rates, we seek to understand what fraction of the observed variation in these metrics can be attributed to changes in economic conditions. Furthermore, we are also interested in splitting the remainder of the variation between changes that affect the banking sector overall and changes driven by idiosyncratic factors specific to individual banks.

The connection between macroeconomic performance and bank performance is at the center of stress tests, a standard supervisory tool used across the world. In practice, stress tests rely on only one or two severe scenarios each round. Consequently, stress test scenarios are typically designed to be stressful for a generic bank. However, not all banks have the same business model. Apart from the traditional banking model of maturity transformation, some banks have significant trading operations, others specialize in the provision of custodial functions, and others specialize in the provision of consumer credit. To the extent that bank-specific variation is important, it becomes central to consider scenarios that can stress different business models.

We find that macroeconomic factors can explain the preponderance of the fluctuations in loan charge-off rates. However, we find that bank-specific idiosyncratic factors explain a sizable share of the variation in bank revenues. Therefore, it would be important to consider scenarios specifically tailored to idiosyncratic bank risk when developing stress scenarios for revenues.[1]

Our analysis needs to resolve three problems. The first problem is to summarize statistically the state of the macroeconomy. We rely on a large dataset including 132 macroeconomic series, first assembled by Stock and Watson (2002) and later updated and expanded by McCracken and Ng (2015). Following their lead, we use principal components (PCs) to capture the essential sources of macroeconomic variation.

The second problem is to pick measures of bank performance. We select pre-provision net revenue (PPNR) and charge-off rates, key performance measures monitored by bank analysts and bank supervisors.[2] To distinguish between sources of variation in performance that are common across the banking-sector and bank specific factors, we use a panel of large banks holding companies that participated in the latest stress tests in the United States.

[1] One peculiar feature of the U.S. stress-tests run by the Federal Reserve is that participating banks are required to submit scenarios that are tailored to their specific business model. For an analysis based on these scenarios, see for instance Arseneau (2017).

[2] PPNR refers to interest and non-interest income net of expenses prior to the inclusion of loss provisions and taxes.

For our decomposition we use a two-step approach. In the first step, we regress the performance measures on the macro principal components, which gives us the fraction of the variation explained by macroeconomic fluctuations. The residuals from these first-step regressions embody the part of the performance measures driven by banking-wide and bank-specific variation. In the second step, we use another PC to capture banking-sector variation, with the remainder then attributed to bank-specific factors.

The third problem is that the bank performance data start at different times for the various banks depending on when they became bank-holding companies. We rely again on Stock and Watson (2002) to impute or backcast the missing data, balancing the panel. Their procedure summarizes the variation common across banks to impute any unbalanced data. We extend their method to include an additional set of factors, our macro principal components. Considering this additional information is especially important for our analysis. Intuitively, excluding the macroeconomic variation from the backasting step would artificially reduce the fraction of the variation in bank performance driven by macroeconomic changes for the imputed values and for the overall dataset.

Since our statistical procedure orthogonalizes the three sources of variation—macroeconomic, banking-sector, and idiosyncratic—we can use R-squares statistics from each regression to size the contribution of the three different sources to the variation in the bank performance measures. We find that only for 3 out 34 banks in our dataset, idiosyncratic bank factors explain slightly more than half of the variation in charge-off rates according to adjusted R-squares statistics. By contrast, for about one-third of the banks we consider, idiosyncratic factors account for more than half of the variation in PPNR.

Aside from our main findings on the importance of bank-specific variation, we provide MATLAB routines that implement our extended backcasting procedure. This toolbox is generally applicable to balancing a dataset using both variation from complete series in the dataset and factors external to the dataset. When this additional external information is not relevant, our extended algorithm collapses to the algorithm proposed by Stock and Watson (2002).[3]

Moreover, our analysis contributes to the literature on charge-off rates and PPNR. There is a significant body of literature focused on modeling credit risk and, relatedly, charge-off rates, whereas the literature on modeling PPNR is much thinner.[4] An exception is Hirtle et al. (2016), which provides a top down econometric procedure, the CLASS model, for modeling all of the performance measures that accumulate to capital. Similarly, Hale, Krainer and Erin (2015), determine the optimal level of aggregation for modeling different bank performance measures.

[3] The MATLAB routines implementing the algorithm and replications code for this paper are available at `https://github.com/lucashare/backcasting`. An online appendix available at `http://www.lguerrieri.com/the_drivers_of_bank_perform.pdf`.

[4] For instance, for credit risk see McNeil, Frey and Embrechts (2015), Frye and Pelz (2008), Barth et al. (2018).

2 Data

Our bank performance data rely on two commonly used measures, loan charge-offs and pre-provision net revenue (PPNR). Charge-offs encompass losses declared on loans, which typically lag macroeconomic variables. We express charge-offs as rates relative to total loans and leases for each given bank, as is standard practice. PPNR is defined as the difference between, on one side, interest and non-interest income and, on the other side, interest and non-interest expenses. We express PPNR as a percent of average assets, a common empirical choice. In our application, we obtain PPNR and charge-off data from the FR Y-9C Release, a quarterly report for income and balance sheet data of bank holding companies (BHCs).[5] We focus on the 34 BHCs that participated in the 2020 stress tests conducted by the Federal Reserve but drop 6 firms with fewer than 40 quarterly observations (ten years of data), resulting in a panel of 28 BHCs.[6] Our sample ranges from the first quarter of 2002 to the third quarter of 2019. Table 1 lists the firms in the sample. As an example, Figure 1 shows annualized PPNR and charge-offs for two BHCs with comparable business models, JPMorgan Chase and Bank of America. The PPNR series show jagged and idiosyncratic movements. By contrast, charge-off series are much smoother than PPNR and generally move more closely with one another and with aggregate macroeconomics series.

To calculate our macro PCs, we also use 132 macroeconomic time series from McCracken and Ng (2015). These series run from the second quarter of 1959 to the third quarter of 2020. They encompass a broad list of macroeconomic series on economic activity, factors of production, and interest rates. To extract the key fluctuations in these series, we take principal components. The test of Bai and Ng (2002) calls for 12 factors.

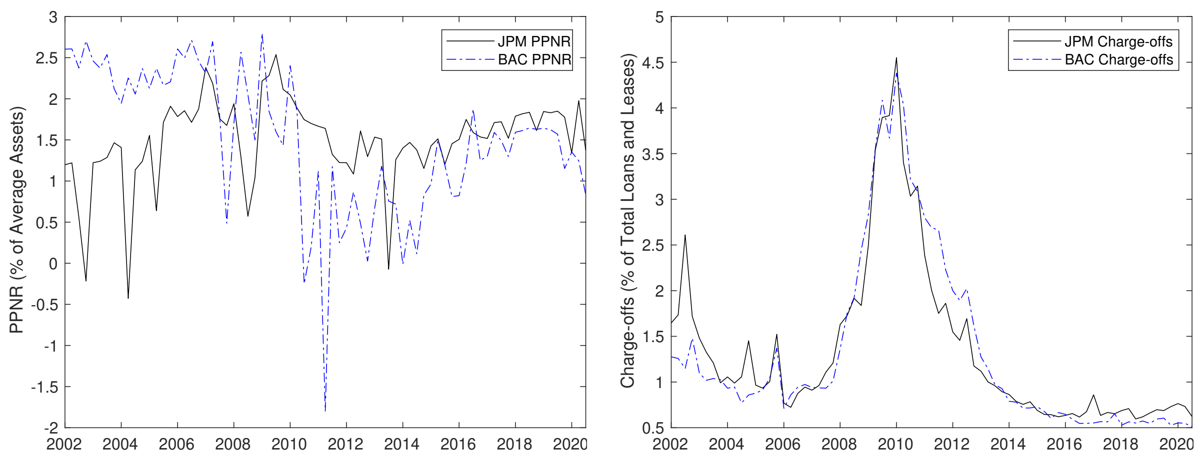
[5]The data are adjusted for mergers and acquisitions of firms also subject to statutory reporting in the quarter in which they occur.

[6]The stock market tickers for the six firms we dropped are: CS, BNP, TD, SAN, UBS, and BARC. In an online appendix, we show that our results are little changed when the estimation panel also includes these firms.

Table 1: Data Range

Bank	Ticker	Start Date	End Date
ALLY FINANCIAL INC.	ALLY	2009:2	2020:3
AMERICAN EXPRESS COMPANY	AXP	2009:1	2020:3
BANK OF AMERICA CORPORATION	BAC	2002:1	2020:3
BANK OF NEW YORK MELLON CORPORATION, THE	BNYM	2007:3	2020:3
BMO FINANCIAL CORP.	BMO	2002:1	2020:3
CAPITAL ONE FINANCIAL CORPORATION	COF	2004:4	2020:3
CITIGROUP INC.	C	2002:1	2020:3
CITIZENS FINANCIAL GROUP, INC.	CFG	2002:1	2020:3
DB USA CORPORATION	DB	2002:1	2020:3
DISCOVER FINANCIAL SERVICES	DFS	2009:2	2020:3
FIFTH THIRD BANCORP	FITB	2002:1	2020:3
GOLDMAN SACHS GROUP, INC., THE	GS	2009:1	2020:3
HSBC NORTH AMERICA HOLDINGS INC.	HSBC	2004:1	2020:3
HUNTINGTON BANCSHARES INCORPORATED	HBAN	2002:1	2020:3
JPMORGAN CHASE & CO.	JPM	2002:1	2020:3
KEYCORP	KEY	2002:1	2020:3
MORGAN STANLEY	MS	2009:1	2020:3
MUFG AMERICAS HOLDINGS CORPORATION	MUFG	2002:1	2020:3
M&T BANK CORPORATION	MTB	2002:1	2020:3
NORTHERN TRUST CORPORATION	NTRS	2002:1	2020:3
PNC FINANCIAL SERVICES GROUP, INC., THE	PNC	2002:1	2020:3
RBC US GROUP HOLDINGS LLC	RBC	2018:2	2020:3
REGIONS FINANCIAL CORPORATION	RF	2004:3	2020:3
STATE STREET CORPORATION	STT	2002:1	2020:3
TRUIST FINANCIAL CORPORATION	TFC	2002:1	2020:3
U.S. BANCORP	USB	2002:1	2020:3

Figure 1: A First Look at the Data, Left: PPNR, Right: Charge-offs



Source: Federal Reserve Y-9C Release.
Note: The ticker JPM refers to JPMorgan Chase & Co. The ticker BAC refers to Bank of America Corporation.

3 Statistical Methods

We describe first our procedure for sizing the importance of different types of factors—macroeconomic vs. banking-wide factors—in explaining the variation in the bank performance measures. We then describe how we backcast the missing data.

3.1 Data Decomposition

To size the relative importance of different types of factors we use a two-step procedure. First, we estimate

$$X_{b,t} = \lambda_b MF_t + \epsilon_{b,t}^{MF} \tag{1}$$

by ordinary least squares, where $X_{b,t}$ represents the performance measure, alternatively, charge-offs or PPNR rates. The term λ_b is vector of factor loadings, MF_t is a vector of macro principal components and $\epsilon_{b,t}^{MF}$ represents variation in the performance measure orthogonal to the macro factors.

We use the residuals from the first-step regression, $\epsilon_{b,t}^{MF}$, to extract one more principal component, CF_t, which we interpret as capturing banking-sector variation common across banks but orthogonal to the variation captured by the macro principal components. We estimate the factor loadings γ_b in

$$\epsilon_{b,t}^{MF} = \gamma_b CF_t + \epsilon_{b,t}^{CF} \tag{2}$$

by ordinary least squares. The residuals from this regression, $\epsilon_{b,t}^{CF}$, is the bank-specific variation in the performance measures, i.e., the variation not explained by either the macro factors or the cross sectional factors.

3.2 Balancing the Dataset

We re-purpose the two-step procedure in Section 3.1 to backcast the bank performance measures that do not start at the beginning of the dataset and thus balance our panel of banks. In step 1), we identify banks with a full sample of data. Using this data, we run regressions 1 and 2. We then use the estimated coefficients $\hat{\lambda}_b$ and $\hat{\gamma}_b$ to impute any missing values.[7] In step 2), we re-estimate the coefficients $\hat{\lambda}$ and $\hat{\gamma}$ using the original data and the imputed data from step 1). We then re-impute the data that were missing in step 1) using these re-estimated coefficients. We repeat step 2) until the maximum difference in the missing data across iterations is smaller than a given tolerance, which we set at $10e^{-4}$. If we were to remove the regression of Equation 1, this procedure would collapses to that of Stock and Watson (2002).

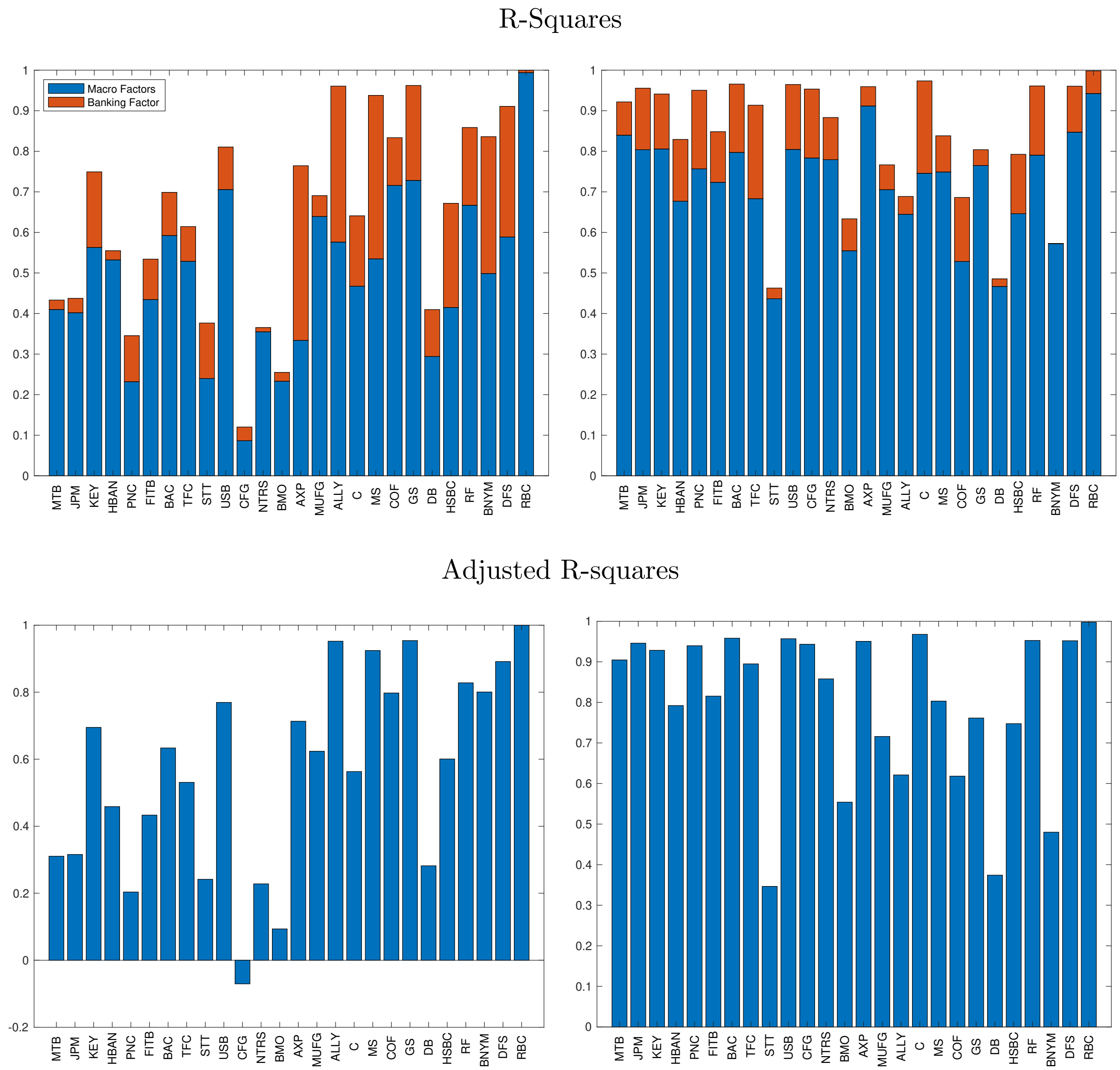
4 Results

We find that the macro factors explain a large portion of the variation in our performance measures across banks, although these factors seem to more consistently explain the variation in charge-offs than in PPNR.

Figure 2 shows the cumulative R-squares from the regressions of macro factors and banking factors on charge-offs and PPNR for each bank in our panel. The macro factors explain a large proportion of the variation in charge-offs across all of the banks, with R-squares exceeding 0.5 for all but one bank. Furthermore, the addition of the banking factor, on top of the the macro factors, leads to R-squares that exceed 0.9 for about two-thirds of the banks in our panel. By contrast, the same factors, explain a lower fraction of the variation in PPNR. About a third of the banks show R-squares below 0.5 and only a handful of banks tally R-Squares above 0.9. These differences are also evident in the lower panels of the figure, which report adjusted R-Squares. While the adjusted and standard R-Squares are close to each other for charge-offs the differences are more pronounced for PPNR, with one bank even showing a *negative* adjusted R-Square. Idiosyncratic, bank-specific variation is more prevalent in the case of PPNR than for charge-off rates.

[7] In the case of chargeoffs, if our estimates point to negative chargeoff rates, we use a floor of 0, instead.

Figure 2: Macro Factors Explain a Large Portion of the Variation in Charge-off Rates as Opposed to PPNR. Left PPNR, Right: Charge-offs.



Note: The legal entity names corresponding to the bank tickers used in this figure are given in Table 1.

5 Conclusion

We decomposed the variation in a dataset of bank performance measures into the proportion explained by macroeconomic fluctuations and the proportion explained by one factor common across the banking sector, leaving the remainder for idiosyncratic, bank-specific variation. For our decomposition, we extended the backcasting procedure by allowing for factors drawn outside the unbalanced dataset of interest.

Macroeconomic factors and one banking factor can explain a large proportion of the variation in bank performance measures, as is the case for charge-off rates. However, the same factors only explain a smaller proportion of the variation of PPNR rates. Our results point to the importance of considering bank-specific, idiosyncratic factors when modelling PPNR rates. This finding is relevant for the design of stress-test scenarios.

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