2018-15

Monitoring Bank Failures in a Data-Rich Environment

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Août / August 2018

Centre de recherche sur les risques
les enjeux économiques et les politiques publiques

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Abstract

This paper develops a monitoring and forecasting model for the aggregate monthly number of commercial bank failures in the U.S. We extract key sectoral predictors from the large set of macroeconomic variables proposed by McCracken and Ng (2016) and incorporate them in a hurdle negative binomial model to predict the number of monthly commercial bank failures. We uncover a strong and robust relationship between the predictor synthesizing housing industry variables and bank failures. This relationship suggests the existence of a link between developments in the housing sector and the vulnerability of commercial banks to non-performing loans increases and asset deterioration. We assess different specifications

JEL Classification: E60, F37, F38, G01.
Keywords: Financial Regulation, Financial Crises, Factors Models, Diffusion Index Models.

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We thank Benoît Carmichael, Gilles Koumou, Jonathan Morneau-Couture and Christian Friedrich for useful comments and discussions. Any errors and omissions are own.

1 Introduction

Banking crises and other episodes of distress in financial markets have important macroeconomic consequences: they cause disruptions in the flow of credit, enhance risks of corporate or personal failures, lead to output losses relative to trend and to sharp declines in tax revenues and other measures of the fiscal health of governments. The 2007-2009 subprime crisis has reaffirmed this fact and caused significant and worldwide economic damage.[1]

Considering the costs they generate, an important body of work has long sought to analyze banking and financial crises and identify "early warning" variables –key factors associated with heightened crisis probabilities– signaling developing vulnerabilities. This body of work, originating in contributions such as Demirgüç-Kunt and Detragiache (1998), Kaminsky and Reinhart (1999) or Borio and Lowe (2002), has been energized by the recent subprime events and has since grown exponentially.[2]

One recurring challenge to this literature is the correct manner to measure the presence of a banking or financial crisis. As such events often stem from different causes, develop at differing speeds and have different lengths, it is perhaps unavoidable that they be identified with subjective criteria. One well-used database (Laeven and Valencia, 2013) identifies banking crises as dummy variables taking the value 1 when "significant signs" of financial distress in banking systems (bank runs, losses and bank liquidations) are observed, or "significant banking policy interventions". This is related to Reinhart and Rogoff (2013)'s measure, for whom the presence of a banking crisis occurs when bank runs occurr or when government assistance, closure, merging and other large-scale regulatory actions are taken. Other measures add additional signals of distress, such as nonperforming banking assets, as signals of crisis (Demirgüç-Kunt and Detragiache, 1998, 2005) or other additional variables (Babecky et al., 2014).

[1] Reinhart and Rogoff (2013) and Laeven and Valencia (2013) present assessments of the fiscal consequences of banking crises. In addition, Laeven and Valencia (2013) documents the extent to which economies suffer output and bank equity losses following such crises. See also Hutchison and McDill (1999) for an earlier exploration of the consequences of Japanese banking crises.

[2] A non-exhaustive review of recent contributions includes Bussiere and Fratzscher (2006), Davis and Karim (2008), Borio and Lowe (2009), Barrell et al. (2010), Barrell et al. (2010), Duca and Peltonen (2013), Betz et al. (2014), Gogas et al. (2018) or Antunes et al. (2018).

The present paper provides an original and complementary contribution to the literature studying banking crises. We develop a count-data framework to analyze the monthly aggregate number of bank failures in the United States. This strategy offers three potential advantages to the literature on monitoring baking crises and distress. First, using the number of bank failures as the proxy for crisis provides an additional measure to the binary alternatives used elsewhere (Reinhart and Rogoff, 2013; Demirgüç-Kunt and Detragiache, 1998). Second, the monthly availability of our measure allows our monitoring framework to provide regulatory authorities a finer, high-frequency and real-time tool providing early insights about developing financial vulnerabilities . Finally, a framework to monitor and predict the aggregate occurrence of bank failures in the United States is interesting in its own right, particularly for institutions such as the Federal Deposit Insurance Corporation (FDIC) whose mandate includes such monitoring responsibilities.

More specifically, we employ a hurdle-negative binomial model to analyze the number of monthly commercial bank failures. This extension of the standard Poisson process for count data allows our analysis to accommodate the high frequency of zero counts (an absence of bank failures) and the high dispersion in our data. In addition, our explanatory variables are drawn from the McCracken and Ng (2016) database, which includes more than one hundred different macro-financial variables, to which we add several additional bank and banking sector variables.

Using such a large dataset allows our framework to include all available information potential relevant to the study of bank failures in an efficient manner. To circumvent the practical challenges related to estimation with large numbers of regressors, we follow an established literature that analyzes and documents the ability of a few key predictors extracted from large databases to outperform standard estimation frameworks (Stock and Watson, 2002a,b, 2006; Bai and Ng, 2008, 2009). One rationale behind this approach lies in the inability of only a handful of variables to uncover the multiple signals from the larger economy (Ludvigson and Ng, 2009). To the best of our knowledge, our work is the first contribution to employ a data-rich framework to analyze banking crises and financial distress.

Our results indicate that the predictor related to the housing industry contains the most robust, statistically and economically meaningful information about future bank failures. This leading result confirms some previous findings in related research undercovering a link between the housing sector and bank failures (Barrell et al., 2010; Bernanke, 2013; Ghosh, 2015). Booms and busts in housing generally go together with expansions and contractions in banking activities, with boom periods experiencing rising home values, easier lending or refinancing terms while increasing banks' exposure to loan defaults and busts, by contrast, seeing house price decreases, rising interest and mortgage rates and many households finding themselves struggling to face their contractual obligations with the attendant rise in mortgage and other credit defaults and banks vulnerable to failure.

Our results also identify predictors related to production, labor markets, interest rates and money variables as important forecasters for bank failures. Predictors related to output growth (Demirgüç-Kunt and Detragiache, 1998; Kaminsky and Reinhart, 1999; Louzis et al., 2012) and low unemployment rates (Louzis et al., 2012; Ghosh, 2015) are negatively associated with bank failures, as a dynamic economy usually enjoys a boyuant housing sector, while accommodating monetary policies encourage banks to offer more loans. However, the statistical significance of these other predictors appears irregular across our different experiments with forecasting horizons and other model specifications, while the result about the capacity of housing variables is robust throughout.

Our work is a broad contribution to the literature on banking crises and is more specifically related to two strands of this literature. One the one hand, it contributes to the study of the determinants of bank failures. In that context, our monthly-data framework provides an attractive monitoring strategy, relative to other work using annual data on bank failures and only a few explanatory variables (Davutyan, 1989; Herger, 2008). On the other hand, to the extent that the aggregate number of bank failures represents an alternative proxy measure of banking crises, our paper relates to West (1985), Wheelock and Wilson (2000) and Canbas et al. (2005), who analyze the potential of factor models for explaining banking and financial crises. We extend the scope of these works by considering a large set of macro-financial variables and by modeling explicitly the number of bank failures.

The rest of this paper is organized as follows. Section 2 briefly reviews the theoretical literature on the determinants of bank failures. Section 3 describes the data. Section 4 presents the econometric framework and Section 5 the results. Section 6 concludes.

2 Determinants of bank failures

Monitoring financial systems is one key task of regulatory authorities and has typically focused on bank-specific, industry-specific and macroeconomic determinants of bank failure. We hereafter briefly review these three categories.

Poor management is seen as playing the major role among bank-specific factors leading to bank failures (Berger and DeYoung, 1997; Salas and Saurina, 2002; Podpiera and Weill, 2008). Profit-seeking incentives may sometimes encourage bank managers to take innovative actions that result in poor credit scoring, spurious collateral appraisal, inadequate borrowers monitoring and subpar overall loan quality. A lack of diversification in such activities may also exacerbate these problems, with diversification usually proxied by the proportion of non-interest income as a share of total income and expected to to be negatively related to non-performing loans. Finally, insufficient loan loss provisions may reflect the overall disinterest of banks towards risks control as increases in such provisions could be perceived by investors and shareholders as signals of trouble and bad management.

Researchers have also identified important industry-specific factors driving bank failures. These factors may be related to monetary policy or to banking regulation (Keeton, 1999; Bernanke, 2013). An over-accommodating monetary policy stance characterized by low interest rates and growing money supply may be associated with rapid expansions of credit and subsequent deterioration in credit-allocation standards. In addition, weak banking regulation, such as low capital requirements in a competitive industry as well as generous deposit insurance, may encourage banks managers to take on too much risk. A lively ongoing debate about the impacts of deposit insurance and the role of central banks as lenders of last resort during times of financial system instability is exemplified by contributions in Boyd and Gertler (1994), Stern and Feldman (2004), Ennis and Malek or Bernanke (2013). Insufficient banking regulation may be exacerbated by the inability of regulators to adequately monitor banking activities. Development of sophisticated financial instruments also add difficulties to the supervision of the banking industry by the regulatory authorities.

Finally, aggregate macro-financial factors also play a key role in financial system stability (Demirgüç-Kunt and Detragiache, 1998; Kaminsky and Reinhart, 1999;

Louzis et al., 2012). Sustained output growth and well-anchored inflation are generally positively associated with banking system stability. Low unemployment rate and dynamic housing industry foster booms in banking activities. Breuer (2006) suggests that other national factors such as corruption may also be important.

3 Data

As stated above, this paper's goal is to provide a robust and workable monitoring and forecasting tool for the aggregate number of commercial bank failures in the US. To this end, we analyze monthly frequency data on bank failures and relate them to the information contained in the McCracken and Ng (2016) dataset, which comprises a large set of macro-financial explanatory variables while being easily available on a timely basis.[3] Considering our objective, we supplement the McCracken and Ng (2016) data with additional banking variables that are continuously updated and publicly available from the Federal Reserve Bank of St. Louis website.

3.1 Response Variable

Our variable of interest is the monthly number of bank failures and we measure it with the total number of failures and assistances reported by the Federal Deposit Insurance Corporation (FDIC).[4] A bank failure is defined as the closing of a financial institution by its chartering authority, while an assistance pertains to a situation where a failing institution is acquired by another (healthy) institution, possibly with financial assistance from the FDIC. Our benchmark results pertain to the sum of failures and assistances but our robustness analysis also assesses how our model performs with the separate components.

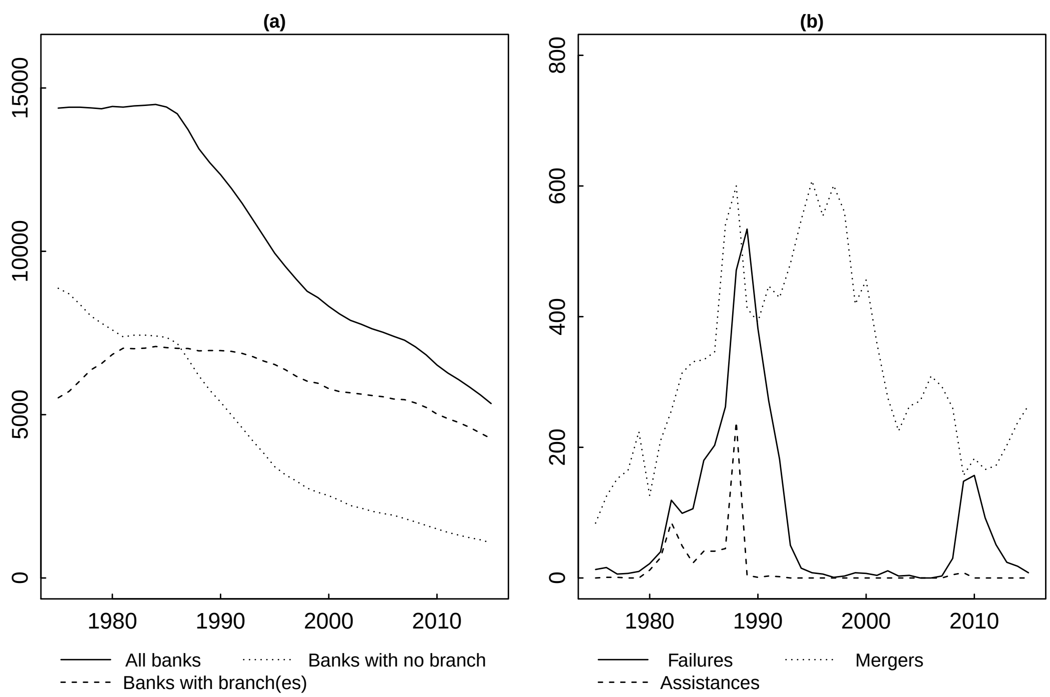
Figure 1 depicts the evolution of the US banking industry since the mid 1970s. As depicted in Panel (a) of the figure, more than 14,000 commercial banks were

[3] See De Nicolo and Lucceta (2016), Smeekes and Wijler (2018) or Forni et al. (2018), among others, for recent uses of the McCracken and Ng (2016) dataset in forecasting.

[4] As the primary deposit insurance provider for US banks, the FDIC supervises both federally-chartered banks as well as most of their state-chartered counterparts. Each insured bank must report to the FDIC, which is involved in the large majority of bank failures or assistances.

operating in the United States in the mid 1970s, largely as a result of strict regulations on branching. In the 1980s, a progressive ease in the regulation on branching induced a significant period of mergers and the number of banks with no branch steadily decreased whereas the number of banks with branches increased till the late 1980s (but has slowly declined since). These two effects combine to create a a significant downward trend in the total number of commercial banks in the United States.

Figure 1: Evolution of the U.S. banking industry: 1975 - 2013

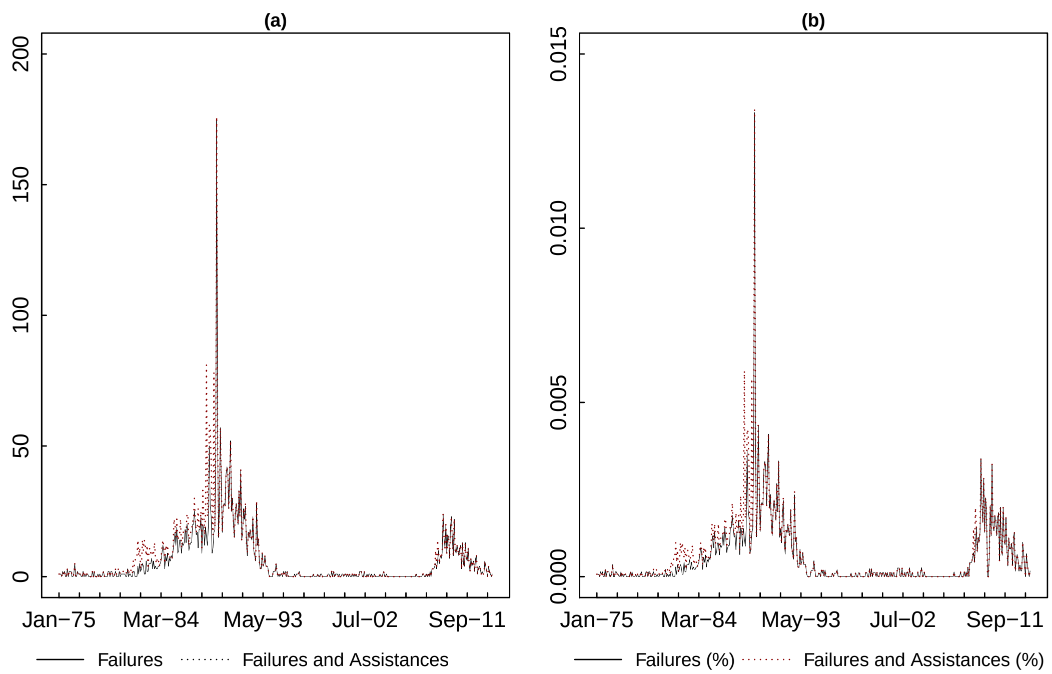


Notes: Data on the U.S. banking industry are expressed in levels and retrieved from Federal Deposit Insurance Corporation. Panel (a) depicts the progressive concentration of the U.S. banking industry. Panel (b) reports creation, mergers and failures of U.S. banks.

Panel (b) of Figure 1 provides the data on failures, assistances and mergers. The evolution of failures and assistances clearly depict the two major disruptive episodes experienced by the U.S. banking system over the last 40 years, namely the *Savings and Loans crisis* (late 1980's) and the *subprime crisis* (2007-2009).

Next, Figure 2 scrutinizes the monthly number of bank failures and assistances further. In Panel (a) the level is reported while Panel (b) reports the number of bank failures and assistances in proportion of the total number of banks at the beginning of the year. The magnitude of the 2007-2009 subprime crisis thus appears slightly amplified when the proportion of bank failures is considered. However, since we are explicitly interested in modeling the number of bank failures, our work below emphasizes the number of bank failures and not the proportion.[5]

Figure 2: U.S. bank failures and assistances (in levels and in proportion of total)



Source: FDIC

Table 1 provides additional information about the process of bank failures. From 1975 to 2013, the U.S. banking system experienced an average of almost eight bank failures each month, with an important variability that suggests overdispersion (ie. when the variance is higher than the mean, an important aspect of Poisson count data, see Section 4). The two distress episodes (the *Savings and Loans* and *subprime* crises) are also clearly perceivable: during the period 1985-1994, an average of more

[5]Results are robust to considering bank failures and assistances in proportion of the total number of banks, which is not surprising considering how similar the two panels of Fig. 2 appear.

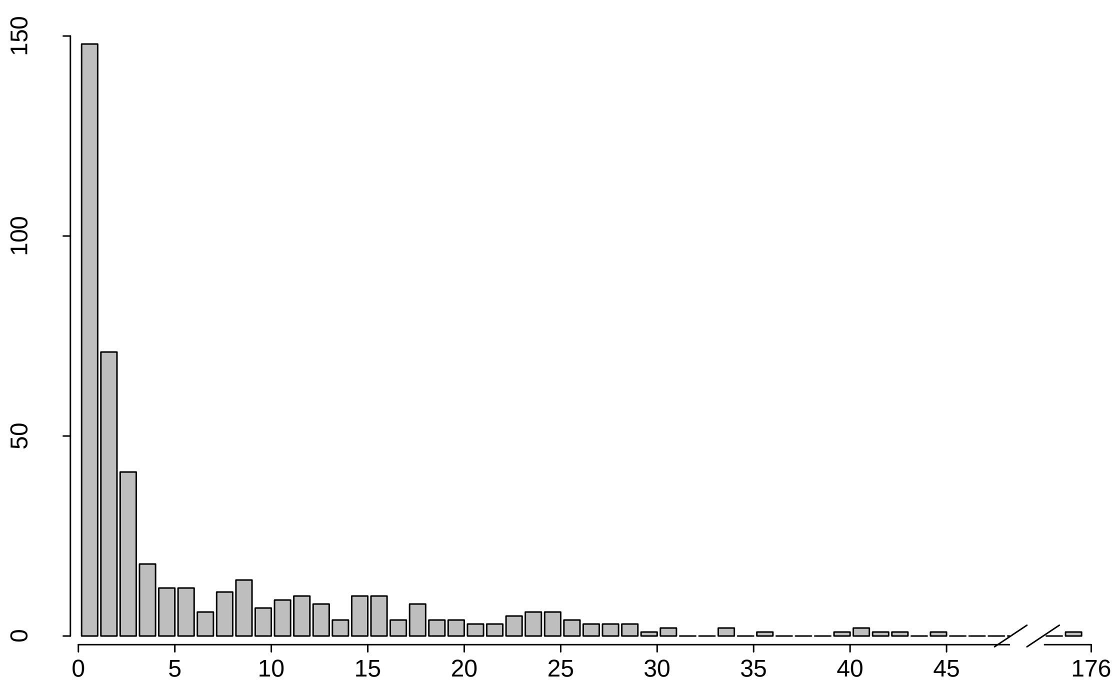
than 21 banks failed each month whereas in 2005-2103, an average of almost five bank failed each month. The pattern of overdispersion also appears in all historical episodes.

Table 1: U.S. bank failures and assistances: descriptive statistics

Period	Nb. of Failures	Monthly Mean	Std. Dev.
1975 - 1984	438	3.65	4.12
1985 - 1994	2550	21.25	20.92
1995 - 2004	55	0.46	0.66
2005 - 2013	505	4.68	5.82
1975- 2013	3548	7.58	13.81

Source: FDIC

Figure 3: Histogram of the U.S. monthly bank failures and assistances



Note: U.S. monthly bank failures and assistances in levels: the x-axis reports the number of bank failures and the y-axis the number of months in our sample during which the corresponding number of bank failures occurred. Data are retrieved from the Federal Deposit Insurance Corporation.

Figure 3 depicts the data on the form of a histogram showing the number of failures on the x-axis and the number of months during which the corresponding number of bank failures occurred. The figure shows that bank failures remain a relatively rare event: nearly 150 months in our samples experienced no bank failure. Conversely, the distress episodes imply that a relatively fat tail is present in the histogram with months experiencing important numbers of bank failures. In March 1989, for instance, 175 banks went into bankruptcy. Our dependent variable is hence characterized by a large proportion of zeroes and overdispersion, features that our econometric strategy, discussed below, will take into account.

3.2 Explanatory Variables

McCracken and Ng (2016) propose a comprehensive database of many dozen of macroeconomic time series for the United States, organized by sectors. They aim to provide a convenient starting point for research on *big data*. To the extent that our variable of interest is the number of commercial bank failures, we consider it important to represent the banking sector in a comprehensive manner and thus add additional banking variables to the McCracken and Ng (2016) dataset. These additional banking variables are all continuously updated and publicly available from the Federal Reserve Bank of St. Louis website. Overall, our complete database contains 153 different variables, all observed at a monthly frequency over the sample 1975M1 - 2013M12. In accordance with McCracken and Ng (2016) all data series have been transformed to induce a weakly stationary behaviour: most $I(1)$ series are thus used in first difference of logarithms, for example. Table 2 presents the thematic sectors around which these variables are classified, as well as the number of variables in each sector (a detailed list of all data used in presented in the Appendix). Considering the large number of variables considered, a procedure by which the dimension of the estimation is reduced becomes necessary and our analysis via principal components is designed to achieve this.

We favor monthly data to emphasize rapidly available data capable of identifying occurrence of banking difficulties in a timely manner. In turn, the large number of variables we consider ensures we take advantage of all available relevant information, through the use of sectoral predictors extracted from the large database.

Table 2: Data description

Group ID	Data ID	Sector Description
Variables from McCracken and Ng (2016)		
1	001 - 015	Production
2	016 - 018	Consumption
3	019 - 027	Orders and Inventories
4	028 - 037	Housing Industry
5	038 - 068	Labor Market
6	069 - 088	Prices
7	089 - 105	Interest Rates
8	106 - 112	Exchange Rates
9	113 - 126	Money
10	127 - 131	Stock Market
Variables added by the authors		
11	132 - 153	Banking Industry

4 Econometric Framework

This section discusses our econometric strategy for first, constructing and selecting our predictors, and second, modeling the occurrence of aggregate commercial bank failures in the United States.

4.1 Predictors

The modeling of a large set of variables as the one presented in Table 2 (more than one hundred and fifty) can prove challenging. We detail below the approach we use to construct and select our predictors.

Construction

For each group of variables presented in Table 2, we perform a principal component analysis (PCA). Principal component analysis is a multivariate statistical procedure that transforms a set of N correlated variables into a new set of N uncorrelated variables, the *principal components* (PCs). By construction, the principal components are orthogonal to each other and represent linear combinations of the original variables. They exhibit no redundant information and form as a whole an orthogonal basis on which the observations are projected. These components are ordered, in the sense that the first principal component explains the largest fraction of the overall covariance or correlation matrix of the N original variables.[6]

Concretely, denote $\mathbf{X}_t^j$ as the data matrix for the N_j time series in sector j (one of the 11 present in our dataset). A principal component decomposition of $\mathbf{X}_t^j$ will uncover $\mathbf{F}_{it}^j, i = 1, \ldots, N_j$ with each $\mathbf{F}_{it}^j$ a linear combinations of the underlying data, such that

$$\mathbf{F}_{it}^j = \mathbf{c_i}'\mathbf{X}_t^j, \tag{1}$$

where $\mathbf{c_i}$ is the ith eigenvector associated to the variance-covariance or correlation matrix of $\mathbf{X}_t^j$. One can show (Stock and Watson, 2006) that (1) can be used to estimate unobserved factors and as such, provide a collection of potential predictors for our modeling of bank failures.

Selection

The PCA (1) yields N_j possible components $\mathbf{F}_{it}^j$ per sector j, which can be viewed as potential predictors summarizing the information contained in each of the sectors. From this set of potential predictors, one needs to select the ones to keep in the forecasting exercise. In recent years, selection of the first principal components (those explaining the largest variance of the sector), has been popularized in the macro-financial literature. This strategy relates to the factor analysis framework developed and applied in different works (Stock and Watson, 2002a,b; Forni et al., 2005; Bai and Ng, 2006). The rationale behind the factor model is that a *few* latent factors, represented by the first PCs when (1) is used to estimate them, can efficiently summarize all useful information contained in a set of variables. However, as noticed by Jolliffe (1982), some low-variance principal components could be as important as those placed earlier in the decomposition for forecasting a given variable, suggesting that principal components retained in the analysis should be selected according to their association with the dependent variable.

As such this paper follows the spirit of Bai and Ng (2009) and conducts a search for the most promising $\mathbf{F}_{it}^j$ of each sector for explaining the monthly occurrence

[6] For an extensive discussion of principal component analysis see Jolliffe (1986), Timm (2002), Jackson (2005), Basilevsky (2009) and Abdi and Williams (2010).

of bank failures. Specifically, we regress our dependent variable on each principal component in each sector and keep the one with the best in-sample fit to represent information from that sector. That selected $\mathbf{F}_{it}^{j}$ is the one we then enter in the count data models we explore (see below). We therefore obtain a specification both concise (one variable per sector) and efficient, as that one variable is a linear combination of all others in the sector and thus includes information for all the sector.[7]

4.2 Models

We present our econometric strategy for analyzing the monthly occurrence of aggregate commercial bank failures in the United States. We first discuss the standard Poisson model often used as a starting point in the count data literature, before introducing refinements to this model aimed at accommodating data features, such as overdispersion and excess zero counts.

4.2.1 Standard Poisson Model

The Poisson distribution generally represents the starting point in modeling count data. Its probability mass function (p.m.f) is given by:

$$f_{Y_t}(y_t) = \frac{e^{-\lambda_t}\lambda_t^{y_t}}{y_t!}, \tag{2}$$

where y_t represents the realization of a count variable of interest Y_t (the number of bank failure occurrences during period t in our case) and λ_t is the corresponding expected mean and also variance, as both coincide in the standard model:

$$E[Y_t] = V[Y_t] = \lambda_t. \tag{3}$$

The standard Poisson regression model uses (3) to relate predictors to the conditional mean of y_t via the following:

$$E[Y_t|X_t] = \lambda_t = \exp(X_t'\beta), \tag{4}$$

[7]Following a more traditional strategy, wherein only the first principal component of each sector is chosen as the "representative" of that sector results in qualitatively similar but quantitatively weaker results. Details are available on request.

with X_t the vector of predictors and β the vector of associated parameters.

This framework has been used by a considerable literature analyzing the determinants of health services demand, insurance and accident claims and several other types of count data; see Cameron and Trivedi (2013) for a survey. It has, however, seldom been applied to the study of bank failures, with the notable exception of Davutyan (1989). Davutyan's analysis, however, studies the *annual* count of bank failures using the standard Poisson model. By contrast, our analysis pertains to the monthly count of bank failures, which requires that we use the refinements to the Poisson model discussed below.

The standard Poisson regression model cannot be applied successfully to all count data analysis. Notably, data features such as overdispersion (where the variance exceeds the mean) and excess zero-counts are at odds with the implications of the standard model. We discuss refinements that can accommodate these features.

4.2.2 Negative Binomial Model

Equidispersion refers to the equality of the mean and the variance of a count data variable of interest. By constrast, overdispersion (underdispersion) occurs when this property is violated and the variance exceeds (is less than) the mean. As stated above, Poisson regression models assume equidispersion and as such cannot account for overdispersion in data.

One class of count data model that can account for dispersion is the negative binomial (NB) model. Negative binomial models relax the strict assumption of equality of mean and variance and instead work with models admitting the following relationship between the conditional mean and the conditional variance of the variable of interest:

$$V[Y_t] = \lambda_t + \frac{\lambda_t^p}{\alpha}, \quad p \in \mathbb{R}, \quad \alpha \in \mathbb{R}^*, \tag{5}$$

where the two common parameterization specify $p = 1$ or $p = 2$. In the latter case, the expression thus becomes

$$V[Y_t] = \lambda_t + \frac{\lambda_t^2}{\alpha}, \tag{6}$$

and α is an overdispersion parameter to be estimated. This specification is the *NegBin2* model discussed in Cameron and Trivedi (2013) and the one we use below.[8]

[8]Note that (6) is obtained by introducing an idiosyncratic, unobserved and multiplicative dis-

4.2.3 Hurdle Negative Binomial Model

Hurdle models were introduced by Mullahy (1986) and are designed to handle count data featuring excess zeros and overdispersion. These *two-part* models specify a process for the zero counts (the absence of bank failures in our case) that is different from the process for the positive counts (the number of bank failures when occurring). An economic interpretation of this structure could therefore be that two regimes can affect banking activities, namely *normal times*, for which $k = 0$, and *abnormal times* with increasing severity according to which $k = 1, 2, ...$

More specifically, let $f_1(0)$ denote the probability that y_t takes a zero value and $f_2(k)$, a truncated p.m.f. governing the intensity for values greater than zero ($k = 1, 2, ...$). Note that the two p.m.f. functions are not constrained to be the same processes and/or to depend on the same predictors. The p.m.f of a such a "hurdle-at-zero" model is given by:

$$f_{Y_t}(y_t = k) = \begin{cases} f_1(0) & k = 0, \\ \dfrac{(1 - f_1(0))f_2(k)}{1 - f_2(0)} & k = 1, 2, ... \end{cases} \tag{7}$$

where p.m.f. $f_1(\cdot)$ and $f_2(\cdot)$ then depend on the various predictors examined: $f_2(\cdot)$ is typically defined as a Poisson or negative binomial model, while $f_1(\cdot)$ can be a binomial or a geometric model. The expected value arising from (7) is

$$E(Y_t) = \frac{(1 - f_1(0))}{1 - f_2(0)} \sum_{k=1}^{\infty} k f_2(k), \tag{8}$$

while the variance obeys

$$Var(Y_t) = \frac{(1 - f_1(0))}{1 - f_2(0)} \sum_{k=1}^{\infty} k^2 f_2(k) - \left[\frac{(1 - f_1(0))}{1 - f_2(0)} \sum_{k=1}^{\infty} k f_2(k) \right]^2. \tag{9}$$

turbance ϵ in the standard model, so that the p.d.f. now reads

$$f_{Y_t}(y_t) = \frac{e^{-\lambda_t \epsilon_t} \lambda_t {\epsilon_t}^y}{y_t!};$$

Assuming a Gamma distribution for ϵ and solving for the unconditional first moments for y implies relationship between $V[Y_t]$ and $E[Y_t]$ as in (6). See Cameron and Trivedi (2013) for details.

Parameters of hurdle models are estimated with maximum likelihood and the log-likelihood function (L) of a hurdle-at-zero model is expressed as follows:

$$L = \sum_{t=1}^{T} \mathbb{I}_{\{y_t=0\}} \log f_1(0;\theta_{1,t}) + \mathbb{I}_{\{y_t>0\}} \log(1 - f_1(0;\theta_{1,t})) + \sum_{t=1}^{n} \mathbb{I}_{\{y_t>0\}} \log \frac{f_2(y_t;\theta_{2,t})}{1 - f_2(0;\theta_{2,t})} \tag{10}$$

with $\theta_{1,t} = \{X_t, \beta_1\}$, $\theta_{2,t} = \{X_t, \beta_2\}$, T the number of observations and β_1 and β_2 the parameters associated to the p.m.f f_1 and f_2, respectively.

The specific assumptions we use are as follows. We consider a hurdle-with-negative-binomial (HNB) model in which a binomial function governs the process generating the zeros (f_1) and a negative binomial distributions explains the positive counts (f_2): the "hurdle-at-zero" feature is designed to capture the high occurrence of zeros noticed in Figure (3), while the negative binomial aspect seeks to address the high dispersion of positive counts.

Now recall that the p.m.f of a binomial distribution is given by:

$$f_1(s; n, p_s) = \frac{n!}{s!(n-s)!} p_s^r (1 - p_s)^{n-s}, \tag{11}$$

with n the number of trials, p_s the success probability for each trial and s the number of success. Since we posit a logit link function for the binomial regression, this implies that the probability p_s of success for each trial (the presence of non-zero bank failures for that month) is related to our predictors in the following manner:

$$log(\frac{p_s}{1 - p_s}) = X'\beta. \tag{12}$$

4.2.4 Zero-Inflated Model

A related strategy to address high counts of zeros is known as the zero-inflated model (Cameron and Trivedi, 2013). It considers that zeros can arise either from the occurrence of Regime 1, which always results in a zero-count, or from Regime 2, a standard count model which includes the possibility of zeros. One would thus get

$$f_{Y_t}(y_t = k) = \begin{cases} \pi + (1-\pi) f_2(0) & k = 0, \\ \\ (1-\pi) f_2(k) & k = 1, 2, ... \end{cases} \tag{13}$$

where the unobserved probability π of belonging to the point mass component could be a constant or itself depend on regressors via a binary outcome model such as a binomial model. Below we analyze a zero-inflated negative binomial (ZINB) model wherein $f_2(\cdot)$ is the negative binomial described above and π modelled by a binomial distribution. As we show below, results arrived at using the *HNB* described above of this *ZINB* are very similar.

5 Results

This section presents our results. Section 5.1 first analyzes the contemporaneous link between our predictors and bank failures' count. This allows us to single out the Hurdle negative binomial model (HNB) as the most promising framework. Next, Section 5.2 studies the ability of the HNB model to predict bank failures at horizons between one and 24 months ahead. Section 5.3 then allows dynamic elements to enter the analysis by including lagged values of the response variable, ie. past occurrences of bank failures. Finally, section 5.4 gauges the sensitivity of our results to different measures of bank failures, notably by separating bank failures and assistances into separate components and moving to a quarterly specification instead of our benchmark (monthly) framework.

5.1 Benchmark

Table 3 reports results from fitting the monthly occurrence of bank failures with the standard Poisson process, the negative binomial and the two extensions discussed above: the Hurdle negative binomial (HNB) and the zero-inflated negative binomial (ZINB). For each model, the variable to be explained is the contemporaneous number of bank failures while the predictors are one single principal component for each sector, extracted by the procedure, discussed above, that identifies the principal component most likely to help predict bank failures. Recall that in each of the extended models (HNB and ZINB), two probability mass functions, $f_1(\cdot)$ and $f_2(\cdot)$, are analyzed, one that controls the number of zero-counts and the other governing positive counts, ie. the intensity of bank failures given that some are present. As such, two sets of parameter estimates are present for each of the extended models.

Table 3: Estimation of the number of commercial bank failures

	Poisson	NB	ZINB		HNB	
Factor			Zeros	NB2	Zeros	NB2
Production	0.89***	1.97***	1.88	2.15***	1.40**	1.90***
Consumption	0.02*	0.03	−0.35	0.02	0.21**	−0.02
Orders & Inventories	0.02**	0.08**	−0.40*	0.02	0.15*	0.01
Housing Industry	−0.65***	−1.04***	4.01***	−0.80***	−1.53***	−0.84***
Labor Market	0.15***	0.30***	−0.58	0.22**	0.32*	0.24**
Price	−0.52***	−0.67***	−0.08	−0.63***	−0.51**	−0.58***
Interest Rate	0.21***	0.41***	−3.41***	0.18	1.01***	0.19
Exchange Rate	−0.09***	−0.05	−0.99*	−0.14**	0.23*	−0.14*
Money	−0.22***	−0.53***	1.33**	−0.32**	−1.14***	−0.24*
Stock Market	0.67***	−0.88	1.84	−0.40	0.28	−0.78
Banking Industry	0.18***	0.11	1.70***	0.33***	−0.70***	0.42***
−Log Likelihood	2834.06	1214.55	1188.89		1188.37	
AIC	5692.12	2455.10	2427.78		2426.73	
BIC	5741.85	2508.97	2531.39		2530.33	

Symbols *,** and *** indicate statistical significance at 10%, 5% and 1% level.

Significance of sector-specific predictors

One standout result reported in the table is the robust significance of some predictors. Indeed one can see that the predictor associated to the housing sector is significant at high levels in each model analyzed and for both branches or regimes (extensive and intensive margins) associated with the two extended models. As shown below, this high significance of the housing sector predictor for bank failures is a robust result that will extend to all our experiments, notably when the variable to be explained becomes *future* values of bank failures.[9]

Other sector-specific predictors do not exhibit an equivalent robustness. For example, the predictors associated with the Production or Labour Market sectors are often statistically significant but not always and some others, such as the one associated with the Consumption or even the Stock Market, show little promise for explaining bank failures' counts.

[9]Recall however that predictors are identifiable only up to a square matrix and as such interpretation of their sign may be misleading.

Model Selection

The three classic measures of model performance reported in Table 3 are the log likelihood, the Akaike Information criterion (AIC) and the Bayesian Information criterion (BIC). The log-likelihood is multiplied by -1, so that smaller values indicate better performance, as is also the case for the AIC and BIC criteria.

The three criteria agree in their assessments of the models. First, Table 3 indicates that the negative binomial (NB) model represents a very significant improvement with respect to the standard Poisson model. Further, the two extended models (ZINB and HNB) also improve performance, but by less of a margin. Finally, the performance of the ZINB and HNB models are very similar, with the HNB model retaining a very small advantage. The nature of bank failures' data, with excess counts of zeros and significant dispersion of positive counts, clearly requires that the ZINB or HNB structures be used.

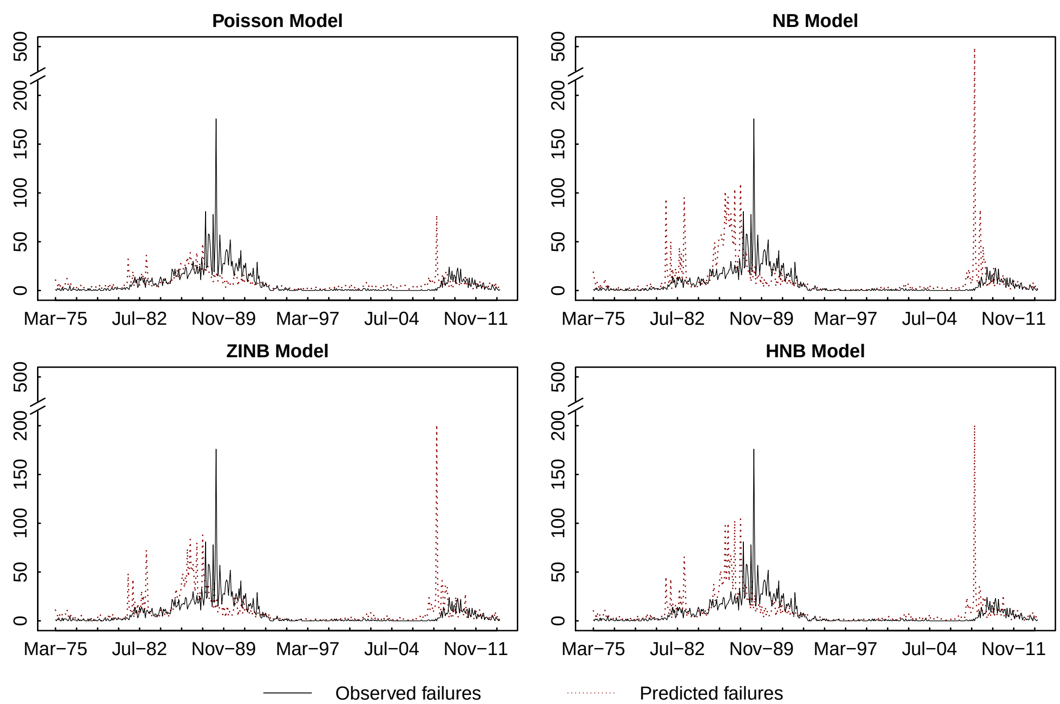
Table 4: Actual and fitted cumulative frequencies

	0	1	2	3-5	6-10	11-20	21-30	31-40	41-50	50+
Frequency										
Observed	0.32	0.15	0.09	0.09	0.10	0.14	0.08	0.01	0.01	0.02
Poisson	0.00	0.03	0.11	0.42	0.25	0.12	0.05	0.02	0.00	0.00
NB	0.03	0.19	0.15	0.25	0.14	0.09	0.05	0.02	0.03	0.06
ZINB	0.06	0.17	0.11	0.25	0.17	0.11	0.05	0.03	0.03	0.02
HNB	0.05	0.15	0.13	0.27	0.15	0.11	0.06	0.03	0.02	0.03
Cumulative										
Observed	0.32	0.47	0.55	0.64	0.74	0.88	0.96	0.97	0.98	1.00
Poisson	0.00	0.03	0.14	0.56	0.81	0.93	0.98	1.00	1.00	1.00
NB	0.03	0.22	0.37	0.62	0.77	0.86	0.90	0.92	0.95	1.00
ZINB	0.06	0.23	0.34	0.59	0.76	0.88	0.92	0.95	0.98	1.00
HNB	0.05	0.20	0.33	0.61	0.76	0.87	0.93	0.96	0.97	1.00

To gain further insight about the different models' ability to match the monthly occurrence of bank failures, Table 4 reports actual and predicted frequencies and cumulative frequencies. The relatively poor performance of the standard Poisson model for fitting zero counts is clearly depicted, as are the improvements obtained by moving first to the NB model and next to the extended ZINB or HNB models. Looking at positive counts, the standard Poisson model continues to perform relatively poorly for low counts (an 0.15 observed frequency of counts of 1, while the Poisson only predicts 0.03); meanwhile the NB has a tendency to overpredict these low counts while the ZINB or HNB are shown to match them the best.

Figure 4 depicts yet another dimension along which to compare results. It provides time-series plots of observed and predicted occurrence of monthly bank failures for the four models considered. The Poisson model (top left of the figure), first, is seen to face significant challenges to fit periods of high bank failuer counts such as the mid-1980s or 2008-2010 crisis episodes. Next, the NB model (top right) has the tendency to overpredict at times, most notably at the beginning of the two main crisis episodes. The two bottom panels of Figure 4 show that the additional flexibility extended by the ZINB et HNB models allows them to match counts significantly better than the other two models. Since the differences between ZINB et HNB appear modest, henceforth we consider the Hurdle Negative Binomial (HNB) as our main framework for analyzing and monitoring future counts of bank failures.

Figure 4: Predicted number of bank failures by model



5.2 Predicting future occurrences of bank failures

The results discussed so far pertain to the contemporaneous link between macroeconomic predictors and bank failures. We now perform a series of estimations aimed at predicting the occurrence of bank failures at horizons ranging from 0 to 24 months ahead. Note that for each forecasting horizon, the procedure described in Section 4 is repeated: the most promising principal component of each sector is thus chosen in a manner specific to the forecasting horizon considered and as such, the principal component chosen employed for the model predicting at the three-month-ahead horizon, say, might be different than the one use for the six-months-ahead horizon. We add the Pearson Statistic as measure of predictive success, in addition to the three criteria discussed above. Recall that the Pearson statistic's measure of goodness of fit for count data is computed as

$$P = \sum_{i=1}^{n} \frac{(y_t - \hat{\lambda}_t)^2}{\hat{\omega}_t}, \tag{14}$$

where as before y_t is the number of bank failures in month t while $\hat{\lambda}_t$ and $\hat{\omega}_t$ represent estimates of the mean and variance of y_t, respectively.

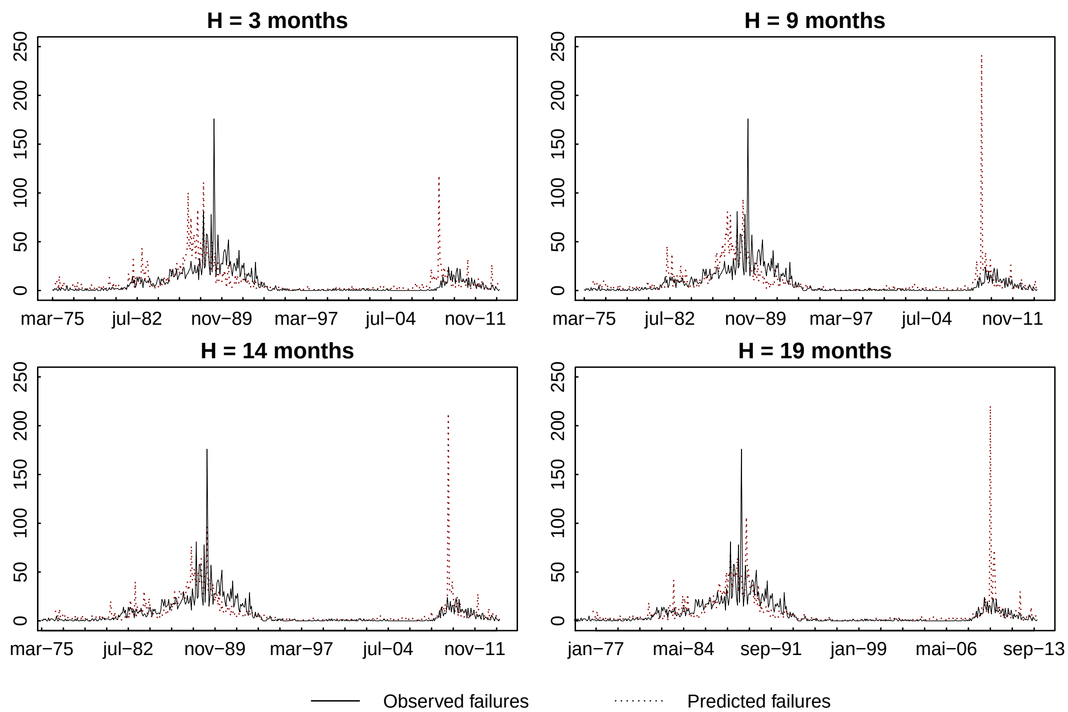
Figure 5 presents results for the three-months ahead, 9-months ahead, 14 months-ahead and 19 months ahead predictions horizons; these were chosen from intrinsic criteria –such as the need to identify a good near-term prediction of bank failures– or because the model's performance is relatively good for the chosen horizon. The complete set of results for all horizons (zero to twenty-four months' ahead) are presented in Figure 7 in the Appendix. Overall the graphs in Figure 5 and Figure 7 illustrate the significant potential of our framework as a workable predictor of future bank failures.

Next, Table 5 presents further details about one specific experiment, whereby bank failures are predicted at the *three-month-ahead* interval. We consider this experiment as one of "near monitoring" of bank failures. The table reveals that information drawn from the *Housing Industry* sector retains its statistically significant signalling value, both for the extensive (zero or non-zero counts) and intensive (number of positive counts) margins.[10] The information contained in the *Housing*

[10] The statistically significant impact of information drawn from the Housing sector remains in all forecasting horizons considered, from 0 to 24-months-aheads. Full results are available on request.

Industry block of variables from the McCracken and Ng (2016) database is thus a meaningful predictor for future bank failures, a result congruent with other findings obtained in related theoretical and empirical work (Barrell et al., 2010; Ghosh, 2015).

Figure 5: Bank failures prediction with the HNB model: Various forecasting horizons



It is perhaps natural to expect housing sector information to play a key role in explaining bank failures. Typically, banks transform short-term deposits into long-term loans, with mortgage loans representing the major part of these loans. Booms in the housing industry, marked by accelerating housing starts and home loans growth generally constitute periods of high profitability and low rates of non-performing mortgage loans for the banking sector. However, housing conditions can evolve rapidly and interest rates increases or deteriorating labor markets lead vulnerable households to default on bank loans. Banks with high exposition to such risky loans quickly experience important difficulties, some resulting in failures.

Table 5: Bank failures prediction with the HNB model:
Predicting at the $t+3$ (Three-months-ahead) horizon

	Zeros			NB2		
	Coef.	*Std. Err.*	*Signif.*	*Coef.*	*Std. Err.*	*Signif.*
Explanatory Variable						
Production	1.57	(0.56)	***	1.69	(0.40)	***
Consumption	0.11	(0.18)		−0.05	(0.08)	
Order & Inventories	0.13	(0.09)		0.05	(0.04)	
Housing Industry	−1.51	(0.28)	***	−0.80	(0.11)	***
Labor Market	0.53	(0.19)	***	0.27	(0.10)	***
Price	−0.27	(0.14)	*	−0.23	(0.07)	***
Interest Rate	1.23	(0.35)	***	0.19	(0.15)	
Exchange Rate	0.18	(0.13)		−0.11	(0.06)	*
Money	0.51	(0.34)		0.05	(0.16)	
Stock Market	0.28	(0.24)		−0.23	(0.17)	
Banking Industry	0.08	(0.20)		0.50	(0.10)	***
Log Likelihood			−1179			
Akaike Information Criterion			2407.91			

Symbols *,** and *** indicate statistical significance at 10%, 5% and 1% level.

Table 5 additionally reports that information from the *Production*, *Labor Market* or *Interest Rates* sectors also feature statistically significant impacts. This is also consistent with results obtained elsewhere in the literature on the determinants of banking crises; Output growth (Demirgüç-Kunt and Detragiache, 1998; Kaminsky and Reinhart, 1999; Louzis et al., 2012) and a low unemployment rate (Louzis et al., 2012; Ghosh, 2015) are often negatively associated with bank failures, whereas loose monetary policy, such a periods of low interest rates and growing money base have been found to mitigate immediate banking systems' vulnerabilities. Notice however that unlike the case for our housing industry predictor, statistical significance for these other sectors appears irregular across the different estimations.

5.3 Dynamic HNB Model

One implicit assumption of the static HNB model is that the residuals are independent and identically distributed, whereas time series are often characterized by autocorrelation, especially in the macro-financial realm. This section modifies our framework in order to allow for such effects. Specifically, we assume that past occurrences of bank failures can induce further bank failures, over and above explanatory variables considered so far. A number of observations and theories tend to support this assumption. First, recent trends in the banking industry, namely movements towards consolidation and integrated communication technologies, have rendered banks more interconnected than ever. Such connectedness may have left banks more vulnerable to the collapse of one individual systemically important bank.[11] Additionally, the self-fulfilling prophecies and bank run theory of Diamond (1983) provides solid theoretical grounds for this type of phenomenon.

To account for this dependency between past and current bank failures, we follow Cameron and Trivedi (2013) and add lagged values of our dependent variable to the model. As above, we experiment with various forecasting horizons, between 0 and 24-months-ahead and for each horizon, we successively incorporate 1 to 12 lagged values of our response variable and assess the forecasting improvement.[12]

Table 6 reports a representative sample of the results obtained in this experiment: it corresponds to a case where at of period t, bank failures are forecast *four-months ahead*, ie. up to period $t + 4$, using our explanatory variables dated of period t and up to *seven* lags of the number of bank failures. Full results for all our (forecasting horizons, number of lags of bank failures) specification pairs are presented in Table 10 in the Appendix. Table 6 has important findings. First, it largely confirms results obtained until now in our analysis about the signalling properties of information drawn from the *Housing Industry* sector: they remain statistically significant, especially to explain the intensive margin (the number of bank failures conditional on them being positive). Additionally, the lagged dependent value also has important effects, with the date-t count being especially important in the determination of the extensive margin (the presence of at least one bank failure) four-months hence. This provides confirmation that bank failures are interconnected. Finally, note that the presence of lagged values for the dependent variables has reduced the impact

[11]For example, the collapse of Lehman Brothers on September 15, 2008 is considered by many researchers to have sparked the Subprime crisis.

[12]As indicated above, for each of these iterations, the best principal component to represent information from each sector j might be changing: The complete analysis described in Section 4 is thus repeated for each possible forecasting horizon and each lag for the dependent variable.

of some other sectoral variables such as Production, Price and Interest Rates while leaving Housing Industry's impact on bank failures unaffected.

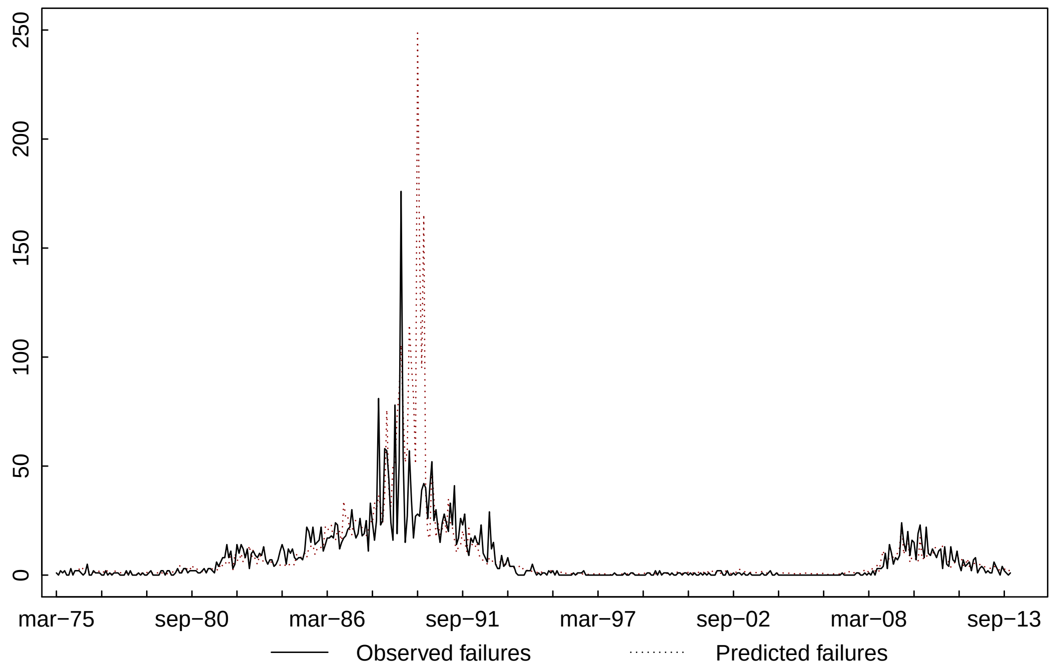
Table 6: Bank failures prediction with the HNB model with lagged information: *Predicting at the $t+4$ (Four-months-ahead) horizon*

	Zeros			NB2		
	Coef.	*Std. Err.*	*Signif.*	*Coef.*	*Std. Err.*	*Signif.*
Explanatory Variable						
Production	−0.14	(0.63)		1.24	(0.24)	***
Consumption	−0.36	(0.34)		0.01	(0.08)	
Order & Inventories	0.13	(0.09)		0.08	(0.02)	***
Housing Industry	−0.63	(0.35)	*	−0.46	(0.06)	***
Labor Market	−0.08	(0.23)		0.01	(0.06)	
Price	0.23	(0.19)		−0.15	(0.05)	***
Interest Rate	0.20	(0.35)		0.15	(0.08)	*
Exchange Rate	−0.10	(0.10)		0.04	(0.02)	
Money	0.81	(0.42)	*	0.17	(0.10)	*
Stock Market	−1.28	(1.73)		0.01	(0.43)	
Banking Industry	−0.05	(0.28)		−0.07	(0.07)	
Lagged Response Variable						
Bank Failures (t)	0.38	(0.15)	***	0.01	(0.00)	***
Bank Failures ($t-1$)	0.04	(0.14)		0.00	(0.00)	
Bank Failures ($t-2$)	0.13	(0.15)		0.01	(0.00)	*
Bank Failures ($t-3$)	−0.21	(0.08)	***	0.00	(0.00)	
Bank Failures ($t-4$)	0.06	(0.14)		0.01	(0.00)	**
Bank Failures ($t-5$)	0.13	(0.13)		0.011	(0.00)	**
Bank Failures ($t-6$)	0.16	(0.14)		0.01	(0.00)	
Bank Failures ($t-7$)	0.26	(0.13)	*	0.01	(0.00)	***
Log Likelihood			−987.26			
Bayesian Information Criterion			2225.45			

Symbols *,** and *** indicate statistical significance at 10%, 5% and 1% level.

Figure 6 shows the in-sample forecasting of the specific dynamic-HNB model whose results are reported in Table 5. Recall that this uses information as of period t to predict the aggregate number of bank failures at the four-months-ahead horizon. The figure depicts a very encouraging fit, which appears able to capture not only the two systemic bank failures episodes in our sample but also the non-crisis periods.

Figure 6: Bank failures prediction with the HNB model with lagged information: Four-months-ahead horizon



5.4 Sensitivity Analysis

To gauge the robustness of our main findings, Table 7 considers three alternative specifications of the benchmark HNB model. The first specification (Panel 1 of Table 7) considers only effective bank failures (thus leaving our bank assistances in the definition of failure); the second (Panel 2) considers *quarterly* variables as opposed to the monthly frequency used in our benchmark analysis and, finally, the third specification (Panel 3) considers only assistances to distressed banks.

Overall, the statistically significant of information drawn from the *Housing Industry* sector remains robust throughout the table. Housing Industry proves able to explain both the two Regimes (non-occurrence and occurrence) of bank failures, confirming hence the robustness of our key result. Moreover, the set of significant sectoral variables identified in the previous estimations also remain relatively unchanged.

Table 7: Bank failures prediction with the HNB model: Sensitivity Analysis

	(1)		(2)		(3)	
	Zeros	NB2	Zeros	NB2	Zeros	NB2
Production	2.26***	1.61***	−0.37	−1.37***	1.44	6.16***
Consumption	0.12	0.01	0.54	−0.04	0.08	0.24
Orders & Inventories	0.06	0.12***	0.39*	0.17***	−0.26*	−0.33***
Housing Industry	−1.31***	−0.81***	2.27**	1.03***	−1.56***	−0.56***
Labor Market	0.22	0.19*	0.43	0.15	−0.42***	−0.26***
Price	−0.29	−0.65***	0.17	0.85***	0.07	−0.32**
Interest Rate	−0.43	−1.87***	1.60	0.02	1.85***	0.13
Exchange Rate	0.06	−0.07	−0.64	0.08	−0.42	−0.25
Money	−0.70***	−0.29**	1.32**	0.70***	1.53***	1.12*
Stock Market	0.07	−0.02	0.31	−0.22	−1.62	0.29
Banking Industry	−0.01	0.18***	−35.62***	−7.16**	0.10	0.38***
−Log Likelihood	1109.12		508.07		386.07	
AIC	1109.12		1066.15		822.14	
BIC	1109.12		1142.07		925.75	

Symbols *,** and *** indicate statistical significance at 10%, 5% and 1% level.

6 Conclusion

The literature studying banking crises has employed various measures to characterize and classify banking crises, such as non-performing loans increase, bank runs occurrence, public rescue and bank failures, among others (Demirgüç-Kunt and Detragiache, 1998; Kaminsky and Reinhart, 1999; Borio and Lowe, 2002; Carmichael et al., 2015; Antunes et al., 2018).

This paper analyses banking distress and crises by employing a different and complementary proxy measure of crisis, the aggregate monthly number of commercial bank failures. To this end we develop a monitoring and forecasting framework for the monthly aggregate occurrence of bank failures in the United States. We extract key sectoral predictors from a large set of potential (macro-financial) explanatory variables and incorporate them in a hurdle negative binomial model for bank failures counts. Our result uncover a strong and consistent relationship between housing industry variables and banking failures. We also find that production, labor market, interest rates and money variables display some forecasting power through different horizons of prediction. One important area for future research would perform an out-of-sample forecasting experiments with repeated estimations at each stage, to verify the real-time robustness of the link uncovered between housing industry variables and bank failures.

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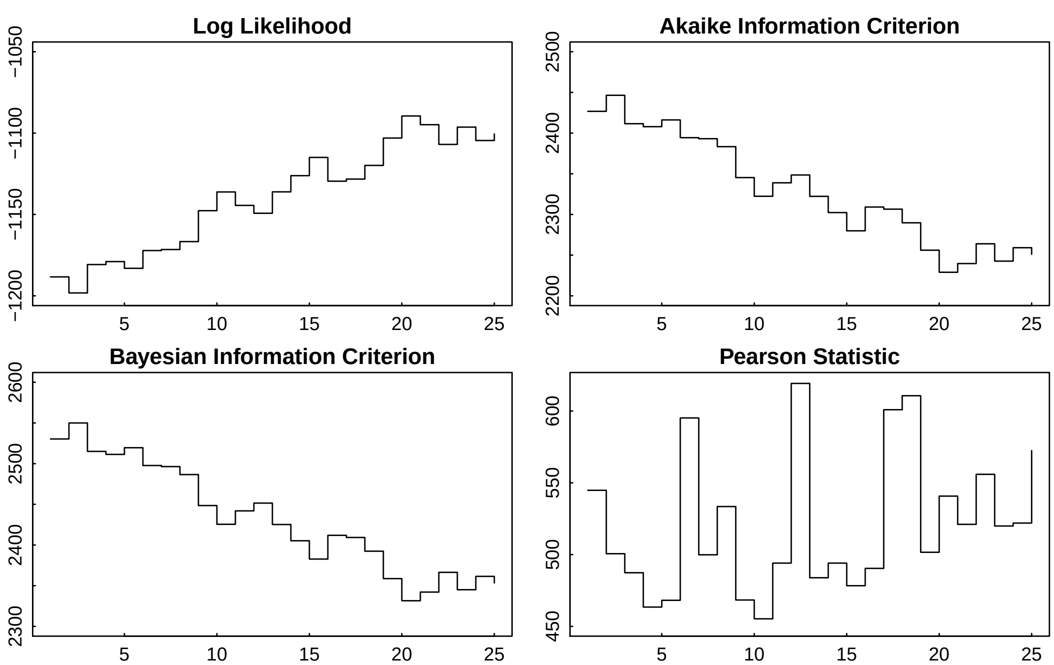
Appendix

HNB Model: Additional analysis

Static Model

To select the best horizon of prediction, we assess four measures: the log likelihood, the Akaike Information Criterion (AIC), the Bayesian Information Criterion (BIC) and the Pearson Statistic. We compare the values of these criteria across the different horizons of prediction ranging from 0 to 24 months. No clear-cut result emerges, but we notice four local minimum for each criterion, namely for predictions of three, nine, fourteen and nineteen months ahead. We consider in a first attempt these horizons and select the one with the best in-sample fit of the dependent variable. Figure 7 presents the performance through the 25 horizons of predictions.

Figure 7: Static HNB forecasting performance through different horizons



We assess the persistence of the extracted predictors in the static HNB model with their first-order autoregressive coefficient. As shown in Table 8, we find no persistence greater than 0.84 and not much volatility within the estimated factors.

Table 8: Static HNB predictors summary statistics

Sectors	Std. Dev.	AR(1)
Production	0.22	0.67
Consumption	0.73	-0.37
Orders and Inventories	1.39	-0.23
Housing Industry	0.73	0.84
Labor Market	0.72	0.28
Prices	0.91	0.53
Interest Rates	0.48	0.51
Exchange Rates	0.99	0.28
Money	0.41	0.58
Stock Market	0.48	0.34
Banking Industry	0.64	0.44

There is also no strong endogeneity across predictors. Table (9) presents their correlation, with *housing industry* and *interest rates* being the most correlated (-0.29). This lack of strong correlation across predictors reinforces the robustness of our approach.

Table 9: Correlation across predictors in the static HNB model

	Prod.	Cons.	Ord.	Hous.	Lab.	Prices	Int.	Exch.	Money	Stck.
Cons.	-0.03	1.00	-0.22	-0.05	0.07	0.11	0.10	-0.03	0.01	-0.02
Ord. & Inv.	0.04	-0.22	1.00	0.01	0.05	-0.00	-0.02	-0.04	-0.05	-0.01
Hous.	-0.23	-0.05	0.01	1.00	-0.20	0.18	-0.29	-0.01	-0.26	0.07
Lab.	-0.07	0.07	0.05	-0.20	1.00	-0.04	0.09	0.03	0.02	-0.04
Prices	-0.08	0.11	-0.00	0.18	-0.04	1.00	0.02	0.05	-0.04	-0.00
Int. Rates	0.20	0.10	-0.02	-0.29	0.09	0.02	1.00	0.08	0.16	0.08
Exch. Rates	0.04	-0.03	-0.04	-0.01	0.03	0.05	0.08	1.00	0.13	-0.01
Money	0.13	0.01	-0.05	-0.26	0.02	-0.04	0.16	0.13	1.00	0.02
Stck. Mkt.	-0.07	-0.02	-0.01	0.07	-0.04	-0.00	0.08	-0.01	0.02	1.00
Bank. Ind.	-0.06	0.03	-0.02	-0.08	0.19	-0.05	0.17	0.05	0.11	0.06

Dynamic model

For each specification, the BIC relative to the static HNB model's BIC is reported. The row refers to the forecasting horizon and the column to the number of included lags of the dependent variable. Table 10 suggests the model with seven lags, used to forecast bank failures four months ahead, be used. Other specifications perform as well, but we favor that one for the sake of parsimony in reporting.

Table 10: Dynamic HNB model Grid Search

	l=0	l=1	l=2	l=3	l=4	l=5	l=6	l=7	l=8	l=9	l=10	l=11	l=12
h = 0	0.92	0.92	0.91	0.89	0.89	0.89	0.89	0.89	0.89	0.89	0.89	0.89	0.89
h = 1	0.92	0.91	0.89	0.89	0.89	0.89	0.89	0.89	0.89	0.89	0.89	0.89	0.89
h = 2	0.93	0.91	0.90	0.90	0.90	0.90	0.89	0.89	0.89	0.89	0.89	0.89	0.89
h = 3	0.92	0.90	0.90	0.90	0.90	0.90	0.90	0.90	0.90	0.90	0.90	0.89	0.90
h = 4	0.91	0.90	0.89	0.89	0.89	0.89	0.89	0.88	0.88	0.88	0.88	0.88	0.88
h = 5	0.92	0.91	0.90	0.90	0.90	0.90	0.90	0.90	0.90	0.89	0.89	0.90	0.90
h = 6	0.92	0.91	0.90	0.90	0.90	0.90	0.90	0.91	0.90	0.90	0.90	0.91	0.91
h = 7	0.92	0.91	0.90	0.89	0.89	0.89	0.89	0.89	0.89	0.89	0.89	0.90	0.90
h = 8	0.93	0.91	0.91	0.90	0.90	0.91	0.90	0.90	0.91	0.91	0.91	0.91	0.92
h = 9	0.93	0.92	0.91	0.91	0.91	0.91	0.91	0.91	0.91	0.92	0.92	0.92	0.92
h = 10	0.93	0.91	0.91	0.91	0.90	0.91	0.91	0.91	0.91	0.92	0.92	0.92	0.92
h = 11	0.92	0.91	0.91	0.91	0.91	0.91	0.92	0.92	0.92	0.93	0.93	0.93	0.93
h = 12	0.93	0.93	0.92	0.92	0.92	0.92	0.93	0.93	0.93	0.93	0.94	0.94	0.94
h = 13	0.96	0.95	0.94	0.94	0.95	0.95	0.95	0.95	0.95	0.96	0.96	0.96	0.96
h = 14	0.96	0.95	0.95	0.95	0.95	0.95	0.96	0.96	0.96	0.96	0.96	0.97	0.97
h = 15	0.96	0.96	0.95	0.95	0.96	0.96	0.96	0.96	0.97	0.97	0.97	0.98	0.98
h = 16	0.97	0.96	0.96	0.96	0.96	0.96	0.97	0.97	0.97	0.97	0.97	0.98	0.98
h = 17	0.97	0.97	0.97	0.97	0.97	0.97	0.98	0.98	0.98	0.98	0.99	0.99	0.99
h = 18	0.97	0.97	0.97	0.97	0.97	0.98	0.98	0.98	0.98	0.99	0.99	0.99	0.99
h = 19	0.98	0.97	0.97	0.97	0.97	0.98	0.98	0.98	0.98	0.99	0.99	0.99	0.99
h = 20	0.98	0.97	0.97	0.97	0.98	0.98	0.98	0.99	0.99	0.99	0.99	0.99	1.00
h = 21	0.97	0.97	0.97	0.97	0.98	0.98	0.98	0.98	0.98	0.99	0.99	0.99	1.00
h = 22	0.99	0.99	0.98	0.98	0.99	0.99	0.99	1.00	1.00	1.00	1.00	1.01	1.01
h = 23	0.99	0.98	0.98	0.98	0.99	0.99	0.99	0.99	1.00	1.00	1.00	1.01	1.01
h = 24	0.98	0.98	0.98	0.98	0.99	0.99	0.99	0.99	1.00	1.00	1.00	1.01	1.01

Next, Table 11 presents the summary statistics of the predictors selected in the dynamic HNB model. Once again, we uncover no significant persistence.

Table 11: Dynamic HNB predictors summary statistics

Sectors	Std. Dev.	AR(1)
Production	0.22	0.67
Consumption	0.46	−0.09
Orders and Inventories	1.94	0.85
Housing Industry	0.73	0.84
Labor Market	0.72	0.28
Prices	0.91	0.53
Interest Rates	0.48	0.51
Exchange Rates	1.76	0.32
Money	0.41	0.58
Stock Market	0.09	0.33
Banking Industry	0.64	0.44

Table (12) presents the correlation across predictors in the dynamic HNB model. Here again, *housing industry* and *interest rates* display the highest correlation (-0.29).

Table 12: Correlation across predictors in the dynamic HNB model

	Prod.	Cons.	Ord.	Hous.	Lab.	Prices	Int.	Exch.	Money	Stck.
Cons.	-0.04	1.00	0.01	0.04	-0.02	-0.01	0.02	-0.11	0.01	-0.03
Ord. & Inv.	0.01	0.01	1.00	-0.02	0.22	0.15	0.28	-0.08	0.06	-0.06
Hous.	-0.23	0.04	-0.02	1.00	-0.20	0.18	-0.29	-0.06	-0.26	0.06
Lab.	-0.07	-0.02	0.22	-0.20	1.00	-0.04	0.09	-0.10	0.02	0.06
Prices	-0.08	-0.01	0.15	0.18	-0.04	1.00	0.02	-0.04	-0.04	-0.03
Int. Rates	0.20	0.02	0.28	-0.29	0.09	0.02	1.00	-0.11	0.16	-0.13
Exch. Rates	0.04	-0.11	-0.08	-0.06	-0.10	-0.04	-0.11	1.00	-0.07	-0.07
Money	0.13	0.01	0.06	-0.26	0.02	-0.04	0.16	-0.07	1.00	0.09
Stck. Mkt.	-0.13	-0.03	-0.06	0.06	0.06	-0.03	-0.13	-0.07	0.09	1.00
Bank. Ind.	-0.06	0.06	0.22	-0.08	0.19	-0.05	0.17	-0.01	0.11	-0.09

LIST OF VARIABLES

N.	VARIABLE	DEFINITION	UNIT
VARIABLES CONSIDERED BY McCracken and Ng (2016)			
PRODUCTION AND BUSINESS ACTIVITY			
1	INDPRO	Industrial Production (IP)	Index
2	IPFPNSS	IP: Final Products and Nonindustrial Supplies	Index
3	IPFINAL	IP: Final Products (Market Group)	Index
4	IPCONGD	IP: Consumer Goods	Index
5	IPDCONGD	IP: Durable Consumer Goods	Index
6	IPNCONGD	IP: Nondurable Consumer Goods	Index
7	IPBUSEQ	IP: Business Equipment	Index
8	IPMAT	IP: Materials	Index
9	IPDMAT	IP: Durable Materials	Index
10	IPNMAT	IP: Nondurable Materials	Index
11	IPMANSICS	IP: Manufacturing (SIC)	Index
12	IPB51222S	IP: Residential Utilities	Index
13	IPFUELS	IP: Fuels	Index
14	NAPMPI	ISM Manufacturing: Production index	Percent
15	CUMFNS	Capacity Utilization : Manufacturing	Percent
CONSUMPTION			
16	DPCERA3M086SBEA	Real Personal Consumption Expenditures	Index
17	CMRMTSPL	Real Manufacturing and Trade Industries Services	Millions USD
18	RETAILx	Retail and Food Services Sales	Millions USD
ORDERS AND INVENTORIES			
19	NAPM	ISM : PMI Composite Index	Index
20	NAPMNOI	ISM: New Orders Index	Index
21	NAPMSDI	ISM: Supplier Deliveries Index	Index
22	NAPMII	ISM: Inventories Index	Index
23	AMDNOx	New Orders for Durable Goods	Millions of Dollars
24	ANDENO	New Orders for Nondefense Capital Goods	Millions of Dollars
25	AMDMUO	Unfilled Orders for Durable Goods	Millions of Dollars
26	BUSINV	Total Business Inventories	Millions of Dollars
27	ISRATIO	Total Business: Inventories to Sales Ratio	Ratio
HOUSING INDUSTRY			
28	HOUST	Housings Starts: Total New Privately Owned	Thousands of Units
29	HOUSTNE	Housing Starts, Northeast	Thousands of Units
30	HOUSTMW	Housing Starts, Midwest	Thousands of Units
31	HOUSTS	Housing Starts, South	Thousands of Units
32	HOUSTW	Housing Starts, West	Thousands of Units
33	PERMIT	New Private Housing Permits (SAAR)	Thousands of Units
34	PERMITNE	New Private Housing Permits, Northeast (SAAR)	Thousands of Units
35	PERMITMW	New Private Housing Permits, Midwest (SAAR)	Thousands of Units
36	PERMITSx	New Private Housing Permits, South (SAAR)	Thousands of Units
37	PERMITW	New Private Housing Permits, West (SAAR)	Thousands of Units

Table – List of variables (Continued)

N.	VARIABLE	DEFINITION	UNIT
LABOR MARKET			
38	HWIx	Help-Wanted Index for United States	Index
39	HWIURATIOx	Ratio of Help Wanted/Number of Unemployed	Ratio
40	CLF16OV	Civilian Labor Force	Thousands of Persons
41	CE16OV	Civilian Employment	Thousands of Persons
42	UNRATE	Civilian Unemployment Rate	Percent
43	UEMPMEAN	Average Duration of Unemployment	Weeks
44	UEMPLT5	Civilians Unemployed - Less Than 5 Weeks	Thousands of Persons
45	UEMP5TO14	Civilians Unemployed for 5 - 14 Weeks	Thousands of Persons
46	UEMP15OV	Civilians Unemployed - 15 Weeks and Over	Thousands of Persons
47	UEMP15T26	Civilians Unemployed for 15 - 26 Weeks	Thousands of Persons
48	UEMP27OV	Civilians Unemployed for 27 Weeks and Over	Thousands of Persons
49	CLAIMSx	Initial Claims	Units
50	PAYEMS	All Employees: Total nonfarm	Thousands of Persons
51	USGOOD	All Employees: Goods-Producing Industries	Thousands of Persons
52	CES1021000001	All Employees: Mining and Logging: Mining	Thousands of Persons
53	USCONS	All Employees: Construction	Thousands of Persons
54	MANEMP	All Employees: Manufacturing	Thousands of Persons
55	DMANEMP	All Employees: Durable Goods	Thousands of Persons
56	NDMANEMP	All Employees: Nondurable Goods	Thousands of Persons
57	SRVPRD	All Employees: Service-Providing Industries	Thousands of Persons
58	USTPU	All Employees: Trade, Transportation and Utilities	Thousands of Persons
59	USWTRADE	All Employees: Wholesale Trade	Thousands of Persons
60	USTRADE	All Employees: Retail Trade	Thousands of Persons
61	USFIRE	All Employees: Financial Activities	Thousands of Persons
62	CES0600000007	Average Weekly Hours: Goods-Producing	Hours
63	AWOTMAN	Average Weekly Overtime Hours: Manufacturing	Hours
64	AWHMAN	Average Weekly Hours: Manufacturing	Hours
65	NAPMEI	ISM Manufacturing: Employment Index	Percent
66	CES0600000008	Average Hourly Earnings: Goods-Producing	Dollars Per Hour
67	CES2000000008	Average Hourly Earnings: Construction	Dollars Per Hour
68	CES3000000008	Average Hourly Earnings: Manufacturing	Dollars Per Hour
PRICES			
69	PPIFGSx	Personal Producer Index: Finished Goods	Index
70	PPIFCGx	PPI: Finished Consumer Goods	Index
71	PPIITMx	PPI: Intermediate Materials	Index
72	PPICRMx	PPI: Crude Materials	Index
73	PPICMM	PPI: Metals and Metal Products	Index
74	NAPMPRIx	ISM Manufacturing: Prices Index	Percent
75	CPIAUCSL	CPI: All Items	Index
76	CPIAPPSL	CPI: All Urban Consumer: Apparel	Index
77	CPITRNSL	CPI: Transportation	Index

Table – List of variables (Continued)

N.	VARIABLE	DEFINITION	UNIT
78	CPIMEDSL	CPI: Medical Care	Index
79	CUSR0000SAC	CPI: Commodities	Index
80	CUUR0000SAD	CPI: Durables	Index
81	CUSR0000SAS	CPI: Services	Index
82	CPIULFSL	CPI: All Items Less Food	Index
83	CUUR0000SA0L2	CPI: All Items Less Shelter	Index
84	CUSR0000SA0L5	CPI: All Items Less Medical Care	Index
85	PCEPI	PCE: Chain Index	Index
86	DDURRG3M086SBEA	PCE: Durable Goods	Index
87	DNDGRG3M086SBEA	PCE: Nondurable Goods	Index
88	DSERRG3M086SBEA	PCE: Services	Index
INTEREST RATES			
89	FEDFUNDS	Effective Federal Funds Rate	Percent
90	CP3Mx	3-Month AA Financial Commercial Paper Rate	Percent
91	TB3MS	3-Month Treasury Bill	Percent
92	TB6MS	6-Month Treasury Bill	Percent
93	GS1	1-Year Treasury Rate	Percent
94	GS5	5-Year Treasury Rate	Percent
95	GS10	10-Year Treasury Rate	Percent
96	AAA	Moody's Seasoned Aaa Corporate Bond Yield	Percent
97	BAA	Moody's Seasoned Baa Corporate Bond Yield	Percent
98	COMPAPFFx	3-Month Commercial Paper Minus FEDFUNDS	Percent
99	TB3SMFFM	3-Month Treasury C Minus FEDFUNDS	Percent
100	TB6SMFFM	6-Month Treasury C Minus FEDFUNDS	Percent
101	T1YFFM	1-Year Treasury C Minus FEDFUNDS	Percent
102	T5YFFM	5-Year Treasury C Minus FEDFUNDS	Percent
103	T10YFFM	10-Year Treasury C Minus FEDFUNDS	Percent
104	AAAFFM	Moody's Aaa Corporate Bond Minus FEDFUNDS	Percent
105	BAAFFM	Moody's Baa Corporate Bond Minus FEDFUNDS	Percent
EXCHANGE RATES			
106	TWEXBMTH	Trade Weighted \$U.S. Index: Broad	Index
107	EXUSAL	U.S./Australia Foreign Exchange Rate	\$U.S. to 1 Aus. \$
108	TWEXMMTH	Trade Weighted \$U.S. Index: Major Currencies	Index
109	EXSZUS	Switzerland/U.S. Foreign Exchange Rate	CHF to 1 U.S. \$
110	EXJPUS	Japan/U.S. Foreign Exchange Rate	Jap. Yen to 1 U.S. \$
111	EXUSUK	U.S./U.K. Foreign Exchange Rate	\$U.S. to 1 U.K. £
112	EXCAUS	Canada/U.S. Foreign Exchange Rate	CAD to 1 U.S \$
MONEY			
113	M1SL	M1 Money Stock	Billions of Dollars
114	TCDSL	Total Checkable Deposits	Billions of Dollars
115	DEMDEPSL	Demand Deposits: Total	Billions of Dollars
116	M1REAL	Real M1 Money Stock	Billions of Dollars

Table – List of variables (Continued)

N.	VARIABLE	DEFINITION	UNIT
117	OCDCBS	Other Checkable Deposits at Commercial Banks	Billions of Dollars
118	CURRDD	Currency Component of M1 Plus Demand Deposits	Billions of Dollars
119	M2SL	M2 Money stock	Billions of Dollars
120	M2REAL	Real M2 Money Stock	Billions of Dollars
121	M2OWN	M2 Own Rate	Percent
122	MZMOWN	MZM Own Rate	Percent
123	MZMSL	MZM Money Stock	Billions of Dollars
124	AMBSL	St. Louis Adjusted Monetary Base	Billions of Dollars
125	TOTRESNS	Total Reserves of Depository Institutions	Billions of Dollars
126	NONBORRES	Reserves of Depository Institutions, Non-borrowed	Millions of Dollars
STOCK MARKET			
127	S&P 500	S&P's Stock Price Index: Composite	Index
128	S&P: INDUSTx	S&P's Stock Price Index: Industrials	Index
129	S&P DIV YIELDx	S&P's Stock Composite: Dividend Yield	Index
130	S&P PE RATIOx	S&P's Stock Composite: Price-Earnings Ratio	Index
131	NASDAQCOM	Nasdaq Composite Index	Index
VARIABLES ADDED BY THE AUTHORS			
BANKING INSDUSTRY			
132	SAVINGSx	Total Savings Deposits at all Depository Instutions	Billions of Dollars
133	RMFSL	Retail Money Funds	Billions of Dollars
134	STDSL	Small Time deposits - Total	Billions of Dollars
135	SAVINGSL	Savings Deposits - Total	Billions of Dollars
136	SVGCBSL	Savings Deposits at Commercial Banks	Billions of Dollars
137	SVSTSL	Savings and Small Time Deposits - Total	Billions of Dollars
138	STDCBSL	Small Time Deposits at Commercial Banks	Billions of Dollars
139	SVGTI	Savings Deposits at Thrift Institutions	Billions of Dollars
140	BUSLOANS	Commercial and Industrial Loans	Billions of Dollars
141	LOANSx	Loans and Leases in Bank Credit	Billions of Dollars
142	REALLN	Real Estate Loans	Billions of Dollars
143	TLAACBM027SBOG	Total Assets	Billions of Dollars
144	IBLACBM027SBOG	Interbank Loans	Billions of Dollars
145	CASACBM027SBOG	Cash Assets	Billions of Dollars
146	TLBACBM027SBOG	Total Liabilities	Billions of Dollars
147	FRPACBM027SBOG	Fed Funds andd Reverse RPs with Banks	Billions of Dollars
148	INVEST	Securities in Bank Credit	Billions of Dollars
149	RALACBM027SBOG	Residuals (Assets Less Liabilities)	Billions of Dollars
150	BOWACBM027SBOG	Borrowings	Billions of Dollars
151	NONREVSL	Total Nonrevolving Credit Owned and Securitized	Billions of Dollars
152	CONSPIx	Nonrevolving Consumer Credit to Personal Income	Ratio
153	DTCTHFNM	Total Consumer Loans and Leases Outstanding	Billions of Dollars