Animal Spirits in Regulation: Evidence from Banking

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"True law is [...] of universal application, unchanging and everlasting; it summons to duty by its commands, and averts from wrongdoing by its prohibitions."

Marcus Tullius Cicero, On The Republic

"As finance academics, we should care deeply about the way the financial industry is perceived by society [...] And even if we thought there were no truth, we should care about the effects that this reputation has in shaping regulation and government intervention in the financial industry."

Luigi Zingales, 2015 AFA Presidential Address

Caveat Emptor

Unfortunately, we are unable to show some of our core results, as Federal Reserve (FRS) policy disallows sharing results based on confidential supervisory information until vetted. We hope to be able to convey the "flavor" of our work with the results presented blow, however.

Introduction

Are banking regulation and supervision consistent? There is evidence in the literature that they are not, at least across regulators: notably, Agarwal, et al. (2014) document how regulator incentives lead to state bank examiners being relatively lenient in their evaluations; Bischof et al. (2015) document variation in risk disclosures of banks subject to quasi-identical disclosure rules under securities laws and banking regulation, but subject to *enforcement* by different regulators across time.

Two questions arise given this evidence. First, is it the case that there is also *within*-regulator inconsistency in regulatory and supervisory practice? Second; if so, what is its cause? In this paper, we hypothesize that there *is* regulatory inconsistency in this sense, and that this inconsistency is influenced by variation in media sentiment and attention toward banks. This is of particular importance as we face an increasingly politically polarized media ecosystem: indeed, Engelberg et al. (2021) document growing partisanship among financial regulators.

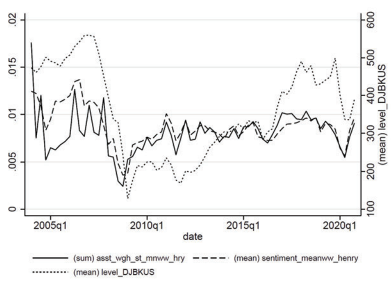

Figure 1: Covariance between media sentiment and DJUSBK index

It is quite easily established that sentiment has bearing on financial intermediaries. Figure 1 above shows the close covariance of sentiment indices we define below with the Dow Jones US Bank Index, which we use as a proxy for bank equity returns. It is less clear a priori that this effect flows through bank fundamentals, however: we expound on this issue below.

Data

We use several data sources in this project. Bank-level financials are extracted from FR-Y9C regulatory filings, while the textual corpus of bank-level newspaper coverage comes from the Factiva Analytics database. In analyses not shown, we use proprietary FRS data on bank-level operational losses, BHC and bank ratings, as well as MR(I)As and other supervisory actions.

We derive our bank sentiment measures from a set of financial news articles (around 600K in total) extracted from Factiva. To construct our base measure, we identify articles discussing our set of banks (DFAST banks in 2020q4), and perform sentiment scoring at the sentence level based on a financial dictionary (Henry, 2008). We briefly describe our variable construction below.

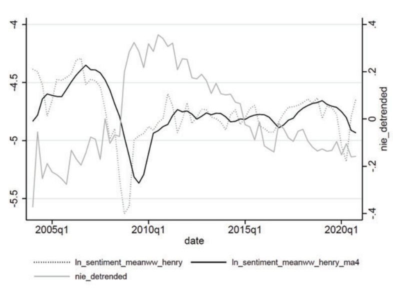

Figure 2: Covariance between noninterest expense and sentiment

As instruments, we use (i) *Mean WW Henry*, or the contemporaneous word-weighted mean sentiment score across media articles mentioning a given bank; (ii) *Mean WW Henry MA(4)*, the four-quarter backward-looking moving average of *Mean WW Henry* and (iii) *L4.WW Henry MA(4)*, a four-quarter lagged *Mean WW Henry MA(4)* measure.

As dependent variables, we use the modified Z-Score of Noth & Schüwer (2018), bank ROA, and Tier 1 Capital ratio. As controls, we incorporate into our regressions the logarithm of, respectively, bank assets, number of employees, and the one-quarter lag of (each) Moody's Baa-10Y Treasury spread, GDP, VIX, and PCEPILFE, as a measure of inflation.

Our key (instrumented) endogenous regressor is bank noninterest expense (NIE). Figure 2 shows the covariance of the (detrended) NIE industry-wide series with our (logged) measures of sentiment: the tight inverse variation shows that indeed, the effect of sentiment on banks flows through fundamentals. Why should sentiment shocks flow through NIE? The intuition here is that (non-trend) variation in NIE is largely due to operational losses –and, in turn, the lion's share of operational losses is the payment of regulatory fines and legal damages.

Empirical Strategy

We use a 2SLS-IV strategy for identification, in which we estimate the first-stage equation

$$\widehat{NIE_{it}^k} = \alpha_i + \delta_k Sentiment_{i,t-j}^k + \mathbf{X}_i'\Gamma \tag{1}$$

in which $\widehat{NIE_{it}^k}$ is the estimate of net interest expense for bank i at time t, instrumented by the k-th element of the instrument vector, $Sentiment_{i,t-j}^k$, $\mathbf{X}_i$ is a vector of controls, and α_i is a bank fixed effect.

We then estimate the second stage

$$Y_{it} = \alpha_i + \beta_k \widehat{NIE_{it}^k} + \mathbf{X}_i'\Gamma + \varepsilon_{it}^k \tag{2}$$

in which variables are defined as above, and Y_{it} is a vector of dependent variables. Our identification rests upon the assumption that sentiment affects bank fundamentals *at most* solely through noninterest expense. We believe that, given the relative stickiness of our dependent variables, this is reasonable.

Results

We first present results, in Table 1, for a set of baseline reduced-form regressions with the following general specification:

$$Y_{it} = \alpha_i + \beta_k Sentiment_{i,t-j}^k + \mathbf{X}_i'\Gamma + \varepsilon_{it}^k \tag{3}$$

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Explanatory vars. in logs		*Modified Z-Score*			*ROA*			*Tier 1 Capital Ratio*	
Mean WW Henry	**-0.028**			**0.001****			**-0.559**		
	(0.022)			(0.0004)			(0.464)		
Mean WW Henry MA(4)		**-0.058**			**0.001****			**-1.084**	
		(0.039)			(0.001)			(0.739)	
L4.WW Henry MA(4)			**-0.101*****			**0.0003**			**-1.617*****
			(0.034)			(0.001)			(0.500)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1,633	1,531	1,400	1,634	1,532	1,401	1,631	1,532	1,401
R-squared	0.945	0.946	0.948	0.279	0.280	0.306	0.703	0.702	0.692
Number of clusters (banks)	32	32	32	32	32	32	32	32	32

Robust standard errors in parentheses
*** p<0.01, **p<0.05, *p<0.1

Table 1: Baseline regressions

As can be seen in Table 1, sentiment seems to have only a slight (positive) effect on short-run profitability; less intuitively, perhaps, sentiment seems to have longer-run negative effects on distance-to-default and Tier 1 capitalization.

	(1)	(2)	(3)
Explanatory vars. (in logs)		*ln(Noninterest Expense)*	
Mean WW Henry	**-0.019**		
	(0.017)		
Mean WW Henry MA(4)		**-0.039****	
		(0.019)	
L4.WW Henry MA(4)			**-0.076*****
			(0.025)
Controls	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes
Observations	1,634	1,532	1,401
R-squared	0.975	0.978	0.981
Number of clusters (banks)	32	32	32

Robust standard errors in parentheses
*** p<0.01, **p<0.05, *p<0.1

Table 2: First stage regression

Table 2 shows results for a first-stage regression of the log of noninterest expense on our measures of sentiment. Clearly, sentiment satisfies the relevance condition as an instrument, except in the very short run. This further solidifies the contention that the effect of sentiment on banks flows through NIE.

Instrumented: Noninterest expense

	(1)	(2)	(3)	(4)	(5)	(6)
Explanatory vars. in logs	*Modified Z-Score*		*ROA*		*Tier 1 Capital Ratio*	
Mean WW Henry MA(4)	**1.505**		**-0.015***		**27.92***	
	(1.152)		(0.008)		(16.01)	
L4.WW Henry MA(4)		**1.334****		**-0.004**		**21.38*****
		(0.534)		(0.006)		(5.234)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1,531	1,400	1,532	1,401	1,532	1,401
Number of clusters (banks)	32	32	32	32	32	32

Robust standard errors in parentheses
*** p<0.01, **p<0.05, *p<0.1

Table 3: 2SLS estimation

Finally, Table 3 shows results of our 2SLS estimation. As can be seen, the resulting loadings on both distance-to-default and Tier 1 capitalization are large and (mostly) significant. Taken together with our first stage results, we interpret these findings to point towards a counter-cyclical pattern of regulatory stringency. Indeed, positive variation in sentiment is associated with a short-term rise in bank profitability, but higher risk-taking, leading to higher likelihood of default and lower capitalization.

Conclusions

- There is an apparent tension between short-term sentiment-driven profitability shocks and long term bank stability.
- There is some evidence that regulatory stringency evolves counter to sentiment cycles: more nuanced results to be made available, based on analysis conducted using proprietary data.
- We find common variation in noninterest expense (a relatively good proxy of pecuniary regulatory penalties) and sentiment; however, we cannot condition outright on regulators' information sets using the data here reported. Results of such an exercise are forthcoming, which will allow us to provide causal interpretation to our findings.

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