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Stress-Testing and "Incorrect" Signs

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Abstract

In dealing with model validation teams, the requirement to understand every aspect of the behavior of stress-testing models—by business units as well as quants—has been apparent. Ostensibly, we are trying to build regression models relating some aspect of bank performance to a range of economic drivers; the stress scenarios are then applied and the performance of the bank under stress is inferred. If we are interested, say, in probability of default for some portfolio of loans and one of the drivers is, say, the unemployment rate, shouldn't the sign in the regression always be positive? Does a negative relationship imply that the model is wrong?

Stress-Testing and “Incorrect” Signs

BY TONY HUGHES

In dealing with model validation teams, the requirement to understand every aspect of the behavior of stress-testing models—by business units as well as quants—has been apparent. Ostensibly, we are trying to build regression models relating some aspect of bank performance to a range of economic drivers; the stress scenarios are then applied and the performance of the bank under stress is inferred. If we are interested, say, in probability of default for some portfolio of loans and one of the drivers is, say, the unemployment rate, shouldn’t the sign in the regression always be positive? Does a negative relationship imply that the model is wrong?

Yes and no. It depends on the circumstances.

In this article, we will discuss situations in which an “incorrect” sign may actually be a useful thing to encourage accurate stressed predictions. We will make the point that an insistence on “correct” signs makes stress-testing models bland, uninformative and potentially inaccurate.

In an excellent resource for practitioners who are curious about the how, why and wherefore of wrong signs, Peter Kennedy (2002, available at http://www.stat.columbia.edu/~gelman/stuff_for_blog/oh_no_I_got_the_wrong_sign.pdf) outlines 19 explanations of and remedies for such signs in regression models. Most of the examples cited are cases where the model really is seriously misspecified and thus inappropriate for use in bank stress-testing (or anything else, for that matter). Here we want to concentrate on the subset of Kennedy’s list in which the “incorrect” signs, while causing one to scratch one’s head and think carefully through the model, are not incorrect at all, and thus promote improved understanding of the behavior of the modeled entity. He also points out, in conclusion, that if signs remain “wrong” after all diligent model-building steps have been pursued, such results pose new research questions that can deepen our understanding of what is going on. Though unacceptable for the next round of Comprehensive Capital Analysis and Review, such results should actually be welcomed by modelers and managers committed to fully understanding the behavior of their bank.

Long-run multiplier effects

To keep things simple, unless otherwise stated, we will assume that the unemployment rate is the only factor needed to explain the behavior of the target variable of interest. If this is some negative aspect of performance, like probability of default, the total effect of a positive unemployment rate shock should necessarily be to increase PD. In other words, if the economy tanks, PD should be higher than under baseline conditions.

Now consider a situation in which the PD variable you are seeking to model looks like Chart “The Great Recession Clearly Worse Than 2001.”

Clearly, the series has peaks around the time of the 2001 and 2008-2009 recessions, with the second recession being clearly worse than the first. The dynamic behavior of this series closely mimics the recent performance of many retail credit portfolios.

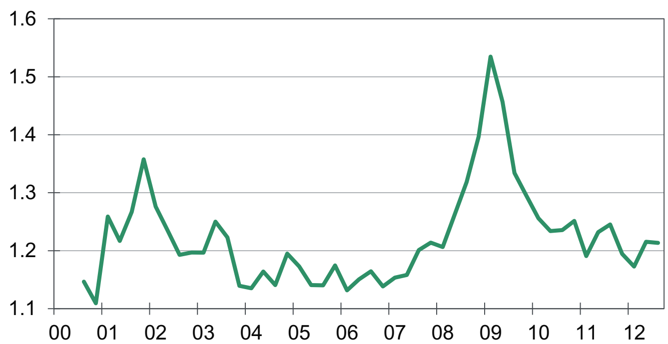
You suspect that unemployment may be a good economic driver to use, so you run the regression in Table 1.

You feel relief that the unemployment rate variable is indeed significant and positively associated with PD, but you view the 25% R^2 figure as unacceptably low. A look at the residual plot in Chart “Portfolio Responds Faster Than Unemployment” tells you why.

It seems that delinquency is positively related to unemployment but that the response is much faster—rising unemployment quickly causes PD to jump, while the default rate tends to fall quickly as the un-

The Great Recession Clearly Worse Than 2001

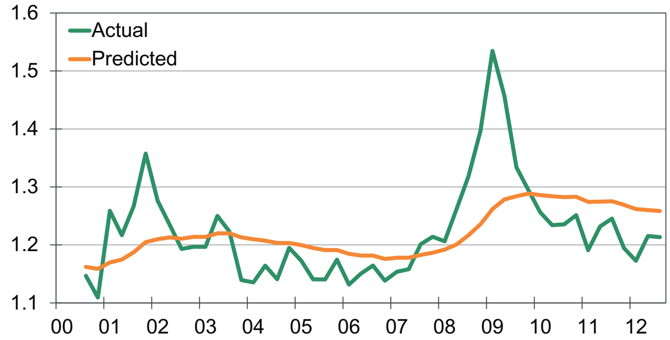
Probability of default, %



Source: Moody’s Analytics

Portfolio Responds Faster Than Unemployment

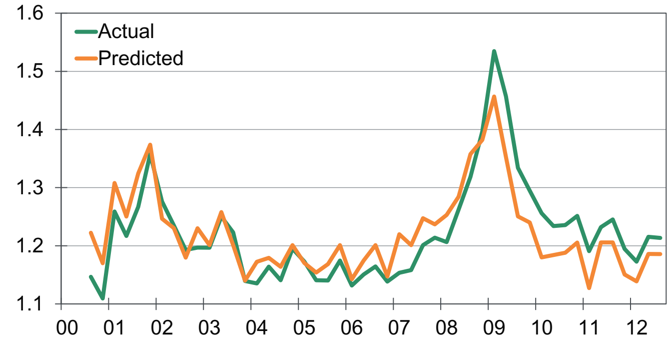
Probability of default, model with untransformed UER, %



Source: Moody's Analytics

Model Used for Submission Looks Wonky

Probability of default, model used for submission, %



Source: Moody's Analytics

employment rate stabilizes. Because of the quick spike, you theorize that the change in the unemployment rate might be a better driver, yielding the following regression in Table 2.

Now this is looking much better. The R^2 has jumped all the way to 72%, your coefficient has the inferred positive sign, and your lunch seems to taste that little bit better. You figure this one might pass validation. The residual plot in Chart "Model Used for Submission Looks Wonky" looks decent

Sure, the model looks a bit wonky since about 2005, but the recession was very weird and the model does pretty well in representing it. Just for completeness, you try the original model but with a couple of extra lags included. You get the result shown in Table 3.

You look longingly at that R^2 number, but you ultimately reject the model. There is no way those negative signs will ever pass validation—how would I explain it to senior management or the Federal Reserve's examiners? Higher unemployment causing lower default? Preposterous! It simply can't be.

Instead, you decide to stick with the second model, using the change in unemployment rate, and hope for the best. After a small calibration to adjust for recent errors (which you ascribe to unusual circumstances in the economy), your submission looks like Chart "Submission Shows Stress, Then Rapid Recovery."

You calculate capital accordingly and pass CCAR with no matters requiring attention. Mission accomplished.

As you can probably guess, the submission is wrong—the third model should have been selected. The original data were generated by the author, and that model was the correct specification. If the submission had been based on the model used to generate the data, it would have looked like Chart "Negative Signs Boost Scale of Stressed Losses."

Note that the actual submission based on the misspecified model is not disastrous, though it does understate the overall scale of stressed losses. The peak in the projected PD curve is lower than it should be but only to the tune of a few basis points. Slightly more troubling is the fact that the recovery from the initial surge in defaults is too rapid in the misspecified model, meaning that overall losses are quite a bit lower under the submitted projections than they should be. The bank may remain marginally undercapitalized because the model used to project losses was incorrectly specified.

Of course, the change in unemployment rate model is quite similar in many respects

Table 1.

Source	SS	df	MS		
Model	.051033245	1	.051033245	Number of obs	= 49
				F(1, 47)	= 15.27
				Prob > F	= 0.0003
Residual	.157109154	47	.003342748	R-squared	= 0.2452
				Adj R-squared	= 0.2291
Total	.2081424	48	.0043363	Root MSE	= .05782

ln_delinq_~b	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
ln_flbr_fedb	.113419	.0290276	3.91	0.000	.055023	.171815
_cons	-.0069303	.0532118	-0.13	0.897	-.1139787	1001181

Table 2.

Source	SS	df	MS		
Model	.151038537	1	.151038537	Number of obs	= 49
				F(1, 47)	= 124.31
				Prob > F	= 0.0000
Residual	.057103863	47	.001214976	R-squared	= 0.7257
				Adj R-squared	= 0.7198
Total	.2081424	48	.0043363	Root MSE	= .03486

ln_delinq_~b	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
ln_flbr_fedb D1.	1.039912	.0932688	11.15	0.000	.8522789	1.227544
_cons	.1832201	.0051638	35.48	0.000	.1728319	.1936083

Table 3.

Source	SS	df	MS
Model	.203459834	3	.067819945
Residual	.004682566	45	.000104057
Total	.2081424	48	.0043363

Number of obs	=	49
F(1, 45)	=	651.76
Prob > F	=	0.0000
R-squared	=	0.9775
Adj R-squared	=	0.9760
Root MSE	=	.0102

ln_delinq_~b	Coef.	Std. Err.	t	P>|t|	[95% Conf. Interval]	
ln_flbr_fedb						
--.	.940889	.0932688	23.87	0.000	.8522789	1.227544
L1.	-.5694456	.0710928	-8.01	0.000	-.7126339	-.4262573
L2.	-.2708173	.038817	-6.98	0.000	-.3489987	-.192636
_cons	.0000209	.0096184	0.00	0.998	-.0193515	.0193934

to the true model in this situation. Expansion of the underlying regression equation reveals that the submission model has lagged as well as contemporaneous unemployment rates with opposite signs. The coefficient on each variable is constrained to be equal on both terms—it is this constraint that is not supported by the data. The point here is that in order to obtain an "acceptable" coefficient interpretation, a poorly specified constraint was applied to the model.

Relaxing the constraint and allowing the inclusion of negative terms on unemployment actually caused the measured total impact of joblessness to rise, not fall. The initial impact of a rising unemployment rate is, in reality, larger than the long-term impact of unemployment on default likelihood. Therefore, we should expect the lagged unemployment terms in our regression to take negative signs while the contemporaneous unemployment rate variable takes the "correct" positive sign with a larger coefficient. By including the negative lagged effects, we can boost the scale of the short-term effect, meaning that our stressed projections are then higher.

The moral of the story is that stress-testing or prediction models should not necessarily be rejected if lagged terms are "incorrectly" signed. If the long-run marginal effect of the variable goes the wrong way, meaning that stressed default projections are actually lower than baseline, this is an entirely different matter. In many situations, it is enough to demonstrate that the total effect of a shock "goes the right way" and that the model fits the observed data well.

Combing through coefficient lists and expunging all variables with a counterintuitive sign is a recipe for inaccuracy, even if you do not know it at the time.

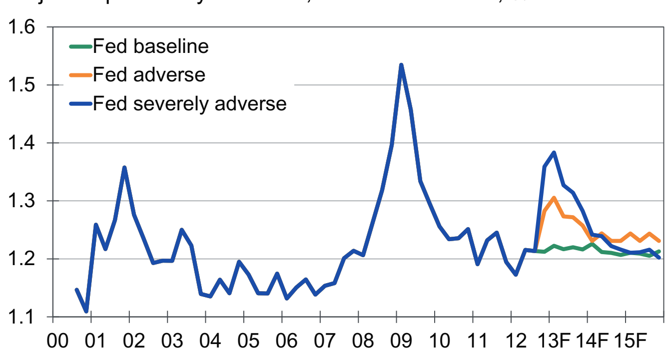
Omitted variables

In our stylized world where the unemployment rate is the only game in town, the threat of omitted variables might seem rather limited. The point here, though, is that unemployment can affect the behavior of the portfolio in a number of ways. At the onset of a recession, rising joblessness will necessarily increase the observed default rate among legacy borrowers. In addition, there will be both a supply and demand response to the changed economic conditions. On the supply side, management of the lending institution will respond by tightening underwriting standards for new borrowers and by aggressively managing the credit lines allowed by existing clients. Consumers, meanwhile, will often have little appetite for extended credit commitments in a recession, especially if high debt loads contributed to the initial onset of the downturn.

Focusing only on the recession responses and abstracting from the effect on legacy borrowers, the unemployment rate will actually have a negative effect on future default behavior. Obviously, banks and consumers will never respond in anticipation of a recession—meaning that the confounding effect will typically be smaller than the primary effect of unemployment and that losses will invariably rise in the early months of a recession. The lower volume of credit underwritten under recession conditions will also tend to be dwarfed by the higher quantity of credit

Submission Shows Stress, Then Rapid Recovery

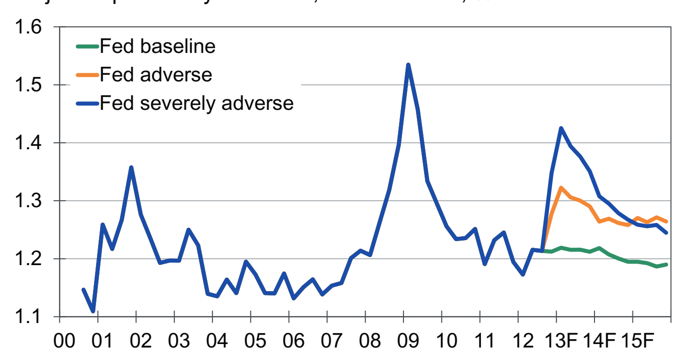
Projected probability of default, submission model, %



Source: Moody's Analytics

Negative Signs Boost Scale of Stressed Losses

Projected probability of default, correct model, %



Source: Moody's Analytics

kicked off during the preceding boom. Because of this "cleaning out" effect and the underlying impact of lifecycle factors on portfolio behavior, many banks will be surprised that credit losses will tend to be low, even by historical standards, in the latter part of recessions. This will hold true despite the fact that the unemployment rate remains elevated.

One key point to note here is that management actions are quite clearly correlated with economic outcomes. Omitting all management action-related variables from the model will thus bias estimates of the effect of the economic factors on performance. Though managers typically act in a procyclical manner, this is in no way an immutable law of nature. In assessing a bank's likely performance under stress, it is very desirable to have models that are capable of expressing the effects of a variety of management responses. We have seen stress-testing models that include economic variables but do not control for past management shifts; in our view, these models do not accurately capture the effect of the economy on the portfolio, lumping together the direct effect of the recession on legacy accounts and the subsequent management responses to the recession. Biased coefficient estimates are often unpredictable, indeed they may even cause expected signs to flip in regression models.

Ceteris paribus conditions

The interpretation of regression coefficients is often less than straightforward. We all remember from intro stats courses that a coefficient is the estimated rise in the dependent variable that can be associated with a unitary increase in a particular independent variable, **holding everything else constant**. This is critical. The problem with interpreting coefficients in regressions with macroeconomic data is that when one thing changes in the economy, typically everything changes.

Multicollinearity is a fact of life. In all interesting statistical problems of any level of complexity, included regressors will be correlated with each other to some degree. Far from being a problem, in a certain sense, multicollinearity is what makes life worth living. In bank stress-test models employing economic data, these issues will be to the fore. The Fed's scenarios, for example, reflect the fact that a rapidly rising unemployment rate will be accompanied by commensurate shifts in all other aspects of the economy. House prices will fall, GDP growth will slow or retreat, and interest rates will remain low. The key point with stress-testing models is that the combined effect of a worsening economy should be reflected in losses elevated to an appropriate magnitude and with correct timing of occurrence.

Thinking about the effect of interest rates on credit losses, for example, the direct result of a rising cost of money should be to increase losses. Rising rates on loans whose repayments can vary over time tend to increase the repayment burden for troubled borrowers, pushing them in the direction of default. Further, higher borrower costs make refinancing of fixed repayment loans less desirable or self-defeating. In the context of a competing risk model, reducing the possibility of a prepayment should tend, if anything, to increase the threat of default. Intuitively, we should therefore expect to see positive signs on interest rate variables in a standard probability of default regression model.

Higher interest rates are also symptomatic of a booming economy. Oftentimes, the inclusion of interest rate variables in a credit loss model will therefore yield strongly negative coefficient signs. The question then, given the difficulty we have in interpreting the rate variables, is should they still have a place in the stress tester's toolkit?

We would argue that they should. While correlation does not imply causality, the lack of a causal relationship does not necessarily invalidate the existence or usefulness of an observed correlation. In medicine, for example, certain drugs will be known to be effective in treating a particular illness long before researchers unearth the specific causal relationship. Should I reject my doctor's advice to lose weight because she cannot tell me precisely why being fat makes me more prone to heart disease? In the context of forecasting, of which stress-testing is an important new sub-branch, strong correlations are generally far more effective in reducing prediction errors than weak causations.

The other advantage of using interest rates in credit-loss models is that, all told, they are reasonably easy to forecast. Because of forward guidance by the Fed and the fact that rates are scrutinized and followed so closely by markets, we usually have a fair amount of success in projecting interest rate paths. Although we should seek to understand why interest rates fall and credit losses rise in recessions, in predicting stressed losses it may be sufficient merely to observe that they do. Therefore, models with negative interest rate coefficients should not overly trouble stress-test model validators.

Conclusion

While we understand the imperative that CCAR models be accessible to managers of portfolios, we fear that the push to simplify stress-testing models has gone too far. Taking a list of strong potential model candidates and rejecting those with challenging results yields final model specifications that are often bland and offer little true insight into the behavior of the bank under stress. The alternative to this is to let the data speak for itself to tell users what may be important dynamic behavior should a stress scenario actually unfold. It is very important that the stress scenario, viewed in its entirety, exhibit an appropriate level of stress with appropriate timing. Less important is the need for all model components to point squarely in the same direction.

Banks generally do not move in lockstep with the economic cycle. Sometimes they experience capital shortfalls or elevated losses in response to unrelated economic crises, and sometimes banking sector problems cause recessions. The former situation is dangerous for banks, while the latter—of which the Great Recession is a prime and all-too-recent example—is downright frightening. Arguably, it is this latter situation that CCAR should be designed to address. Models that are not permitted to possibly capture these timing effects and causal relationships are next to useless for the purpose of assessing situations in which bank capital may prove inadequate.

The current situation—where model validators and, it seems, Fed regulators are insisting on tiny models that assume coincidence with the economic cycle—is an elaborate form of econometric window dressing. Instead, we need to move to a situation where stress-test models at least attempt to shine light on sometimes complex underlying processes, even if bank managers are sometimes left scratching their heads about exactly why the data are as they are.

About the Author

Tony Hughes

Tony Hughes is managing director of Credit Analytics at Moody's Analytics, where he oversees the company's credit analysis consulting projects for global lending institutions. An expert applied econometrician, Dr. Hughes manages the Moody's CreditCycle and CreditForecast.com products. He has helped develop approaches to stress testing and loss forecasting in retail, C&I and commercial real estate portfolios and lately he has introduced a methodology for stress-testing a bank's deposit book. Currently he is developing ways to streamline the economic scenario building process and exploring ways to simulate economic paths more effectively.

A native Australian, Dr. Hughes was formerly the lead Asia-Pacific economist for Moody's Analytics, before which he held academic positions at the University of Adelaide, the University of New South Wales, and Vanderbilt University. He has been published in leading statistics and economics journals as well as several major industry publications. He received his PhD in econometrics from Monash University in Melbourne, Australia.

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