Predicting Recessions with LASSO Estimation

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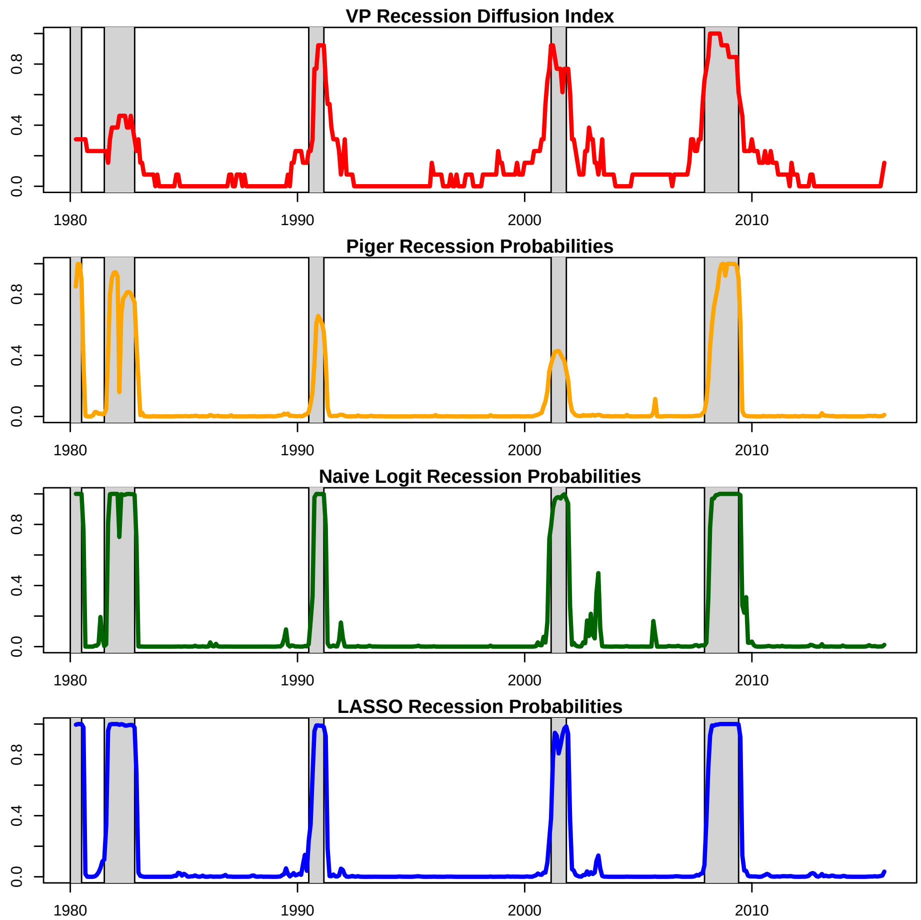
1 Summary

This note presents a predictive model of US Recessions based on LASSO estimation.[1] The model accurately predicts recessions 99.3% of the time, up from 93.2% with our firm's existing model ("VP Recession Diffusion Index", below). LASSO also outperforms a standard logit-based recession forecast, as well as the popular "Piger" recession probabilities.[2] Below are the recession probabilities implied from each model, with NBER recessions shaded in grey.



[1] stands for "least absolute shrinkage and selection operator"

[2] See `http://pages.uoregon.edu/jpiger/us_recession_probs.htm/`.

2 Motivation for the LASSO

Many different inputs might effectively predict recessions – the VP Recession Diffusion Index includes 30+ transformations of common leading indicators – so selecting the "best" model is no small task. This is especially true when subsets of inputs come from the same sectors of the economy and are highly correlated with each other. There are at least two common problems forecasters face when selecting from such a large set of inputs:

- **Arbitrary variable selection** Standard "stepwise" regression methods, which add or discard inputs one-by-one to maximize various goodness-of-fit statistics, are sensitive to the method used. For example, adding inputs one-by-one to a small model, versus discarding them one-by-one from a large model, often produces different results. For this reason, stepwise selection becomes increasingly problematic as more and more inputs are considered.

- **Overfitting** The larger we allow our model to be – in the sense of incorporating more inputs – the more susceptible it will be to overfitting. If we don't place some restrictions on the size of our model, cross-validation does not fix the overfitting problem, as large models will tend to "learn too much" from training data before being fit out-of-sample.

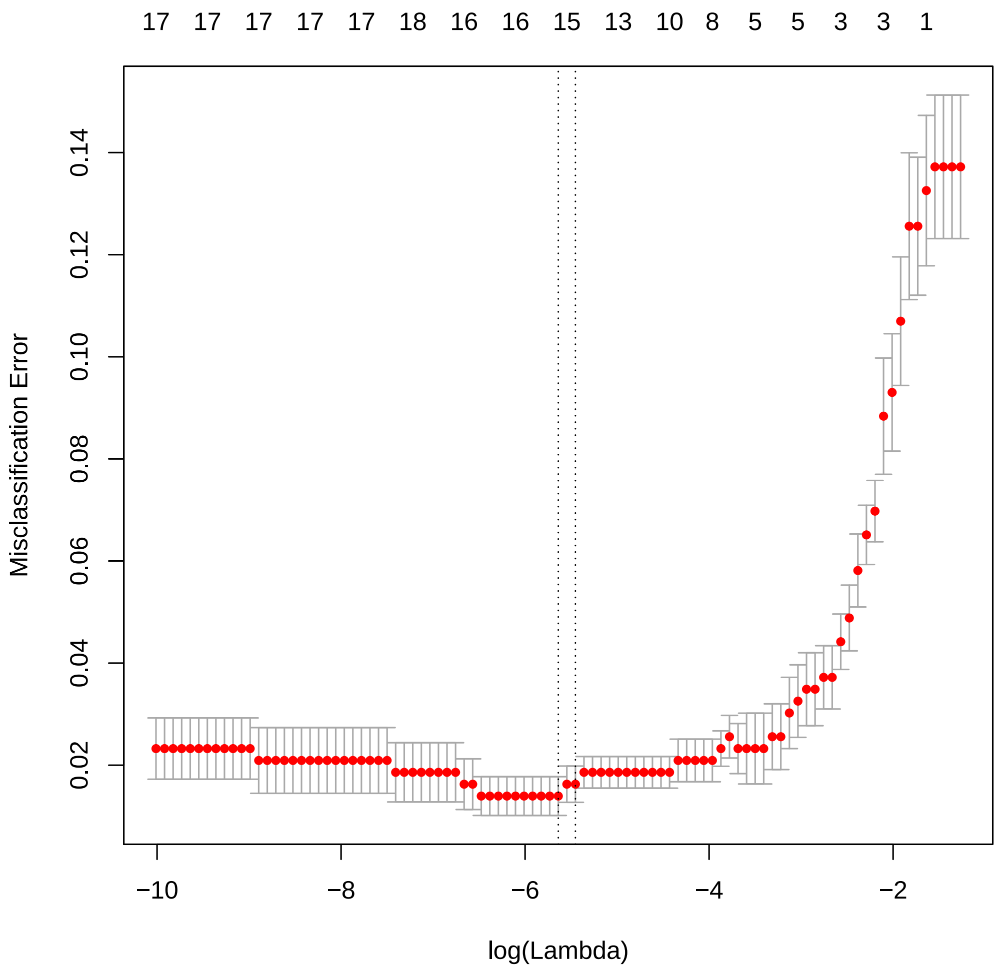
LASSO estimation mitigates these problems; it efficiently selects a model from a large set of inputs that are highly correlated with one another by forcing some regression coefficients to zero. Limiting the size of regression coefficients in this way – a process called "regularization" – generally reduces overfitting, and generates a tractable model with reasonable coefficient estimates. Moreover, cross-validating the lasso model allows us to select the one which gives the most accurate out-of-sample recession calls.

3 Implementing the LASSO

1. I collected all the raw inputs listed in Table 4, monthly from January 1978 to December 2015. Various proprietary transformations were then applied to each, including simple moving averages, counts of increases and decreases in these averages, comparisons to annual minima and maxima, and YoY changes. (Throughout, "inputs" refers to transformed values of the Bloomberg tickers given in Table 4). To facilitate cross-validation, I excluded any inputs missing values for more than 50 months.[3] This left all blue variables in Table 4 from March 1980 - December 2015. During the sample period, 13.7% of months were recessions according to NBER.

2. Using the `glmnet` package I performed LASSO regression with all blue variables, using 10-fold cross validation to select the model with the lowest misclassification error. We immediately see the importance of constraining our coefficient sizes, as the mean misclassification error of the model varies substantially with the magnitude of the size penalty λ. We can also see that, after a certain point, including more inputs in the model actually decreases its accuracy: when more than 15 inputs are included (as indicated by the top axis), misclassification error begins to increase past its minimum. The penalty that minimizes misclassification error is $\lambda^* \approx 3.56 \times 10^{-3}$.

[3] Excluded variables: S&P 500 Financials Sector Index, Conf. Board Leading Credit Index, CRB Raw Materials Index, JoC ECRI Industrial Price Index, Oil Price (WTI Spot), Conf. Board M2 LEI, US Non-Farm Employees Temporary Help Services, and High Yield Spreads



We then fit the LASSO model to the inputs with penalty λ^*, which gives us the intuitive and broad-based logit recession model in Table 1.

Sector	**Variable**	**Coefficient**
	(Intercept)	1.86
Credit	Moody's Average Corp. Yields	0.14
Broad Indices	Aruoba-Diebold-Scotti Business Conditions Index	-2.84
	Chicago Fed National Activity Index	-0.12
Housing	Conf. Board Building Permits Index	-0.22
	US New One Family Houses Sold (Annual Total)	-0.003
	Primary Mortgage Market Survey Rates	1.38
Manufacturing	New Orders to Inventory Ratio	-2.10
	US Auto Production	-0.72
Macro	Real M1 YoY	-0.06
Equities	Conf. Board Stock Price LEI	-0.33
	Dow Transportation Index	-2.26
Employment	Initial Jobless Claims	7.13
	State Unemployment Claims	-0.08
Yield Curve	Conf. Board Interest Rates LEI	0.39
	3s10s	0.03

Table 1: Model Estimates: LASSO Logit with $\lambda = \lambda^*$

Interpreting the coefficients requires a bit more work, as logit regressions model the log odds of a recession, not the direct probability of recession. We can see which inputs have the largest effects on the odds of recession by seeing what happens to the probability of recession when we increase each input by 1 standard deviation. This is equivalent to computing $\exp(\beta SD(X)) - 1$.

Sector	**Variable**	**Change in Odds(Recession) from 1SD increase**
Credit	Moody's Average Corp. Yields	+ 32%
Broad Indices	Aruoba-Diebold-Scotti Business Conditions Index	$-$ 89%
	Chicago Fed National Activity Index	$-$ 11%
Housing	Conf. Board Building Permits Index	$-$ 4%
	US New One Family Houses Sold (Annual Total)	$-$57%
	Primary Mortgage Market Survey Rates	+ 86%
Manufacturing	New Orders to Inventory Ratio	$-$28%
	US Auto Production	$-$17%
Macro	Real M1 YoY	$-$32%
Equities	Conf. Board Stock Price LEI	$-$45%
	Dow Transportation Index	$-$20%
Employment	Initial Jobless Claims	+33%
	State Unemployment Claims	$-$60%
Yield Curve	Conf. Board Interest Rates LEI	+25%
	3s10s	+10%

Table 2: Marginal Effects: LASSO Logit with $\lambda = \lambda^*$

The signs and magnitudes of coefficients are all intuitive (keep in mind that a 1SD increase for some inputs would be quite large). (The coefficient on State Unemployment Claims is negative because higher values of (50 - OUST#NEG Index) mean fewer states have negative monthly changes in employment.)

4 Comparing Models

How accurate is our firm's existing model vs. the LASSO? One measure is the confusion matrix, which reports Type I errors (recession "false alarms") and Type II errors ("failure to warn" of actual recessions). It shows that the LASSO estimation far outperforms our existing model.

Model	False Alarms	Failure to Warn	Total Misclassification Rate
VP Recession Diffusion > 10	1 (0.23%)	28 (6.54%)	6.78%
VP Recession Diffusion > 8	4 (0.93%)	25 (5.84%)	6.77%
VP Recession Diffusion > 5	10 (2.33%)	12 (2.80%)	5.14%
Piger	0	21 (4.91%)	4.91%
Naive Logit	2 (0.47%)	5 (1.17%)	1.64%
Lasso	0	3 (0.07%)	0.07%

Table 3: Confusion Matrix

How about a naive model? Select the 5 inputs that have the highest absolute correlation with the incidence of recessions – transformations of Initial Jobless Claims, State Unemployment Claims, the ADS Business Conditions Index, and the Philadelphia Fed Diffusion Index have upwards of 0.7 correlation with recessions. Now fit a logit with these five inputs on the entire sample (a logit with the top 15 correlates of recession was too large to converge).

- In statistics terms, the naive 5-input logit explains 87% of the null deviance, where the lasso explains 99% of the null deviance, so the lasso is a significantly better fit. This is akin to saying that we go from explaining 87 to 99% of variation in the data.

- The naive logit also misclassifies 1.64% of months, up from the lasso misclassification rate of 0.07%.

Which months did the lasso get wrong? July 1981, July 1990, and December 2007: the very first months of each corresponding recession. This is good news – it means the model is predicting recessions accurately 100% of the time by their second month, long before most analysts would have the confidence to cry "recession" in real time.

5 Would LASSO Have Predicted the Great Recession in Real-Time?

Yes. I partitioned the data in to a training set, spanning from March 1980 to February 2005, and a test set, spanning from March 2005 to December 2015. Next, I performed internal cross-validation on the training set to determine the penalty size that minimized misclassification error *within the training set*. This optimal penalty size, in turn, implied a set of logit model coefficients. Using these coefficients, we can make in-sample predictions on the training data, shown in blue. These are 99.3% accurate. We can also make **out-of-sample** predictions on the test data, shown in red. These are 95.38% accurate. From March 2005 to December 2015, there were three false recession calls and four failures to call an existing recession, so the total misclassification rate was $6/130$ months, or about 4.62%.

Commentators arguing that Recession 2008 was fundamentally different must have been missing something. The high out-of-sample accuracy implies that in fact, there was no big shift in the data-generating process after 2007.

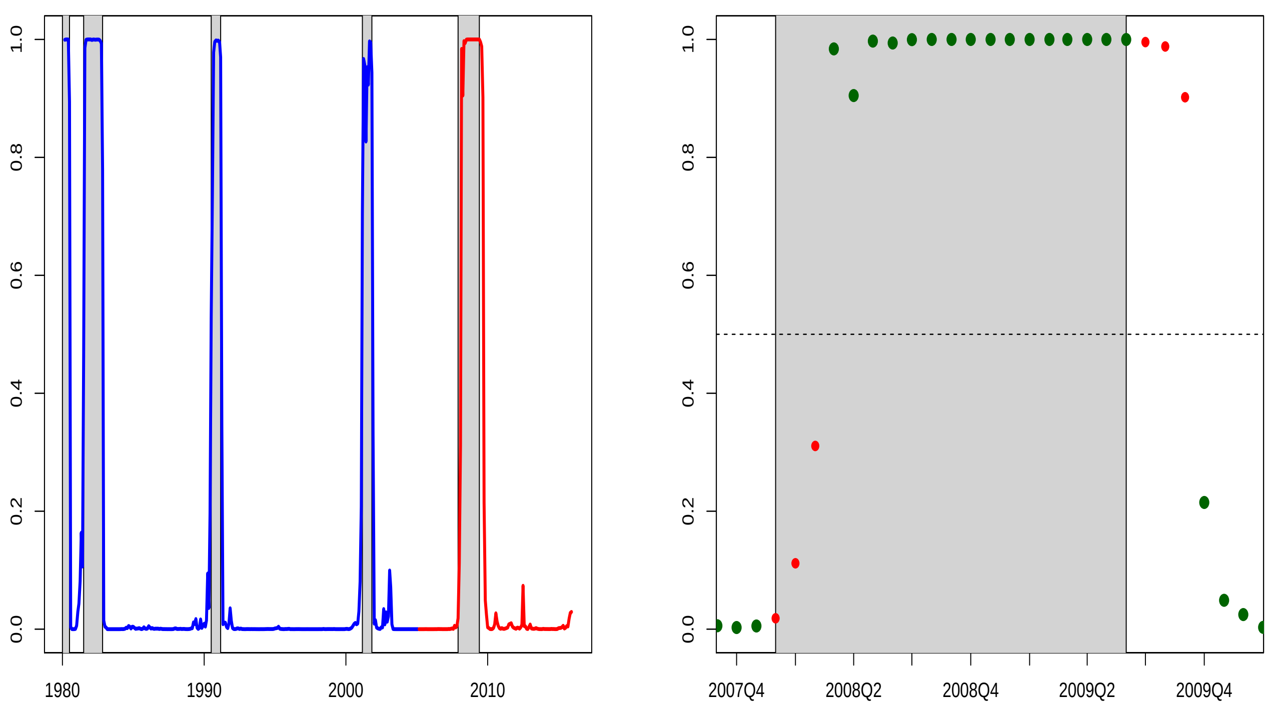


Figure 1: **Out-of-sample Recession Forecasts**: The left panel shows the in-sample (blue) and out-of-sample (red) monthly predicted recession probabilities from the LASSO logit. The righthand panel zooms in upon these monthly predictions during the Great Recession, with accurate forecasts in green and inaccurate forecasts in red.

	Inputs	BBG Tickers
Consumer Expectations	Michigan Consumer Sentiment Index	CONSSENT Index
	Conf. Board Consumer Expectations LEI	LEI CEXP Index
Corporate Credit	Moody's Average Corp. Yields	MOODCAVG Index
	Moody's BAA Spreads	MOODCBAA Index, USGG10YR Index, MOODCAAA Index
Broad Indices	Aruoba-Diebold-Scotti Business Conditions Index	ADS BCI Index
	Chicago Fed National Activity Index	CFNAI Index
	Classification Orders Total Index	COI TOTL Index
	Conf. Board Leading Credit Index	LEI LCI Index
	Conf. Board LEI	LEI YOY Index
	Philadelphia Fed Diffusion Index	OUSTDIFF Index
	Survey of Professional Forecasters Anxious Index	PHFFANX0 Index
	S&P 500 Financials Sector Index	S5FINL Index
Housing	Conf. Board Building Permits Index	LEI BP Index
	New One Family Houses For Sale	NHSLNFS Index
	US New One Family Houses Sold (Annual Total)	NHLSTOT Index
	Primary Mortgage Market Survey Rates	NMCMFUS Index, USGG10YR Index
Manufacturing	New Orders to Inventory Ratio	NAPMNEWO Index, NAPMINV Index
	PMI	NAPMPMI Index
	CRB Raw Materials Index	CRB RIND Index
	JoC ECRI Industrial Price Index	ECRSUSCP Index
	US Auto Production	IPVPTRMH Index
	Conf. Board Consumer Goods LEI	LEI NWCN Index
Macro	Oil Price (WTI)	USCRWTIC Index
	REER	DXY Index
	GDP growth	GDP CYOY Index
	Conf. Board M2 LEI	LEI M2 Index
	Real M1 YoY	M1% YOY Index, CPI YOY Index
Equities	S&P Returns	SPX Index
	Conf. Board Stock Price LEI	LEI STKP Index
	Stocks-Bonds RSI	SPX Index, USGG10YR Index
	DJ Transportation Index	TRAN Index
Employment	Initial Jobless Claims	INJCJC4 Index
	Conf. Board Average Workweek LEI	LEI AVGW Index
	Conf. Board Hours Worked LEI	LEI WKIJ Index
	Total Non-Farm Payrolls	NFPT Index
	State Unemployment Claims	OUST#NEG Index
	US Non-Farm Employees Temporary Help Services	USESTEMP Index
Yield Curve	High Yield Spreads	DLJHYTW Index, USGG10YR Index
	Conf. Board Interest Rates LEI	LEI IRTE Index
	10s	USGG10YR Index
	3s10s	USGG3M Index
	5s10s	USGG5YR Index

Table 4: Recession Model Inputs