Nateé & Dmitry explore:

### What's happening to the small banks?

An analysis of the shrinking US bank market



#### Dramatic decline in the number of de novo banks



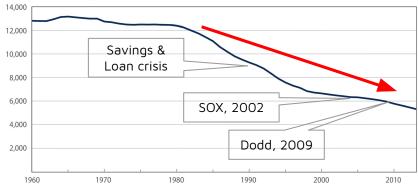
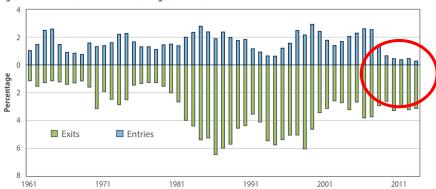


Figure 2: Bank Entries and Exits as Percentages of Total Banks



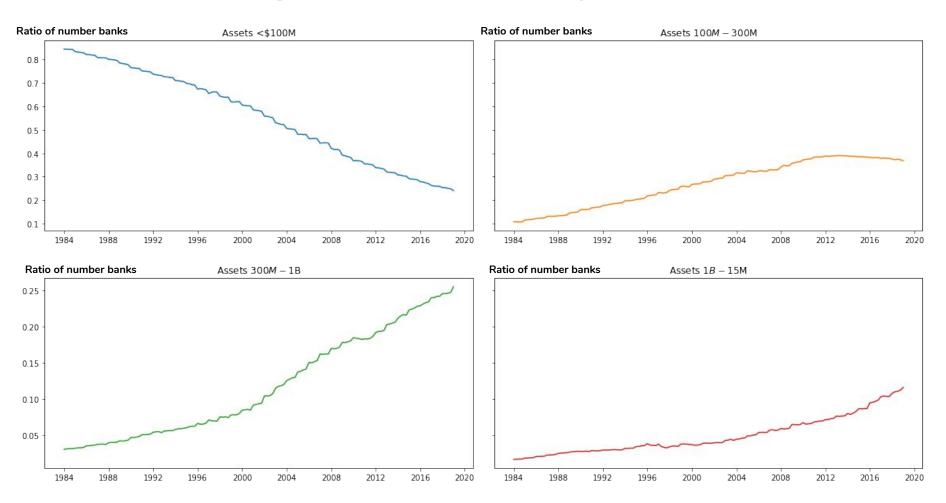
Although many banks failed during the crisis and its aftermath, this decline was driven largely by a lack of new banks.

The number of newly formed banks (called de novo banks) has fallen sharply since 2010. In 2012, there were no de novos, and in 2013 there was only one: Bank of Bird-in-Hand, formed in Lancaster County, Pa., to serve the Amish community.

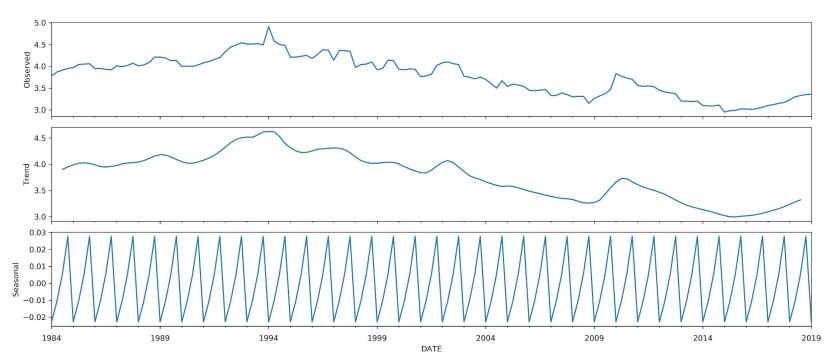
This collapse in new bank entry has no precedent during the past 50 years, and it could have significant economic repercussions. In particular, the decline in new bank entry disproportionately decreases the number of community banks because most new banks start small.

Source:https://www.richmondfed.org/~/media/richmondfedorg/publications/research/economic\_brief/2015/pdf/eb\_15-03.pdf

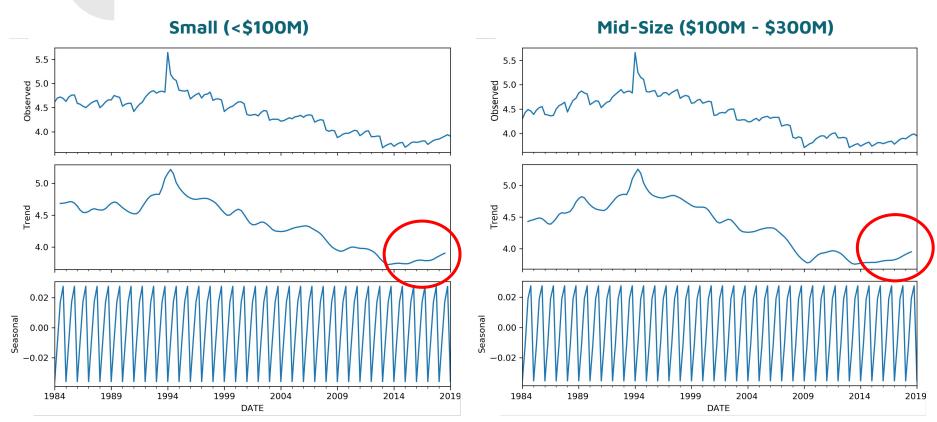
Figure 3: Ratio of number of banks by asset size



### Net Income Seasonal Decomposition for all US Banks



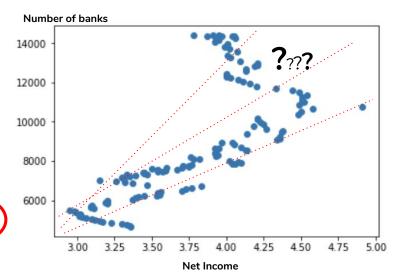
### Net Income Seasonal Decomposition for Small & Mid-size Banks



### Basic linear regression for Number of banks

Number of banks from 1984-2018 and Net Income:  $NUM = b_0 + b_1(NI)$ 

OLS Regression Results											
Dep. Variable: Model: Method: Date: Time: No. Observation Df Residuals: Df Model: Covariance Type	ıs:	Least Squa ed, 31 Jul 2 09:34	OLS 7 7 7 7 7 7 7 7 7 7 7 7 7 7 7 7 7 7 7	Adj. F-sta Prob	ared: R-squared: atistic: (F-statistic Likelihood:	):	0.525 0.521 153.4 3.31e-24 -1273.4 2551. 2557.				
	coef	std err		===== t	P> t	[0.025	0.975]				
	17.0984 53.2461	1460.536 383.766	-6. 12.		0.000	-1.19e+04 3994.473	-6159.360 5512.019				
Omnibus: Prob(Omnibus): Skew: Kurtosis:		0. 1.	000 032	Jarqı Prob	in-Watson: ie-Bera (JB): (JB): . No.		0.058 25.308 3.10e-06 34.6				



#### Multivariate linear regression for Net Income of the banks

Net Income in 1990s and now NI =  $b_0 + b_1(ROA) + b_2(ROE) + B_3(LLR) + b_4(NPL)$ 

OLS Regression Results

OLS Regression Results

Dep. Variable: Model: Method: Date: Time: No. Observations Df Residuals: Df Model:			S Adj. s F-sta 9 Prob	ared: R-squared: tistic: (F-statistic) ikelihood:	:	0.581 0.493 6.590 0.00168 37.199 -64.40 -58.51	Dep. Variabl Model: Method: Date: Time: No. Observat Df Residuals Df Model:	W		S Adj. s F-sta 9 Prob	ared: R-squared: tistic: (F-statisti ikelihood:	c):	0.763 0.713 15.26 9.60e-06 48.042 -86.08 -80.19
Covariance Type:		nonrobus	t				Covariance I	Type:	nonrobus	t			
=========	coef	std err	t	P> t	[0.025	0.975]	========	coef	std err	t	P> t	[0.025	0.975]
US100ROA 4 US100ROE -0 US100LLRTL -0	.2453 .0582 .3598 .3098	0.255 1.403 0.129 0.106 0.039	20.558 2.892 -2.798 -2.922 -0.805	0.000 0.009 0.011 0.009 0.431	4.711 1.121 -0.629 -0.532 -0.114	5.779 6.995 -0.091 -0.088 0.051	const US100ROA US100ROE US100LLRTL US100NPTL	4.4632 0.5342 -0.0166 -0.9968 0.3690	0.782 0.584 0.073 0.645 0.243	5.710 0.915 -0.227 -1.546 1.518	0.000 0.372 0.823 0.139 0.145	2.827 -0.688 -0.170 -2.347 -0.140	6.099 1.756 0.137 0.353 0.878
Omnibus: Prob(Omnibus): Skew: Kurtosis:		0.08 0.96 0.07 2.75	0 Jarqu 3 Prob(	,		1.275 0.081 0.960 1.18e+03	Omnibus: Prob(Omnibus Skew: Kurtosis:	;):	1.23 0.54 -0.42	0 Jarqu 0 Prob(	3000 CO. 100	:	1.296 1.148 0.563

## Removing parameters to model Net Income today

Today's small banks model:  $NI = b_0 + b_1(ROA) + b_2(ROE) + B_3(LLR) + b_4(NPL)$ 

OLS Regression Results							OLS Regression Results						
Dep. Variabl Model: Method: Date: Time: No. Observat Df Residuals Df Model: Covariance I	We ions:	US100NIM OLS Least Squares ed, 31 Jul 2019 09:36:07 24 19 4 nonrobust	Adj. F-sta Prob Log-I AIC: BIC:	uared: R-squared: atistic: (F-statistic) Likelihood:	:	0.71 15.2 9.60e-0	Time:	Tu ons:	US100NIM OLS Least Squares ne, 30 Jul 2019 15:10:59 24 21 2 nonrobust	Adj. F F-stat Prob (	ared: R-squared: cistic: (F-statistic kelihood:	):	0.736 0.711 29.30 8.38e-07 44.676 -83.35 -79.82
	coef	std err	t	P> t	[0.025	0.975		coef	std err	 t	P> t	[0.025	0.975]
CONST US100ROA US100ROE US100LLRTL US100NPTL	4.4632 0.5342 -0.0166 -0.9968 0.3690		5.710 0.915 -0.227 -1.546 1.518	0.000 0.372 0.823 0.139 0.145	2.827 -0.688 -0.170 -2.347 -0.140	0.13 0.35 0.87		3.9619 1.1794 -0.7241	0.238 0.219	16.675 5.378 -6.550	0.000 0.000 0.000	3.468 0.723 -0.954	4.456 1.636 -0.494
Omnibus 1 224 Dumbin Matson 1 20					Omnibus:		9.318	Durbir	n-Watson:		0.796		

Jarque-Bera (JB):

Prob(JB):

Prob(Omnibus):

Prob(Omnibus):

Jarque-Bera (JB):

0.0261

Prob(JB):

# Penalized estimation with Ridge and Lasso algorithms

```
v = df.SmallBanksNum
x = df[['US100NIM', 'US100ROA', 'US100ROE', 'US100LLRTL', 'US100NPTL']]
# Perform test train split
X train , X test, y train, y test = train test split(x, y, test size=0.3, random state=12)
# Note how in scikit learn, the regularization parameter is denoted by alpha (and not lambda)
ridge = Ridge(alpha=0.1)
ridge.fit(X train, y train)
print('Ridge parameter coefficients:', ridge.coef )
print('Training r^2:', ridge.score(X train, y train))
print('Testing r^2:', ridge.score(X test, y test))
print('Training MSE:', mean squared error(y train, ridge.predict(X train)))
print('Testing MSE:', mean squared error(y test, ridge.predict(X test)))
lasso = Lasso(alpha=0.1)
lasso.fit(X train, y train)
print('Lasso parameter coefficients:', lasso.coef )
print('Training r^2:', lasso.score(X train, y train))
print('Testing r^2:', lasso.score(X test, y test))
print('Training MSE:', mean squared error(y train, lasso.predict(X train)))
print('Testing MSE:', mean squared error(y test, lasso.predict(X test)))
Ridge parameter coefficients: [-0.12505165 0.22573377 -0.03018296 0.0744907
                                                                               -0.036782681
Training r^2: 0.9561552215149846
Testing r^2: 0.890746063803487
Training MSE: 0.00035583514725787976
Testing MSE: 0.0011686933813400183
Lasso parameter coefficients: [-0.
Training r^2: 0.3245168726875955
Testing r^2: 0.0794844482073205
Training MSE: 0.005482081250782666
Testing MSE: 0.009846788777162566
```

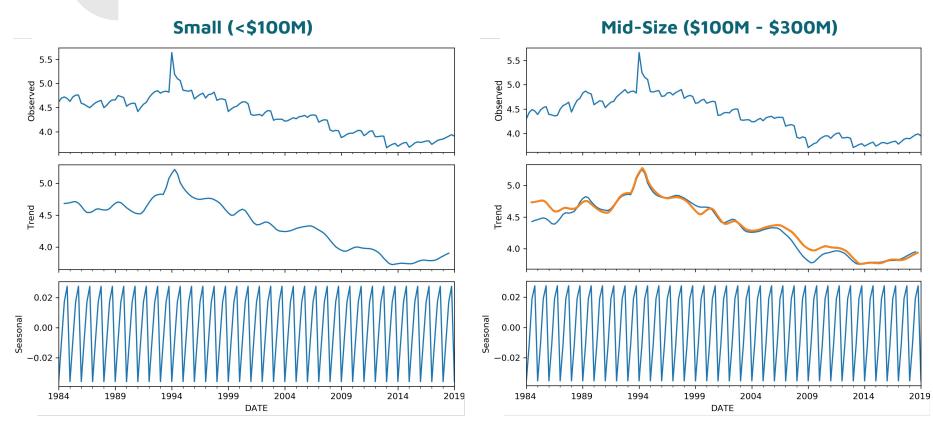
Regressing proportion of small banks on all the features of small banks: NIM, ROA, ROE, LLR, and NPL

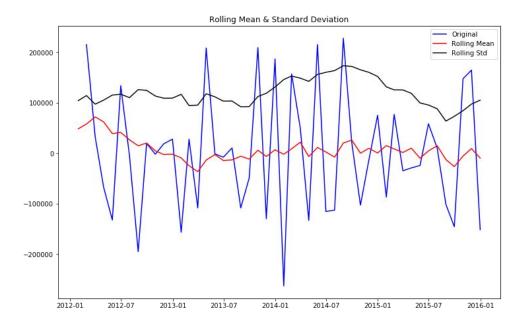
Findings are not conclusive: Ridge vs. Lasso

Further research: drop net income from and also consider adding asset size or non-interest expense to account for costs of compliance.

### So maybe open a small bank...?

### Net Income Seasonal Decomposition for Small & Mid-size Banks





Results	of	Dickey-Fuller	Test:
Test Statist	ic	-7.95627	5e+00
p-value		3.03137	74e-12
#Lags Used	d	1.00000	0e+00
# of Observ	ations Use	ed 5.70000	0e+01
Critical Valu	ue (1%)	-3.55067	0e+00
Critical Valu	ıe (5%)	-2.91376	6e+00
Critical Valu	ue (10%)	-2.59462	4e+00

