“The Financial Transmission of a Climate Shock: El Niño and US Banks,” by Filippo De Marco and Nicola Limodio

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Discussion

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Purpose of the Paper

- Study of how climate shocks (El Niño as instrument) are transmitted through the financial system (1979–2019).
- Empirical strategy uses climate data on the geographic incidence of El Niño effects and bank lending and balance sheet data at the county and bank-level.
  - Identifying variation is defined by the years when El Niño is particularly intense.
  - These serious El Niño effects are treated as quasi-random heterogenous shocks to temperature.
  - Indentification strategy supports causal evidence for the transmission of climate shocks to the supply of bank lending.

El Niño Measures

- Use NOAA's Multivariate El Niño Index (MEI.v2) from January to May to define indicator measures:
  - **Positive County-level exposure** – "bit" higher-than-average level and volatility of temperature (e.g. Northern U.S. dryer)
  - **Negative County-level exposure** – "bit" lower than average level and volatility of temperatures (e.g. Southern and gulf coast cooler)
  - **5 Strong El Niño events** where average is above a threshold of more than 1 degree Celsius **(1987, 2016, 1992, 1998, 1983).**
  - **Bank branch exposures:** 1) if bank branch's county-level exposures are positive; 0) if bank branch's county unaffected; -1) if bank-branch's county-level exposures are negative.
- Also, provide robustness tests on continuous MEI.v2 measure.

Temperature Measures

- U.S. Historical Climatology Network NOAA
  - Daily measures from 1219 weather station data.
  - Aggregate data to the county-year level for 3,108 counties.
  - May induce considerable spatial autocorrelation and grid unit is not standardized.
- Might consider **Gridmet data**
  - Daily high-spatial resolution (~4-km, 1/24th degree) surface meteorological data covering the contiguous US from 1979 – yesterday.
  - Blends spatial attributes of gridded climate data from PRISM with desirable temporal attributes from regional reanalysis (NLDAS-2).
  - For validation measures see Abatzoglou (2013).

County-level Empirical Strategy

- Validate the county-level effects of El Niño on temperature.
- Validate county-level positive/negative El Niño effects on bank lending:
  - Lending measured as HMDA county-level bank residential lending:
    - **One-to-four family loans (purchase, refi, and/or improvement)?**
    - **Multifamily loans (purchase, refi, and/or improvement)?**
    - **How to define a bank over the sample period?**
  - Finding:
    - Counties with positive El Niño treatments experience a large decline in lending (15%)
    - Counties with negative El Niño treatments exhibited increased lending.

Bank-level Empirical Strategy

- Bank Exposure:

$$\sum_c Exposure_c \times Share_c$$

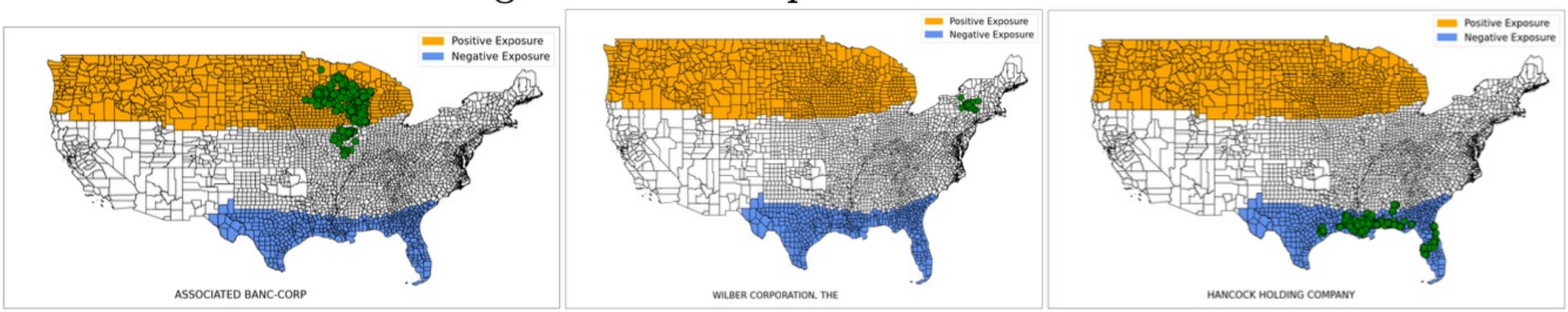
  - $Exposure_c = 1, 0, -1.$
  - $Share_c$ = HMDA lending that bank **originates (not holds in balance sheet)** in county to total HMDA origination in county.
  - Create a measure of bank exposure, lending share, and locate bank branches relative to the county-level climate map.

Identification

- Time series variation: hard to predict
  - "the accuracy of these models in predicting the onset of an El Niño episode is fairly high, the intensity is much more difficult to predict due to random atmospheric disturbances"
- Cross-sectional variation:
  - "scientific evidence allows us to measure the areas that are affected by the climate effects of El Niño and those that are not. It is also possible to know in advance the counties that will experience cooler-than-average or warmer-than-average temperatures."
- **Aggregate to county-level deterministic maps and use indictor variables: positive effect (1); unaffected (0); negative effect (-1); 5 strong El Niño events.**

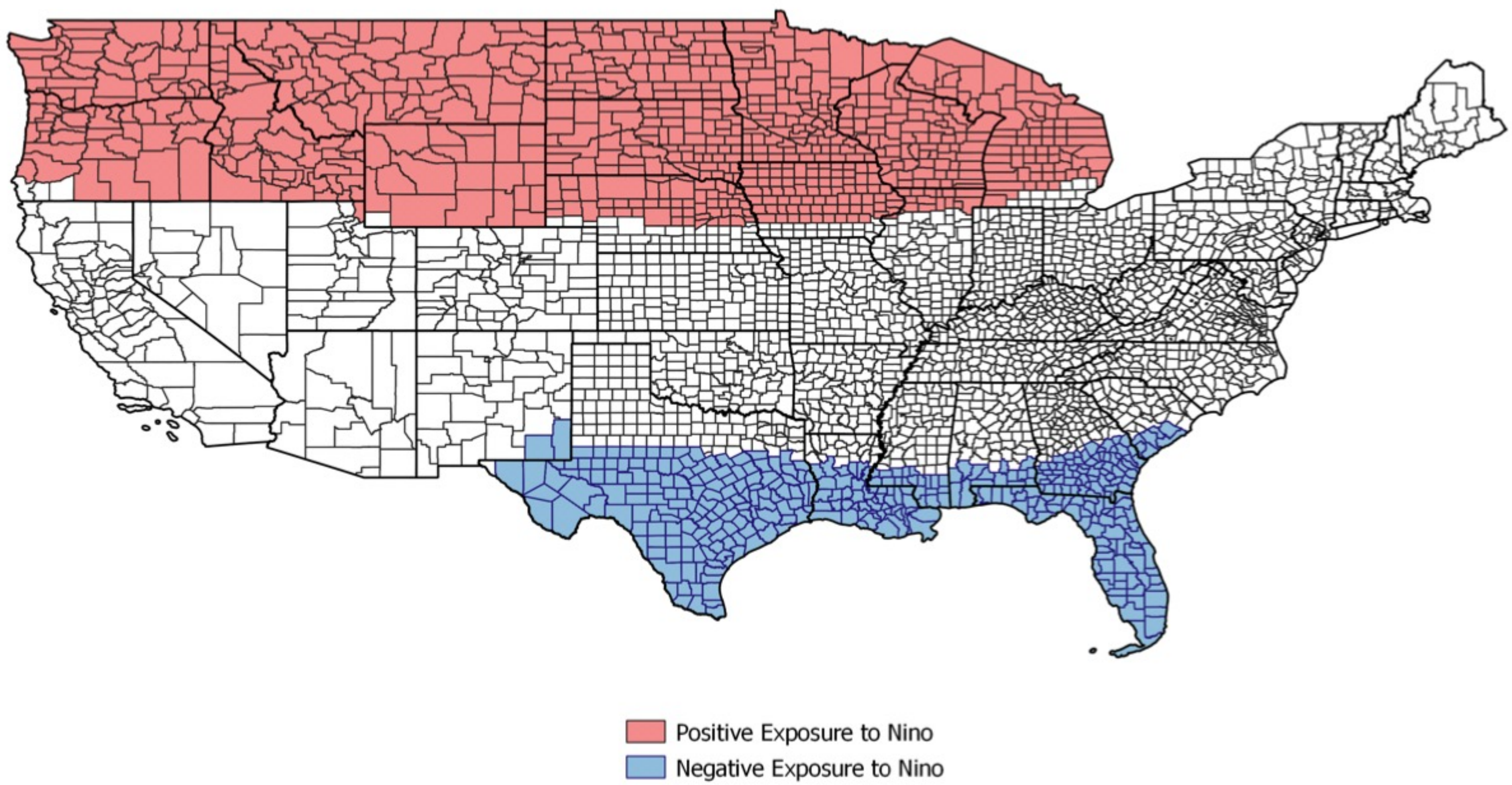
Banking Impact

Figure 4: Bank exposure to El Niño



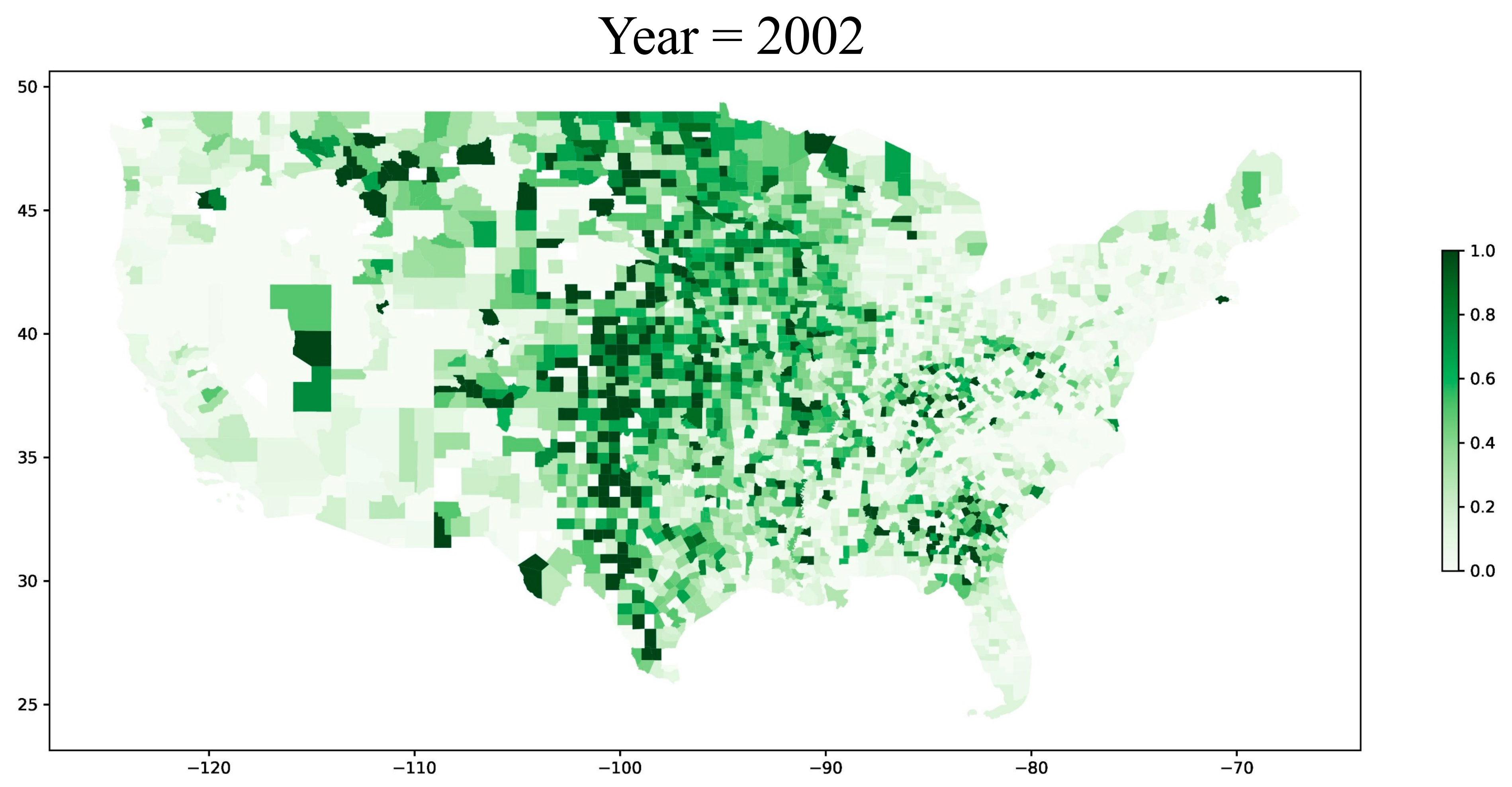
Notes: This figure shows three examples of bank exposure to El Niño. The bank exposure is defined as a weighted sum between the climatic exposure of a county in which the bank operates and the share of HMDA lending that the bank conducts in that county as a share of total. The left panel shows a bank with a highly positive exposure (Associated Bank-Corp), the middle figure shows a bank with a zero exposure (The Wilber Corporation) and the right figure presents a bank with a highly negative exposure (Hancock Holding Company).

Heterogeneity in County Sizes (e.g. Western counties are systematically larger than Eastern, Midwestern, and Southern counties)



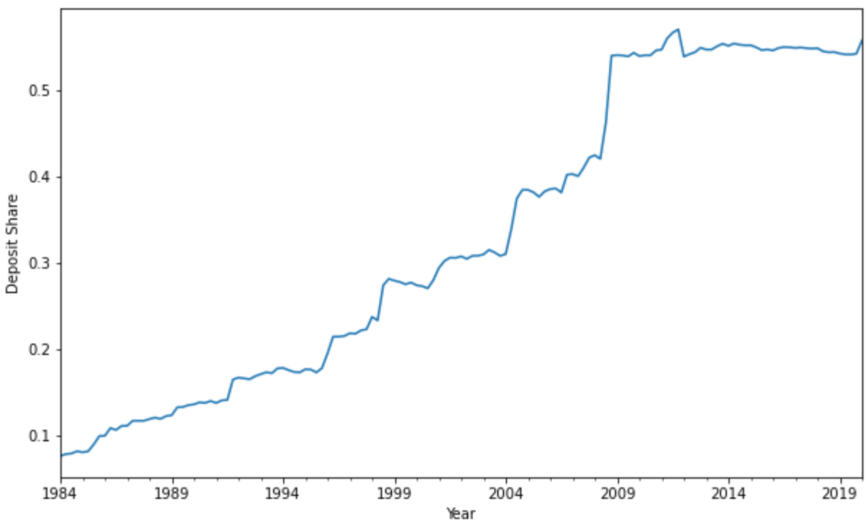
Census tract: Would standardize to homogeneous grid unit

Systematic heterogeneity in county-level small-bank branch concentration (higher in Northern and Midwestern, and Texas/Florida counties)



Largest 19 Banks Dominate (Deposit holdings and effects on sample)

Example: Time series of Top 19 Deposit shares



Evidence in Summary Stats

Panel D - Bank-Level Variables

$Lending_{bt}$	85,887	11.76	1.526	-4.605	20.49
$Deposits_{bt}$	85,887	12.15	1.394	0	21.01
$Assets_{bt}$	85,887	12.32	1.430	7.947	21.50
$RE\ Lending_{bt}$	85,802	11.41	1.571	0	20.00
$CI\ Lending_{bt}$	85,540	9.791	1.685	0	19.42
$Ind.\ Lending_{bt}$	85,536	8.844	1.704	0	18.99
ROE_{bt}	85,887	0.117	5.603	-1,638	27.49
NIM_{bt}	85,886	0.0563	0.0782	-0.397	4.654
$Interest\ Income_{bt}$	85,880	8.725	1.378	1.099	17.36

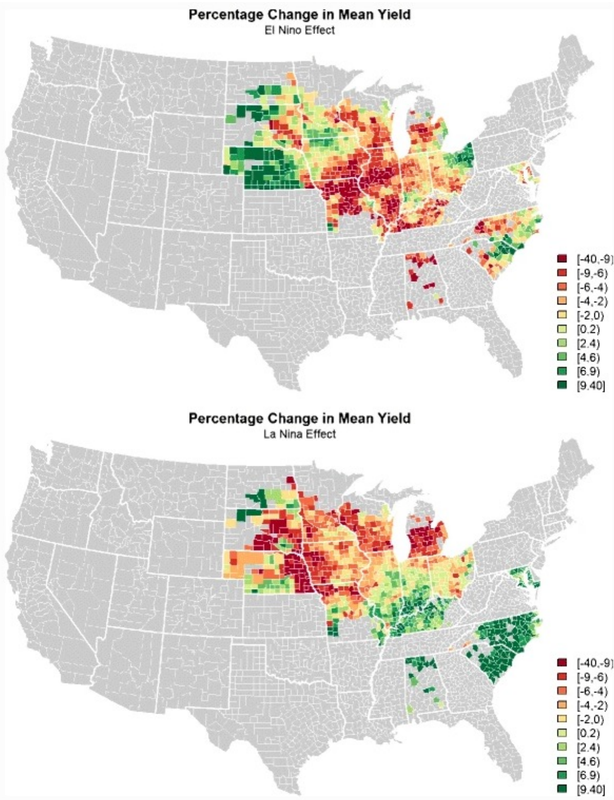
Panel D - Bank-Level Variables selected by LASSO

$Physical\ Capital_b$	6,234	0.00232	0.00108	0.0000179	0.0298
$Leverage_b$	6,234	0.840	0.0651	0.0932	0.972
$Unused\ Commitments_b$	6,233	0.0155	0.0191	0	0.237
$Operating\ Capital_b$	6,234	0.00578	0.00548	0.000717	0.347
$Dividends_b$	6,234	0.00214	0.00242	0	0.0533
ROA_b	6,234	0.0123	0.0282	-0.163	0.773

Source: Call Reports

The El Niño climate risk literature focuses on shocks to agricultural production

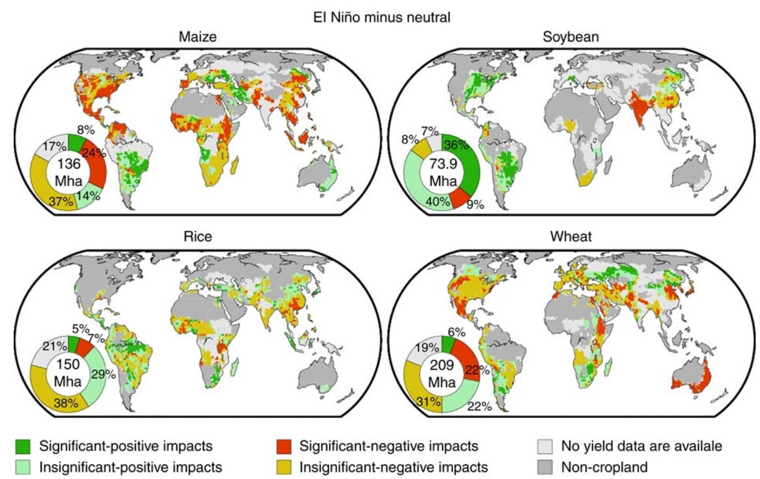
Example: U.S. Corn Yields



Spatial representation of the ENSO impacts on mean yields. Thresholds are chosen so that each band around zero contains roughly 20 % of observations

Tack and Ubilava, *Climate Change*, 2013.

Other Crop Yields in U.S.

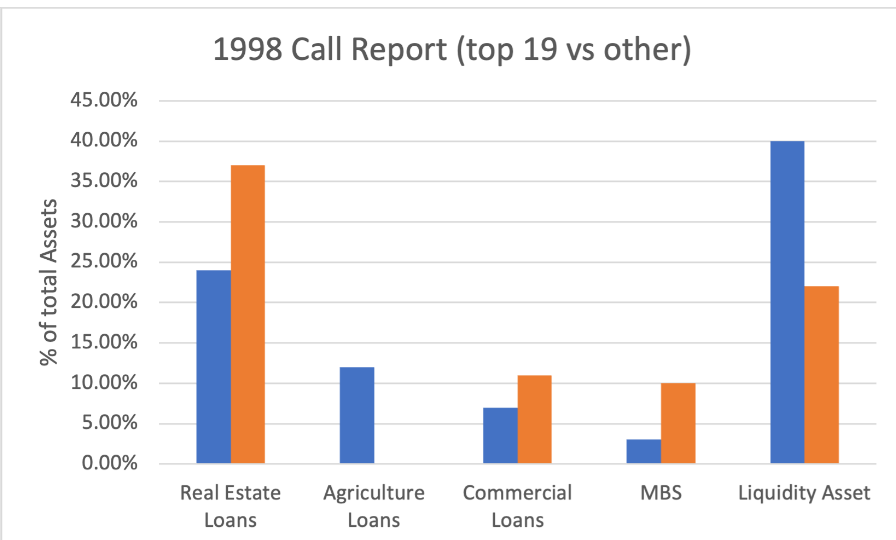


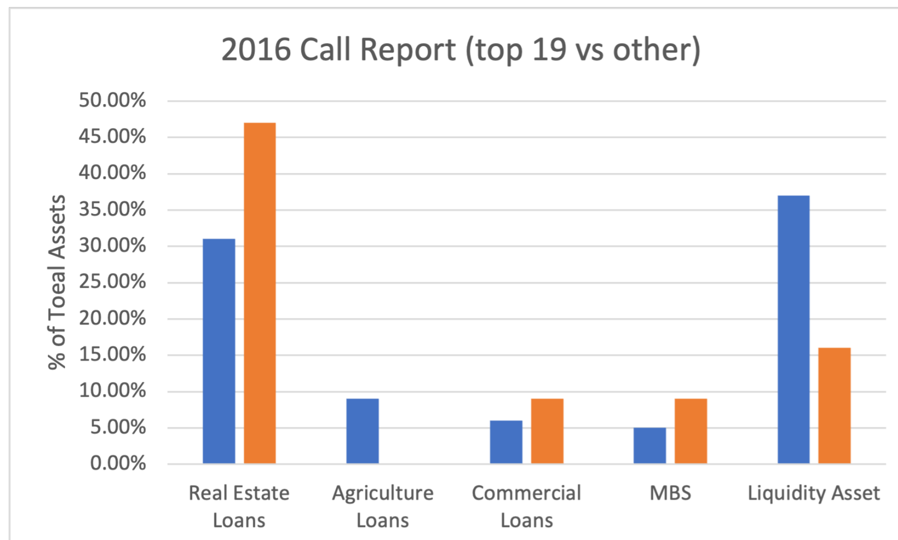
Oshichika, Luo, Challinor, Sakurai, Yokozawa, Sakuma, Brown & Yamagatan, *Nature Communication*, 2013

Small Banks are Important Agricultural Lenders

Orange - banks in highest asset decile, Blue - banks in lowest asset decile, 1998

Orange - banks in highest asset decile, Blue - banks in lowest asset decile, 2016





Source: Call Reports

Concerns about Staggered Treatment Effects

- With just 1 treatment period, results could be due to factors other than the treatment.
  - **Parallel trends** assumption does not hold.
- Much recent empirical research extends the basic DiD design to include multiple time periods and staggered treatment events (see, Goodman-Bacon (2021), de Chaisemartin and D'Haultfœuille (2020), Borusyak, Jaravel, and Spiess (2022), Sun and Abraham (2021), Strezhnev (2018))
- Different units get treated at different times.
  - » Coefficient is interpreted as **Average Treatment Effect on the Treated (ATT).**
- **Must assume:** Treatment effect is homogeneous and occurs instantaneously and permanently.

What goes wrong?

- In TWFE regression, units whose treatment status varies serve as controls for units whose treatment status does not.
  - Already-treated units serve as controls for newly treated units.
- While we may think of some observations as being treatment and some control, OLS doesn't care about our labels.
- Goodman-Bacon (2021) show that
  - TWFE estimator is a weighted average of all possible 2×2 DD estimators comparing timing groups to each other.
  - Weights on the 2×2 DDs are proportional to timing group sizes and variance of the treatment dummy in each pair.
    - » Highest for units treated in the middle of the panel.
    - » Weights may even be negative if treatment effects vary over time.

LASSO (Least Absolute Shrinkage and Selection Operator)

- Machine learning analysis of the correspondence of bank balance sheet and climate resilience.
- Use LASSO to set to zero the balance sheet regressors that contribute little to the fit.
- Use two step estimator, corrects for omitted variable bias

$$\underbrace{y_{bt}}_{\text{Log of loans}} = \mathbf{x}_b' \times El\ Ni\tilde{n}o_t\beta + \varepsilon_{bt}$$

$$Exposure_b \times El\ Ni\tilde{n}o_t = \mathbf{x}_b' \times El\ Ni\tilde{n}o_t\beta + \kappa_{bt}$$

- Recommendation: Add share of agricultural loans.

Robustness

- Continuous measures of El Niño – do not work well.
- La Niña effects
- Precipitation
- Alternative clustering

Conclusions

- Novel and exhaustive empircal analysis testing for the transmission channel from a climate shock (El Niño) to the U.S. banking system.
  - Strongest "causal" transmission evidence (indicator measures) of "strong El Niño" effects (workhorse climate measure) on residential lending.
  - Other "fine-tuning" robustness checks would be helpful (census tract measurement, controls for large and small banks, controls for local agricultural outcomes)
- Very nice application of LASSO – harnesses the power of maximum likelihood while retaining out-of-sample predictive performance.