# The Role of Financial Connectedness in Predicting Crises


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|---|---|
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*The views expressed herein are those of the authors and should not be attributed to the IMF or IMF

# Goal

- **Assess whether <u>financial connectedness</u> is a strong predictor of financial crises.**
  - Type of crises: Systemic banking crises
  - Empirical tests: Global banking network (GBN)
  - **Provide an Early Warning System for banking crises using a mix of**:
  - Data mining models ("classification algorithm")
    - Leverage methods already proven successful in many different applications (manufacturing, terrorist attacks, etc.)
  - Standard regression analysis (probit/logit)
    - Drawing on larger 'early warning systems' literature, especially for currency crises in emerging market countries

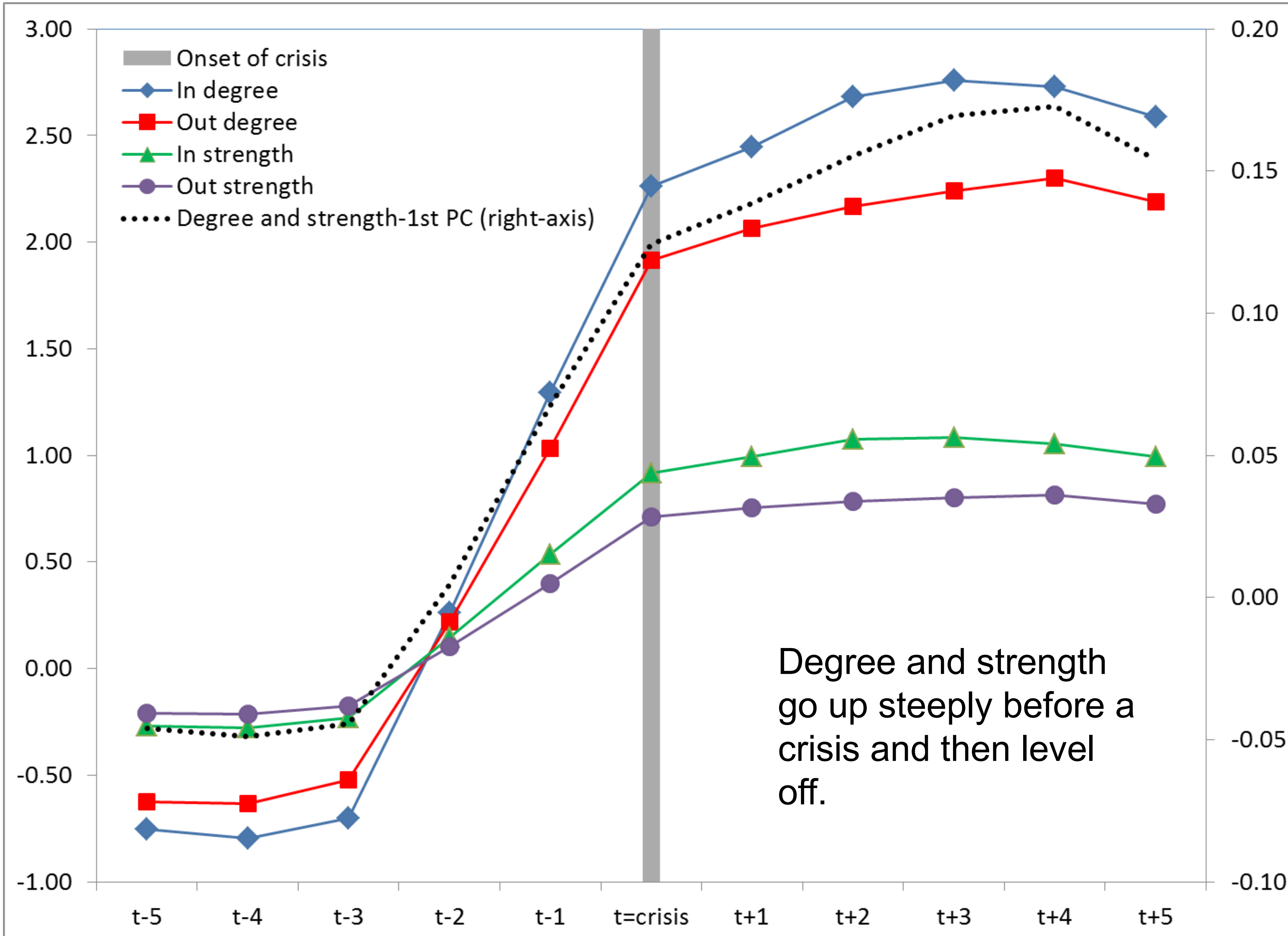
# Key Results

- **The paper's key results are summarized in the next 3 charts.**

- **These depict the evolution of network indicators conditional on country-specific factors and global shocks before and after the onset of systemic banking crises**

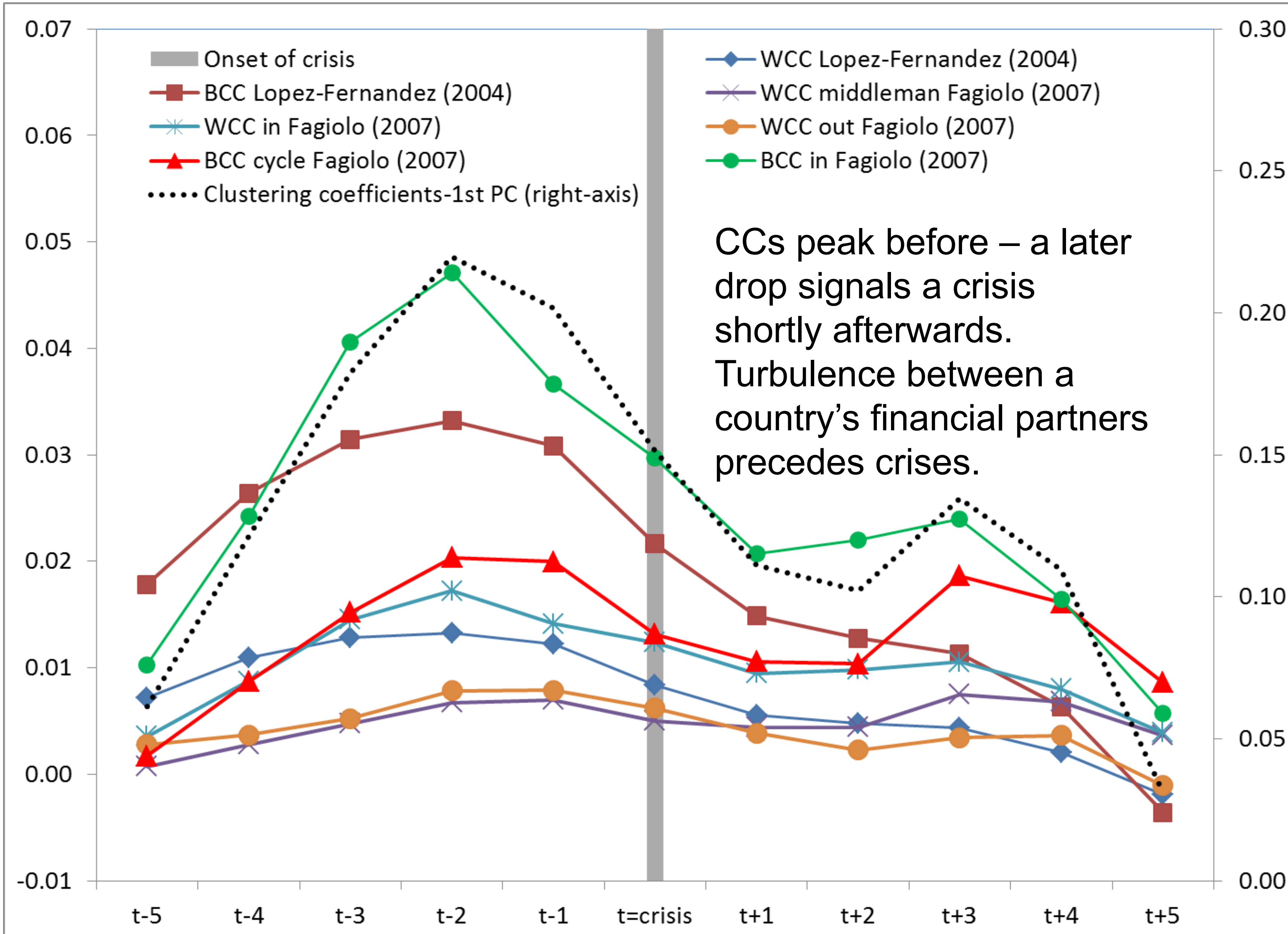
- We have removed the correlation of the network indicators with global factors and country-specific unobserved factors by regressing them against a full set of country and year dummies.

# Key Result #1

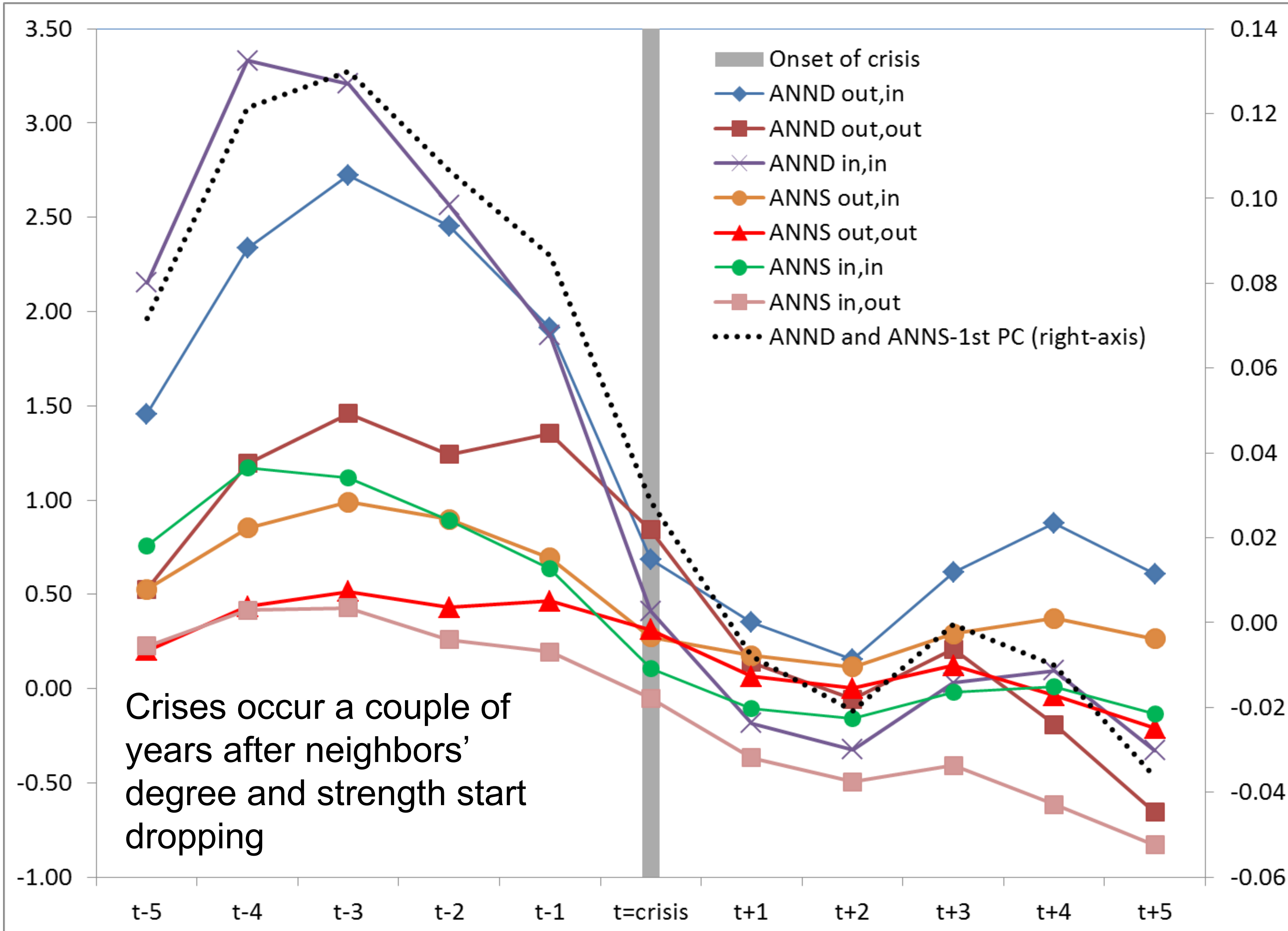


3.00
2.50
2.00
1.50
1.00
0.50
0.00
-0.50
-1.00
0.20
0.15
0.10
0.05
0.00
-0.05
-0.10
Onset of crisis
In degree
Out degree
In strength
Out strength
Degree and strength-1st PC (right-axis)
t-5
t-4
t-3
t-2
t-1
t=crisis
t+1
t+2
t+3
t+4
t+5
Degree and strength go up steeply before a crisis and then level off.

# Key Result #2


0.07
0.06
0.05
0.04
0.03
0.02
0.01
0.00
-0.01
0.30
0.25
0.20
0.15
0.10
0.05
0.00
Onset of crisis
BCC Lopez-Fernandez (2004)
WCC in Fagiolo (2007)
BCC cycle Fagiolo (2007)
Clustering coefficients-1st PC (right-axis)
WCC Lopez-Fernandez (2004)
WCC middleman Fagiolo (2007)
WCC out Fagiolo (2007)
BCC in Fagiolo (2007)
CCs peak before – a later drop signals a crisis shortly afterwards. Turbulence between a country's financial partners precedes crises.
t-5
t-4
t-3
t-2
t-1
t=crisis
t+1
t+2
t+3
t+4
t+5

# Key Result #3



3.50
3.00
2.50
2.00
1.50
1.00
0.50
0.00
-0.50
-1.00
0.14
0.12
0.10
0.08
0.06
0.04
0.02
0.00
-0.02
-0.04
-0.06
t-5
t-4
t-3
t-2
t-1
t=crisis
t+1
t+2
t+3
t+4
t+5
Onset of crisis
ANND out,in
ANND out,out
ANND in,in
ANNS out,in
ANNS out,out
ANNS in,in
ANNS in,out
ANND and ANNS-1st PC (right-axis)
Crises occur a couple of years after neighbors' degree and strength start dropping

***The rest of the talk focuses on the evidence supporting the intuition provided by these results.***

# The Data

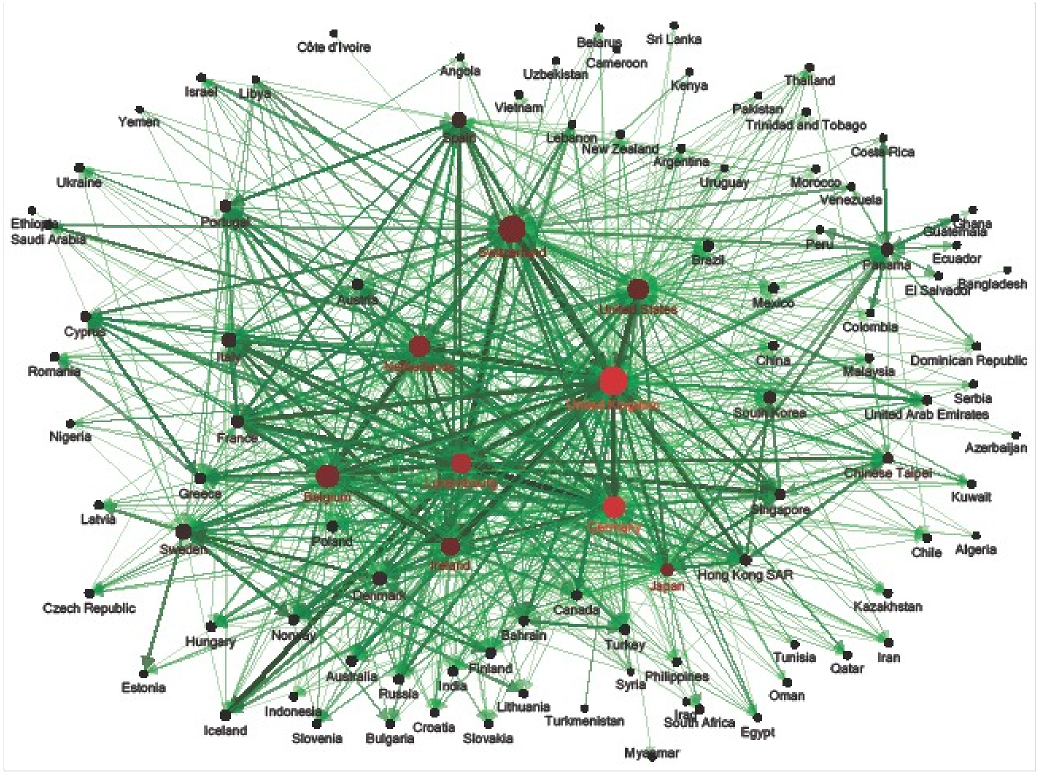
- **BIS locational banking statistics (1978-2010) on cross-border banking system exposures/assets (stocks of claims)**
- **Data represent the claims of banks in BIS reporting countries vis-à-vis borrowers in foreign countries**
  - Exposures include loans, securities and other bank assets
  - **Good coverage of cross-border banking activity**
  - Reporting banks in each reporting country account for more than 90% of total banking assets in that country
  - **Sample: 210 countries**
  - 29 “core” (BIS reporting) countries
  - 181 “periphery” countries
  - **Banking crisis incidence data: Laeven & Valencia (2012)**

# From Data to Network Time Series

Global banking network, 2007

- **We build binary and weighted directed networks for each year**
- **Nodes are countries**
- **Edge (a,b) from country a to b**
  - Exists in our binary network if “a” has non-zero exposure to “b”
  - Edge is weighted by the size of the exposure (log) divided by the log-product of country GDPs.

- **We do not have edges among periphery countries.**



# From Network Time Series to Structured Data

- **We represent the network time series data in matrix format:**

  - Rows correspond to country-year pairs
  - Columns correspond to
    - 1 dependent variable denoting whether a systemic banking crisis occurred or not ("crisis year), 0 otherwise ("tranquil year")
    - 27 explanatory variables denoting network-based measures of connectedness in the GBN (+ lagged levels and growth rates up to 5 years ⇒ 162 variables)
      - centrality measures, clustering coefficients, etc.

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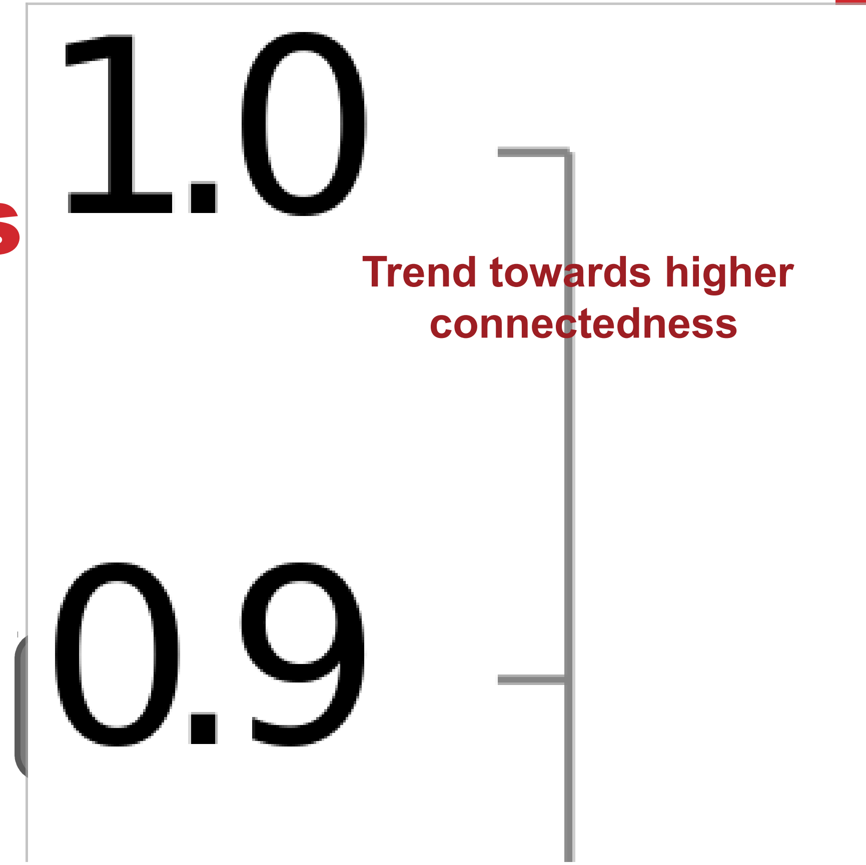
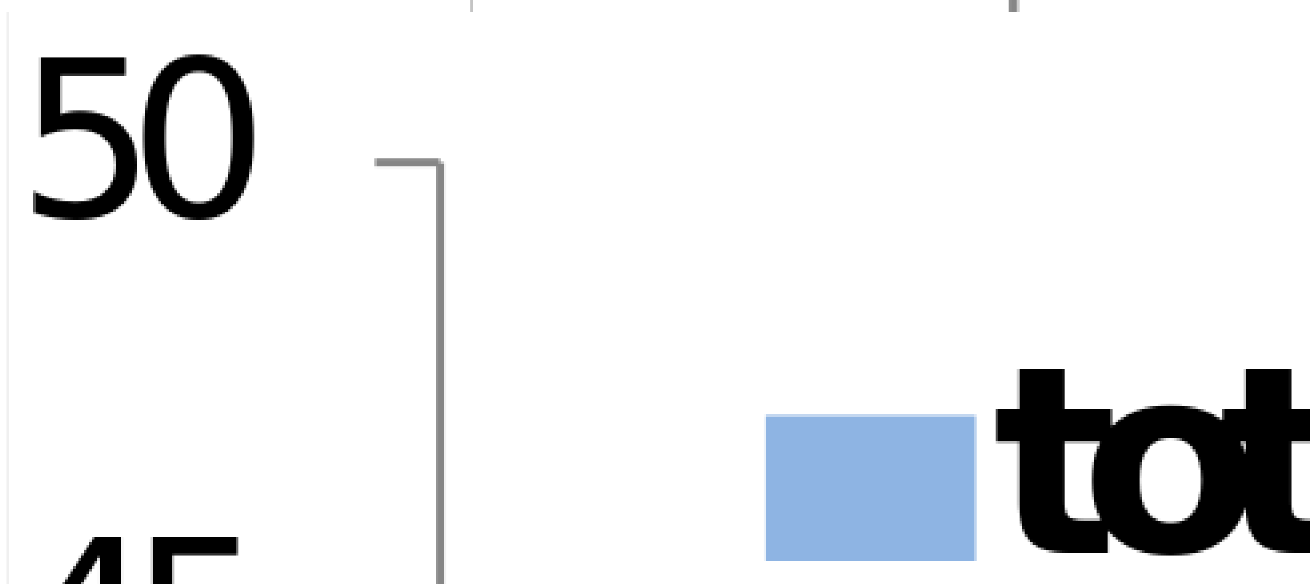
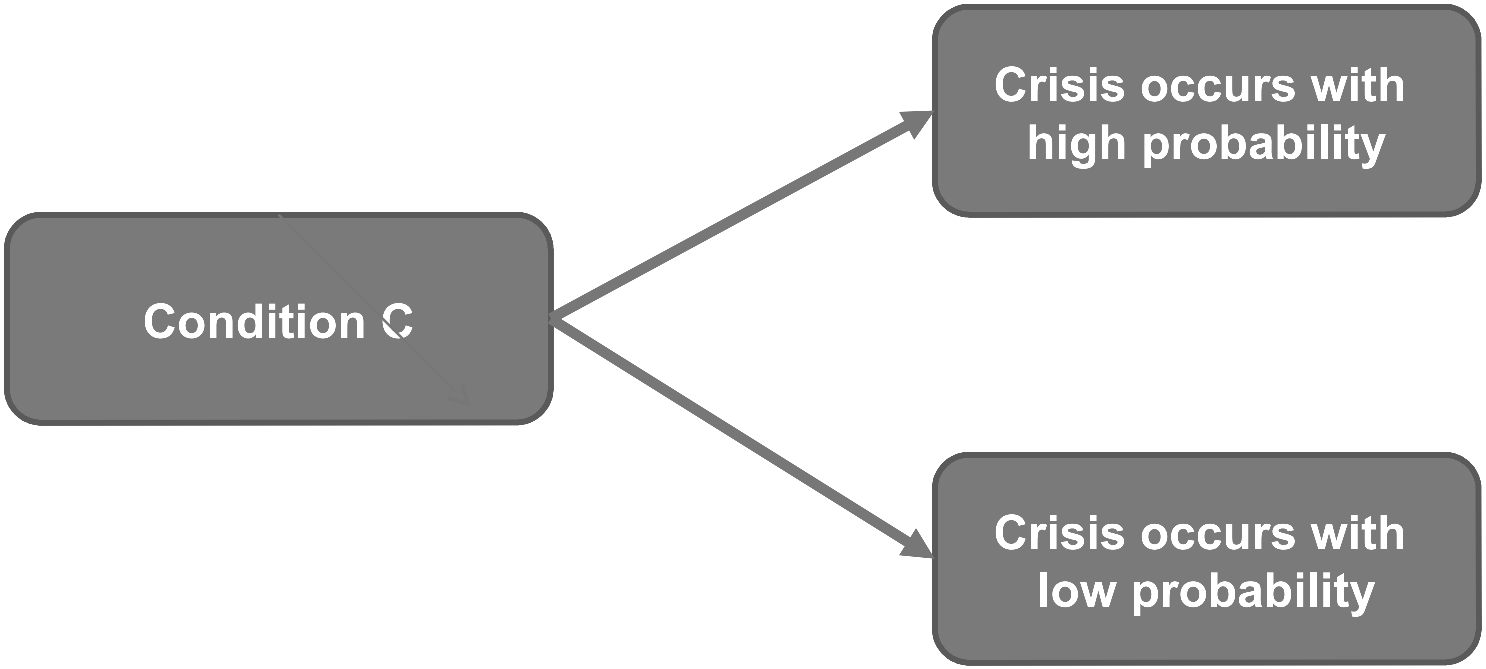
# Connectedness Measures: Examples

- **Degree and strength**
- **Fagiolo's (2007) clustering coefficients:** measures probability that neighbors of a node are connected with each other
- **Lopez-Fernandez (2004) clustering coefficient:** captures effectiveness of connection between neighbors of a node
- **Degree and strength of nearest neighbors (ANND, ANNS)**



# Classification Algorithm




- Find condition C on the network-based measures of connectedness such that:
  **P**(crisis =1 | C) is high

  **P**(crisis = 1| not C) is low

  |crisis = 1 AND C| exceeds a threshold

  |crisis = 0 AND not C| exceeds a threshold

# Classification Algorithm

- **Ran the algorithm on three time periods:**
  - Full period: 1978-2010
  - First- and second-generation ("traditional") crises: 1978-2002
  - Third-generation, advanced economy crises: 2003-2010

- **Evaluated the performance of the algorithm along two dimensions:**
  - Precision $\frac{\#\text{ correctly predicted crises}}{\#\text{ predicted crises}}$ (Max when no "false alarms")
  - Recall $\frac{\#\text{ correctly predicted crises}}{\#\text{ actual crises}}$ (Max when no "missed crises")

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# Results (in-sample)

| Sample | Period | # crises | # predicted crises | Support | Precision | Recall | # sub-rules |
|---|---|---|---|---|---|---|---|
| | | [1] | [2[ | [3] | [4] | [5] | [6] |
| Full | 1978-2010 | 410 | 149 | 136 | 0.91 | 0.33 | 46 |
| Full | 1978-2002 | 330 | 354 | 292 | 0.82 | 0.88 | 297 |
| Full | 2003-2010 | 80 | 57 | 45 | 0.79 | 0.56 | 21 |
| Core | 1978-2010 | 88 | 63 | 58 | 0.92 | 0.66 | 36 |
| Core | 1978-2002 | 46 | 64 | 46 | 0.72 | 1.00 | 202 |
| Core | 2003-2010 | 42 | 25 | 23 | 0.92 | 0.55 | 3 |
| Periphery | 1978-2010 | 322 | 114 | 101 | 0.89 | 0.31 | 31 |
| Periphery | 1978-2002 | 284 | 145 | 133 | 0.92 | 0.47 | 44 |
| Periphery | 2003-2010 | 38 | 43 | 38 | 0.88 | 1.00 | 265 |

Too many rules

# Example of One Specific Rule: All Countries, 1978-2010

When the growth over 3 years in average in-strength of in-neighbor nodes is between 0.12287 and 0.12334, then a crisis will occur.

- If we considered the rules individually, precision was high but recall was low
- So we merged all rules into a “super-rule” by taking the OR of all the individual rules to predict crises
    - Increased recall with no loss of precision

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# Example of One Specific Rule: All Countries, 2003-2010

| Rule | Lower bound | Upper bound |
|---|---|---|
| $GrowthRate(HHI(v), -2)$ | 0.024124534 | 0.043913405 |
| $GrowthRate(BCC^2_{Cycle}(v), -5)$ | -0.253523861 | -0.195630671 |
| $GrowthRate(HHI(v), -5)$ | -0.040088371 | -0.030071167 |
| $GrowthRate(d_v^{in}, -3)$ | 0.005649713 | 0.011494258 |
| $GrowthRate(d_v^{in}, -2)$ | 0.005747121 | 0.007042259 |
| $GrowthRate(d_v^{in}, -2)$ | -0.040000005 | -0.024096381 |
| $WCC^2_{Out}(v)$ | 0.095180728 | 0.09931889 |
| $BCC^2_{In}(v)$ | 0.316091949 | 0.323436609 |
| $AN^{in}(v)$ | 0.615592889 | 0.639510078 |
| $GrowthRate(HHI(v), -1)$ | 0.011667656 | 0.0187932 |
| $GrowthRate(d_v^{out}, -5)$ | 0.042105258 | 0.046875005 |
| $GrowthRate(WCC^2_{Cycle}(v), -5)$ | -0.27239354 | -0.199317272 |
| $GrowthRate(HHI(v), -3)$ | 0.023758372 | 0.047009138 |
| $GrowthRate(d_v^{out}, -2)$ | -0.00961539 | -0.005847948 |
| $ANNS^{out,in}(v)$ | 13.21653627 | 13.37243705 |
| $ANND^{in,in}(v)$ | 38.46590909 | 39.05952381 |
| $GrowthRate(d_v^{out}, -1)$ | -0.029126219 | -0.021276591 |
| $GrowthRate(d_v^{in}, -1)$ | -0.014184402 | -0.01123595 |
| $ANND^{out,in}(v)$ | 37.31764705 | 38.03448276 |
| $d_v^{out}$ | 70 | 72.00000001 |
| $HHI(v)$ | 0.006006213 | 0.006213756 |

If we considered the rules individually, precision was high but recall was low.

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# From Classification Algorithm to Regression Analysis

- **The classification algorithm identifies the following families of variables (sometimes with varying lags)**
  - Degree and strength of a country (node)
  - Clustering coefficients – both binary and weighted
  - Degree and strength of a country's neighbors (ANND, ANNS)
  - Herfindahl-Hirschman Index

- **We group the indicators into 3 categories and extract the 1st and 2nd principal components**
  - 1st principal component typically explains 90% of the variation

# Standard Regression Analysis (Probit)

- **Specified a probit model of banking crisis prediction with the following macroeconomic variables:**
  - Per capita income (GDP)
  - Net foreign assets /GDP
  - Dummy variable for sustained episode of capital inflows (“capital flows bonanza”)
  - Foreign exchange reserves/GDP
  - Real exchange rate misalignment (higher values indicate overvaluation)
  - **Estimated the model with and without network indicators**

**Included predictors both in 1-year lagged levels and growth rates**

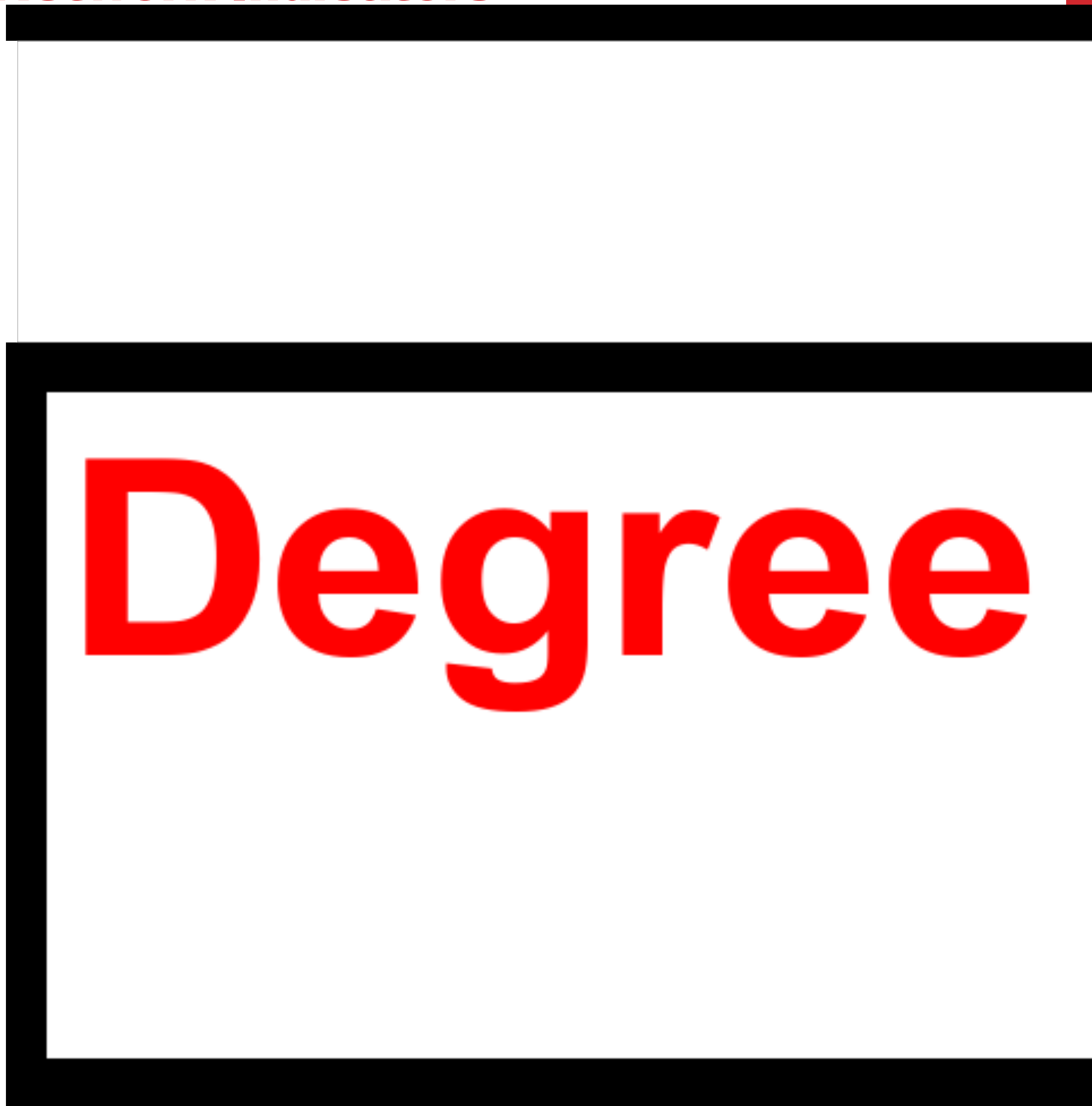
# Probit Results: Macroeconomic Fundamentals

**Coefficients on macroeconomic variables have the expected signs and are statistically significant**

*(continued on next slide)*

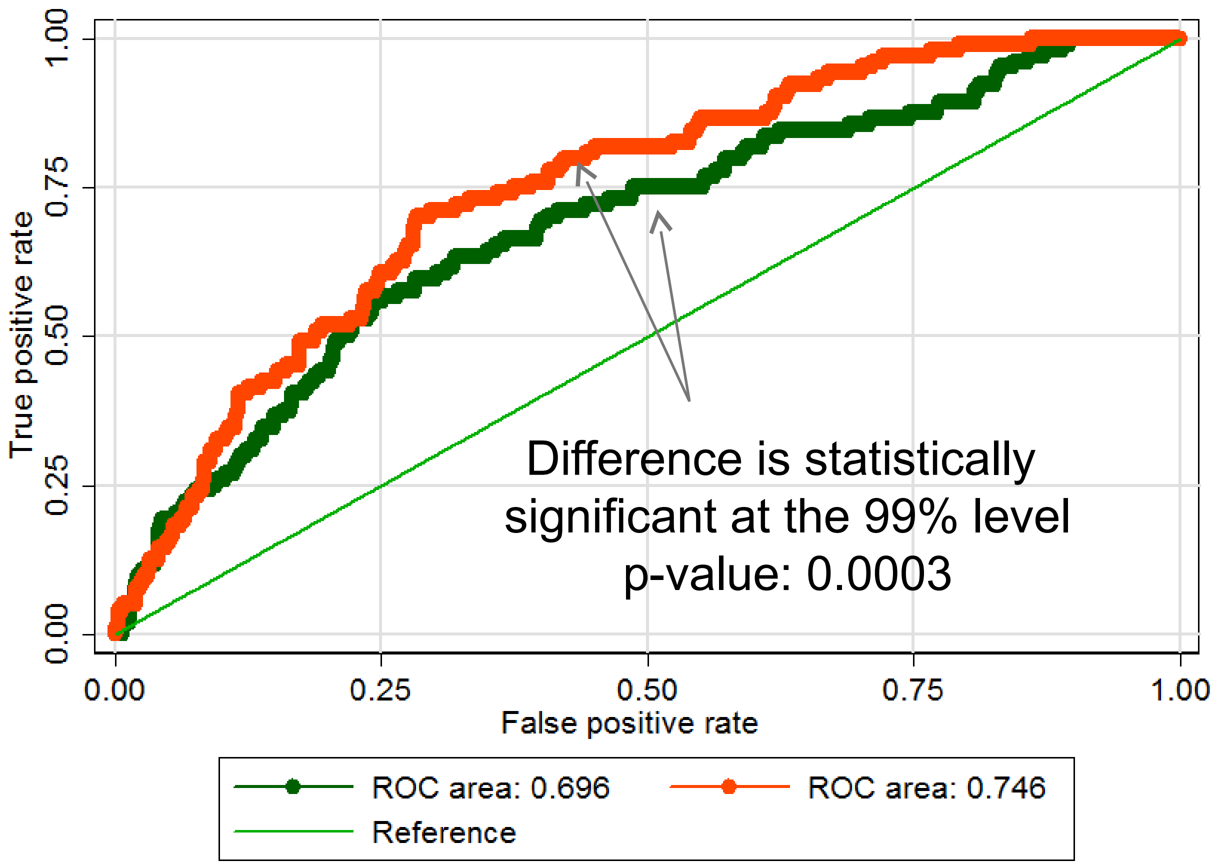
## Probit Results: Add Network Indicators

- **Connectedness is statistically significantly associated with onset of crises**:
  - Higher own connectedness increases the likelihood of crises
  - Lower neighbor connectedness also increases it, suggesting contagion
  - AUROC between the baseline and enhanced models increases



# Probit Results: AUROC Improvement

- **AUROC rises from 0.696 (baseline) to 0.746 (enhanced model)**
- Adding network indicators improves AUROC especially at high levels of false positives
- Financial connectedness helps improve crisis prediction especially for **conservative policymakers**



# In-sample Prediction for Onset of 2007-08 Crises

Notes: For
core count
sample ov

# Out-of-sample Prediction for Onset of 2007-08 Crises

Notes: For
subsample
prediction;

# Take-home Messages

- Degree and strength of countries seem to go up before a crisis – and stabilize after it.
- Clustering coefficients go up 1-2 years before a crisis and then start dropping.
- Degree and strength of neighbors start dropping 3-4 years before a crisis, providing a potentially very early signal of a systemic banking crisis.

**All of these financial connectedness measures can potentially form key signals for an early warning system.**

# Conclusion

- **Assessed the usefulness of network-based connectedness indicators for crisis prediction using an empirical GBN over 1978-2010**
  - Focused on systemic banking crises in the last decade, when connectedness has played a more prominent role
  - **Results based on two methods -- classification algorithm & standard regression model -- suggest that financial connectedness can help predict when crises occur**
  - **Future work:**
  - Alternative sets of network indicators
  - Alternative empirical banking networks (more granular)

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