Did US Politicians Expect the China Shock?

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Question: What did US Politicians know about the China Shock?

- "China Shock": large increase in exports from China since 1990's w/ wide-ranging labor market and social consequences - Autor, Dorn and Hanson (2013), Pierce and Schott (2016)
- From 1990 to 2001 US Congress voted 17 times to maintain China's NTR
- Questions:

1. Did US legislators know how the China shock would affect their constituents?
2. How much did they care about their constituents?
3. Broad question: how do we test for information sets and expectations of politicians?

Estimation challenge

- Answers to questions above (Did they know? Did they care?) are closely related
- Naive approach to estimate importance of constituents' interests: regress roll call vote on **future** shock
- This always causes a **downward bias**: assuming perfect information about future shock leads to underestimate of how much they care about their constituents
- Moment inequality approach borrowed from Dickstein and Morales (2018) solves this challenge
- Policy consequences:
  - China shock not known to politicians $\implies$ information problem
  - China shock known, but little effect on voting $\implies$ accountability problem

Political economy background

- Large literature in political economy on determinants of Congressional roll call votes, e.g. Poole and Rosenthal (1997), Mian, Sufi and Trebbi (2010, 2014), McCarty (2019), Lee, Moretti and Butler (2004)
- Best known early empirical study of Congressional roll call voting on trade is Baldwin and Magee (2000)
- Probability of voting in favor of bill modeled as a function of constituents interests, special interests and ideology:

$$Pr(Vote_i = Yes) \;=\; \Phi(\beta' X + \alpha' PACContrib_i + \alpha_I Ideology_i)$$

  - Constituent interests: X vector of employment shares by industry, hard to tie to specific trade deals

China shock and its political consequences

- Renewed interest in the electoral consequences of trade shocks, particularly of the “China Shock”
  - Autor, Dorn, Hanson and Majlesi (2020): areas affected by the China shock saw an increase in FOX viewership, more likely to elect more conservative Republicans and more liberal Democrats (more polarization)
  - Che, Lu, Pierce, Schott and Tao (2020): areas affected by China shock vote more for Republicans after 2010, but more for Democrats in 2000's (Republicans become more anti-trade after Tea Party 2010)
  - Colantone and Stanig (2018) in Europe: China shock caused an increase in polarization, particularly on the right
  - Older papers like Margalit (2011) find similar importance of trade shocks for voting
- Faigenbaum and Hall (2015) correlates China Shock with index of voting on trade-related bills: retrospective approach

Recent US-China Trade War

- Blanchard, Bown and Chor (2019): recent trade war explains 10% of the drop in Republican vote share in 2018 midterm election
  - Republican vote share declined in counties negatively hit by retaliatory tariffs (did not in counties positively affected by US tariffs)
- Fajgelbaum, Goldberg, Kennedy and Khandelwal (2019): Section 201/301 US tariffs were increased the most in pivotal counties (50% GOP share)

Preview of the results

- US legislators possessed substantial knowledge of future shock (enough to predict 58-68% variation of shock)
    - Less precise information in second half of 1990s
    - Democrats were better informed than Republicans
    - Constituent interests have higher weight in tighter races
- Constituents' interests played a moderate role in voting decisions compared to ideology
- Giving full information to politicians would have not substantially changed their votes on China

Empirical Model

Spatial model of voting for trade policy

- Year $t = 1, 2, ..., T$
- Individual legislators/districts $i = 1, ..., N$
- Politician's utility depends on three elements:
  1. distance between bill and ideological position
  2. an electoral motive: expected future electoral support $V_{i,t+1}$
  3. random utility term

$$
\begin{aligned}
U(\xi_{i,t}, d_{i,t}; \theta_i, \mathcal{I}_{i,t}) &= \underbrace{u\left(\| \, d_{i,t} - \theta_i \, \|\right)}_{\text{spatial comp}} + \underbrace{\tilde{\delta}\mathbb{E}\left[V_{i,t+1} | d_{i,t}, \mathcal{I}_{i,t}\right]}_{\text{electoral motive}} \\
&+ \underbrace{\begin{cases} \xi_{i,t,x} & \textit{if } d_{i,t} = \text{vote for } x_t \\ \xi_{i,t,q} & \textit{if } d_{i,t} = \text{vote for } q_t \end{cases}}_{\text{unobserved idiosyncratic term}}
\end{aligned}
$$

1. Spatial component

$$U(\xi_{i,t}, d_{i,t}; \theta_i, \mathcal{I}_{i,t}) = \underbrace{u\left(\| \, d_{i,t} - \theta_i \, \|\right)}_{\text{spatial comp}} + \underbrace{\tilde{\delta}\mathbb{E}\left[V_{i,t+1} | d_{i,t}, \mathcal{I}_{i,t}\right]}_{\text{electoral motive}}$$
$$+ \underbrace{\begin{cases} \xi_{i,t,x} & \textit{if } d_{i,t} = \text{vote for } x_t \\ \xi_{i,t,q} & \textit{if } d_{i,t} = \text{vote for } q_t \end{cases}}_{\text{unobserved idiosyncratic term}}$$

- Define a policy space such that:
  - $x_t \in \mathbb{R}$ is a policy position favorable to NTR
  - $q_t \in \mathbb{R}$ is a policy position against NTR
- Voting decision $d_{i,t}$
- Ideological position of politician θ_i
- Assume $u\left(\| \, d_{i,t} - \theta_i \, \|\right)$ quadratic loss

2. Electoral motive

$$U(\xi_t, d_t; \theta_i, \mathcal{I}_{i,t}) = \underbrace{u\left(\| \; d_{i,t} - \theta_i \; \|\right)}_{\text{spatial comp}} + \underbrace{\tilde{\delta}\mathbb{E}\left[V_{i,t+1} | d_{i,t}, \mathcal{I}_{i,t}\right]}_{\text{electoral motive}}$$
$$+ \underbrace{\begin{cases} \xi_{i,t,x} & \textit{if } d_{i,t} = \text{vote for } x_t \\ \xi_{i,t,q} & \textit{if } d_{i,t} = \text{vote for } q_t \end{cases}}_{\text{unobserved idiosyncratic term}}$$

- Electoral support depends on voting decision d_t and China shock: $V_{i,t+1} = h_t(d_{i,t}, S_{i,t+1}) + e_{i,t+1}$
  - $S_{i,t+1}$ is future labor market impact of the China shock
  - $\mathbb{E}\left[e_{i,t+1} | d_{i,t}, S_{i,t+1}, \mathcal{I}_{i,t}\right] = 0$

$$\begin{aligned} h_t(d_t, S_{i,t+1}) = \; & \gamma_t^0 + \gamma_t^1 S_{i,t+1} \times \mathbb{1}\left\{d_{i,t} = \text{vote for } x_t\right\} \\ & + \gamma_t^2 S_{i,t+1} \times \mathbb{1}\left\{d_{i,t} = \text{vote for } q_t\right\} \end{aligned}$$

- $\mathcal{I}_{i,t}$ information of politician i at time t

3. Unobserved idiosyncratic term

$$U(\xi_{i,t}, d_{i,t}; \theta_i, \mathcal{I}_{i,t}) = \underbrace{u\left(\| \, d_{i,t} - \theta_i \, \|\right)}_{\text{spatial comp}} + \underbrace{\tilde{\delta}\mathbb{E}\left[V_{i,t+1} | d_{i,t}, \mathcal{I}_{i,t}\right]}_{\text{electoral motive}}$$
$$+ \underbrace{\begin{cases} \xi_{i,t,x} & \text{if } d_{i,t} = \text{vote for } x_t \\ \xi_{i,t,q} & \text{if } d_{i,t} = \text{vote for } q_t \end{cases}}_{\text{unobserved idiosyncratic term}}$$

- $\xi_{i,t,d} \sim N(0, \sigma_\xi^2)$ so that $\xi_{i,t} = \xi_{i,t,q} - \xi_{i,t,x} \sim N(0, 2\sigma_\xi^2)$
- Normalize $2\sigma_\xi^2 = 1$

Voting decision (1)

- Define Y_{it} as indicator function: $Y_{it} = 1$ if politician votes in favor of NTR, $Y_{it} = 0$ if against

$$Y_{it} = \mathbb{1}\{U(\xi_t, x_t; \theta_i, \mathcal{I}_{i,t}) > U(\xi_t, q_t; \theta_i, \mathcal{I}_{i,t})\}.$$

- Probability of $Y_{it} = 1$:

$$\begin{aligned} & Pr(Y_{i,t} = 1 | \mathcal{I}_{i,t}) \\ & = \Phi \left(\begin{array}{c} -\frac{1}{2}\left((x_t - \theta_i)^2 - (q_t - \theta_i)^2\right) \\ +\tilde{\delta}\left(\mathbb{E}\left[V_{i,t+1} | x_t, \mathcal{I}_{i,t}\right] - \mathbb{E}\left[V_{i,t+1} | q_t, \mathcal{I}_{i,t}\right]\right) \end{array} \right) \end{aligned}$$

Voting decision (2)

- Main voting equation:

$$Pr(Y_{i,t} = 1|\mathcal{I}_{i,t}) = \Phi\left(a_t\theta_i + b_t + \delta_t \mathbb{E}\left[S_{i,t+1}|\mathcal{I}_{i,t}\right]\right) \qquad (1)$$

- Key parameter of interest: δ_t sensitivity of voting to expected China shock
- $\delta_t = \tilde{\delta}\left(\gamma_t^1 - \gamma_t^2\right)$ is a combination of:
  - $\tilde{\delta}$ sensitivity of voting to electoral support
  - $\left(\gamma_t^1 - \gamma_t^2\right)$ sensitivity of electoral support to shock
- Two remarks:
  - no export shocks (small)
  - no consumption benefits (relatively less dispersed across districts) $\Rightarrow$ subsumed in θ_i

Estimation

Expectations and information set of politicians

- How do we estimate $\omega_t = \{a_t, b_t, \delta_t\}$?
- Fundamental question: do we (econometrician) know what politicians know about $S_{i,t+1}$ at the time of the vote?
  - Yes $\Longrightarrow$ Maximum Likelihood Estimation of (1) e.g. Manski (1991) and Ahn and Manski (1993)
  - No $\Longrightarrow$ Moment Inequality Estimation

Possible information sets

- Throughout the paper, we define three possible information sets:

  (i) Minimal Information: $\mathcal{I}_{i,t} = \{ShareMfg_{it}\}$

  (ii) Baseline Information: $\mathcal{I}_{i,t} = \{ShareMfg_{it}, S_{it}\}$

  (iii) Perfect Foresight $\mathcal{I}_{i,t} = \{S_{i,t+1}\}$

When we know what politicians know: MLE

- Once we specify the information set $\mathcal{I}_{i,t}$, we can estimate ω_t by MLE

$$\begin{aligned} \max_{\omega_t} \quad & ln\mathcal{L}\left(\omega_t \middle| \left\{Y_{i,t}, \theta^i, \mathcal{I}_{i,t}\right\}_{i=1}^{N}\right) \\ & = \sum_{i=1}^{N} Y_{i,t} ln\left[\Phi\left(a_t\theta_i + b_t + \delta_t \mathbb{E}\left[S_{i,t+1}|\mathcal{I}_{i,t}\right]\right)\right] \\ & + \left(1 - Y_{i,t}\right) ln\left[1 - \Phi\left(a_t\theta_i + b_t + \delta_t \mathbb{E}\left[S_{i,t+1}|\mathcal{I}_{i,t}\right]\right)\right] \end{aligned} \tag{2}$$

- Example: if perfect foresight then replace $\mathbb{E}\left[S_{i,t+1}|\mathcal{I}_{i,t}\right]$ with $S_{i,t+1}$
- Example: if $\mathcal{I}_{i,t} = \{ShareMfg_{it}\}$ then take predicted value from OLS regression $S_{i,t+1} = \beta_0 + \beta_1\theta_i + \beta_2 ShareMfg_{it} + \varepsilon_{i,t+1}$

Monte-Carlo Simulations: MLE bias

Table: Simulation with Baseline Information $a = 0.5, b = 0.3$

Correct info set Baseline	Assumed Information Set	Avg $\hat{a}$ (std.)	Avg $\hat{b}$ (std.)	Avg $\hat{\delta}$ (std.)
$\delta = -1.3$	(1) Minimal Information	0.449 (0.066)	0.303 (0.027)	-1.060 (0.047)
	(2) Baseline Information	0.498 (0.079)	0.319 (0.034)	-1.306 (0.058)
	(3) Perfect Foresight	0.421 (0.090)	0.304 (0.040)	-0.813 (0.190)
$\delta = 0$	(4) Minimal Information	0.499 (0.073)	0.300 (0.029)	-0.001 (0.046)
	(5) Baseline Information	0.499 (0.072)	0.300 (0.029)	-0.000 (0.036)
	(6) Perfect Foresight	0.500 (0.072)	0.300 (0.029)	-0.002 (0.041)

Moment inequality approach

- More plausibly we do not know the precise information set possessed by politicians
- Dickstein and Morales (2018) methodology addresses this informational problem
    - Moment inequality approach allows us to specify only a subset of information that we are sure politicians know: $Z_{it} \subseteq \mathcal{I}_{i,t}$
- We maintain that politicians have rational expectations:
    - define $\varepsilon_{i,t+1} = S_{i,t+1} - \mathbb{E}\left[S_{i,t+1} | \mathcal{I}_{i,t}\right]$ as expectational error
    - rational expectations $\Longrightarrow \mathbb{E}\left[\varepsilon_{i,t+1} | \mathcal{I}_{i,t}\right] = 0$
- Instead of point identification, moment inequalities allow for set identification

Odds-based moment inequalities

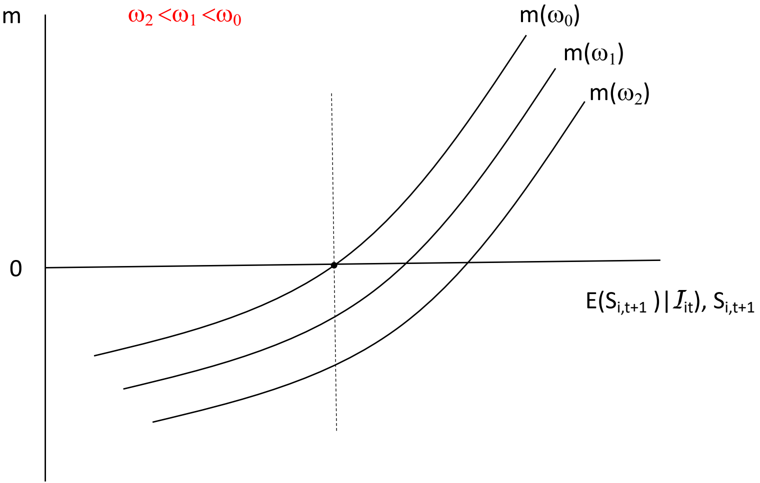
- From the definition of Y_{it}:

$$\mathbb{1}\{a_t\theta_i + b_t + \delta_t \mathbb{E}\left[S_{i,t+1}|\mathcal{I}_{i,t}\right] - \xi_{it} \geq 0\} - Y_{it} = 0$$

- We cannot observe $\mathbb{E}\left[S_{i,t+1}|\mathcal{I}_{i,t}\right]$ and ξ_{it}
- Take expectations over ξ_{it} conditional on $\mathcal{I}_{i,t}$ + some algebra steps:

$$\mathbb{E}\left[(1 - Y_{it})\frac{\Phi\left(a_t\theta_i + b_t + \delta_t \mathbb{E}\left[S_{i,t+1}|\mathcal{I}_{i,t}\right]\right)}{1 - \Phi\left(a_t\theta_i + b_t + \delta_t \mathbb{E}\left[S_{i,t+1}|\mathcal{I}_{i,t}\right]\right)} - Y_{it}\middle| \mathcal{I}_{i,t}, \theta_i\right] = 0$$

Point identification with moment equality

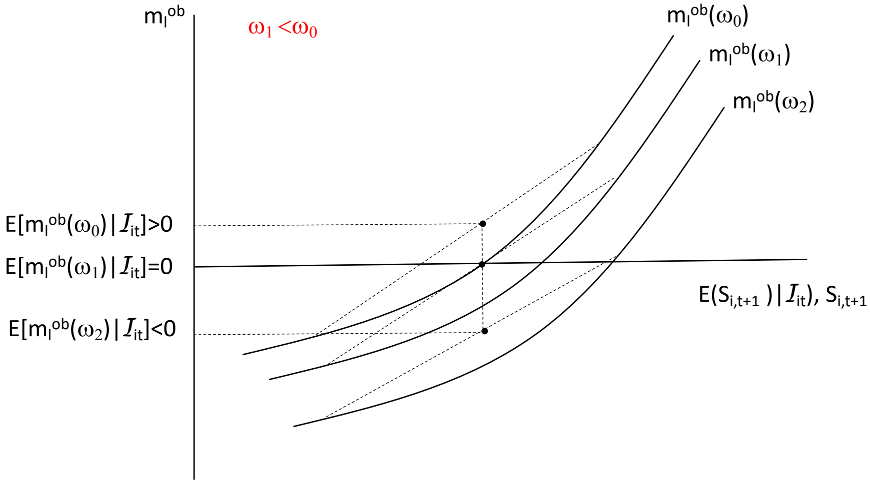


Set identification with moment inequality - Step 1

- Under assumption that ξ_{it} is normally distributed $\frac{\Phi}{1-\Phi}$ is convex (normality sufficient, but not necessary)
- Since expectational error $S_{i,t+1} - \mathbb{E}\left[S_{i,t+1} | \mathcal{I}_{i,t}\right]$ has mean zero, by Jensen's inequality we obtain:

$$\mathbb{E}\left[\left.\underbrace{(1 - Y_{it}) \frac{\Phi\left(a_t \theta_i + b_t + \delta_t S_{i,t+1}\right)}{1 - \Phi\left(a_t \theta_i + b_t + \delta_t S_{i,t+1}\right)} - Y_{it}}_{m_l^{ob}} \right| \mathcal{I}_{i,t}, \theta_i\right] \geq 0 \quad (3)$$

Set identification with moment inequality - Graphical intuition



Set identification with moment inequality - Step 2

- Consider now a subset of the information set $Z_{i,t} \subseteq \mathcal{I}_{i,t}$
- We now show that: $\mathbb{E}\left[m_l^{ob} \middle| \mathcal{I}_{i,t} \right] = 0 \Rightarrow \mathbb{E}\left[m_l^{ob} \middle| Z_{i,t} \right] = 0$
- Apply the Law of Iterated Expectations:

$$\mathbb{E}\left[m_l^{ob} \middle| Z_{i,t} \right] = \mathbb{E}_{\mathcal{I}}\left[\mathbb{E}\left[m_l^{ob} \middle| Z_{i,t}, \mathcal{I}_{i,t} \right] \right] = \mathbb{E}_{\mathcal{I}}\left[\mathbb{E}\left[m_l^{ob} \middle| \mathcal{I}_{i,t} \right] \right] = 0$$

- Then (3) implies:

$$\mathbb{E}\left[m_l^{ob} \middle| Z_{i,t}, \theta_i \right] \quad \geq \quad 0$$

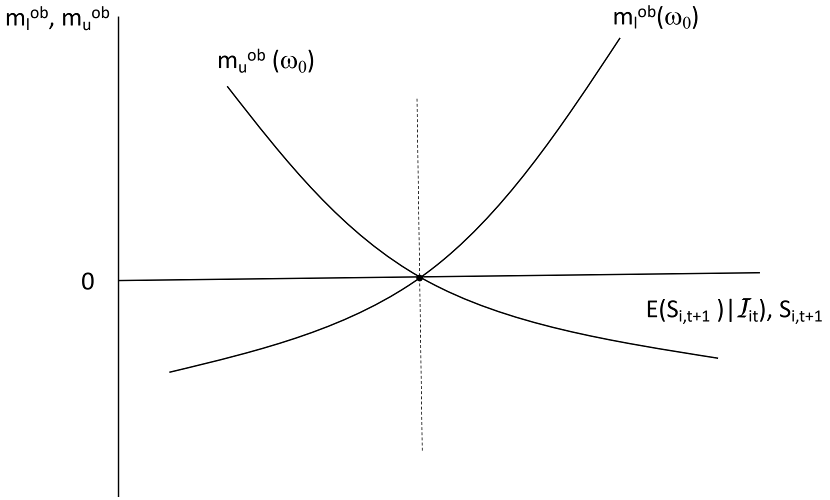
Additional moment inequalities

- One additional moment derived similarly:

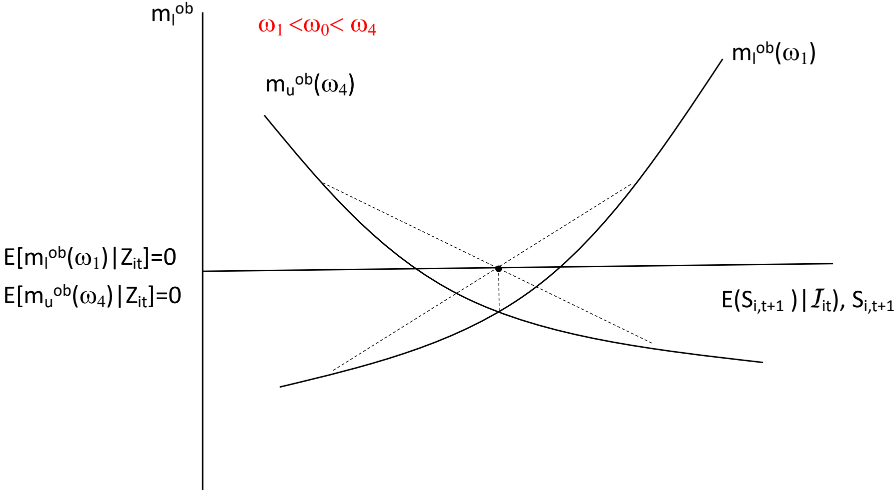
$$
\begin{aligned}
m_u^{ob} &= Y_{it} \frac{1 - \Phi\left(a_t \theta_i + b_t + \delta_t S_{i,t+1}\right)}{\Phi\left(a_t \theta_i + b_t + \delta_t S_{i,t+1}\right)} - 1 + Y_{it} \\
\mathbb{E}\left[m_u^{ob} \middle| Z_{i,t}, \theta_i \right] &\geq 0
\end{aligned}
$$

- Notice how two moments would be redundant for point identification

Redundant moments with moment equality



Non-redundant moment inequalities



Revealed preferences moment inequalities

- Two additional moments derived from revealed preference inequality:

$$Y_{it}\left[a_t\theta^i + b_t + \tilde{\delta}_t\mathbb{E}\left[S_{i,t+1}|\mathcal{I}_{i,t}\right] - \xi_{it}\right] \geq 0$$

- Skipping derivation becase it is similar to Odds-Based moment inequalities
- All these moments will "bound" the true parameter ω

From conditional to unconditional moment inequalities (1)

- Conditional moment inequalities are cumbersome computationally, we would need an inequality for each value of each variable entering Z_{it}
- Employ unconditional moment inequalities implied by conditional moment inequalities
- In general we will lose information, in the sense that confidence sets will be larger

From conditional to unconditional moment inequalities (2)

- We follow DM in using unconditional moment inequalities:

$$\mathbb{E}\left[\left\{\begin{array}{c} m_l^{ob} \\ m_u^{ob} \\ m_l^{rp} \\ m_u^{rp} \end{array}\right\} \times g\left(Z_{it}\right)\right] \geq 0$$

- where

$$g_a\left(Z_{it}\right) = \left\{\begin{array}{l} \mathbb{1}\left\{Z_{it} > med\left(Z_{it}\right)\right\} \times \left(\left|Z_{it} - med\left(Z_{it}\right)\right|\right)^a \\ \mathbb{1}\left\{Z_{it} \leq med\left(Z_{it}\right)\right\} \times \left(\left|Z_{it} - med\left(Z_{it}\right)\right|\right)^a \end{array}\right.$$

  and $a \in \{0, 1\}$

- Example: when we have Baseline Z_{it} then the number of inequalities is $3 \times 2 \times 4 \times 2 = 48$

Inference: building Confidence Sets (CS)(1)

- We follow DM's implementation of Andrews and Soares (2010) Generalized Moment Selection (GMS) method
- Consider moment inequalities $k = 1, ..., K$ and drop t

$$\bar{m}_k(\omega) \equiv \frac{1}{N} \sum_i m_k\left(\omega, Z_i, \theta^i\right)$$

- Define MMM (modified method of moments) statistic as:

$$Q(\omega) = \sum_k \left(min \left\{ \frac{\bar{m}_k(\omega)}{\hat{\sigma}_k(\omega)}, 0 \right\} \right)^2$$

where

$$\hat{\sigma}_k^2(\omega) = \frac{1}{N} \sum_i (m_k - \bar{m}_k)^2$$

- Notice how $Q(\omega)$ is a sort of "loss function" in the sense that if a moment inequality is violated, i.e. $\frac{\bar{m}_k(\omega)}{\hat{\sigma}_k(\omega)} < 0$ then Q increases with how far moment is from being satisfied

Inference: building Confidence Sets (CS)(2)

- For each ω_p in a grid
  - compute $Q(\omega_p)$
  - simulate asymptotic distribution of $Q(\omega_p)$
  - find 95% critical value $c(\omega_p, 95\%)$
  - include ω_p in confidence set if $Q(\omega_p) \leq c(\omega_p, 95\%)$

Specification Tests

- We can employ model specification tests to distinguish which information sets politicians possessed
- Intuition: when model is correct, but the information set specified by researchers contains elements not available to agents, i.e., $Z_{i,t} \nsubseteq \mathcal{I}_{i,t}$, some moment inequalities will be violated $\Rightarrow$ confidence set is likely to be empty
- This is the BP test from Bugni, Canay and Shi (2015)
- We report also less restrictive RC and RS tests p-values

Data and Results

Normal Trade Relations with China

- Normal Trade Relations is MFN (Most Favored Nation) status
- Carter was the first to grant NTR status to China in 1980
- NTR would be renewed annually unless Congress voted to disapprove it
- After the 1989 Tiananmen Square events Congress brought resolutions to the floor 16 times
  - 12 of those votes were identical
  - 4 votes sought to modify NTR to include specific clauses related to human rights issues, so votes are less comparable
- In 2000 HR 4444 gave China Permanent Normal Trade Relations as it entered WTO

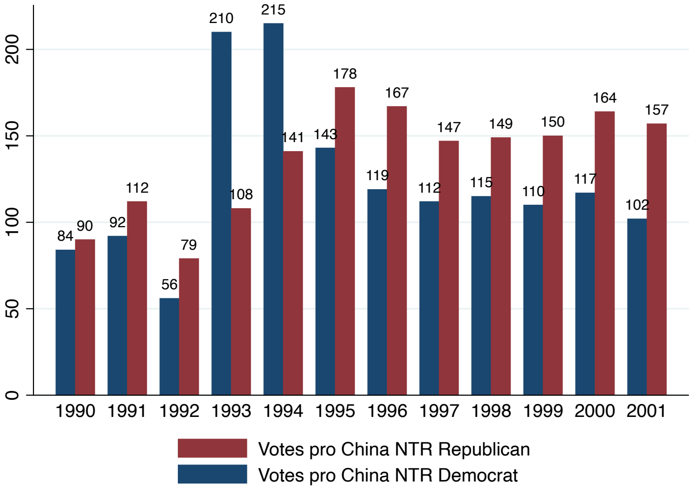
Data: Roll Call Votes

- Data on roll call votes is from voteview.com
  - House members (icpsr code)
  - party code: Democrat, Republican or Independent
  - DW nominate dimension 1: continuous variable proxy for ideology from Poole and Rosenthal (1997) - proxy for θ_i
    - negative for "liberal", positive for "conservative"

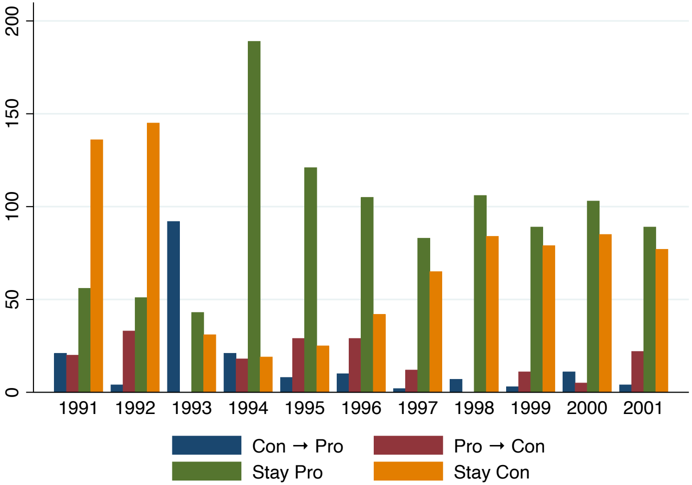
Data: Roll Call Votes

Year	Congress	President	House	Bill number	NTR approved in House	Additional action
1990	101	G.H.W. Bush	D	HJRES647	No	No action in Senate
1991	102	G.H.W. Bush	D	HJRES263	No	No action in Senate
1992	102	G.H.W. Bush	D	HJRES502	No	Did not pass in Senate
1993	103	Clinton	D	HJRES208	Yes	
1994	103	Clinton	D	HJRES373	Yes	
1995	104	Clinton	R	HJRES96	Yes	
1996	104	Clinton	R	HJRES182	Yes	
1997	105	Clinton	R	HJRES79	Yes	
1998	105	Clinton	R	HJRES121	Yes	
1999	106	Clinton	R	HJRES57	Yes	
2000	106	Clinton	R	HJRES103	Yes	
2001	107	G.W. Bush	R	HJRES50	Yes	

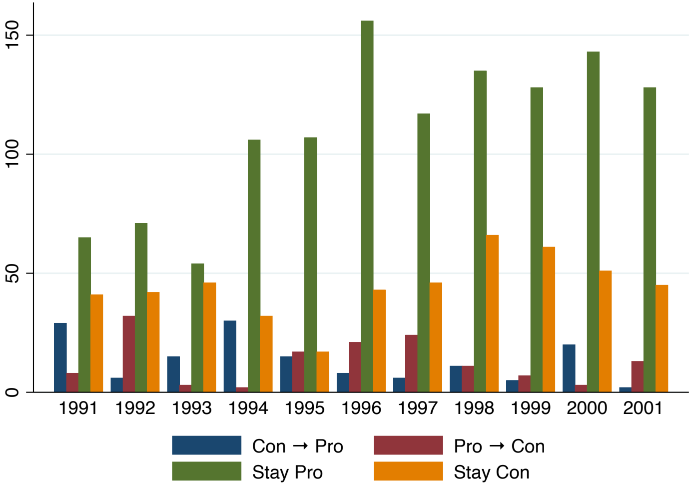
Votes pro China NTR



Vote Switching: Democrats



Vote Switching: Republican



Data: China shock (1)

- Exposure at the Commuting Zone (CZ) level

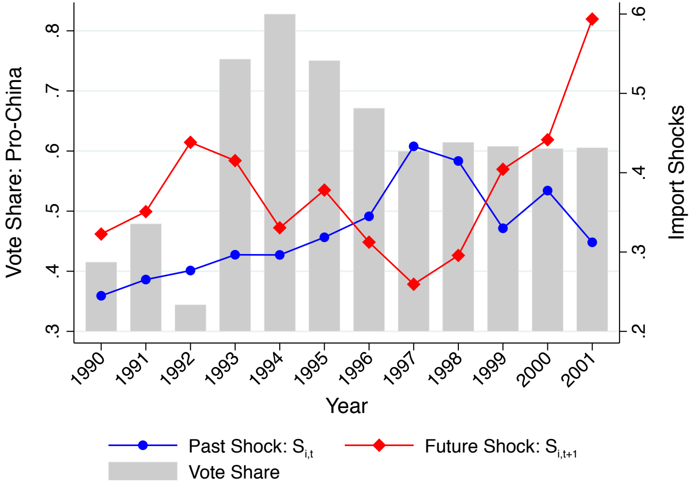
$$S_{jt+1} = \sum_k \frac{L_{jk,t}}{L_{j,t}} \frac{\Delta M^{oth}_{kt+1}}{Y_{k,t} + M_{k,t} - X_{k,t}}$$

- ΔM^{oth}_{kt+1} is the change in import of good k from China by eight other (non-US) high-income countries (Australia, Denmark, Finland, Germany, Japan, New Zealand, Spain, and Switzerland) over 5 years in the future.
- normalized by the contemporaneous absorption $Y_{k,t} + M_{k,t} - X_{k,t}$
- $L_{jk,t}/L_{j,t}$ share of industry k in CZ j's total employment in the period t
- we employ 5-year windows for future and current China shock, e.g. for 1995 vote, future shock is 1995-2000
  - except for years 1990-1992 (2-year lag)

Data: China shock (2)

- Trade data: 1988-2006 4-digit Standard International Trade Classification (SITC) from UN Comtrade Database
  - matched to SIC via HS cross-walk $\Longrightarrow$ 397 industries
- Output data: NBER-CES data
- Convert to exposure from CZ (722) level to Congressional District (CD) level (435) using US counties (3000)
  - each county contained in one CZ
  - Missouri Census Data Center: mapping from counties to CD

Past and future shocks



Parameter estimates: pooled sample 1990-2001

CS of a	CS of b	CS of δ	p-value BP	p-value RC	p-value RS	Num obs.
Panel A: Minimal information $Z_{it} = \{Share\ Mfg_{it}, \theta_i\}$						
[0.495, 0.615]	[0.210, 0.270]	[-1.188, -0.137]	0.185	0.185	0.185	5494
Panel B: Baseline information $Z_{it} = \{S_{it}, Share\ Mfg_{it}, \theta_i\}$						
[0.515, 0.620]	[0.240, 0.270]	[-1.275, -0.825]	0.085	0.070	0.070	5494
Panel C: Perfect Foresight $Z_{it} = \{S_{it}, Share\ Mfg_{it}, S_{it+1} - E[S_{it+1} \mid S_{it}, Share\ Mfg_{it}], \theta_i\}$						
–	–	–	0.010	0.010	0.010	5494

Parameter estimates: sample 1997-2001

CS of a	CS of b	CS of δ	p-value BP	p-value RC	p-value RS	Num obs.
Panel A: Minimal information $Z_{it} = \{Share\ Mfg_{it}, \theta_i\}$						
[0.465, 0.765]	[0.165, 0.275]	[-2.062, -0.137]	0.520	0.520	0.520	2546
Panel B: Baseline information $Z_{it} = \{S_{it}, Share\ Mfg_{it}, \theta_i\}$						
[0.450, 0.795]	[0.190, 0.280]	[-1.670, -0.020]	0.360	0.360	0.360	2546
Panel C: Perfect Foresight $Z_{it} = \{S_{it}, Share\ Mfg_{it}, S_{it+1} - E[S_{it+1} \| S_{it}, Share\ Mfg_{it}], \theta_i\}$						
–	–	–	0.010	0.010	0.010	2546

Parameter estimates: sample 1993-1996

CS of a	CS of b	CS of δ	p-value BP	p-value RC	p-value RS	Num obs.
Panel A: Minimal information $Z_{it} = \{Share\ Mfg_{it}, \theta_i\}$						
[-0.280, 0.100]	[0.583, 0.703]	[-2.375, 0.887]	0.330	0.330	0.330	1698
Panel B: Baseline information $Z_{it} = \{S_{it}, Share\ Mfg_{it}, \theta_i\}$						
[-0.325, 0.130]	[0.598, 0.740]	[-3.125, -0.125]	0.395	0.395	0.395	1698
Panel C: Perfect Foresight $Z_{it} = \{S_{it}, Share\ Mfg_{it}, S_{it+1} - E[S_{it+1} \mid S_{it}, Share\ Mfg_{it}], \theta_i\}$						
–	–	–	0.010	0.010	0.010	1698

Parameter estimates: sample 1990-1992

CS of a	CS of b	CS of δ	p-value BP	p-value RC	p-value RS	Num obs.
Panel A: Minimal information $Z_{it} = \{Share\ Mfg_{it}, \theta_i\}$						
[0.800, 1.550]	[-0.325, -0.125]	[-1.125, 2.125]	0.955	0.955	0.955	1232
Panel B: Baseline information $Z_{it} = \{S_{it}, Share\ Mfg_{it}, \theta_i\}$						
[1.025, 1.438]	[-0.275, -0.150]	[-1.300, 0.000]	0.165	0.145	0.145	1232
Panel C: Perfect Foresight $Z_{it} = \{S_{it}, Share\ Mfg_{it}, S_{it+1} - E[S_{it+1} \mid S_{it}, Share\ Mfg_{it}], \theta_i\}$						
[1.000, 1.550]	[-0.200, -0.200]	[-1.400, 0.025]	0.235	0.225	0.225	1232

Magnitudes

- Effects of China shock expectations: going from 25th to 75th percentile of $E\left[S_{i,t+1}\right]$ at mean $\theta^i = 0$

	$\Phi\left(b+\delta S_{t+1}^{75th}\right)-\Phi\left(b+\delta S_{t+1}^{25th}\right)$
1997-2001	[-0.077,-0.004]
1993-1996	[-0.080,-0.009]
1990-1992	[-0.087,-0.004]

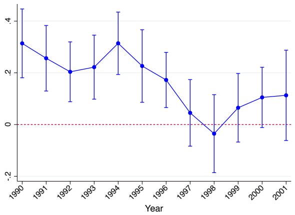
- Effects of ideology:

	$\Phi\left(a\theta^{75th}+b+\delta\bar{S}_{t+1}\right)-\Phi\left(a\theta^{25th}+b+\delta\bar{S}_{t+1}\right)$
1997-2001	[0.132, 0.215]
1993-1996	[-0.051, 0.034]
1990-1992	[0.186, 0.344]

What did politicians know?

- Three main results:

1. Cannot reject Baseline for all sub-periods (enough to explain 59-68% shock)
2. Reject at 1% confidence level that politicians had Perfect Foresight in the pooled sample
3. Cannot reject Perfect Foresight in earlier period 1991-1993
   - Intuitive in light of high correlation between China shocks earlier on
   - Plot $Corr(S_{i,t}, S_{i,t+1})$



Heterogeneity by party, tenure and vote margin

Table: Baseline Information

	CS of a	CS of b	CS of δ	p-value BP	p-value RC	p-value RS
Democracts	[1.500, 3.075]	[0.600, 1.200]	[-3.140, -0.667]	0.805	0.795	0.795
Republicans	–	–	–	0.010	0.010	0.010
Tenure $<$ median	[0.825, 0.825]	[0.225, 0.250]	[-1.420, -0.775]	0.095	0.095	0.095
Tenure $>$ median	[0.375, 0.375]	[0.275, 0.325]	[-1.420, -0.452]	0.120	0.120	0.120
Winmargin $>$ med	[0.600, 0.600]	[0.150, 0.200]	[-0.555, 0.240]	0.115	0.115	0.115
Winmargin $<$ med	[0.150, 0.375]	[0.300, 0.400]	[-2.495, -0.882]	0.435	0.435	0.435

Heterogeneity discussion

- We reject that Republicans have Baseline information, we cannot reject that Democrats have Baseline information
  - Democrats would appear to be better informed than Republicans
  - it is also possible that Republicans had small δ and in that case hard to disentangle information
- Tenure has no discernible effect on information, but slightly increases accountability
- Win-margin has large effect on accountability: δ is large (in absolute value)

Counterfactual: giving politicians information

- When information of politicians is less than perfect, what happens if we give them additional information?
- Remember the definition:

$$Y_{it}(\omega_t, \mathcal{I}_{it}, \xi_{it}) = \mathbf{1}\left\{a_t\theta_i + b_t + \delta_t \mathbb{E}[S_{i,t+1}|\mathcal{I}_{it}] - \xi_{it} \geq 0\right\}.$$

- Example: number of politicians switching from pro-CHN to against-CHN if information goes from Baseline to Perfect:

$$\begin{aligned} & N^{+-}(\omega_t, \mathcal{I}^b_{i,t} \to \mathcal{I}^p_{i,t}, \mathcal{N}_t) \\ = & \int_{\xi,t} Y_{i,t}(\omega_t, \mathcal{I}^b_{i,t}, \xi_{i,t})(1 - Y_{i,t}(\omega_t, \mathcal{I}^p_{i,t}, \xi_{i,t}))\phi(\xi_{i,t}) d\xi_{i,t} \end{aligned}$$

Counterfactual 1: Baseline to Perfect Foresight

	1997-2001	1993-1996	1990-1992
Change in share of pro-CHN votes (%)	[-0.030, 0.012]	[-0.161, -0.000]	[-0.008, 0.064]
Share always pro-CHN (%)	[55.956, 61.668]	[70.382, 76.967]	[36.634, 42.352]
Share of pro-CHN to against-CHN (%)	[0.078, 1.694]	[0.054, 1.610]	[0.000, 1.265]
Share of against-CHN to pro-CHN (%)	[0.078, 1.694]	[0.054, 1.485]	[0.000, 1.317]
Share always against-CHN (%)	[36.720, 42.187]	[21.997, 27.645]	[56.264, 62.309]

Counterfactual 1: discussion

- Notice how the overall vote change is small
- This is because:
  - politicians already have substantial information (expectational error is small)
  - δ_t is small

Counterfactual 2: Heightened Sensitivity to Constituent Interests

	1997-2001	1993-1996	1990-1992
		Panel A: Baseline	
(1) Value of δ	[-1.670, -0.020]	[-3.125, -0.125]	[-1.300, 0.000]
(2) Share of votes pro-CHN (%)	[57.663, 61.760]	[71.999, 77.034]	[37.682, 42.427]
		Panel B: Lower bound of CS for Democrats	
(3) Value of δ	-4.740	-5.800	-3.700
(4) Share of votes pro-CHN (%)	[15.711, 30.443]	[38.005, 61.502]	[11.983, 23.131]
		Panel C: Lower bound of CS for Win Margin $<$ median	
(5) Value of δ	-1.905	-8.550	-4.375
(6) Share of votes pro-CHN (%)	[37.992, 58.049]	[24.606, 45.485]	[9.682, 19.424]

Conclusions

- Broad contribution: introduce methodology to formally test among information sets possessed by politicians in the context of Congressional voting, a large branch of political economy and political science literature
- Back to initial question: did US politicians know about the China shock? Did that knowledge play a large role in their voting?
  - US politicians had substantial knowledge about the China shock early on when year-on-year changes in the China shock are more stable
  - they seemed to have had less precise knowledge in the years leading up to granting of PNTR (Permanent Normal Trade Relations)
  - constituents interests played a moderate role in shaping their vote
    - additional information would have not substantially changed the overall vote outcome