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Bilateral trade and shocks in political relations: Evidence from China and some of its major trading partners, 1990–2013☆

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ABSTRACT

An extensive number of studies investigate the effects of political relations on trade by estimating a gravity model using annual (or quarterly) data. We argue that the use of low-frequency data introduces an aggregation bias because the cycle of moderate political shocks is much shorter (measured in weeks). Using monthly data from 1990 through 2013 for China, we estimate a model of political relations and conclude that political shocks are short-lived. Narrative evidence from two case studies illustrates the transitory nature of these shocks. A VAR model shows that although political shocks influence exports to China, the effects largely vanish within two months. A comparison of the monthly- and annual-frequency gravity equation regressions illustrates the effects of temporal aggregation.

1. In d c i n

The extent to which political relations between nations affect trade has been the topic of a significant amount of research not just in economics but also in political science, especially international relations. Many empirical studies find that political relations, and more specifically deterioration in political relations, significantly affect bilateral trade in a variety of contexts. For example, Long (2008), Hegre et al. (2010), and Morrow (1999) observe that bilateral trade is adversely affected in the presence of military conflicts. Simmons (2005) indicates that disputes over territories likewise tend to reduce trade. And Pollins (1989a, 1989b) finds that the existence of conflicting political objectives lessens bilateral trade. More recently, Che et al. (2015) find that the 1937–1945 Japanese invasion of China had a significant and protracted impact on cross-border trade and investment.

It is perhaps not overly surprising to observe that trade is negatively affected when political relations deteriorate enough that a military confrontation seems inevitable.[1] As Long (2008) points out, when a military conflict is imminent, rational market participants reduce risk by curtailing business transactions with the opposing state.

But most variability in political relations does not involve the extreme outcome of war. In most cases, relations fluctuate along a continuum that ranges from "friendly" to "normal" to "tense," and occasionally "threatening" (Davis and Meunier, 2011; Yan et al., 2010). Disputes over territory and conflicting political objectives are examples of difficulties in political relations that fall short of war. Given that most of the time changes in political relations operate in the less extreme range, a number of papers have sought to investigate the extent to which political relations in this basically moderate range

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[1] This effect has been empirically verified in numerous other studies. See, for example, Keshk et al. (2004), Goenner (2011), Glick and Taylor (2010), and Martin et al. (2008). There are a few papers, such as such as Morrow et al. (1998), which report an unstable or insignificant relationship between military conflict and trade. Morrow (1999) argues that those results are not necessarily inconsistent with the notion that military conflicts adversely affect trade if agents are rational and forward-looking. Other papers that do not find a consistent conflict-trade relationship are surveyed and thoroughly discussed in Hegre et al. (2010), as well as Long (2008).

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also affect bilateral trade. Recent examples of papers in this category are Davis and Meunier (2011), Davis et al. (2014), and Fuchs and Klann (2013).[2]

The literature that investigates the effect on trade of less than extremely antagonistic political relations generally does so by estimating a traditional gravity model augmented by the inclusion of a metric that captures the strength of political relations between nations (correlation in UN votes, aggregated Goldstein-scaled events, etc.).[3] The typical regression model in these papers involves the use of annual

example, as Fuchs and Klann (2013) note, meetings of the Dalai Lama with high ranking government officials in other countries are generally met with disapproval in China since, from the Chinese perspective, such meetings indicate that a foreign state is meddling in China's internal affairs. Temporary disputes of this kind generate the variation necessary for successfully identifying the effects of political shocks on trade by using high frequency data.

A third reason for focusing on China is that one of that country's leading scholars of international relations, Yan Xuetong, has constructed a comprehensive dataset measuring China's political relations with other major powers—Australia, France, Germany, India, Japan, Pakistan, Russia, U.K, and U.S.—at a monthly frequency.[8] This dataset permits our hypothesis to be empirically tested.[9]

Our main findings indicate that political shocks do affect exports, but the effects appear to be short-lived, dissipating after just a few months. Using a vector autoregression analysis, we find that, following a one-standard-deviation adverse shock to the political relations index, export growth to China (from the partner country) tends to deteriorate in the first month following the shock for about half of the sample, or in month two for the remaining half. After the third month, the effect is essentially nil. No long-term effects are detected.

We also compare gravity equation regressions estimated at both monthly and annual frequencies to get a better sense of the bias that temporal aggregation may engender. The monthly-based regressions indicate that political relations affect exports, but the effect is temporary—they typically start one month after the shock, and last about three months. By contrast, the annual-based regressions indicate that the effect of political shocks on exports is observed only on the contemporaneous (current) period (a consequence of temporal aggregation, as we argue below) and is much more persistent.

We complement our empirical tests by investigating the mechanisms that may explain how political shocks affect trade. To do so, we estimate a gravity model at the firm level using data from China's General Administration of Customs for the 2000 to 2006 period. Given our findings that the effects of political shocks last about three months, our gravity regressions are augmented by the inclusion of the political shocks averaged over month 0 to month 3. We find that State-Owned Enterprises (SOEs) display the highest sensitivity of imports to political relations. Imports mediated through privately-owned firms are also sensitive to political shocks, but the magnitude of the coefficient is substantially lower than the one observed for SOEs. Imports transacted through Sino-Foreign Ventures, or through Foreign-Owned enterprises display the lowest sensitivity. These results are consistent with the arguments and evidence from other studiep49(h)-(u)-n[illegible](on)22.3(,)-01(i)13(4)0(;)24.5(4(D)0(e)-3.6(t)0(i)21.9(

(1). In this case, the aggregation period, denoted by p, is 12 since the researcher employs yearly data to conduct the analysis. Let t denote the year. With this notation, the aggregation can be expressed as follows:

$$ _{t-k} = \sum_{j=0}^{p-1} _{m-pk-j} = \left(\sum_{j=0}^{p-1} L^j\right) _{m-pk} = (\mathbf{I}-L^p)(\mathbf{I}-L)^{-1} _{m-pk} \quad (2) $$
$$ k = \{0, 1, \ldots\} $$

where L is the lag operator and $\mathbf{I}$ is the (3×3) identity matrix. By lagging Eq. (1) back $p-1$ periods, and substituting forward the last term of the period we can re-write (1) as:

$$ _m = \mathbf{B}^p _{m-p} + \sum_{j=0}^{p-1} \mathbf{B}^j _{m-j} \quad (3) $$

The last term in (3) can be simplified further as follows:

$$ \sum_{j=0}^{p-1} \mathbf{B}^j _{m-j} = \left(\sum_{j=0}^{p-1} \mathbf{B}^j L^j\right) _m = (\mathbf{I}-\mathbf{B}^p L^p)(\mathbf{I}-\mathbf{B}L)^{-1} _m \quad (4) $$

Hence, (3) becomes:

$$ _m = \mathbf{B}^p _{m-p} + (\mathbf{I}-\mathbf{B}^p L^p)(\mathbf{I}-\mathbf{B}L)^{-1} _m) \quad (5) $$

Multiply both sides of (5) by $(\mathbf{I}\text{-}L^p)(\mathbf{I}\text{-}L)^{-1}$to obtain:

$$ (\mathbf{I}-L^p)(\mathbf{I}-L)^{-1} _m = \mathbf{B}^p(\mathbf{I}-L^p)(\mathbf{I}-L)^{-1} _{m-p} + (\mathbf{I}-\mathbf{B}^p L^p)(\mathbf{I}-\mathbf{B}L)^{-1}(\mathbf{I}-L^p)(\mathbf{I}-L)^{-1} _m \quad (6) $$

We can then use (2) (for $k = 0$ and 1) to re-write (6) in its temporally aggregated form:

$$ _t = \mathbf{B}^p _{t-1} + (\mathbf{I}-\mathbf{B}^p L^p)(\mathbf{I}-\mathbf{B}L)^{-1}(\mathbf{I}-L^p)(\mathbf{I}-L)^{-1} _m \quad (7) $$

A regression using annual data, $_t = \tilde{\mathbf{B}} _{t-1} + \tilde{}_t$, will produce inconsistent estimates of $\mathbf{B}^p$ because, as (7) shows, the covariance between $_{t-1}$ and the error term $\tilde{}_t$ will not be zero, as the resulting equation takes on a moving average structure of the monthly (and unobserved) white noise process.

This point can be articulated more clearly using a straightforward illustration. To that end, let $p = 3$. In this case, $\tilde{}_t$ becomes:

$$ \begin{aligned} \tilde{}_t &= \left(\mathbf{I}-\mathbf{B}^3L^3\right)(\mathbf{I}-\mathbf{B}L)^{-1}\left(\mathbf{I}-L^3\right)(\mathbf{I}-L)^{-1} _m \\ &= _m + (\mathbf{I}+\mathbf{B}) _{m-1} + \left(\mathbf{I}+\mathbf{B}+\mathbf{B}^2\right) _{m-2} + \left(\mathbf{B}+\mathbf{B}^2\right) _{m-3} \\ &\quad + \mathbf{B}^2 _{m-4} \end{aligned} $$

Note that $_{t-1}$ can also be expressed as a moving average structure of $_m$ using (1) and (2):

$$ \begin{aligned} _{t-1} &= \left(\mathbf{I}-L^3\right)(\mathbf{I}-L)^{-1} _{m-3} = (\mathbf{I}-\mathbf{B}L)^{-1}\left(\mathbf{I}-L^3\right)(\mathbf{I}-L)^{-1} _{m-3} \\ &= _{m-3} + (\mathbf{I}+\mathbf{B}) _{m-4} + \left(\mathbf{I}+\mathbf{B}+\mathbf{B}^2\right) _{m-5} \\ &\quad + \ldots + \left(\mathbf{B}^{i-2}+\mathbf{B}^{i-1}+\mathbf{B}^i\right) _{m-i-3} + \ldots \end{aligned} $$

Hence, the covariance between $_{t-1}$ and $\tilde{}_t$ in this case is:

$$ \begin{aligned} \mathrm{cov}(_{t-1}, \tilde{}_t) &= \left(\mathbf{B}+\mathbf{B}^2\right) \mathrm{var}(_{m-3}) + \mathbf{B}^2(\mathbf{I}+\mathbf{B}) \mathrm{var}(_{m-4}) \\ &= \left(\mathbf{B}+\mathbf{B}^2+\mathbf{B}^3\right)\boldsymbol{\Sigma} \end{aligned} $$

As noted above, an additional complication that arises with temporal aggregation is the aliasing problem, which makes it impossible for the researcher to detect the presence of higher frequency cycles within the aggregated intervals (Priestly, 1981; Rossana and Seater, 1995).

3. Mea ing he d namic f China' li ical ela i n

The political relations index (PRI) developed by Yan Xuetong and colleagues (Yan and Qi, 2009; Yan et al., 2010) is based on reports of bilateral political events from the Chinese newspaper *Renmin Ribao* (People's Daily), as well as information from the Ministry of Foreign Affairs of the People's Republic of China. The index measures the overall level of relations between China and nine major countries (Australia, France, Germany, India, Japan, Pakistan, Russia, U.K, and U.S.) from 1950 through 2013. The political events identified in the newspaper reports and in the information from the ministry include military conflicts, protests against the foreign country, diplomatic events, etc., and they are weighted by severity (similar to the Goldstein scale, which is widely used in political science research). The reports are amassed monthly. The coding process involves converting events related to the political relations between China and the foreign country into a uniform scale bounded above by 9, the highest degree of friendship, and below by −9, the most severe degree of confrontation. Although the index takes on a continuous variable in the [−9.9] range, it can be represented as a diagram (see Fig. 2) encompassing various categories in the political relations spectrum.[13]

The most straightforward way of modeling the PRI series is to use the Box and Jenkins (1976) methodology of model identification and selection. This methodology involves testing for stationarity, as well as the use of autocorrelation and partial autocorrelation plots to identify a parsimonious autoregressive component and a moving average component of the underlying process. Formally, it is assumed that the stochastic generating process takes the following form:

$$ (L^p)\Delta^d PRI_t = \ (L^q) _t \quad (8) $$

where underlying PRI_t series are differenced d times ($d \geq 0$) to achieve stationarity, and the (L) and (L) are lag polynomials of degrees p and q respectively. The outcome of this modeling methodology delivers a parsimonious ARIMA (p,d,q) process that best explains the time series behavior of the modeled series.

Standard Dicky-Fuller, as well as augmented Dicky-Fuller tests, reveals that the PRI series are non-stationary in levels, but the first differences are stationary. For that reason, the original series are differenced once, before optimal p and q parameters are identified for each China–foreign country dyad.

The PRI_t series is designed to capture all events that relate to political relationships between China and other major countries. These events inevitably include those related to trade. For example, the signing of a trade pact or a trade agreement can be categorized as an improvement in political relations, thereby leading to an increase in the PRI series. Although it is important to quantify the extent to which events with a relationship to trade ultimately affect trade, it is equally important to

where the “Trade_News_Index” tracks all trade-related news that involves China and partner country i, reported in month t. Formally, the index is constructed as follows:

$$Trade\_News\_Index_{i,t} = \frac{\#Trade\_News_{i,t}}{\#Morning_t}$$

In the equation above, the numerator, $\#Trade\_News_{i,t}$, is the count in month t of all articles that contain the following three keywords: “trade,” “China,” and “[partner country i],” where [partner country i] = {Australia, France, Germany, India, Japan, Pakistan, Russia, UK, and U.S.}. The denominator, $\#Morning_t$, is the count of all articles in month t thatMo tneyor

Table 1
Dynamics of China's political relations: optimal ARIMA model selection.

Country	PRI	Trade-filtered PRI
Australia	(0,1,0)	(1,1,1)
Germany	(0,1,0)	(1,1,1)
Great Britain	(0,1,0)	(1,1,1)
France	(0,1,0)	(1,1,1)
India	(0,1,0)	(1,1,1)
Japan	(0,1,0)	(2,1,2)
Pakistan	(0,1,0)	(0,1,0)
Russia	(0,1,0)	(2,1,2)
United States	(0,1,0)	(0,1,0)

Note: This table presents the optimal ARIMA model selection based on the Box and Jenkins (1976) approach. In each cell, entry (p,d,q) represents the optimal autoregressive parameter (p), whether integration was necessary (d = 0 or 1); and the optimal moving average parameter (q). "PRI" represents the Political Relations Index of Yan et al. (2009), Yan et al. (2010). "Trade-filtered PRI" is the PRI series after trade-related news has been removed.

Table 2
Spectral density analysis of integrated political relations index.

Country	Δ*PRI*			ΔTrade-filtered *PRI*		
	WN test	Low freq cycles	High freq cycles	WN test	Low freq cycles	High freq cycles
Australia	1.109	0.130	0.360	3.318***	0.035	0.567
Germany	0.942	0.162	0.261	3.010***	0.029	0.504
Great Britain	0.546	0.161	0.311	3.883***	0.041	0.588
France	0.822	0.202	0.315	2.637***	0.063	0.434
India	0.399	0.186	0.328	2.917***	0.034	0.482
Japan	2.496***	0.332	0.221	1.774***	0.277	0.272
Pakistan	0.372	0.153	0.321	0.525	0.144	0.321
Russia	0.776	0.188	0.281	3.253***	0.031	0.426
United States	1.399**	0.269	0.309	1.435**	0.272	0.314

Note: This table presents three statistics that analyze the spectral density of the integrated Political Relations Index (Δ*PRI*) and the integrated Trade-filtered Political Relations Index (ΔTrade-filtered *PRI*). The first statistic is the Bartlett's test of white noise based on the series' spectral cumulative periodogram. Failure to reject the null suggests that cycles are important at every frequency. A statistically significant test (indicated with *** at the <1%, and ** at the <5%) rejects the null of a white noise process, in favor of unevenness in the prevalence of cycles at different frequencies. The second statistic, "Low Freq. Cycles", reports the cumulative spectral distribution function at "low" frequencies (cycles of 12 months or longer). Thus, a figure like 0.130 for the integrated PRI series for Australia indicates that 13% of the cycles occur at frequencies of 12 months or longer. The third statistic, "High Freq. Cycles", reports the cumulative spectral distribution function at "high" frequencies (cycles of 3 months or shorter). Thus, a figure like 0.567 for the integrated, trade-filtered PRI series for Australia indicate that nearly 57% of the cycles occur at frequencies of 3 months or shorter.

The fact that a significant proportion of the movements in the PRI series occur at relatively high frequencies underscore the aliasing concern addressed above—with temporally aggregated series it is not possible to detect important dynamics that are taking place within the aggregated intervals.

4. Ca e die

The empirical findings discussed in the previous section indicate that the dynamics of PRI shocks can be modeled with low-order ARIMA processes and that high-frequency cycles form an important portion of the dynamics of PRI shocks. This section presents two examples of significant political shocks between China and another major power to illustrate the temporary aspects of the shocks. By implication, less significant shocks dissipate even more rapidly.

The two cases we explore are (1) the U.S. bombing of the Chinese embassy in Belgrade in May 1999, and (2) the Senkaku boat collision incident (involving Japan) in 2010. The reasons these cases were chosen are twofold. First, both resulted a substantial shock to the political relations between China and the foreign country. Second, sufficient time has elapsed since the occurrence of these incidents to allow for a thorough evaluation of their effects on trade.

4.1. U.S. bombing of the Chinese embassy in Belgrade in May 1999

The U.S. bombing of the Chinese embassy in Belgrade in May 1999 marked one of the most serious adverse political shocks to China–U.S. relations since 1990. In fact, according to Yan and Qi (2009) and Yan et al. (2010), it resulted in the largest drop in the political relations index during the sample period (see Fig. 3). Below, we summarize the main events surrounding this incident, from its inception to its diplomatic conclusion.

On May 7, 1999, during the NATO bombing of the former Yugoslavia, five US JDAM (Joint Direct Attack Munition) guided bombs hit the Chinese embassy in Belgrade, killing 3 Chinese nationals and injuring at least 25 others. The Chinese government made a statement on May 8 condemning the event, and expressed its utmost indignation in the strongest possible form. Despite President Bill Clinton's personal apologies beginning on May 10, stating that the bombing was an accident, the reaction in China was one of unparalleled indignation and sheer anger.[20] The Chinese public was outraged. In major cities such as Beijing, Shanghai, and Chengdu, students and other residents protested the bombing in marches outside the U.S. embassy and consulates. On the same day as the bombing, the Chinese Ministry of Foreign Affairs announced the suspension of high-level military contact with the United States, as well as the suspension of all negotiations dealing with nuclear nonproliferation, arms control, and international security. It also terminated the Sino-American dialogue with respect to human rights. Unquestionably, the China-U.S. relationship took a deep dive, becoming very tense during that month. Indeed, news media reported that the incident dealt a very serious blow to relations between the two countries.[21]

But despite the seriousness of the incident, the Chinese reaction dissipated quickly. In fact, market indicators in China seem to have brushed the entire event aside within days. For example, although the Shanghai Stock Exchange index dipped about 4% on Monday May 10 (the first trading day after the bombing), on Tuesday May 11 market commentators opined that, despite the increase in political tension between the two countries, the fallout on financial markets would be very limited as in fact proved to be the case.

Yet diplomatic cooperation between Beijing and Washington continued, with the result that tensions eased within two months. Even though Beijing never accepted Washington's explanation that the embassy bombing was a mistake, by the end of the summer the two countries had worked out the first stage of a settlement. In August, the U.S. government made a "voluntary humanitarian payment" of $4.5 million to the families of the 3 Chinese nationals who were killed and to the 27 injured in the bombing. On December 16, 1999, the two governments reached a settlement under which the United States would pay $28 million as compensation for damage to the Chinese embassy facility, and China would pay $2.87 million in compensation for damage inflicted on the U.S. embassy and other diplomatic facilities in China.[22] On January 22, 2000, Chinese Lieutenant General Xiong Guangkai, the Deputy Chief of Staff of the Army and the head of China's National Security Council, visited the United States, marking the formal resumption of military contact between Washington and

[20] President Clinton made several apologies following the event, beginning with an official letter to Chinese President Jiang Zeming on May 9, continuing with several personal apologies in subsequent days. For example, on May 10 a news report from Reuters mentions: "美国总统克林顿首次亲身就误炸中国大使馆一事向中国和中国人民道歉." (U.S. President Bill Clinton for the first time issues a personal apology to China for the accidental bombing of the Chinese Embassy.) On May 11, another report from the same agency notes: "美国总统克林顿向中国人民道歉,北京仍施压促彻查惩凶." (U.S. President Bill Clinton apologizes to the Chinese people. Beijing demands a thorough investigation of the incident.)

[21] For example, on May 10, 1999, Reuters in China reports: "中国中止与美国军事等交流.双方关系陷入20年来最低点,对北约提公开道歉等四要求.美也暂停所有官员访中活动." (China suspends military exchanges with the U.S. Bilateral relations now at a 20 year low. Beijing also indicates that all official visits to the U.S. would be suspended.) 10 May 1999路透社-中文新闻 (Reuters-Chinese news).

[22] See article by Kerry Dumbaugh entitled: "Chinese Embassy Bombing in Belgrade: Compensation Issues." Congressional Research Service, April 12, 2000.

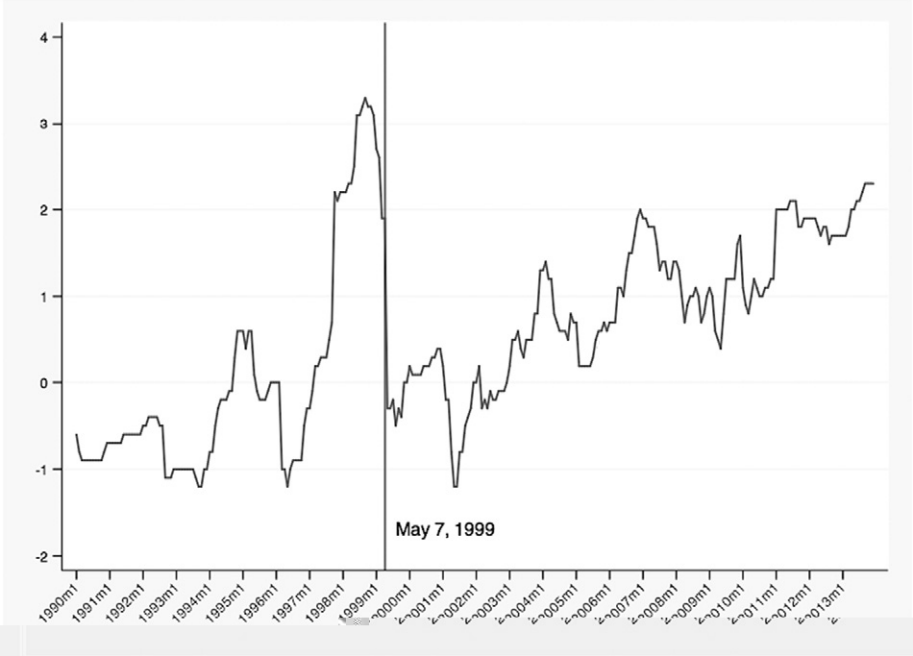

Fig. 3. PRI between the U.S. and China: January 1990 through December 2013. Note: Vertical line marks the date of the Belgrade bombing incident.

Beijing (as noted above, China's immediate response to the embassy bombing had included suspending all high-level military contact between itself and the United States). By the time of Xiong's visit, the conflict around the embassy bombing was essentially settled, and the military relationship had been largely restored.

Newspaper reports suggest that the effect of this incident on bilateral economic relations was very limited. For example, on May 19, just 10 days after the bombing, a trade delegation from China visited the U.S. to strengthen economic ties. The detachment of the bombing incident from economic ties was evident as one of the delegation members, Mr. Ye Jian, then the director general of the Economic Relations and Foreign Trade Commission from Jiangsu province, remarked "The Governor, Lieutenant Governor [of Jiangsu province] and myself have been very dismayed at the incident committed by U.S.-led NATO… But I deal with the economy and trade, so I must come."[23]

4.2. The Senkaku boat collision incident in 2010

On September 9, 2010, a Chinese trawler seeking to flee the scene collided with several of the Japanese Coast Guard's patrol boats in disputed waters near the Senkaku Islands (known in Mainland China as the Diaoyu Islands); Japanese authorities arrested the trawler's captain, Zhan Qixiong, and accused him of obstructing Japanese public officers during the performance of their duties. The incident resulted in a serious shock to Sino-Japanese political relations, as Fig. 4 illustrates.[24] Beijing protested and demanded the captain's immediate and unconditional release. Japan, by contrast, claimed to be handling the incident "in accordance with domestic law," insisting that the Senkaku Islands "are clearly an inherent territory of Japan."[25]

The incident provoked diplomatic jousting between Beijing and Tokyo, as well as large-scale protests in both China and Japan. On the day the captain was arrested, public protests began in many major Chinese cities. But China's repeated demands were refused; instead, the Japanese government extended the captain's detention for an additional 10 days, to September 19. The Chinese government reacted by canceling all official meetings with Japan at the ministerial level and above. In addition, on September 20, China detained four Japanese employees of Fujita Corporation for allegedly filming military targets in Hebei province. And on September 23, China suddenly halted exports of rare earth minerals to Japan. Though neither country linked the export restriction to the case of the detained captain, the restriction certainly seemed to be a consequence of the rising tension between China and Japan stemming from the arrest.

Just a day later, on September 24, the Japanese government released the captain, thereby avoiding further deterioration of bilateral relations. But on both sides, outrage and anger on the part of the government and public alike had still not diminished. Beijing was demanding an apology and compensation from Tokyo, while Japan was demanding compensation for damage done to its coast guard ships. On October 2, in Tokyo and six other major Japanese cities, anti-China protesters gathered to criticize what they saw as their government's weak-kneed handling of the event.[26]

A few days later, however, the two countries began mending their relationship. On October 5, for example, Chinese Premier Wen Jiabao and Japanese Prime Minister Naoto Kan met informally on the sidelines of the Asia–Europe Meeting in Brussels. According to the Xinhua news agency, Wen and Kan "agreed to step up people-to-people exchange and communication between the governments, and hold China–Japan high-level meeting at an appropriate time."[27] On October 9, China released all the Fujita employees. Although protests still took place throughout China during the month, they began to dwindle after the

[23] See article entitled "China Trade Group Ready for Business" from the May 20, 1999 issue of the New York Times, p. 17.

[24] This incident in by no means the only one that has affected Sino-Japanese relations in recent years. In 2012, for example, bilateral relations endured the most significant blow after the Japanese government purchased three of the Senkaku islands from a private owner. This event is also illustrated in Fig. 4.

[25] "Statement by the Press Secretary on the Collision between Japan Coast Guard Patrol Vessels and a Chinese Fishing Trawler in Japan's Territorial Waters off the Senkaku Islands," September 25, 2010. Ministry of Foreign Affairs of Japan. Retrieved from http://www.mofa.go.jp/announce/announce/2010/9/0925_01.html.

[26] "Tokyo Protests Blast China's Response to Collision," *Wall Street Journal*, October 3, 2010, http://online.wsj.com/news/articles/SB10001424052748704419504575527664218726440.

[27] "Japan Expecting to Improve Ties with China: Top Gov't Spokesman," *Xinhua News*, October 5, 2010, http://news.xinhuanet.com/english2010/china/2010-10/05/c_13543179.htm. "Conversation between Prime Minister Kan and Premier Wen Jiabao," Ministry of Foreign Affairs of Japan, October 5, 2010, http://www.mofa.go.jp/region/asia-paci/china/summit_conv1010.html.

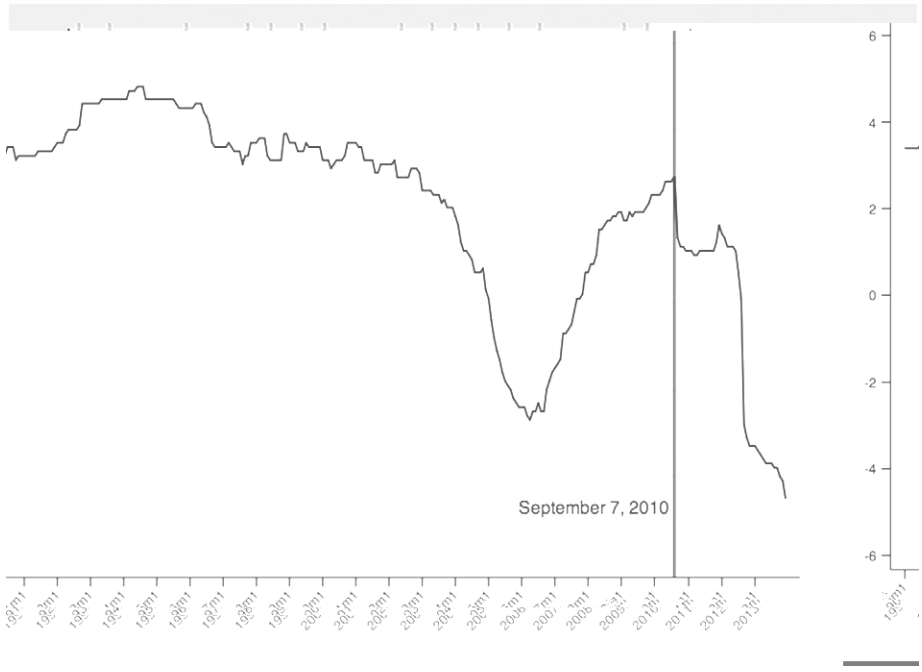

Fig. 4. PRI between China and Japan: January 1990 through December 2013. Note: Vertical line marks the date of the Senkaku boat collision incident.

Chinese government discouraged further protests. By October 28, when a final demonstration was reported, anti-Japanese sentiment had substantially cooled. In Japan, however, anti-China protests and demonstrations continued for a while longer,[28] after a video showing the collisions, filmed by the Japanese coast guard on September 7, was leaked on YouTube on November 4.[29] Many Japanese citizens interpreted the video as demonstrating that the Chinese trawler deliberately rammed the Japanese coastguard vessels.

The aftermath of the incident was largely over by the end of 2010. On January 20, 2011, Japanese prosecutors officially dropped all charges against Zhan Qixiong, and the next day the video leaker was also exempted from charges. The tensions caused by the Senkaku boat collision incident had subsided in less than five months.

Media reports indicate that the adverse effects on trade were short-lived. Although two weeks after the incident there were reports of an increase in Customs inspections of merchandise from Japan, thereby slowing trade, other reports indicate that by January 2011, Japanese exports to China had increased significantly, especially in automobiles and luxury goods.[30]

5. D namic m del f li ical ela i n n ade

As mentioned in the introduction, most the studies that investigate the effect of political shocks on trade do so within the context of the gravity model (Anderson and van Wincoop, 2003). This model posits that bilateral trade is an increasing function of economic activity in both countries and that it decreases with geographical distance. Often other covariates (such as bilateral exchange rates or population) are included in the model as well.[31] The chosen measure of political relations is, of course, also added to the model.

Our model, too, is motivated by this framework. However, since we seek to investigate the extent to which political shocks affect bilateral trade over time, we adopt a vector autoregression (VAR) model. This modeling technique is particularly useful in our context because it is designed to quantify the magnitude of the effect at different time periods, enabling us to make inferences about the dynamic impact of the shocks. In addition, its flexibility permits the symmetric treatment of all covariates as endogenous variables in the system.

Formally, our model is

$$_{j,m} = \boldsymbol{c}_j + \sum_{i=1}^{n} \mathbf{A}_{j,i} \; _{j,m-i} + \mathbf{e}_{j,m} \tag{9}$$

$$_{j,m} = \left(\Delta \boldsymbol{ex}_{j,m}, \Delta \boldsymbol{PRI}_{j,m}, \Delta \boldsymbol{y}_{c,m}, \Delta \boldsymbol{y}_{j,m}, \Delta \boldsymbol{er}_{j,m}\right)'$$

where subscript "j" represents the country = {Australia, Germany, France, India, Japan, Pakistan, Russia, U.K., U.S.}, "m" represents the month = {Jan. 1990, …, Dec. 2013}. The column vector contains (i) the percentage change in partner j's exports to China at time m ($\Delta \boldsymbol{ex}_{j,m}$); (ii) the change in the China–partner j' s political relations index at time m ($\Delta \boldsymbol{PRI}_{j,m}$); (iii) the percentage change in the industrial production index for China at time m ($\Delta \boldsymbol{y}_{c,m}$); (iv) the percentage change in partner j's industrial production index at time m ($\Delta \boldsymbol{y}_{j,m}$); and (v) the change in the ratio of partner j's real effective exchange rate to China's real effective exchange rate at time m ($\Delta \boldsymbol{er}_{j,m}$).[32]

[28] For example, "Japan Protesters Rally over China, Kan as APEC Looms," Reuters, November 6, 2010, http://in.reuters.com/article/2010/11/06/idINIndia-52713420101106.

[29] According to the report by Reuters, the Japanese government had decided not to make the video public and released it for viewing only by a small number of lawmakers for fear of inflaming anti-Chinese sentiment ("Japan Investigating China Collision Video," Reuters, November 5, 2010, http://in.reuters.com/article/2010/11/05/idINIndia-52690020101105).

[30] The increase in Customs inspections is reported in an article entitled "China steps up checks on Japanese shipments" printed in My Paper (Singapore Press Holdings), on September 28, 2010. The rise in Japanese exports to China is reported in an article entitled "Japanese Firms Thriving on Chinese Demand" printed on Nikkei (NKRP), on January 5, 2011.

[31] We include a measure of exchange rates in the model, but do not include population or distance variables because our model is identified with time series, and those two variables are eithe completely time-invariant (e.g., geographical distance) or nearly so in the short-run (e.g., population).

[32] All percentage changes are computed as differences of log transformations. For variables that can take on negative values (such as the political relations index), a sufficiently high positive constant is added before the log transformation is computed to ensure that its value is well defined. Export and industrial production data are seasonally adjusted. We use industrial production (for China as well as the partner countries), as GDP figures are available on a quarterly basis only. Data sources are listed in Appendix 1.

The $\mathbf{A}_{j,i}$'s in Eq. (9) are 5×5 matrices of the VAR model coefficients, and $E[\mathbf{ee}']$ is the 5×5 variance-covariance matrix of contemporaneous error terms. The lag order ("n" in Eq. (9)) was selected using the standard information criteria: the Final Prediction Error (FPE), the Akaike information criterion (AIC), the Bayesian (Schwarz) information criterion (BSIC), and the Hannan-Quinn information criterion (HQIC). Although different criteria recommended different lag orders, these tended to vary between 2 and 4 lags.[33]

Our model (Eq. (9)) is estimated in changes for two reasons. First, all the variables included are non-stationary in levels, but stationary in first difference.[34] Second, since our aim is to investigate the extent to which political shocks affect the dynamics of partner j's exports to China, estimating the model in changes maintains a natural congruency with the logic of the test.[35]

6. Em i ical e l

The effect of a political shock on trade can be measured using orthogonalized impulse response (OIR) functions.[36] OIR functions illustrate the change that occurs over time to the value of one variable in the model as another variable is shocked.[37] Since we have eight partner countries, we estimated eight sets of OIRs.

Fig. 5 displays the impulse response functions of the partner countries' export growth to China when *PRI* experiences a one-standard-deviation shock. Fig. 6 displays the analogous functions for the trade-filtered *PRI* shocks. Each fi

third month, however, the effects have dissipated. We do not find any statistically significant long-term cumulative effects. For the trade-filtered *PRI* series, although the observed pattern is similar to the pattern observed using the original *PRI* series, the magnitudes are, perhaps not surprisingly, somewhat larger.[39] The duration of the effects is, however, analogous—the effect of trade-filtered PRI shocks on exports is short-lived, lasting no longer than two months.

Although we argue that the estimated dynamic effects (magnitude and duration) are overall limited and short-lived, we do observe some differences in the patterns across countries. For example, according to Fig. 5, the impact of *PRI* shocks on exports peaks in month 1 for the USA, Japan, Australia, and India, while it peaks in month 2 for the remaining countries in the sample (France, Great Britain, Russia, and Germany), and as noted above, it is never statistically significant for Pakistan. In addition, Fig. 5 indicates that for the cases of Germany, France and the U.K. an adverse PRI shocks appears to accelerate exports in month 1, before slowing it down in month 2.

In fact, it is natural to expect different effects across countries as there exist important heterogeneities not explicitly modeled, such as differences in industrial structure, differences in duration of contracts across industries or firms, etc. In an online appendix,[40] for instance, we document that the effect of political shocks on China's imports differs by the type of firms transacting the purchase in China. In particular, we find that, relative to other types of firms (e.g. privately-owned firms, foreign-owned enterprises, and Sino-Foreign joint ventures), state-owned enterprises (SOEs) display the highest sensitivity of imports to political relation shocks. This finding, in combination with the fact that there are cross-country differences among the type of Chinese fi

results, we computed the cumulative long-term effects of the PRI shocks on exports implied by the VAR model. Examining the cumulative effect on the changes is a straightforward way of evaluating whether there are long-lasting effects on levels. The estimated effects are reported in Table 3. The results indicate that in all but two cases (India and Russia) the long-term effects of a *PRI* shock are not statistically different from zero. For the trade-filtered *PRI* series, no long-term effects are detected for any of the countries.[44]

The fact that we detect long-term effects for India and Russia when using the unfiltered *PRI* series, but not when using the trade-filtered *PRI*

Table 5
Gravity equation model regression results.

	(1)	(2)	(3)	(4)	(5)	(6)
	Monthly			Annual		
$\Delta EXP_{j,t-1}$		−0.383***	−0.487***		−0.156	−0.183
		(0.022)	(0.022)		(0.122)	(0.117)
$\Delta EXP_{j,t-2}$			−0.256***			−0.126
			(0.022)			(0.115)
$\Delta TFPRI_{j,t}$	0.010	0.014	0.015	0.025***	0.039**	0.031*
	(0.006)	(0.010)	(0.010)	(0.006)	(0.019)	(0.018)
$\Delta TFPRI_{j,t-1}$		0.022****			0.183	

take place at the monthly frequency. Without a priori knowledge of those effects, it is not possible to back out the timing and magnitude of the underlying (monthly) dynamics from the annual regressions.

We present the new gravity regressions in Tables 4 and 5. Table 4 presents the results for the PRI variable, while Table 5 presents the results for the trade-filtered PRI series.[48] Although the exact timing of the effects differs somewhat between the two set of results, they are qualitatively similar in the sense that both are temporary. In addition, both set of results offer evidence of the aggregation bias.

In each table, there are six regressions. The first three regressions show the results using monthly data with three different autoregressive models. As pointed out above, we include up to four lags (in months) of the political relations variable to ensure that we span the timing detected in the VAR models. The last three regressions show the results using annual data (again, with different autoregressive models, and with up to three lags (in years) of the political relations variable). We start out with zero autoregressive components and zero lags of the political relations variable for both set of regressions (monthly and annual). These are Regressions (1) (monthly) and (4) (annual). These two regressions aim at establishing benchmark results against which the other regressions results can be compared. The next set of regressions (Regression (2) for the monthly, and (5) for the annual), includes one autoregressive process of the dependent variable. The inclusion of this process captures the dynamics of export over time following a political relations shock. A negative coefficient in the autoregressive process implies a fast-moving, mean-reverting effect for exports after the shock takes place. Regression (2) also includes 2 lags (months) of the political relations variable to allow for a delayed monthly effect of the political shocks. Regression (5) (annual regression with the first lagged dependent variable) does not include lags of the political relations variable. This is done to highlight the importance of contemporaneous (current) PRI coefficient (in order to focus on the temporal bias issue), even after one lag of the exports variable has been included. Finally, Regressions (3) (monthly) and (6) (annual) display the results after including two autoregressive lags for exports, as well as various lags of the political shocks variable. The inclusion of a second autoregressive lag aims at ensuring robustness in the results. Both regressions also include a distributive lag of the political shocks variable: up to a 4-month lag for the monthly equation, and up to a 3-year lag for the annual equation.[49]

Comparing the results of regressions (3) and (6) best illustrate the difference in the dynamics between the monthly and annual effect. For instance, in Table 4, Regression (3) indicates that a one-unit decline in PRI adversely affects export growth by 0.073 a month later. However, in the second month after the PRI shock, export growth increases by 0.038 ($= -0.52 \times 0.073$). Thus, after just two months, the cumulative effect on exports is 0.035 ($= 0.073–0.038$). Additional dampening effects take place in month 3 and onwards as the second lag of the dependent variable and higher-order effects of the first lag of the dependent variable further impart an (attenuating) impact. This timing and observed dynamic pattern is consistent with the one detected in the VAR results. By contrast, Regression (6) (annual regression) indicates

that a one unit decline in PRI affect export growth by 0.051 in the same year, and for the entire year. Furthermore, since lagged exports do not appear to instill an effect, the results imply that the PRI effect on exports is essentially permanent.

Our gravity equation findings can be summarized as follows: 1. With monthly data, the current period change in political relations of has no significant effect on exports. However, with annual data, the current period change in political relations does have a positive and significant effect. 2. With monthly data, we find that political relations have a delayed and relatively modest effect on exports. Furthermore, that the effect is short-lived, lasting approximately 3 months. These results substantiate the concern about the practice of using temporally aggregated data to investigate the effect of political relations on trade. Result 1 (comparing the contemporaneous coefficients), indicate that there is an aggregation bias. Result 2 highlights the fact that with temporally aggregated data, it is not possible to unmask the natural dynamics of the effect.

8. C ncl ding ema k

A sizable number of studies in the political science and economics literature find that politics is an important determinant of trade flows. There are many solid theoretical reasons for expecting to observe an effect. For example, shocks in political relations among countries can stir nationalistic sentiments among citizens, thereby affecting consumer preferences and ultimately, trade. Political shocks may also influence government behavior in ways that are detrimental to trade. In addition, political shocks introduce uncertainty, and uncertainty is, after all, associated with lower economic activity.

But although the theoretical underpinnings modeling the relationship between politics and trade is solid, the empirical strategy that many researchers have followed to identify an effect—estimating a gravity model with a measure of political relations using, for the most part, annual data—is potentially problematic.

This paper argues that the underlying problem is that a sizable portion of political shocks are relatively short-lived—with spectral densities of months, if not weeks—whereas researchers have been using data aggregated at much lower frequencies for identifying an effect. Such aggregation can introduce a "temporal aggregation" bias. Hence, to properly investigate whether politics affects trade flows, it is necessary to rely on higher-frequency data.

Using China as our case study, we find that the aftermath of political shocks to the relationships with major trading partners indeed tend to be short-lived; that trade is responsive to political shocks; and that the trade effects of the shocks are likewise short-lived. Based on a vector autoregression analysis, the effects of political shocks on trade are detected only in the first two months following the shock. By the third month, the effects are effectively nil. Results from gravity equation regressions likewise indicate that the effects are temporary, lasting approximately three months. These results validate our concern about using low frequency data to examine the effect of political shocks on trade in general. Temporal aggregation bias is an issue that deserves careful consideration in any investigation of the extent to which political relations affect trade flows.

We also discuss and empirically explore the most commonly highlighted mechanisms through which political shocks affect trade using firm-level import transaction data from China's Administration of Customs. We find that the sensitivity of imports to political relations is highest for SOE firms. We also find that the sensitivity significantly declines, in order, for privately-owned firms, Sino-Foreign joint ventures, and lastly for Foreign-owned enterprises. This ranking is consistent with the mechanisms the literature has highlighted mediating the effect of political relations on trade for the case of China.

In light of our results stressing the importance of temporal aggregation, it seems prudent to investigate how the prevalence of different mechanisms is likewise affected by the temporal aggregation bias. In future research, we plan on investigating this issue in more detail.

A endi 1. Da a ce

Variable	Description	Source
PRI	Political relations index	Yan et al. (2009), Yan et al. (2010); http://www.imir.tsinghua.edu.cn/publish/iis/7522/index.html
ex	Partner country's export to China (in mill of current US$)	IMF Direction of Trade (DOT)
y	Industrial production (monthly and annual) or GDP (annual)	National Bureau of Statistics of China (industrial production value added); OECD iLibrary (industrial production index); World Bank GEM Database (industrial production and GDP).
er	Real effective exchange rate between partner country and China	IMF International Financial Statistics (IFS) and Bruegel.org
TNI	Trade News Index	Factiva
Firm-level imports	Imports transacted by firms in China from 2000 to 2006.	General Administration of Customs of China

A endi 2. De i a i n

2.1. Comparing coefficients from monthly and annual frequency regressions

Under an autoregressive process, the monthly model of export growth and changes in PRI can be described as follows:

$$y_m = \beta_0 + \gamma y_{m-1} + \delta x_m + \varepsilon_m \tag{A.1}$$

where subscript m represents the month, x_m represents the change in PRI, y_m the change in exports, and ε_m is the error term.[50]

The temporally aggregated (at the annual level) version of y and x are:

$$y_t = \left(1-L^{12}\right)(1-L)^{-1} y_m \tag{A.2}$$

[50] Eq. (A.1) is robust to a more general dynamic process, including a distributed lag on the PRI variable. For instance, if one or more lags of the PRI variable are part of the model, we would have: $y_m = \beta_0 + \gamma y_{m-1} + \delta_0 x_m + \delta_1 x_{m-1} + \varepsilon_m$. Notice, however, that with an appropriate lag operation, (e.g. $\cong(\delta_0 + \delta_1 L)$), the model can be transformed into an isomorphic version of (A.1). Thus, there is no loss of generality in considering (A.1).

and

$$x_t = \left(1-L^{12}\right)(1-L)^{-1}x_m \tag{A.3}$$

thus, the monthly to annual frequency operator is: $(1-L^{12})(1-L)^{-1.}$

Note that

$$y_{t-1} = \left(1-L^{12}\right)(1-L)^{-1}y_{m-12}$$

A similar equation applies for x_{t-1}.

By backward substitution of Eq. (A.1) we obtain:

$$y_m = {}_0\left(\sum_{j=0}^{11} {}^{j}\right) + {}^{12}y_{m-12} + \sum_{j=0}^{11} {}^{j}\, x_{m-j} + \sum_{j=0}^{11} {}^{j}\, {}_{m-j} \tag{A.4}$$

The terms with the sums can be simplified as:

$$\sum_{j=0}^{11} {}^{j}\, x_{m-j} = \sum_{j=0}^{11} {}^{j}L^{j}\, x_m = \left(1- {}^{12}L^{12}\right)(1- L)^{-1}\, x_m$$
$$\sum_{j=0}^{11} {}^{j}\, {}_{m-j} = \sum_{j=0}^{11} {}^{j}L^{j}\, {}_{m} = \left(1- {}^{12}L^{12}\right)(1- L)^{-1}\, {}_{m}$$
$$A = {}_0\left(\sum_{j=0}^{11} {}^{j}\right)$$

Thus, Eq. (A.4) can be written as:

$$y_m = A + {}^{12}y_{m-12} + \left(1- {}^{12}L^{12}\right)(1- L)^{-1}\, x_m + \left(1- {}^{12}L^{12}\right)(1- L)^{-1}\, {}_{m} \tag{A.5}$$

Multiplying (A.5) by the aggregate operator yields:

$$\left(1-L^{12}\right)(1-L)^{-1}y_{m} = \left(1-L^{12}\right)(1-L)^{-1}A + \left(1-L^{12}\right)(1-L)^{-1}\, {}^{12}y_{m-12} + \left(1-L^{12}\right)(1-L)^{-1}\left(1- {}^{12}L^{12}\right)(1- L)^{-1}\, x_m + \left(1-L^{12}\right)(1-L)^{-1}\left(1- {}^{12}L^{12}\right)(1- L)^{-1}\, {}_{m}$$

We can now use the temporally aggregated versions of y and x, (A.2) and (A.3), to simplify the above equation, obtaining:

$$y_t = 12A + {}^{12}y_{t-1} + \left(1- {}^{12}L^{12}\right)(1- L)^{-1}\, x_t + \left(1- {}^{12}L^{12}\right)(1- L)^{-1}\, {}_{t}$$

or

$$y_t = 12A + {}^{12}y_{t-1} + x_t + x_{t-1} + \ldots + {}^{11}\, x_{t-11} + \left(1- {}^{12}L^{12}\right)(1- L)^{-1}\, {}_{t} \tag{A.6}$$

Hence, the coefficient of the contemporaneous but temporally aggregated x variable, x_t, displayed in (A.6) is the same as the one from the contemporaneous x variable at the monthly frequency, x_m, displayed in (A.1).

A endi 3. S lemen a da a

Supplementary data to 1(b)17.2(y)-262.8336e22.7(q)1Fv1,4Tf.5547(d)16.5(ix)(e)0(n)21.5(c)0(y)27.j.57815(d)-2460T5320TD.9ag0.47875.5(o)-Tf5.(u)

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