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Research Report

Risky cascading transitions in international relationships

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Abstract

Changing attitudes in diplomatic relations is a common feature of international politics. However, such changes may trigger risky domino-like cascades of "friend-to-enemy" transitions among other counties and yielding catastrophic damage that could reshape the global network of international relationships. While previous attention has been focused on studying single pairs of international relationships, due to the lack of a systematic framework, it remains still unknown whether, and how, a single transition of attitude between two countries could trigger a cascade of attitude transitions among other countries. Here, we develop such a framework and construct a global evolving network of relations between country pairs based on 70,756,728 international events between 1,225 country pairs from January 1995 to March 2020. Our framework can identify and quantify the cascade of transitions following a given original transition. Surprisingly, weaker transitions are found to initiate most of the largest cascades. We also find that transitions are not only related to the balance of the local environment, but also global network properties such as betweenness centrality. Our results suggest that these transitions have a substantial impact on bilateral trade volumes and scientific collaborations. Our results reveal reaction chains of international relations, which could be helpful for designing early warning signals and mitigation methods for global international conflicts.

Keywords: International relationships, Complex system, Cascade effects, Computational framework

Significance Statement

As one commentary stated "If the human race is wiped out in the next 50 years, it will not be because of disease or an asteroid hitting the earth, but because of foreign policy and international relations." However, the underlying mechanisms and concepts of international transitions are currently far from being clear. It has been realized that in contrast to a gradual and continuous transition, a "minor transition" in international relations can invoke a large tide of social earthquakes, such as in World War I. This emotional spreading of suspicion or panic is not linear as in other physical spreading processes. Given this complexity, we have developed a computational framework that quantify clear cascading patterns in international relation transitions.

Introduction

Change is the only permanent feature in life. Changes in complex dynamical systems are often highly interdependent and may lead to unexpected outcomes that are impossible to properly control. This is also true for international politics, where the transition of relations between a pair of countries might yield unexpected risky cascade effects. Aggregated transitions of international relations, i.e., number of good-to-bad turns followed by bad-to-good turn and so on, indicate the strength of the instability in the relations between a pair of countries. During last year, the COVID-19 pandemic has brought about unexpected losses of trust and cascading transitions in international relations, in addition to massive challenges to public health. Diplomatic tensions emerged from lack of medicines resources, diagnostic tests, quarantine policies as well as joint debts. One core reason for this stress is that we are all in a "global network," and a single spark, such as COVID-19, can produce cascading transitions in international relations, which can throw mankind into more unexpected danger than ever. As has been argued previously, "If the human race is wiped out in the next 50 years, it will not be because of disease or an asteroid hitting the earth, but because of foreign policy and international relations (1)."

In fact, throughout history, international relations have always served as the reaction chain of major conflicts or cooperation in human society. While tremendous developments have been made through international relations in areas such as bilateral trade (2), scientific collaborations (3), and cultural exchanges (4), almost all wars are related to transitions of international relations. A famous

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example is World War I, in which the relations between Austria-Hungary and Serbia fully collapsed due to a weak transition in June 1914, which resulted in an outbreak of hostilities involving over 30 countries (5). These cascading transitions killed over 13 million civilians. In order to avoid a similar tragedy in the future, it is critical to understand the transitional nature of country relations systematically, as the driving force of the international reaction chain of collaboration or hostility.

Earlier studies have been aiming to understand international relations from different perspectives. A natural way has been to explore bilateral interaction [Fig. 1(a)] by assuming that inter-country relations arise from sequential games of national diplomatic strategies (6, 7). These include applying reciprocity policy (8) for achieving international cooperation or acting together to make a thaw to stand-offs under the Lijphart effects (9), or even deliberately straining the peace in order to achieve a certain strategic goal (10). However, as noted, any human immersed in international affairs immediately realizes that no important issue exists in isolation (11). Accordingly, changes of relations between one pair of countries could be attributed to the influence of its neighbors (12). The classical social theory of structural balance developed by Heider suggests that a third-party together with two nations can form a triangular relation, which can be in a balanced or imbalanced state (13). Inspired by this, Harary contributed an early example of triangular relations by analyzing the Middle Eastern situation in 1956 with structural theory, which incorporates another country to investigate the relation of a specific country pair (14). The results indicate that a balanced local structure engenders a tendency towards the status quo. Following studies focus on such local structures [Fig. 1(b)] of different balance types (15–18). While these studies provide strong evidence that the country relationship not only depends on the characteristics of the pair itself (19), they remain local interactions (involving neighboring countries) from a network viewpoint.

Indeed, with the fast-growing globalization of economical and cultural collaborations, we hypothesize herein that country relationships are not only shaped by their local network environment, but also by their global role in the country relation network [Fig. 1(c)]. We assume that the establishment of various international interactions could enhance the coupling between different countries, and places each country in a unique global network position (20–24). Recently, some researchers found that the network position of a country is of great importance and can alter the distribution of influential power (25). While a few studies indicate the existence of relationship network between countries (21, 22), this raises one critical yet unsolved question: whether and how the dynamical transitions of country relations are propagated. Understanding this question could secure the ability to predict, mitigate, and even avoid the occurrence of large-scale violent polarization around the world, which is now in a more vulnerable and dangerous state.

To overcome this gap, we develop here a framework for systematically studying transitions of country relations and following their global cascade. In this paper, the state of relation in each month is measured by the average score of all events that occurs between a pair of countries. Relations of country pairs are characterized by positive (*P*) or negative (*N*) states, which represent a relatively cooperative or conflictive relations, respectively. For each pair of countries, the change of state from positive to negative (or from negative to positive) within two consecutive months is defined as a transition, denoted by *PN* (or *NP*). Through this way, we find that cascade transitions in relations between pairs of countries are unfolded in the context of global-scale scenarios, which enable us to reveal patterns in the interactions of country relations from a comprehensive perspective. Our results indicate that although strong transitions cause strong cascading effects over many other country pairs within short periods, weak transitions are surprisingly responsible for a high fraction of the largest cascades. The probability and strength of transitions are found to have a strong correlation with their *local* balanced level and their *global* centrality role in the network. Our findings also suggest that transitions have a high impact on bilateral trade volume and scientific collaborations. These results offer actionable insights about the patterns in how transitions in international relations are propagated, which could help in the design of early warning signals for global conflicts. Moreover, our approach opens new frontiers in capturing and understanding cascading patterns in other dynamical complex systems that are undergoing changes over time.

Results

We analyze the transitions of country relations and their dynamics by extracting the monthly bilateral relations of 1,225 country pairs of 50 large countries for over 25 years from January 1995 until March 2020 based on an international events dataset (26). Temporal relationships between a pair of countries (i, j) are captured by the monthly averaged Goldstein score, g^t_{ij}, which represents their relationship as the combined measures of conflict and cooperation (27). CAMEO event coding system, which represents a standardized encoding of types of interactions between Socio-Political actors, is utilized in GDELT dataset. Each CAMEO event code is assigned a numeric score from −10 to +10, capturing the potential impact that the event could have on the stability of a country. We measured the time-evolving relationship between the two countries as follows: given a complete set of CAMEO events, we calculate the average Goldstein score of a collection of events between a pair of countries every month. We thus, can produce a time series to capture the of countries pair relations. We have constructed the dynamical country relations network based on this dataset (see the "Methods" section for details).

As an example, we show in Fig. 1(d), two monthly networks, which demonstrate positive (*P*, green), and negative (*N*, orange) relations. For each pair of countries, the change of state from positive to negative (or from negative to positive) within two consecutive months is defined as a transition, denoted by *PN* or *NP*. As Fig. 1(d) indicates, the relations between Syria and Israel have a *PN* transition between February and March 2011. To quantify the different transitions, we define the transition strength by measuring the significance of the changes in relationships before and after this transition. We first identify the type of each transition, *PN* (or *NP*), that happened between months t and $t+1$. Then, we calculate its strength as the product of the fraction of *P* (or *N*) in the past n months and the fraction of *N* (or *P*) in the following n months (see also Fig. S2 in SI Appendix for robustness test). The value of strength is defined as

$$S^t_{ij} = [\frac{1}{n}\sum_{u=t-n+1}^{u=t} F(g^t_{ij} \times g^u_{ij})] \times [\frac{1}{n}\sum_{v=t+1}^{v=t+n} F(g^{t+1}_{ij} \times g^v_{ij})] \qquad ((1))$$

where $F(a \times b) = \begin{cases} 1, a \times b > 0 \\ 0, a \times b < 0. \end{cases}$

Figure 1(e) demonstrates that the monthly time series of Goldstein scores between Syria and Israel reflects complex dynamical countries relations, which is usually hostile due to a number of historical and political clashes. For Syria and Israel, the strength of one *PN* transition shown in Fig. 1(d) is 0.876, which is one of

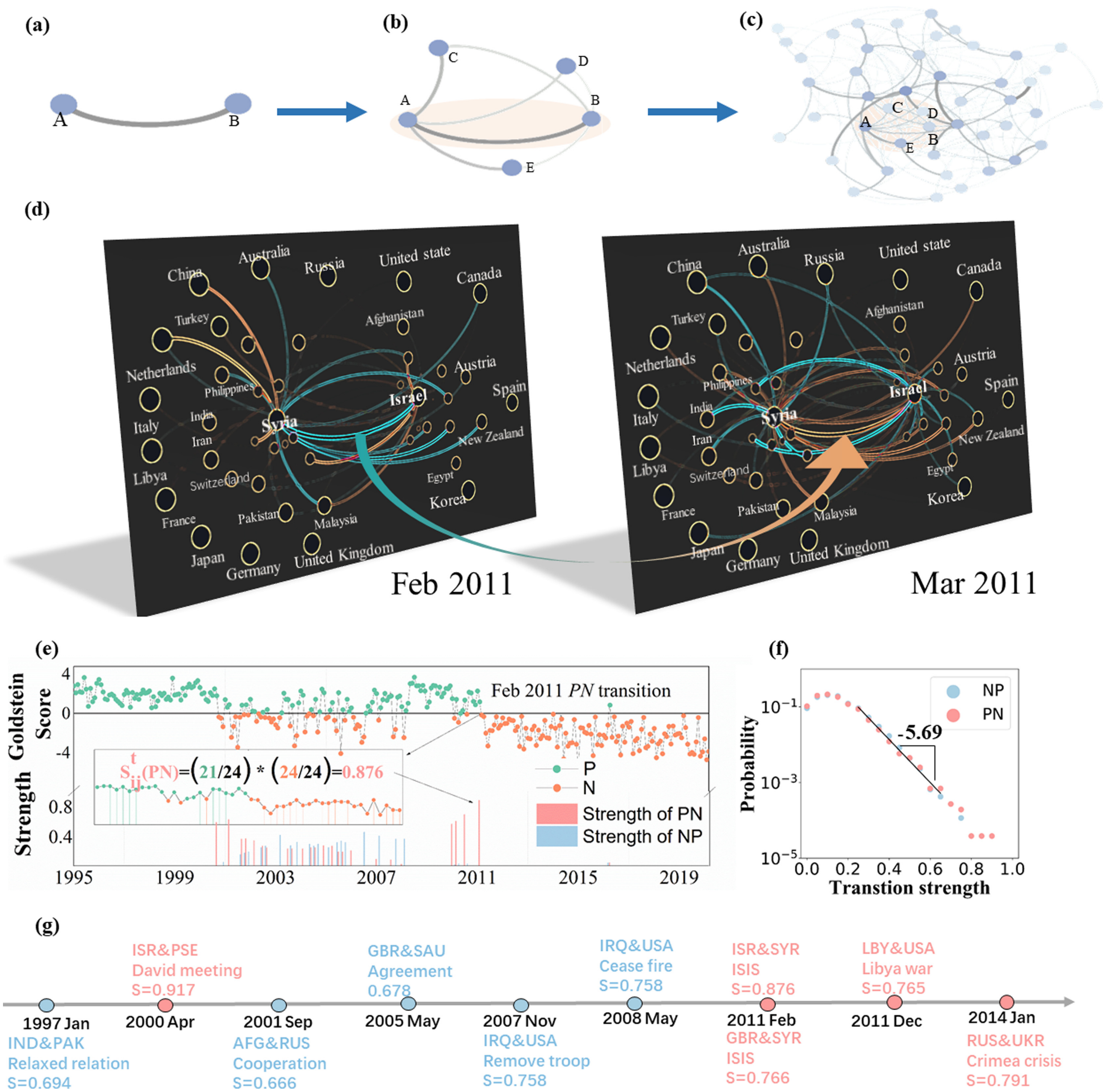

Fig. 1. Demonstration of the country relations network and transitions. Demonstration of (a) individual pair of country relations; (b) its local environment; and (c) network environment. (d) Demonstration of the country relations networks for two months: February 2011 (left), March 2011 (right). Link width represents the average score (Goldstein) of a pair relations in a given month, where links of Syria and Israel to other countries are highlighted for visualization. Orange links represent negative relations and green exhibits positive relations. (e) The average Goldstein time series between Israel and Syria during the last 25 years. Green and orange points exhibit positive (denoted by *P*) and negative relations (denoted by *N*), respectively. The strength of a transition, S^{t}_{ij}, is demonstrated in the inset and is calculated according to Eq. (1), in which *n* equals 24 months (see Fig. S1 in SI Appendix for robustness analysis). If there are no transitions, strength is assumed to be 0. (f) Distributions of all transition strength on a semi-log scale. The straight line suggests exponential distribution with a typical strength close to 0.2. Moreover, approximately 20% *PN* and *NP* transitions are greater than 0.25, which are regarded as strong transitions in this paper. (see Fig. S3 in SI Appendix for more statistical results of transitions). (g) Time-line of the five strongest *PN* transitions and five strongest *NP* transitions in the world during the last 25 years (see Table S1 in SI Appendix for country name and corresponding code).

the strongest transitions in the world over last 25 years, from January 1995 until March 2020. During that period, several violent incidents have been taken place along the Israeli–Syrian ceasefire border during the Syrian Civil War, straining the state of peace between the countries. Figure 1(f) shows that the strength distributions of all the transitions during the 303 months analyzed, of both transition types, *PN* and *NP*, clearly follows an exponential distribution. Furthermore, approximately 80% of transition strengths are less than 0.25, suggesting that global relations are stable for most of the time, with many weak transitions and a few strong transitions. Figure 1(g) shows the five strongest *PN* and five strongest *NP* transitions around the world from the last 25-year period. It is evident that transitions with very high strengths usually correspond to famous historical events.

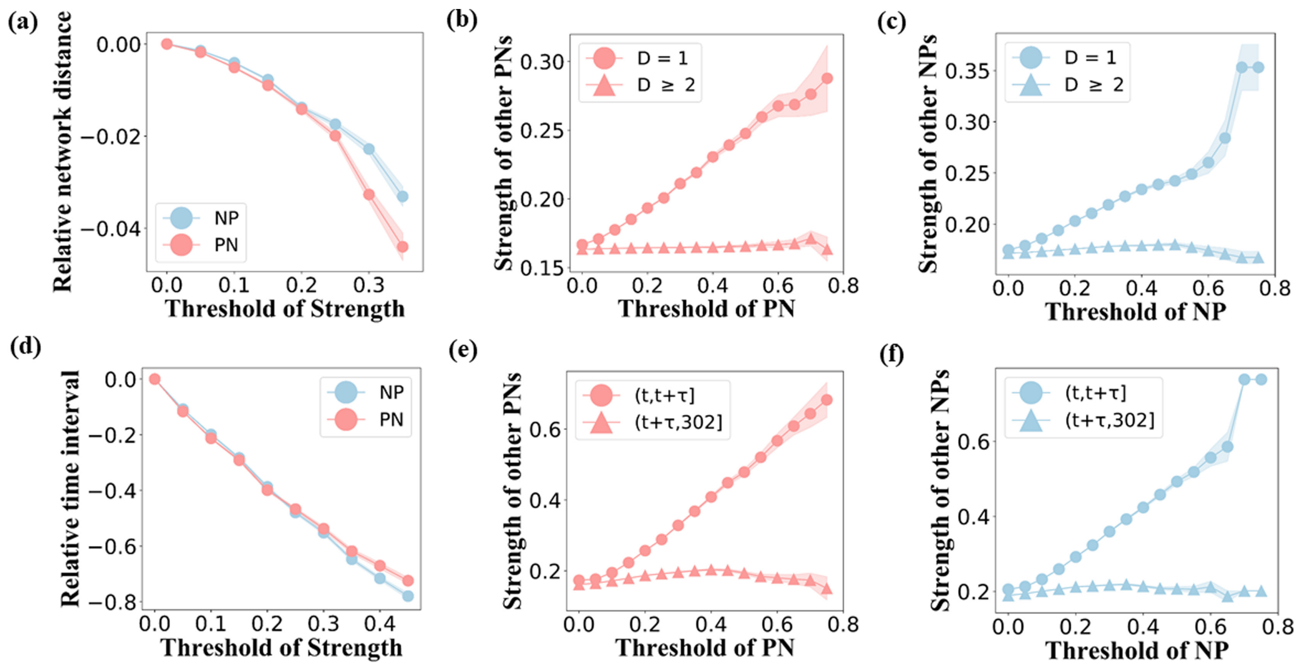

Fig. 2. Spatio-temporal correlations between transitions. (a) We measure the relative network distance between different *PN* (*NP*) transitions that happens in the same month [see also Fig. S5(a) in SI Appendix]. The *x*-axis is the strength threshold of transition. Only transitions with strength above this threshold are considered. The *y*-axis is the relative network distance, defined as $(D - D_r)/D_r$, where D is the distance between the two country pairs in the real network and D_r is the average distance in a corresponding random network (see details in SI Appendix). (b) and (c) The *x*-axis is the strength threshold. For each specific (b) *PN* or (c) *NP* transition, we measure the average strength of its $D = 1$ nearest neighboring transitions (circles) and $D \geq 2$ further neighboring transitions (triangles) in the same month as the *y*-axis. (d) The relative time intervals between successive *PN* (*NP*) transitions of the same country pair are measured [see also Fig. S5(b) in SI Appendix]. The *x*-axis is the strength threshold. The *y*-axis is the relative time interval of each two successive transitions of the same country pair, which is defined as $(l - l_r)/l_r$. Here, l is the real time interval and l_r is the time interval in a controlled random time series (see Fig. S6 in SI Appendix for significant test). (e) and (f) τ is a time window, which is used to measure the transitions within $(t, t+\tau)$. The *x*-axis is the strength threshold. For each specific (e) *PN* or (f) *NP* transition, we measure the average strength of its transitions (circles) of the same country pair within $(t, t+\tau)$ and within $(t+\tau, 302)$ as the *y*-axis. Here, we chose τ to be 12 months (see Fig. S7 in SI Appendix for other parameters analysis).

For example, the Camp David summit meeting, which aimed to end the Israeli–Palestinian conflict, ended without an agreement. Correspondingly, a strong transition from positive to negative between Israel and Palestine occurred in April 2000 (see Fig. S4 in SI Appendix for figures). This brought about the subsequent long-term violence and conflict in the Middle East region. Another example is the Ukraine–Russia country pair that maintained a long-term positive relationship until the Crimean crisis. We can clearly see a *PN* transition between Ukraine and Russia with a very high strength in January 2014 (see Fig. S4 in SI Appendix for figures). After this transition, the regional economy suffered a lot, being described as "returning to the 90s." In short, these strongest examples of *PN* transitions have a significant negative impact on human rights, regional peace, and economic development. Meanwhile, *NP* transitions lead to a relaxation of international tension, such as the withdrawal of US troops from Iraq in 2007 (see Fig. S4 in SI Appendix for figures). Both types of transitions have the effect of deeply re-shaping global situations.

Next, we measured the spatio-temporal correlation between different transitions. As shown in Fig. 2(a), we found that the higher the transition strength, the closer the two transitions are in the country network. Moreover, for any given *PN* or *NP* transition, the average strength of its neighboring transitions increases with the transition strength of their own, as seen in Fig. 2(b) and (c). A similar correlation was identified in the temporal scale. The relative time interval between two successive *PN* or two successive *NP* transitions of the same country pair becomes shorter for stronger transitions as seen in Fig. 2(d). The shorter interval means the same type of transitions happens more frequently. The relative time interval between successive transitions is shorter for strong transitions, which means that strong transitions are unsustainable. These results suggest possible cascading effects of international transitions in network space and time. This is also confirmed in Fig. 2(e) and (f), which indicate that, when the strength of the original transition is increased, same type of transitions in the following 12 months show increasing strength.

Given the static spatio-temporal correlations identified above, it is natural to ask how these transitions interact as a dynamical process. Cascading effects, as a collective phenomenon along time and space, have been observed in many complex systems, from epidemics (28), earthquakes (29), and blackouts (30) to social behaviors (31). In order to demonstrate how we explored the cascading effects of international relations transitions within the country network, selected *PN* and *NP* transitions were chosen as the "seed" points (see Fig. S8 in SI Appendix for more examples). In the following months, new transitions that connected temporally (within 1 month) and spatially (nearest neighbors in the country network) to the previous ones are added up to the cascades that started from the seed transition (see the "Methods" section for details). Here, the strength, S_{ij}^t, of following transitions should be greater than 0.25, while the seed strengths are not limited. Figure 3(a) and (b) show the cascades in a tree-like structure. These cascades can be understood as follows. In February 2011, a *PN* transition occurred between Israel and Syria, which is related to a series of protests and uprisings in Syria called the "Arab Spring."

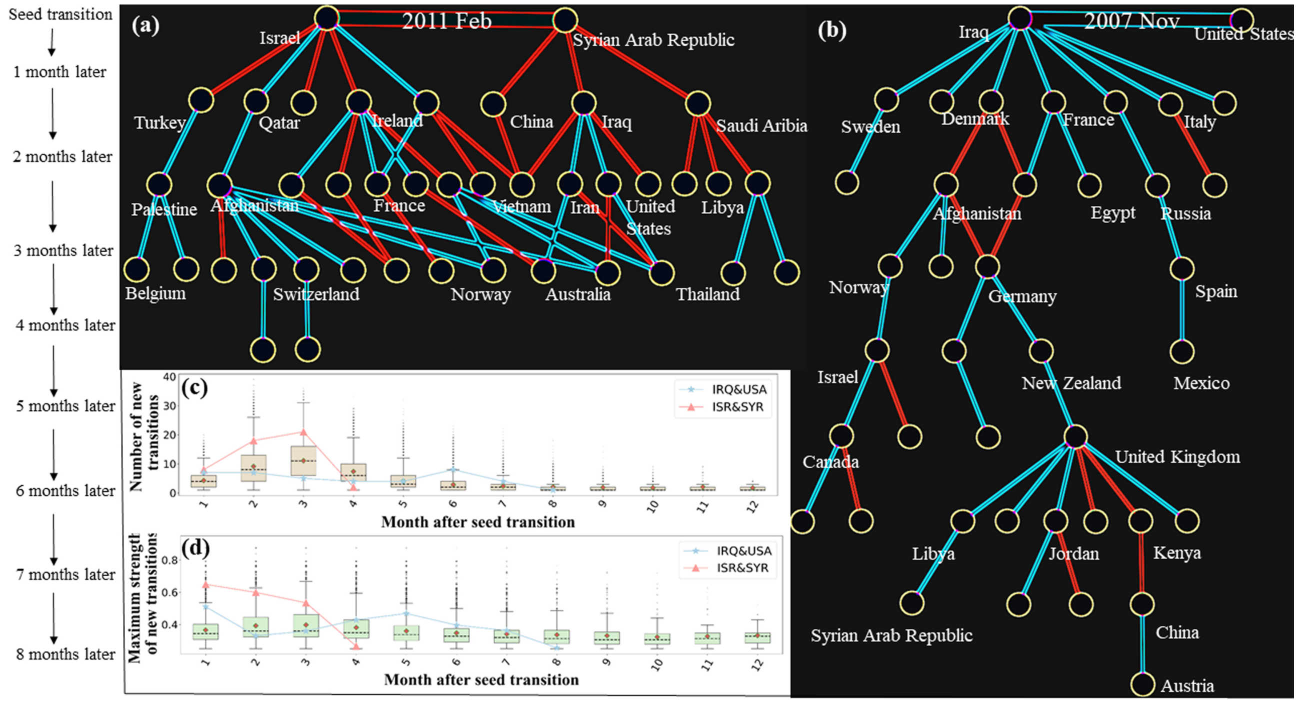

Fig. 3. Cascading transitions. To demonstrate the cascading transition in the country network, we show (a) one *PN* transition and (b) one *NP* transition as the starting events of the cascade and plot their resulting cascades. These two transitions represent the Syria–Israel conflict in 2011 and the easing hostility between United States and Iraq in 2007, respectively. In the tree-like figures, *PN* transitions are shown as red lines and *NP* transitions are shown as blue lines. In (c) and (d), the *x*-axis is the spanning month after the seed transitions. The *y*-axis is (c) the number of new transitions in this month and (d) the maximal strength of new transitions in this month. A box chart is constructed of a set of whiskers and a box, which is drawn from the first quartile to the third quartile with a horizontal line to represent the median.

In the following months, more country relations were involved in the "Arab Spring." For example, a *PN* transition happened between Syria and Saudi Arabia in March 2011 because Saudi Arabia supported the opposition forces in Syria. In April 2011, Saudi Arabia supported the Libyan opposition and intervened in the Libyan conflict that resulted from the Arab Spring, which caused a *PN* transition between the Saudi Aribia and Libya [Fig. 3(a)]. In November 2007, the United States started to remove troops from Iraq, which led to a *NP* transition between these two countries. In the following months, many other countries had *NP* transitions with Iraq [Fig. 3(b)]. Figure 3(c) and (d) present the number and maximal strength of new transitions in each of the following months for the two cascades [in Fig. 3(a) and (b)] compared to the box chart of all cascades. From the box chart in Fig. 3 (c), we find that typically 3 months after the seed transition, there is a rapid expansion of the cascades. Figure. 3(d) shows that the maximal strength is also likely to appear 3 months after the seed transition. After 3 months, the maximal strength decreased gradually.

We analyzed the relations between seed transitions and the subsequent effects on the cascades to further reveal the cascading transitions. Four measures are developed to describe their properties, including size, speed, average strength, and transition type fraction for each seed transition. The size of transitions represents the total number of transitions in a cascade. The speed of cascades is the total number of transitions divided by the spanning months. The average strength is the average strength of all transitions in a cascade. The transition type measures the fraction of the same type of the following transitions as the seed transition. Figure 4(a) and (b) clearly shows that the size of cascades and cascading speed are increasing with seed transition strength. Moreover, we also find that cascades of stronger seed transitions have higher average strength [Fig. 4(c)]. Interestingly, an *NP* seed transition of higher strength can spark a cascade with a larger fraction of *NP* transitions, yet this is different for the PN transition [Fig. 4(d)] (see Fig. S9 and Fig. S10 in SI Appendix for Parameter analysis). The Pearson correlation coefficient of the curves in Fig. 4(a) to (d) are 0.92, 0.94, 0.89, 0.80, respectively, while the *P*-values are 0, 0, 0.0001, 0.002, respectively, showing significant results. Moreover, it is interesting to note that no matter the size of the cascades, the largest cascades or other size cascades, most of them are initiated by weak seed transitions [Fig. 4(e)]. Furthermore, our statistical analysis shows that 79% of the top 10% largest cascades start from seed transitions of strength smaller than 0.25. This reveals the butterfly effect that small perturbations cannot be ignored, because they may have nonlinear impacts on a dynamical system. It is generally believed that a drastic change, in the field of economic, military, technological, cultural influence, as well as diplomatic, can largely reshape the world pattern. This is also supported in this research that larger transitions lead to more dramatic cascades. However, more importantly, Fig. 4(e) also turns our attention to inconspicuous relationship changes, which have been little accounted for in previous studies.

Similar to another typical contagious process—epidemics, to eventually control the spread of a virus, it is essential to understand how the individual transition occurs and the specific features related to it. Previous studies have analyzed inter-personal relationships and how they depend on their *local* balanced structure (32–36). Heider was inspired by the idea that "An enemy of my enemy is my friend" and postulated that a triangle with one or three positive links can maintain a balanced state, otherwise it is unbalanced (13). This concept of balance could help to understand some interactions between countries from their attitude

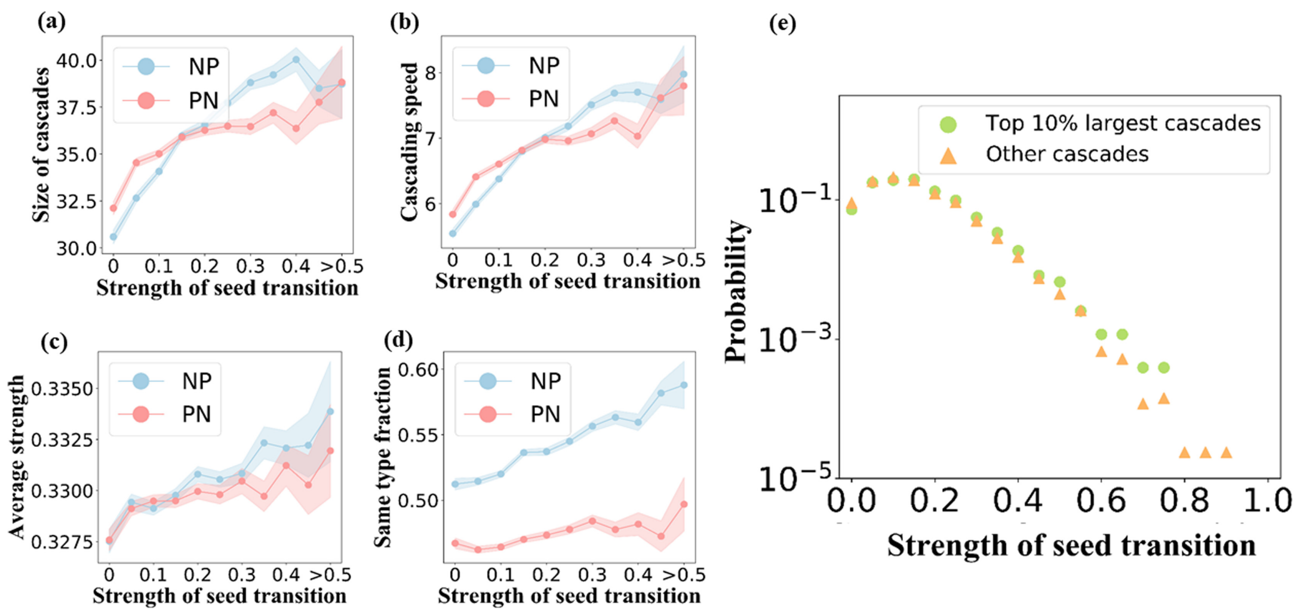

Fig. 4. Statistics of cascading transitions. In (a) to (d), the x-axis is the strength of seed transitions. The y-axis is (a) the size of cascades (number of country pairs), (b) the cascading speed (ratio between number of country pairs and spanning months), (c) the average strength of all the following *PN* and *NP* transitions, (d) the fraction of the same type transitions with respect to all transitions in the cascades. (e) The distributions of seed transition strength for top 10% largest cascades and other cascades. Top 10% largest cascades are ranked by the number of country pairs in the cascades.

to common neighboring countries. However, the cascading effects we found in Fig. 3 suggests, in contrast to earlier studies, the existence of *global* cascading transitions. To explore the underlying global mechanisms, we adopted the concept of betweenness centrality, which represents a node's or link's role of communication from one component of the network to all other components (37). We calculate the link betweenness centrality by averaging the betweenness centrality of both nodes (countries) at the link ends [Fig. 5(c)]. Here, a link which has high betweenness centrality represents a relation between the two *central* countries in the network, which may have many connections in the network serving many shortest paths between pairs of countries. We find in Fig. 5(a) and (b) that the link betweenness, as defined here based on the two nodes, can predict the transition and their strength quite well. Links with high betweenness tend to stay in their original states, i.e., having less transitions, while links with low betweenness are easier to switch from a positive state to negative state, or vice versa (see also Fig. S14 in SI Appendix for the significant test). Furthermore, we find in Fig. 5(b) that the transition strength of links increases almost linearly with its betweenness. That is to say, although links with high betweenness are less likely to change their states, a transition of such a link may be greatly influential once it is finally converted (see also Fig. S13 in SI for more information). A previous study on a microscopic level in social sciences regarding relations between people shows that the links involved in balanced structures tend to be stable, while the links of unbalanced structures tend towards transitions (29). By considering eight possible triangle configurations for a monthly pair relations shown in Fig. 5(c), we confirm that country pairs involved in a more balanced structure also tend to be stable [Fig. 5(d)] (see Figs. S12 and S15 in SI Appendix for the topological properties and the significant test). Interestingly, as shown in Fig. 5(e), unlike betweenness, transition types are dependent on balance environment in a different way. For transitions from a positive to negative state (*PN* transition), strength is decreasing with increasing balance ratio, suggesting that highly balanced positive links are more likely to have a weak transition, while highly balanced negative links tend to have strong transitions. Our findings show that both the global network position and the local environment of a pair are critical factors for predicting the probability and strength of transitions.

Transition means a significant change of bilateral relations between two countries, which may influence other aspects of international collaborations. We collect the monthly bilateral trade data and monthly data on joint scientific papers for each country pair. Figure 6(a) and (b) show that frequent transitions of a country pair correlates to fewer scientific collaborations and less trade cooperation (see also Fig. S16 in SI Appendix for country-level results). These findings apply in both developed and developing countries (see Fig. S17 in SI Appendix). Temporal effects of the transition are presented in Fig. 6(c) to (e). Figure 6 (c) shows the scatter plot of the fraction of transitions in the most unstable period versus other times. Some country pairs (pink circles) are selected to calculate the following results due to their relatively large difference in transitions between the period with the most transitions and the rest of time. Then, the normalized trade and joint paper fractions are calculated, corresponding to the most unstable period and the rest of time, respectively. We identify a continuous 3-year period with the highest transition fraction for each pair of countries to represent the most unstable period and then compare the monthly average trade volume and joint papers during this period with the rest of time. We hypothesize that joint papers as well as trade in unstable periods are lower than the rest of time and calculate a ratio to represent what % of country pairs meet the hypothesis. The normalized fraction is the rate of papers as well as trade per month. Figure 6(d), 75.2% of the scatters (country pairs) above the diagonal meets the hypothesis, which means that these country pairs produced fewer joint papers during the most unstable period. Similarly, Fig. 6(e) shows that 61.9% country pairs have less trade volume during the most unstable period. By controlling the difference in transitions between the most unstable period and the rest of time within a certain range, we can

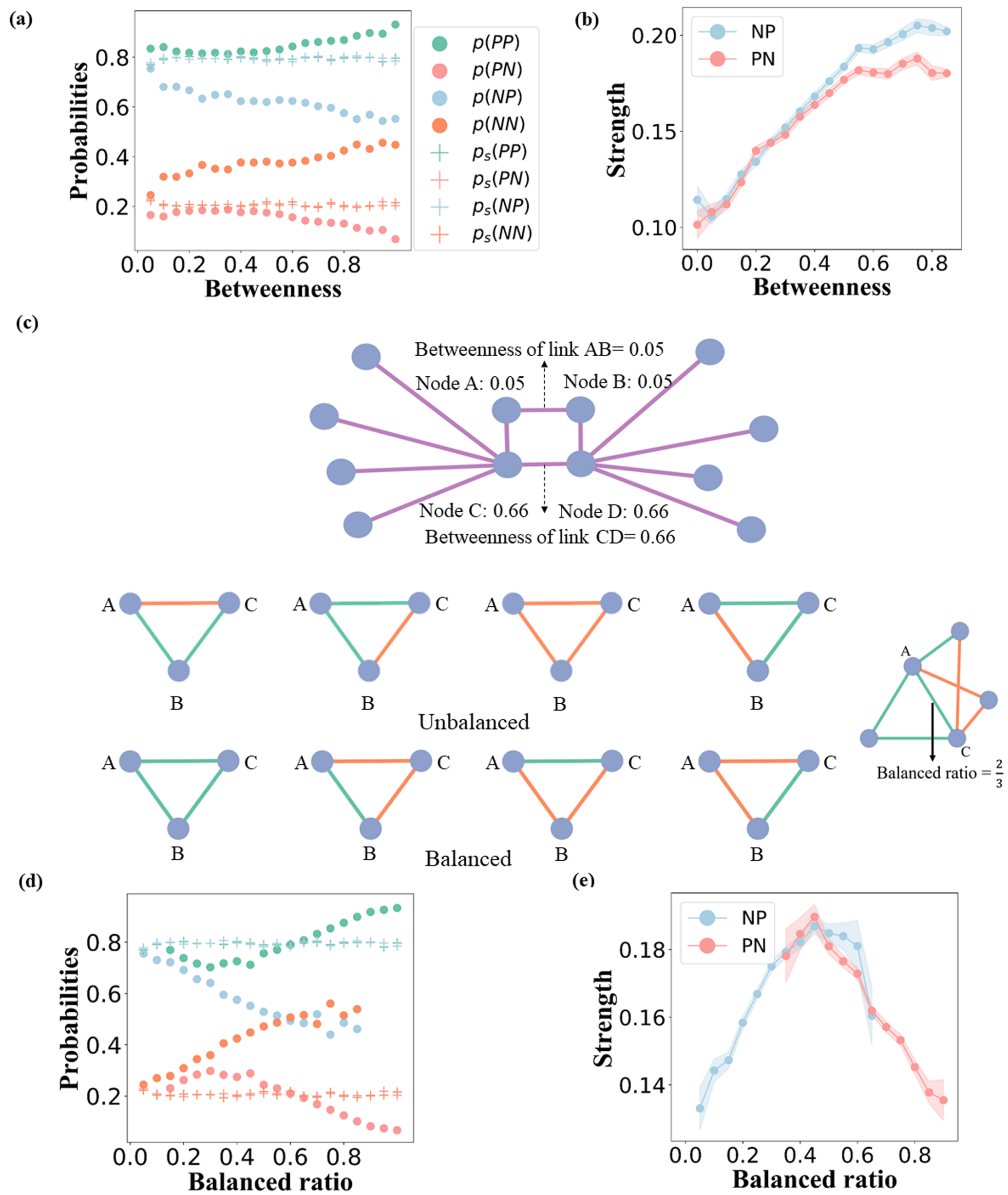

Fig. 5. Network properties of transitions. (a) Green (red) circles represent the transition probability $P(PP)$ [$P(PN)$], which is the fraction of positive (negative) relations in $t + 1$ out of positive relations in month t, when considering all country pairs and all months. Blue (orange) circles represent the transition probability $P(NP)$ [$P(NN)$], which is the fraction of positive (negative) relations in month $t + 1$ out of the negative relations in month t. Plus signs represent the randomized probabilities. The betweenness centrality is normalized between [0,1] by max–min method. (b) Higher betweenness centrality links have on average higher transition strength. (c) Demonstration of the betweenness centrality of links and the eight possible balanced configurations as well as unbalanced structures with respect to an AC pair. As demonstrated, the betweenness centrality of a link in a monthly network is measured here by the average betweenness centrality of the nodes at both ends (see Fig. S11 for the difference between the defined betweenness and traditional link betweenness). The nodes are countries and the links are the relationships among countries. In order to reflect the link centrality from structural level, betweenness centrality is set unweighted and unsigned. The balanced ratio of a link is defined as the number of balanced triangles divided by all triangles for each month. Green and orange links exhibit positive and negative relations, respectively. (d) The x-axis is the balanced ratio of a link in a given month. The symbols have the same meaning as (a). (e) shows that highest strength emerges from links whose balanced ratio is around 0.5.

filter out different groups of country pairs. It is interesting to note (Fig. S18 in SI Appendix) that the fraction of pairs meeting the hypothesis is increasing with the growing difference in transitions between the most unstable period and the rest of time. Moreover, the effects of difference between PN strength and NP strength on papers and trade are also noted (Fig. S19 in SI Appendix) that a country pair with a stronger NP has a higher value of papers and trade on average. These results suggest the importance of understanding international transitions as proposed here.

Conclusions

Relations between countries wax and wane over time, while transitions appear constantly. Transitions of international relations can affect the national statehood, which serves as the basic premise of social utility (38), and can also cause a series of impacts that reshape the distribution of power around the world (39). Hence, it is critical to reveal the universal properties and dynamics of the transitions occurring around the world in order to warn

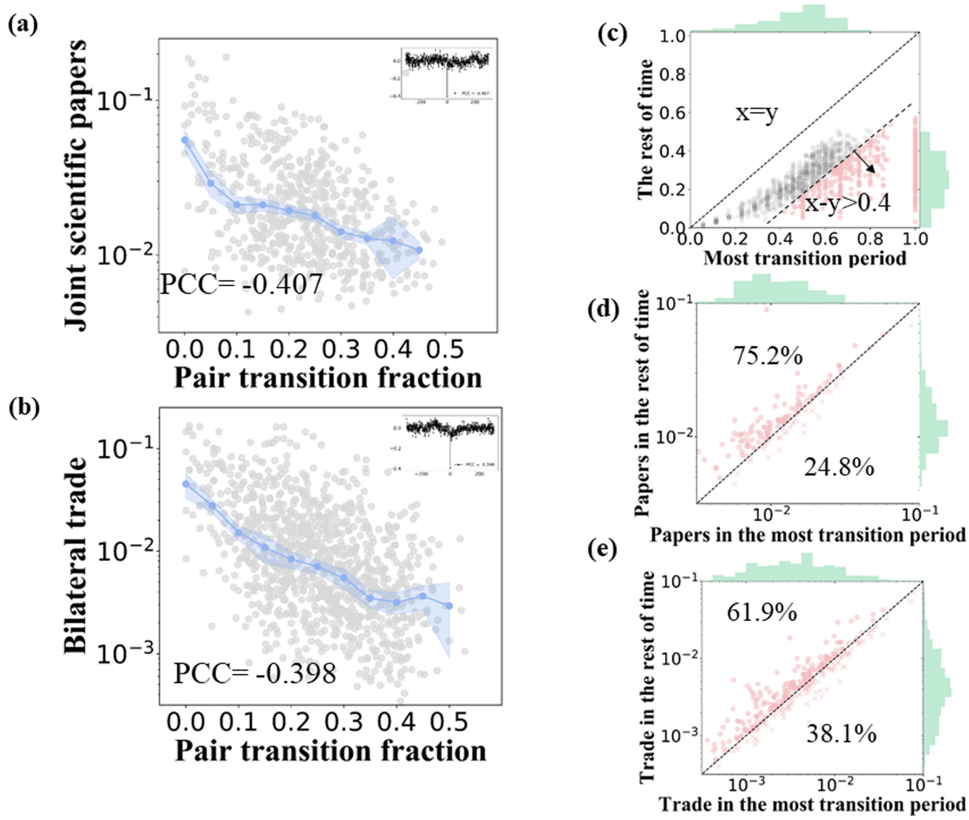

Fig. 6. Relationship between transitions and bilateral trade volume, as well as joint scientific papers. For a country pair, the *x*-axis is the pair transition fraction, calculated by the number of transitions (number of *NP*, *PN*), this pair had divided by the sum of all possible states (number of *PP*, *PN*, *NP*, *NN*). The *y*-axis is (a) fraction of joint scientific papers between a country pair and (b) the fraction of bilateral trade volume between a country pair (see SI for more details). Inset figures show the Pearson cross correlation of each scatter plot. The *x*-axis is the shifting steps and the *y*-axis is the Pearson correlation value. The shifting shows the level of noise in the data, which is significantly smaller than the signal (Pearson correlations) at shifting = 0. (c) The *x*-axis is the largest fraction of transitions within a 3-years period for each country pair (see SI for more details). The *y*-axis is the fraction of transitions in the rest of the corresponding time. The pink circles represent country pairs with relatively large difference of transition between most transition period and the rest of time. These country pairs are utilized to calculate results in (d) and (e). The grey circles are not considered in the following results. (d) The *x*-axis is the normalized fraction of papers in the time period of 3 years with most transitions. The *y*-axis is the normalized fraction of papers in the rest of the time. (e) The *x*-axis is the normalized trade in the time period of 3 years with most transitions. The *y*-axis is the normalized trade in the rest time.

and hedge the risks. However, achieving this goal will be a major challenge due to the lack of a good quantitative analytical framework and relevant big dataset. Despite the different frameworks that have been proposed to combat this challenge, a comprehensive and systematic data-driven framework to study international relationships has not been yet developed, especially from a global dynamical network perspective. In this research, we have developed such a framework and studied the network effects of transitions in international relations using a high-resolution dataset, covering more than 25 years and 1,225 country pairs for each month. By defining the transitions of different strength, we identified large cascading effects of transitions in network space and time. We found that transitions can spark dynamical cascades that reach a peak within several months. While strong transitions can spark larger cascades in a shorter time on average, surprisingly, weak transitions were found to be the starting points of the largest cascades. Our results show that the topological characteristics of the country relations network such as betweenness centrality, are critical for predicting the probability and strength of transitions. Those edges with high betweenness should be focused when establishing the prediction model of risk events. Such mechanism found by combining network theory and the aggregation of diplomatic big data could help, in the future, to construct an accurate diplomatic risk propagation model. Like in epidemic spreading models SIR and SIRS, which provide good prediction and mitigation methods of pandemic, the diplomatic risk propagation model may also help people predict the possible crisis of the world systematically. Our findings also suggest that frequent transitions are associated with more damage to the bilateral trade volume as well as scientific collaborations.

In this sense, our study may be useful for developing realistic models for international relations dynamics under global scenarios. This is particularly important since, due to the COVID-19 pandemic, our world pattern is now accumulating massive risks, and a quantitative framework is urgently needed to address this trend. The lack of a systematic mechanism and knowledge of these risks has rendered international relations management even more vulnerable and unpredictable. Similar to epidemics, the process of international transitions is found here to have contagious tendencies. However, the underlying mechanisms and management of international transitions is currently far from being clear, as in epidemics. Unlike epidemics, this research has confirmed that instead of depending on a significant transition, in many cases even a “minor spark” can trigger a large tide of social earthquakes, such as in World War I. The spread of emotion and sentiment is not linear, as it is with cascade effects in epidemics or other physical spreading processes. More importantly, the spreading process of transitions in international relations could be affected to a large extent by both rational and irrational emotional factors, e.g., suspicion or panic. This is distinctly different from the biological mechanisms at work in epidemics. Given all this complexity, we unexpectedly identified clear cascading patterns of transitions with our developed approach. Especially, edge betweenness centrality is calculated based on countries centrality to capture the critical factor for international relation transitions. This study may embark on a new journey to understand how countries interact with each other and might gain insight into other dynamical systems that are undergoing changes over time.

Material and Methods

Data description and processing

Country relations are extracted from the GDELT (Global Database of Events, Language and Tone). GDELT is one of the most comprehensive datasets, which records all global news in several languages. Event records of GDELT are stored in an expanded version of the dyadic CAMEO (Conflict and Mediation Event Observations) (40) format, which captures two countries and their actions. Moreover, each CAMEO event code is assigned a numerical score between −10 and +10, which reflects the potential negative or positive impact that type of event has on national stability. This is called the Goldstein Scale (41) (see details in Tables S2 and S3 in SI). A large number of international events, from ecological problems, economic development, nuclear proliferation terrorism, nationalism and human rights to culture difference, and citizen communication, enable an opportunity to quantify the interactions between countries. In the present research, 70,756,728 events of 1,225 country pairs from January 1995 to March 2020 were utilized to capture the international dynamics. We measured the time relationship between two countries as follows: given a complete set of CAMEO events, we calculated the average Goldstein score of a collection of events between a pair of countries every month. This way, we produce time series that capture the pair relations along time.

Scientific collaboration is measured by the number of co-authored papers in both countries, which reflects the cooperation in research (42). The co-authored paper dataset contains the international scientific collaboration papers from January 1995 to December 2017 that were included in the Science Index Citation (SCI) and Social Science Citation Index (SSCI). For articles with authors from more than three countries, we add one international cooperation to each country pair. In total, 11,607,282 articles representing scientific cooperation were utilized.

The bilateral trade volume dataset contains monthly bilateral trade volumes from January 1995 to December 2019. We calculated the monthly export–import volume by summing up the export and import between countries A and B. Due to different statistical calibers of countries, export of country A to country B reported by country A is different from that reported by country B. Thus, the export of country A to country B and the import of country B from country A were averaged. In total, 212,295,829.8 million dollars' worth of trade volume was distributed in 1,225 country pairs across different months. The monthly bilateral trade volume and co-authored scientific papers were normalized. The normalization method can be found in the *paper and trade section in SI Appendix*.

Construction of country relation network

The 50 countries with highest number of events from January 1995 to March 2020 are selected. We then extract the 1,225 country pairs of these 50 countries for each month from January 1995 to March 2020, and calculate the monthly average Goldstein score, g_{ij}^t, for country pair ij in month t. For a given pair and month, the link g_{ij}^t between two country pairs represents positive or negative states to represent a relatively cooperative or conflictive link during this month. The links with events less than a fraction of 10^{-5} of the total events in a given month are removed. In this way, in total 303 monthly signed country relation networks can be constructed with countries as nodes and g_{ij}^t as link weights.

International transition

We identify positive (P, green) and negative (N, orange) relations in each month for each pair of countries based on the averaged Goldstein score, g_{ij}^t, which is averaged by the Goldstein scores of all events involving these two countries and occurring in the month t. The change of state from positive to negative (or from negative to positive) within two consecutive months was defined as a transition, denoted by PN (or NP). Then, we calculated transition strength S_{ij}^t as the product of the fraction of P (or N) in the preceding n months and the fraction of N (or P) in the subsequent n months.

Cascading transition

Each transition can be assumed as the seed point that produces a cascade. In the first step, the seed transition can lead to new transitions with $D = 1$ that appear in the subsequent month, and transitions of the cascade at each step continue to lead to other new transitions appearing in the next month within the range of $D = 1$. D is the distance between the two country pairs in the country relation network. In this way, the cascades continue to propagate until no more transitions are included. We have found in Fig. 1(f) that approximately 80% of transition strengths are less than 0.25. In order to capture cascades of relatively strong transitions, only following transitions with a strength greater than 0.25 (top 20%) are considered when identifying the cascades.

Transition probability

Transition probability is a kind of conditional probability, which is used to describe how the state of a link changes. Transition probability is defined as the fraction between the type of relation in $t + 1$ and the type of relation in month t, when considering all country pairs and all months. For example, $P(NP)$ is the ratio between the number of NP transitions and the sum of both the number of NP and NN transitions.

Supplementary Material

Supplementary material is available at *PNAS Nexus* online.

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Authors' Contributions

X.C., W.D., and S.H. made contributions to the conception and idea of the work. M.Z., X.C., and S.H. designed the research. M.Z., W.D., S.C., and J.Z. contributed to the acquisition, analysis, and interpretation of data. M.Z., S.C., and W.D. preformed the research. D.L. designed the concept of cascade. M.Z., X.C., and D.L. drafted the work. D.L., M.Z., S.H., and J.Z. substantively revised it.

Data Availability

All events data created or used during this study are openly available from the GDELT Project at http://data.gdeltproject.org/events/index.html.

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