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Greenfield foreign direct investment: Social learning drives persistence

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This paper argues that the persistence of greenfield foreign direct investment (FDI) comes from information frictions. First, our simple social learning model shows that, through signaling effects, information frictions generate persistent greenfield FDI inflows. Second, we show empirically that the autoregressive coefficient of greenfield FDI increases in value with different proxies for information frictions, including six institutional and governance indicators and two common language measures. We also find that greenfield FDI persistence varies across industries. In particular, greenfield FDI by service firms is more persistent than that by manufacturing firms. Finally, our findings suggest that better governance, predictability, and transparency reduce information frictions and thereby avoiding drastic and persistent ups and downs in FDI.

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1. Introduction

By its very nature, foreign direct investment (FDI) is about long-term business relationships. As firms expand, reinvest, and reorganize, or as new partnerships are formed, and other firms acquired, it is not surprising that FDI data is more persistent than other capital flows like portfolio investment (e.g., Sarno and Taylor, 1999; Bluedorn et al., 2013; Eichengreen et al., 2018). But the same argument does not apply to greenfield FDI where a firm invests in a different country for the first time. Persistent greenfield FDI means that firms follow other domestic firms when investing in a new country. What can explain such behaviors? Is greenfield FDI more persistent in some countries than others? What characteristics contribute to more persistent greenfield FDI? This paper fills a gap in the existing literature by answering these questions.

The dynamics of greenfield FDI are highly policy-relevant. Greenfield FDI is beneficial to the host economies in many aspects. Nocke and Yeaple (2008) show that more productive firms tend to involve in greenfield investment. Compared with mergers and acquisitions (M&As), the other mode of foreign entry, not only greenfield FDI has a stronger impact on growth (Harms and Meon, 2018), but also a more significant influence on the innovation performance of domestic firms (Liu and Zou, 2008). While some studies suggest the optimal policy toward FDI should be tailored to different types of FDI (e.g., Nocke and Yeaple, 2007; Qiu and Wang, 2011), the persistence of greenfield FDI has not been singled out for analysis. This

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paper shows that the persistence (represented by a larger AR coefficient) of greenfield FDI is related to information frictions, and greenfield FDI becomes more volatile when firms are less certain about the investment environment of the destination. If the objective of the policymaker is stability, then sudden surges and stops are bad. The policymaker should aim at reducing information frictions, thereby avoiding drastic and persistent ups and downs in greenfield FDI.

We focus on greenfield FDI, a form of first-time FDI, for two reasons. First, when firms decide to invest in another country and induce information from other firms' decisions, first-time investments from other foreign firms are particularly informative. To decide whether to invest in a particular country for the first time, there is more to learn from other foreign firms' FDI into that country than from investments by that country's domestic firms. However, when foreign firms have settled down in a particular country, their considerations will be more like those of domestic firms, and their actions are less informative for potential investors into that country. Thus, we look at how a firm decision to invest for the first time in a particular country depends on other foreign firms' first-time FDI. Our greenfield FDI, which naturally excludes subsequent investments, is the appropriate measure.

Second, although both are typical channels for first-time overseas investments, greenfield FDI and M&As imply very different information needed. For greenfield FDI, companies are setting up a new company abroad, establishing a supply chain, building a communication system, and integrating culturally. As a result, greenfield investors can learn a lot from the experience of greenfield FDI by similar companies. M&As, on the other hand, represents a change in ownership and control from a domestic firm to a foreign parent company. The target company is well-established, with the market, labor, and business assets are already in place. M&A investors evaluate the potential financial benefit from combining two business entities, and that investment decision is firm-specific for both the M&A investor and the target company. In this sense, while it may still exist, the signaling effect of M&A investment history is not as evident and clear-cut as that of greenfield investment. Given the high costs and high uncertainty features of greenfield FDI, it is difficult for foreign companies to read the investment environment through market research in an economy with little transparency. Therefore, largely irreversible investments made by early movers become an invaluable signal that it is safe to invest in such an economy, and they should encourage further investment. Hence, we postulate that greenfield investment persistence results from information frictions.

A simple statistical procedure would link the greenfield FDI persistence to information frictions. A typical approach to estimating persistence is to estimate an autoregressive (AR) model. In its simplest form, the degree of persistence of an AR(1) process is positively correlated with the variance of the time series.[1] Fig. 1 plots the relationship between the variance of real greenfield FDI inflows and three proxies for information frictions, namely the voice and accountability index, the control of corruption index, and the rule of law index.[2] Voice and accountability measure the extent to which a country's citizens can participate in selecting their government, freedom of expression, freedom of association, and freedom of the press. Suppressed freedom of speech limits the flows of information. Weak control of corruption and an unsound rule of law may result in many unspoken rules and hidden agendas. Fig. 1 shows that countries with greater information frictions tend to have a larger variance in real greenfield FDI inflows.[3] Therefore, if greenfield FDI is an AR(1) process, its persistence may be increasing in information frictions.

Motivated by these stylized facts, we would build a simple social learning model to show that information frictions lead to persistent greenfield FDI inflows through signaling effects. In the model, heterogeneous firms sequentially make a publicly observed FDI decision. The type of each firm, e.g., cost or productivity advantage, is private information. The profitability of the investment project is determined by an unobserved state of the foreign country. Each firm receives a noisy private signal about the state, interpreted as information collected through market research. Also, based on the history of investment, firms form a public belief about the state. As a result, a firm's investment decision is determined by its type and the expected state of the foreign country, given the private signal and the public belief. The model shows that FDI is an ARIMA(1,1,1) process with a positive AR coefficient. The AR coefficient increases in both the variance of the signal and the firm heterogeneity.

To test the theory, we examine the effects of information frictions on the AR persistence of greenfield FDI under a dynamic panel framework. By studying a sample of 454 source–destination pairs of greenfield FDI during 2003–2018, we find that the AR persistence increases with information frictions. Also, we uncover the heterogeneity of greenfield FDI persistence across industries. We find that service firms exhibit the highest AR persistence, followed by the retail firms, while the lowest in the manufacturing firms. The finding is in line with our theory. The profitability of investment in the manufacturing industry is mainly based on hard facts, like production costs. By contrast, the profitability of investment in the service industry depends more on taste and cultural factors. It is more difficult for service firms than manufacturing firms to collect reliable information through market research. Therefore, service firms tend to rely more on the investment history of the early movers.

The remainder of the paper is organized as follows. Section 2 provides a literature review. Section 3 outlines a simple social learning model of greenfield FDI. Section 4 describes the data used in our empirical analysis and presents our empirical methodology. Section 5 presents the empirical results. Section 6 concludes.

[1] Suppose $y_t = \gamma y_{t-1} + \varepsilon_t$ where ε_t is a purely random process with mean zero and variance σ. The variance of y_t is $\frac{\sigma_\varepsilon^2}{1-\gamma^2}$.

[2] Greenfield FDI inflows are re-scaled by dividing the mean and de-trended so that its variance is comparable across economies. The data is from fDi Markets and the World Bank and covers 69 recipient economies from 2003 to 2018.

[3] In Appendix Fig. A1, we restrict the sample to economies with a variance of less than one. The negative correlation remains.

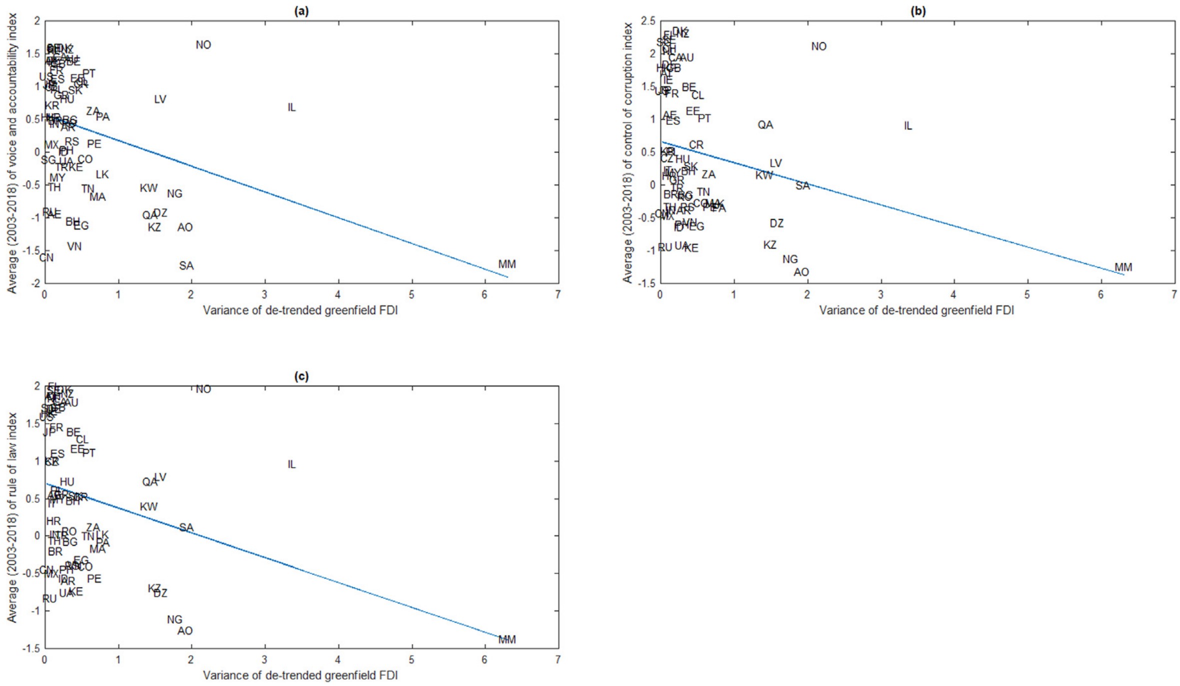

Fig. 1. Relationship between variance of greenfield FDI and information frictions.

Table 1
Summary of literature on FDI persistence.

Literature	Sample	Method	Findings
Sarno and Taylor (1999)	U.S. capital flows to 9 Asian and 9 Latin American countries during 1988–1997	State-space decomposition	FDI flows are almost entirely permanent.
Lipsey et al. (1999)	52 economies during 1980–1995	Average number of reversals in net flows, and CV	The average number of reversals in net flows of FDI is the lowest. The CV of net FDI flows in Southeast Asia, Japan, Europe, and Latin America is the lowest, except the United States.
Lipsey (2001)	Latin American in 1982, Mexico in 1994, and East Asia in 1997	Event study during crisis period	Inflows of FDI into the crisis countries are much more stable than that of the other financial flows.
Levchenko and Mauro (2007)	142 economies during 1970–2003	Defining “sudden stops”	FDI is remarkably stable during the “sudden stop” episodes.
Bluedorn et al. (2013)	147 economies during 1980–2011	CV and AR persistence	FDI flows have the lowest CV and the highest AR persistence among private capital flows.
Eichengreen et al. (2018)	34 emerging economies during 1990–2015	CV and AR persistence	FDI flows are less volatile and more persistent than other private capital flows.

2. Related literature

Our paper connects to three strands of literature. The first studies the dynamics of international capital flows, for which Table 1 provides a summary.[4] Looking at aggregate flows data, they consistently find that FDI flows are “cooler,” i.e., less volatile than other capital flows. Some studies attempt to explain the difference in volatility. For instance, Goldstein and Razin (2006) assume that the FDI investor can obtain refined information about the firm, while portfolio investors cannot. But that advantage comes with the cost: a low resale price when facing a liquidity shock due to the asymmetric information between the FDI owner and potential buyers. As a result, the tradeoff between management efficiency and liquidity of investors results in a less volatile FDI relative to portfolio investment.

[4] More evidence can be found in Chuhan et al. (1996), Nachum (1999), WorldBank (1999), Becker and Noone (2008), among others.

Albuquerque (2003) observes that FDI recipient countries are generally unable to operate the investment without the intangible assets of the indirect investors. In his model, because of inalienability, FDI commands a lower default premium associated with expropriation risk caused by imperfect enforcement of contracts and hence is less sensitive to changes in a country's financing constraints. It is in line with the findings in Lipsey (2001) and Levchenko and Mauro (2007) that FDI is remarkably stable during crisis periods. Similar to Albuquerque (2003), several studies show that international capital flows are subject to institutional factors. Related work includes Wei (2000), Gelos and Wei (2005), Alfaro et al. (2008), and Papaioannou (2009), who unanimously find that low institutional quality reduces international capital inflows.

Our paper is more related to Albuquerque (2003). We consider the informational problems caused by institutional quality and not the asymmetric information with the FDI, as greenfield FDI is purely a new investment inflow that is irrelevant to disinvestment.

The second strand of literature looks at the impacts of informational problems on international capital flows. Razin et al. (1998) introduce a model to study the pecking order of capital inflows. They assume portfolio debt and equity are subject to asymmetric information distortions where domestic investors observe firms' productivity while foreign investors do not, and FDI investors involved in the management of the firms can circumvent such distortions. Neumann (2003), on the other hand, assumes equity claims, even for portfolio equity, convey information on the investment, while debts do not. Her model explains why one may prefer equity financing to debt financing in developing countries. Daude and Fratzscher (2008) provide empirical evidence that information frictions and the quality of host country institutions are key determinants of the pecking order in a sample of 77 countries. They find that FDI is substantially more sensitive to information frictions than portfolio investment. More recently, Burchardi et al. (2019) study the effect of the ancestry composition of U.S. counties on FDI. They find that increasing the number of residents with ancestry from a given foreign country will increase the probability that at least one local firm engages in FDI with that country. And the effect results from a reduction in information frictions.

Finally, this paper belongs to the much smaller strand of literature on greenfield FDI. Existing evidence strongly supports the importance of greenfield FDI to host economies, and greenfield R&D has a significant impact on international technology spillovers. In Chinese high-tech industries, Liu and Zou (2008) find that foreign greenfield R&D creates both intra-industry and inter-industry spillovers on innovation, and there exist only inter-industry spillovers from M&As. Nocke and Yeaple (2008) present a model in which firms enter a foreign market through greenfield investment or cross-border acquisitions. In equilibrium, firms engaging in greenfield investment are systematically more efficient. Moreover, greenfield investment plays a vital role in transferring business from high-cost into low-cost countries.

We contribute to the literature in two directions. First, while greenfield FDI is beneficial to the host economies in many aspects, not much is known about the persistence of different types of FDI, and greenfield FDI has not been singled out for analysis in the literature. From a policy perspective, it may be oversimplified to view FDI as a homogenous capital flow. Qiu and Wang (2011) show that optimum FDI policy should be tailored to different types of FDI. Our paper reveals the persistence of greenfield FDI and its heterogeneity in persistence across industries.

Second, this paper connects information frictions with the persistence of greenfield FDI from a social learning perspective. More specifically, we consider the FDI productivity as a unit root process, and firms are learning the productivity of the foreign countries based on a noisy signal and other firms' past FDI.[5] We show that the persistence of FDI depends on how predictable the productivity is (variance of the productivity shock), how precise the signal is (variance of the signal), and how much information they can extract from others' FDI (similarity between the investing firm and other firms with earlier FDI). Also, our greenfield FDI data, which naturally excludes subsequence investment, allows us to reveal how firms rely on the past investment of the other firms under information frictions.

3. A social learning model of greenfield FDI

We model FDI decisions as a social learning problem in a discrete time model. At period t, $t = 1, 2, \ldots$, a firm indexed $n = t$ is making a greenfield FDI decision. The profitability of the investment project is determined by a hidden state θ_t, which is a unit root process.

$$\theta_t = \theta_{t-1} + e_t^{\theta};\; e_t^{\theta} \sim N(0, v_\theta)\text{i.i.d}$$

The decision rule is to match with the hidden state, θ_t, which determine the profitability of the project, and subject to a normal shock, $a_t \sim N(0, v_a)$, i.i.d.[6] We refer to a_t as the type of firm t, which is the private information of firm t.

$$I_t = E^t(\theta_t) + a_t$$

where $E^t(\cdot) := E(\cdot|\mathscr{I}_t)$ is the expectation operator conditional on the information set of firm t, $\mathscr{I}_t$. The investment decision is publicly observed. Each firm t receives a noise private signal s_t about θ_t.

[5] Khraiche and de Araujo (2021) show that the FDI process is persistent if firms learn the productivity of FDI via a noisy signal and update their expectations adaptively. However, as pointed out by Muth (1960), adaptive learning is rational only when the underlying process is a random walk with noise. In this paper, we account for the persistence of FDI in a more general setting.

[6] This decision rule can be generated by the profit maximization problem that the firm make one time investment with convex cost, and the return rate for each period depends on θ_t. The Appendix provides a detailed proof.

$s_t = \theta_t + e_t^s;\ e_t^s \sim N(0, v_s)$ i.i.d.

Thus, the information set for firm t includes the history of investments $h^{t-1} = \{I_i\}_{i=1}^{t-1}$ and the signal, s_t, i.e., $\mathscr{I}_t = (h^{t-1}, s_t)$.

Since the type of a firm is private information, the public updates their belief on θ_t based on the history of investment only, h^{t-1}. In the following, we present the five propositions of the model. Proofs are provided in the Appendix.

Proposition 1. *If $\theta_t|h^{t-1}$ is normal distributed, $\theta_{t+1}|h^t$ is also normal distributed.*[7]

We define $\theta_t|h^{t-1} \sim N(p_t, v_t)$ as the public belief, since it is the belief of θ_t which is formed with publicly announced investment h^{t-1} only. Proposition 1 shows that for any period t, if the belief is normally distributed, it will be normally distributed for all the periods after t inductively. Thus, we can summarize the belief dynamics in two variables: the mean of belief (p_t) , and the variance of belief (v_t). Next, we show the dynamics explicitly.

Proposition 2. *Suppose $\theta_t|h^{t-1} \sim N(p_t, v_t)$, the dynamics of belief and investment are determined by the following systems:*

$$I_t = \gamma_t s_t + (1-\gamma_t)p_t + a_t \tag{1}$$
$$p_{t+1} = \mu p_t + (1-\mu)I_t \tag{2}$$
$$v_{t+1} = \left(v_t^{-1} + \left(\gamma_t^2 v_s + v_a\right)^{-1}\right)^{-1} + v_\theta \tag{3}$$

where $\gamma_t = \frac{v_s^{-1}}{v_s^{-1}+v_t^{-1}}, \mu_t = \left(v_t^{-1} + \left(\gamma_t^2 v_s + v_a\right)^{-1}\right)^{-1} v_t^{-1}, \gamma_t \in (0,1)$, *and* $\mu_t \in (0,1)$.

Solving (1) and (2) recursively, we can show that investment (I_t) and the mean of public belief (p_t) are AR processes. However, the AR coefficients are time-varying, making the system intractable. The following proposition simplifies the analysis by showing the global convergence of the variance of public belief.

Proposition 3. *Suppose $\theta_t|h^{t-1} \sim N(p_t, v_t)$. For any $v_t \in \mathbb{R}, \lim_{i\to\infty} v_{t+i} = v$, where v is a constant.*

The above proposition shows that if the belief is normally distributed, there is a steady state for the variance of public belief. Then, we can directly impose the stable public belief variance as the initial variance, i.e., $\theta_0|h^0 \sim N(p_0, v), h^0 = \varnothing$ where p_0 is some constant. As a result, the time varying coefficients in the above system become constants, $v_t = v; \gamma_t = \gamma; \mu_t = \mu$.

$$I_t = \gamma s_t + (1-\gamma)p_t + a_t \tag{4}$$
$$p_{t+1} = \mu p_t + (1-\mu)I_t \tag{5}$$

where v is the fixed point of $f(v) = \left(v^{-1} + \left(\gamma^2 v_s + v_a\right)^{-1}\right)^{-1} + v_\theta; \gamma = \frac{v_s^{-1}}{v_s^{-1}+v^{-1}}, \mu = \left(v^{-1} + \left(\gamma^2 v_s + v_a\right)^{-1}\right)^{-1} v^{-1}, \gamma \in (0,1)$, and $\mu \in (0,1)$.

Note that we do not restrict the initial belief to be consistent, i.e., p_0 may not be equal to θ_0. One may doubt whether the belief formed over time is reliable if the initial error of belief (i.e., $|\theta_0 - p_0|$ is large). The following proposition shows that the belief formed will be reliable in some sense for any initial belief. Substituting (4) into (5) and solving the recursion give the following proposition.

Proposition 4. *The mean of public belief is an error correction process and is co-integrated with the hidden state.*

$$\Delta p_t = -(1-\mu)\gamma(p_{t-1} - \theta_{t-1}) + \epsilon_t^p \tag{6}$$

where $\epsilon_t^p = (1-\mu)\gamma e_{t-1}^s + a_{t-1}, (1-\mu)\gamma \in (0,1)$.

Note that θ_t is unobserved. By observing the history of investment, the public forms a reliable belief about θ_t. Although the belief is not always consistent (i.e., p_t is not always equated to θ_t), the mean of belief (p_t) is cointegrated with the actual state (θ_t), and the error is being corrected over time. If there is no further shock on the type and the signal, the public will eventually learn the true state.

Proposition 5. *FDI is an ARIMA(1,1,1) process.*

$$I_t = \gamma(\theta_t - \mu\theta_{t-1}) + (1 - \gamma(1-\mu))I_{t-1} + \epsilon_t^I - \mu\epsilon_{t-1}^I \tag{7}$$

where $\epsilon_t^I = \gamma e_t^s + a_t$, and $(1-\gamma(1-\mu)) \in (0,1)$. Proposition 5 provides the main equation for the empirical analysis. It shows that FDI is an ARIMA(1,1,1) process with a positive AR coefficient. The error correction term in Proposition 4 and the AR term in Proposition 5 depend on the variance of hidden state, signal, and type. In the following, we study their relations via a numerical method.

[7] *With some abuse of notation $\theta_i|h^j$ always refers to the belief of θ_i given information h^j, while θ_i refers to the actual state, which is a constant. We call the belief $\theta_i|h^j$ with $E(\theta_i|h^j) = \theta_i$ a consistent belief.*

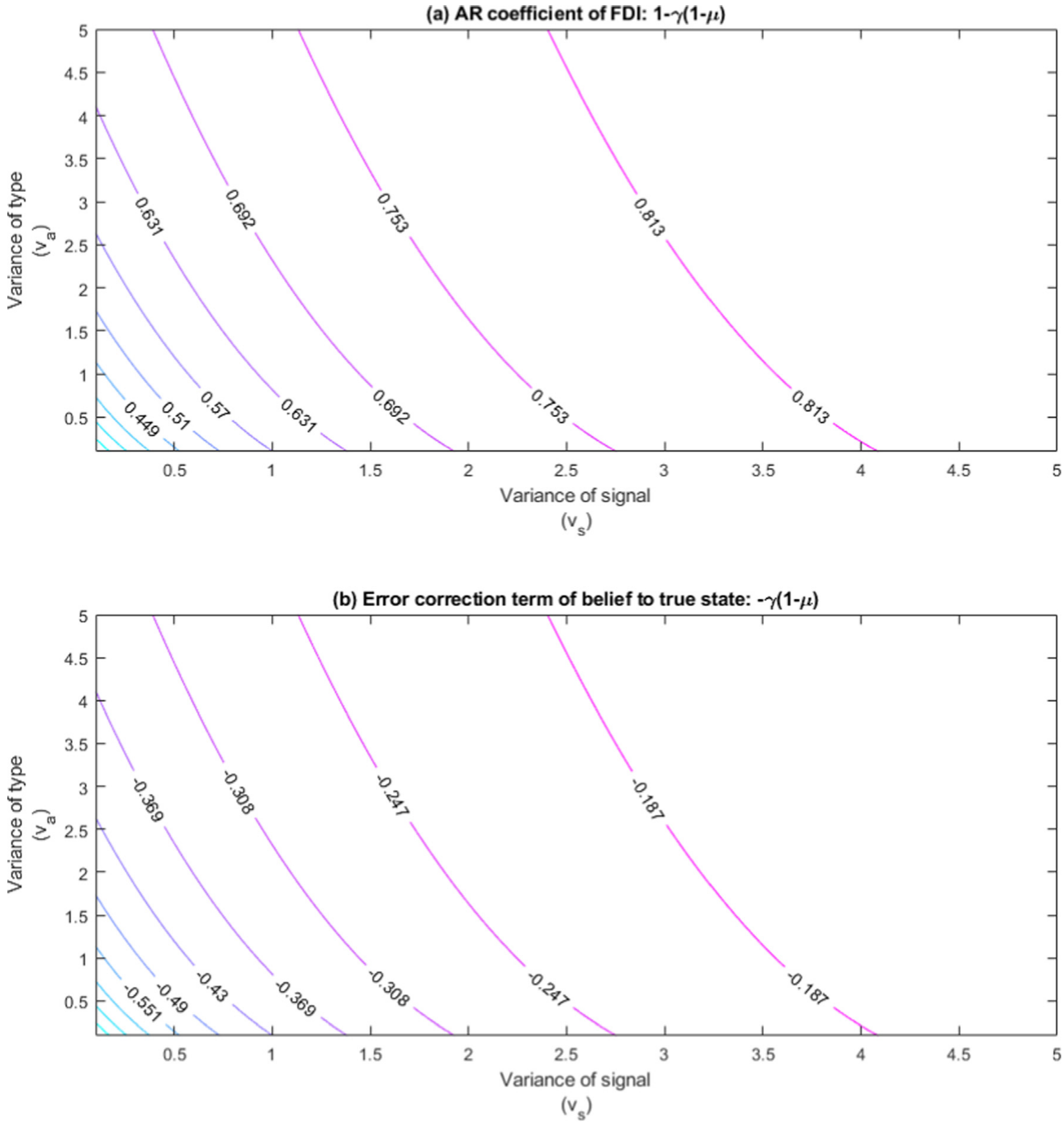

Fig. 2. Comparative statics: AR coefficient vs information frictions.

Proposition 5 allows us to analyze the effect of the variance of signal and type on the AR(1) persistence. Our analysis is based on a numerical method as the fixed point theorem is needed to pin down the variance of public belief, making a clear analytic solution not feasible. Fig. 2a plots the contour map of the AR coefficient in Eq. (7) (i.e., $1-\gamma(1-\mu)$), and the error correction term of public belief in Eq. (6) (i.e., $-(1-\mu)\gamma$). We fix the unit of investment $v_\theta = 1$. The approximation is made on the space $(v_s, v_a) \in [0.1, 5]^2$ with 100 linear steps, corresponding to 0.1 to 5 times the variance of state.

According to Fig. 2a, the AR coefficient increases in both the variance of signal (v_s) and the variance of type (v_a). The result is intuitive. When the signal is unreliable, the decision-maker weighs more on the investment history as a secondary information source. Also, when the type heterogeneity is high, there are two effects. First, decisions of other firms become less informative since they may be driven by the difference in firms' preferences or by the hidden state, while the investing firm cannot distinguish the two. Second, the decision-maker would like to consult more information, and hence she weighs more on the investment history of the early movers. The numerical result shows that the second force dominates, and the AR coefficient increases in the variance of type (v_a).

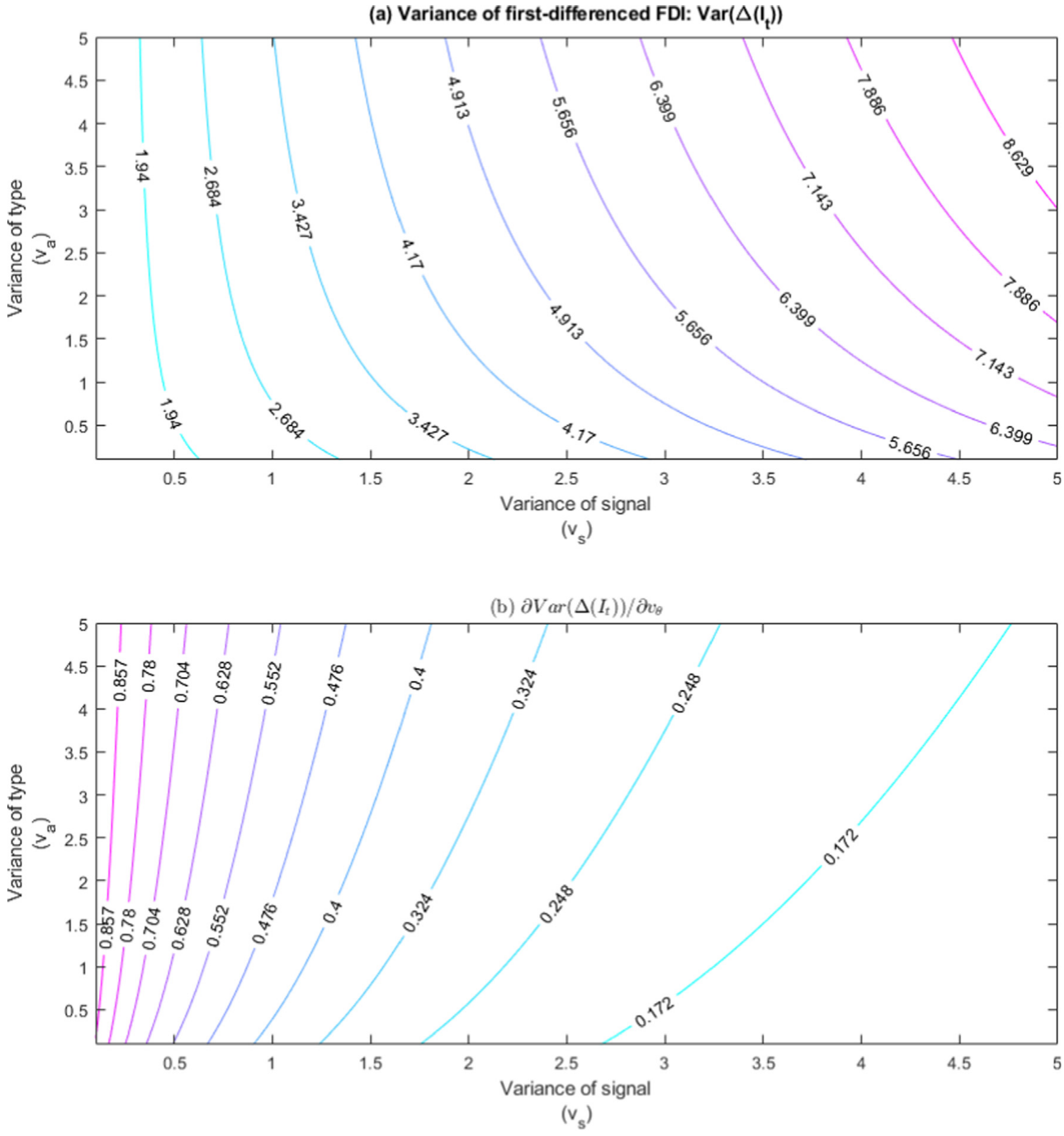

Fig. 3. Comparative statics: variance of FDI vs information frictions.

Fig. 2b shows that the error correction of the mean of belief is stronger when both the variance of signal and the variance of type are small. As information becomes more precise, it is easier for the public to deduce the true state from investment decisions, resulting in faster convergence of the mean of public belief to the true state. Thus, the belief is more reliable when the variance of signal and the variance of type are small.

To show the relationship between the variance of FDI and the variance of information frictions, we derive the theoretical variance of the first-differenced FDI from Eq. (7).[8] Fig. 3a shows that the variance of the first-differenced FDI increases in both the variances of signal and type. Also, Fig. 3b shows that the variance of the first-differenced FDI increases in the variance of productivity ($\frac{\partial Var(\Delta(I_t))}{\partial v^\theta}$).[9] The relationship increases in the variance of type while decreases in the variance of signal. When the signal is not informative, the variance of the first-differenced FDI will be less related to the variance of fundamental (productivity) but more related to information frictions.

[8] $Var(\Delta I_t) = \left(1+\frac{(\xi-\mu)^2}{1-\xi^2}\right)\gamma^2 v_\theta + \left(1+(\xi-(1+\mu))^2+\frac{(\xi^2-(1+\mu)\xi+\mu)^2}{1-\xi^2}\right)Var(\epsilon_t^I)$, where $\xi = 1-\gamma(1-\mu), \xi \in (0,1), Var(\epsilon_t^I) = \gamma^2 v_s + v_a$. The Appendix provides a detailed proof.

[9] $\frac{\partial Var(\Delta(I_t))}{\partial v^\theta} = \left(1+\frac{(\xi-\mu)^2}{1-\xi^2}\right)\gamma^2$.

In sum, for two AR(1) processes with the same shock, the one with higher AR persistence will have higher variance. In our model, the FDI process (the AR terms and the process of the shock of FDI) is endogenously determined by three fundamental shocks: (1) the total factor productivity (TFP) shock; (2) the signal shock; and (3) the type shock. The variances of the latter two shocks capture information frictions. We show that with the same TFP shock, higher variances of the latter two shocks imply a higher persistence and variance of FDI.

4. Data and econometric model

Our model generates a testable implication that greenfield FDI is determined by its realizations at the previous period and the payoff relevant state of the foreign country. Also, the comparative statics shows that the AR(1) coefficient increases in both information frictions in the host economy (represented by the variance of signal, υ_s) and the type heterogeneity of firms (υ_a). This section will describe the dataset we would use and describe how one can empirically test the model's implications. Descriptive statistics are provided in Appendix Table A2 and A3.

4.1. Greenfield FDI and macro-variable data

Our bilateral greenfield FDI data (in real term) is collected from the fDi Markets database compiled by fDi Intelligence, a division of the *Financial Times*. It is the most comprehensive firm-level database of cross-border greenfield investments available. The data includes the name of the investing firm and its parent company, the source and destination countries, the recipient industry sector of the FDI project, the date of investment, and the capital expenditure associated with the project. Sources of the database include *Financial Times* news wire and internal information sources, thousands of media sources, project data received from over 2,000 industry organizations and investment agencies, and data purchased from market research and publication companies. Since our theoretical model provides implications for country-level information frictions, we aggregate the firm-level data at the country level. It results in a sample of 454 country-pairs of greenfield FDI covering 69 source economies and 71 destination economies over the period 2013–2018 (see Appendix Table A1 for the list of economies). Also, as the recipient industry sector is known, we can extract industry-country-pair data of 4 industries (subject to data availability), namely manufacturing, retail, business service, and sales, marketing & support, from the whole sample for further analysis.

Several institutional and governance indicators are used to proxy information frictions in the FDI destination economies. As introduced in Section 1, we employ the voice and accountability index(*VA*), the control of corruption index (*CC*), and the rule of law index (RL) (ranging from approximately −2.5 (weak) to 2.5 (strong) governance performance) from the World Bank's Worldwide Governance Indicators database. This database covers all the economies in the fDi Markets database, meaning no observations are dropped after data matching. One drawback is that the voice and accountability index measures two aspects: freedom of expression and free elections, but the latter may be less relevant to information frictions.

To cope with this, we also employ the freedom of expression index (*FE*), the freedom of academic and cultural expression index (*FACE*), and the media bias index (*MB*) (ranging from 0 (lowest score) to 1 (highest score)). The data comes from the World Bank's Global State of Democracy database. However, this database does not cover Hong Kong (SAR of China), and our sample reduces to 445 country pairs. Furthermore, to be compatible with some of the previous studies,[10] we employ two measures of common language as additional proxies of information friction. They are the common official language (*COL*, which is the usual binary measure where 1 indicates two countries have the same official language, and 0 otherwise), and common native language (*CNL*, which is the 0–1 probability that a random pair from two countries speak the same native language). When both source and destination countries have a common language, it is easier for the firms from the source country to obtain information. The data comes from Melitz and Toubal (2014).

We assume that the payoff relevant state is affected by macroeconomic conditions. Therefore, in addition to the pull factors in the destination economy, we also control for the push factors from the source economy. A large body of literature has been devoted to identifying the determinants of FDI.[11] Among them, Blonigen and Piger (2014) employ the Bayesian Model Averaging procedure to calculate the inclusion probabilities for a group of macro-variables in the OECD countries and some non-OECD countries, and we mainly follow the list of variables with inclusion probabilities over 50% in Blonigen and Piger (2014) to select our control variables. Besides, Desbordes and Wei (2017) find that the source and destination countries' financial development significantly influences greenfield FDI. Therefore, we also include domestic credit to the private sector as a proxy for financial development. Subject to data availability, we employ the following macro-variables of both the source and destination economy (except where otherwise specified) as controls: real GDP (*GDP*), real GDP per capita (*GDPcap*), domestic credit to the private sector as a percentage of GDP (*Credit*), human capital index (*Skill*), real capital per worker (*Capital*), inflation rate (*Inf*), exchange rate (*Exrate*) (between the source and destination economy), and corporate tax rate (*Tax*) (in the destination economy). The data comes from IMF, KPMG, Penn World Table, and World Bank. Overall, our panel is unbalanced, but with only a small number of missing observations.

[10] See, Daude and Fratzscher (2008), among others.

[11] See, among others, Cheng and Kwan (2000); Carstensen and Toubal (2004); Braconier et al. (2005); Eicher et al. (2012).

4.2. Dynamic panel estimation

Fixed effects and endogeneity of regressors are crucial concerns when handling panel data. As shown in Eq. (7), greenfield FDI is a dynamic variable. Also, the other regressors may not be strictly exogenous since greenfield FDI contributes to economic growth, as discussed in Section 2. Given these concerns and a short panel data structure (where N is much larger than T), the system GMM estimator developed by Arellano and Bover (1995) and Blundell and Bond (1998) is a natural choice. The system GMM estimator simultaneously estimates a differenced equation and a level equation, where lagged variables in levels instrument for the differenced equation, lagged differences instrument for levels. It is a general estimator designed to address endogeneity issues with (1) the lagged dependent variable, (2) independent variables that are not strictly exogenous, and (3) fixed individual effects.

Note that endogeneity could also result from omitted variable bias. In system GMM estimation, the Hansen test is a common choice to test whether the instruments as a group are exogenous. But it can also be viewed as a test of structural specification. For instance, omitting important explanatory variables could move components of variation into the error term and make them correlated with the instruments, leading to a rejection of the null hypothesis in the Hansen test (Roodman (2009b)). In other words, if the Hansen test fails to reject the null, it implies no important explanatory variables are omitted.

We use a two-step system GMM estimator, which is more efficient and robust to heteroscedasticity and serial correlation, together with Windmeijer (2005) finite-sample adjustment to correct the downward bias in the computed standard errors in two-step results. We employ the "forward orthogonal deviations" transformation (Arellano and Bover, 1995) instead of first-difference transformation to remove the fixed effects. The latter magnifies gaps in unbalanced panels, while the former minimizes data loss in transforming the data in unbalanced panels (Roodman (2009a)).[12]

Multicollinearity is likely a problem when including all six institutional and governance indicators in the same regression. To test the theory, we estimate the following six reduced form dynamic panel data models for each institutional and governance indicator, for $q = 1, 2, \ldots, 6$:

$$\begin{aligned} GFDI_{i,j,t} = \quad & \alpha_{q1} GFDI_{i,j,t-1} + \alpha_{q2} GFDI_{i,j,t-2} + \alpha_{q3}\{Indicator^q_{j,t-1} \times GFDI_{i,j,t-1}\} \\ & + \alpha_{q4} Indicator^q_{j,t-1} + \sum_{m=1}^{M} \beta_{qm} Controls_{t-1} + YearFixedEffect + u^q_{i,j,t} \end{aligned} \tag{8}$$

where $GFDI_{i,j,t}$ is the real greenfield FDI from economy i to $j, i \neq j$; $Indicator^q_j$ with $q = 1, 2, \ldots, 6$ represents $VA, CC, RL, FE, FACE$, and MB, respectively, in economy j. *Controls* is a vector of the source and destination economy's macro-variables described in Section 4.1. $u^q_{i,j,t}$ is the disturbance term that has two orthogonal components: the fixed effects and the idiosyncratic shocks. To check for serial correlation of order 1 in levels, we test for correlation of order 2 in differences via the Arellano-Bond test. The year fixed effects, *YearFixedEffect*, are included to make the assumption of no correlation across individuals in the idiosyncratic disturbances (the key assumption of the autocorrelation test and the robust estimates of the coefficient standard errors) more likely to hold.

Here, we estimate an AR(2) instead of an AR(1) model for both economic and statistical reasons. It helps us to check whether the coefficient on $GFDI_{i,j,t-2}$ is insignificant, as predicted by the theory, and at the same time, we can account for serial correlation. According to our social learning model, we expect $\alpha_{q1} \in (0, 1)$ and $\alpha_{q2} = 0$. The model also predicts that greenfield FDI increases in information frictions. So, we expect $\alpha_{q3} < 0$ since better institutional quality implies fewer information frictions, resulting in a lower AR persistence.

Next, we use *COL* and *CNL* to proxy information frictions. As the language measures are time-invariant, for each measure, we split the whole sample into two sub-samples: economies with no common language ($COL = 0$, or $CNL = 0$), and economies with (a certain degree of) common language ($COL = 1$, or $CNL > 0$). We estimate the following regressions for each measure and each sub-sample.

$$GFDI_{i,j,t} = \alpha^k_{l1} GFDI_{i,j,t-1} + \alpha^k_{l2} GFDI_{i,j,t-2} + \sum_{m=1}^{M} \beta^k_{lm} Controls_{t-1} + YearFixedEffect + u_{i,j,t} \tag{9}$$

where $l = nc, c; k = COL, CNL$ respectively represents the sub-samples of no common language and common language according to *COL* and *CNL*. Again, we expect $\alpha_{l1} \in (0, 1)$ and $\alpha_{l2} = 0$. Also, as having common language implies fewer information frictions and a lower AR persistence, we expect $\alpha_{nc1} > \alpha_{c1}$.

Finally, we study the industry-country-level sub-samples, namely manufacturing, retail, business service, and sales, marketing & support industry. First, we believe that the information frictions across sectors are different. For instance, the manufacturing industry's profitability is mainly based on "hard facts," like production costs. Also, as many manufacturing firms produce export goods, their profitability is less likely to be influenced by "soft factors" like taste, culture, and social norms in the host economy. By contrast, business service and sales, marketing & support industry sell intangible products related to legal service, logistics service, consulting service, staffing, marketing, etc. Their profitability depends more on those "soft fac-

[12] For example, if y_i, t is missing, then both $\Delta y_{i,t}$ and $\Delta y_{i,t+1}$ are missing in the first-difference transformation. The "forward orthogonal deviations" transformation minimizes data loss by subtracting the average of all future available observations of a variable. It can be computed for all observations except the last for each variable.

tors." Thus, it is more difficult for service firms than manufacturing firms to collect reliable information through market research. In terms of our theoretical model, the variance of the private signal tends to be higher in business service and sales, marketing & support industry than in manufacturing industry. In other words, service firms are expected to rely more on the investment history of the early movers. Moreover, as a traditional service industry, the retail industry is different from the other three industries. It sells tangible products and provides sales services in the local market. Its profitability is subject to both "hard facts" and "soft factors." Thus, its AR persistence may be higher than that of the manufacturing industry but lower than that of the business service and sales, marketing & support industry.

Second, differences in the AR persistence across industries may be related to type heterogeneity. Firms within the same service industry provide very different and customized services. They recruit people with specific knowledge and skills in the service disciplines. In this sense, the type heterogeneity of service firms tends to be larger than that of secondary production firms, where the skill requirement tends to be similar. As our theoretical model predicts the AR persistence increases in the type heterogeneity, we expect the AR persistence of the service industries (i.e., business service, and sales, marketing & support) is higher than that of the manufacturing industry.

We estimate the following model for each industry sub-sample.

$$GFDI_{i,j,t} = \alpha_{d1} GFDI_{i,j,t-1} + \alpha_{d2} GFDI_{i,j,t-2} + \sum_{m=1}^{M} \beta_{dm} Controls_{t-1} + YearFixedEffect + u_{i,j,t} \tag{10}$$

where $d = man, ret, bus, mkt$, respectively represents the manufacturing, retail, business service, and sales, marketing & support industry. We expect $\alpha_{man1} < \alpha_{ret1} < \alpha_{bus1} < \alpha_{mkt1}$.

5. Empirical results

Table 2–4 show the results of the variables of interest in Eqs. (8)–(10), respectively. In the Appendix, Tables A4–A6 provide the estimates of all variables. As mentioned by Roodman (2009b), instrument proliferation can overfit instrumented variables and fail to remove their endogenous components. It also weakens the power of the Hansen test. Therefore, we collapse the instruments and present the estimation results of using lag 2 to 4 for instruments (except where otherwise specified) instead of using all available lags. In the Appendix, Tables A7–A9 provide the estimation results of using lag 2 to 4 up to 14 (the maximum lag) for instruments.

In Table 2, the coefficients on $GFDI_{i,j,t-1}$ are significant at 0.1% level and the coefficients on $GFDI_{i,j,t-2}$ are insignificant in all the specifications. The results indicate that greenfield FDI is an AR(1) process. In column (1), the AR(1) coefficient is around 0.4, meaning that other things being equal, if greenfield investment increases by 1 million USD this year, it will increase by 0.4 million USD next year. However, this result may overestimate or underestimate the AR persistence, as the comparative statics in Section 3.1 shows that the AR coefficient increases in information frictions. In columns (2) to (7), we employ the six institutional and governance indicators to proxy information frictions. In column (2), the interaction term between $GFDI_{i,j,t-1}$ and $VA_{j,t-1}$ is only significant at 10% level or, strictly speaking, insignificant. As mentioned earlier, we notice that the voice and accountability index may not be a good proxy for information frictions. In addition to freedom of expression, it measures free elections, which may be less relevant to information frictions. Despite this, the interaction terms between $GFDI_{i,j,t-1}$ and the other indicators are at least significant at 5% level in columns (3) to (7). The results are consistent with our theoretical prediction. As the range of each index is different, in Fig. 4, we visualize the negative relationship between the time average of each index in destination country j and its AR(1) coefficient on greenfield FDI. Considering our model is linear, the AR coefficients of some countries are smaller than zero in the models with the control and corruption index (Fig. 4, and the rule of law index (Fig. 4c). However, for models with the other indices (Fig. 4a and Fig. 4d–f), all the AR coefficients lie between 0 and 1.

In terms of test statistics, the Arellano-Bond test for AR(1) confirms the presence of serial correlation of order one, and the Arellano-Bond test for AR(2) does not reject the absence of the second-order serial correlation in the error term. The Hansen test, which can be viewed as a test of structural specification, does not reject the null that instruments as a group are exogenous. In most of the cases, the p-values are considerably higher than 10%. Since we limit the lags used in GMM-style instruments, the number of instruments (80) is relatively small compared to the sample size (around 6000 observations and 450 cross-sections). Thus, the risk of overfitting endogenous variables and weakening the Hansen test is low.

In addition to six institutional and governance indicators, we use two common language measures to proxy information frictions. Table 3 shows the estimation results. First, we split our sample into two sub-samples according to whether the source and the destination economy have a common official language (COL). In columns (1), the coefficient on $GFDI_{i,j,t-1}$ is 0.329 and is significant at 1% level.[13] Also, the coefficient on $GFDI_{i,j,t-2}$ is insignificant. Again, it shows that greenfield FDI is an AR(1) process in economies that do not share a common official language ($COL = 0$). It is consistent with our theory as information friction could be high when two economies do not share a common official language. Companies may rely heavily on the signals of the early movers, resulting in a persistent greenfield FDI inflow. On the other hand, in the sub-sample where the economies have the same official language (column (2)), the AR coefficient becomes insignificant. We observe the same pattern

[13] Here, we use a deeper lag for instruments (lag 2 to 6) since the Hansen test fails to reject the null when using lag 2 to 4 and 2 to 5. For details, see Appendix Table A8.

Table 2
Regressions of greenfield FDI: institutional and governance indicators.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
$GFDI_{I,j,t-1}$	0.394***	0.35***	0.429***	0.399***	0.991***	0.968***	0.911***
	(0.118)	(0.109)	(0.124)	(0.12)	(0.265)	(0.245)	(0.259)
$GFDI_{I,j,t-2}$	0.065	0.052	0.024	0.036	0.047	0.047	0.037
	(0.063)	(0.051)	(0.041)	(0.035)	(0.049)	(0.051)	(0.052)
$GFDI_{I,j,t-1} \times VA_{j,t-1}$		−0.145					
		(0.082)					
$GFDI_{I,j,t-1} \times CC_{j,t-1}$			−0.313*				
			(0.13)				
$GFDI_{I,j,t-1} \times RL_{j,t-1}$				−0.353**			
				(0.132)			
$GFDI_{I,j,t-1} \times FE_{j,t-1}$					−0.943*		
					(0.386)		
$GFDI_{I,j,t-1} \times FACE_{j,t-1}$						−0.954**	
						(0.349)	
$GFDI_{I,j,t-1} \times MB_{j,t-1}$							−0.985*
							(0.485)
$VA_{j,t-1}$		16.558					
		(114.669)					
$CC_{j,t-1}$			−20.597				
			(152.152)				
$RL_{j,t-1}$				490.254			
				(266.71)			
$FE_{j,t-1}$					866.912		
					(526.063)		
$FACE_{j,t-1}$						973.286*	
						(423.027)	
$MB_{j,t-1}$							128.145
							(634.082)
Contorls				Yes			
Year dummy				Yes			
Observations	6066	6066	6066	6066	5941	5941	5941
Cross sections	454	454	454	454	445	445	445
Number of instruments	76	80	80	80	80	80	80
Arellano-Bond test for AR(1) p-value	0.001	0	0	0	0	0	0
Arellano-Bond test for AR(2) p-value	0.452	0.353	0.462	0.693	0.295	0.297	0.316
Hansen test of over-identifying restrictions p-value	0.171	0.4	0.657	0.843	0.318	0.318	0.217

Note: *, **, and *** indicate 5%, 1%, and 0.1% level of significance respectively. Standard errors in parentheses.

Table 3
Regressions of greenfield FDI: common language.

	(1) $COL = 0$	(2) $COL = 1$		(3) $CNL = 0$	(4) $CNL > 0$
$GFDI_{i,j,t-1}$	0.329**	0.135		0.426***	0.163
	(0.107)	(0.165)		(0.132)	(0.206)
$GFDI_{i,j,t-2}$	0.121	−0.01		0.093	−0.013
	(0.066)	(0.012)		(0.081)	(0.02)
Contorls			Yes		
Year dummy			Yes		
Observations	4801	1265		3571	2495
Cross sections	352	102		263	191
Number of instruments	106	76		76	76
Arellano-Bond test for AR(1) p-value	0.004	0.04		0.007	0.027
Arellano-Bond test for AR(2) p-value	0.866	0.589		0.519	0.88
Hansen test of over-identifying restrictions p-value	0.152	0.708		0.25	0.219

Note: *, **, and *** indicate 5%, 1%, and 0.1% level of significance respectively. Standard errors in parentheses.

in columns (3) and (4), where the sample is divided by whether the economies have a certain degree of common native language ($CNL = 0$ and $CNL > 0$).

Next, we examine the industry sub-sample, and the results are shown in Table 4. For the manufacturing industry sample, we estimate two specifications. Consistent with the other results, we use lag 2 to 4 for instruments in column (1). However, the number of instruments (76) is quite large relative to the sample size of 751 observations and 55 cross-sections. Also, the p-value of the Hansen test is very close to one, indicating that the risk of overfitting endogenous variables is high. To lower the risk of overfitting, in column (2), we reduce the number of instruments to 62 by removing the most insignificant control

Table 4
Regressions of greenfield FDI: industry sub-samples.

	(1) Manufacturing	(2)	(3) Retail	(4) Business service	(5) Sales, marketing & support
	All controls	Sub-set of controls			
$GFDI_{i,j,t-1}$	0.382***	0.349**	0.565**	0.672***	0.8***
	(0.105)	(127)	(0.207)	(0.183)	(0.167)
$GFDI_{i,j,t-2}$	−0.022	−0.013	−0.014	0.149	−0.019
	(0.06)	(0.07)	(0.069)	(0.163)	(0.12)
Contorls			Yes		
Year dummy			Yes		
Observations	751	760	1193	1016	1620
Cross sections	55	55	87	75	120
Number of instruments	76	56	76	76	76
Arellano-Bond test for AR(1) *p*-value	0.001	0.003	0.014	0.045	0.004
Arellano-Bond test forAR(2) *p*-value	0.138	0.192	0.302	0.603	0.386
Hansen test of over-identifying restrictions *p*-value	0.966	0.375	0.397	0.392	0.262

Note: *, **, and *** indicate 5%, 1%, and 0.1% level of significance respectively. Standard errors in parentheses.

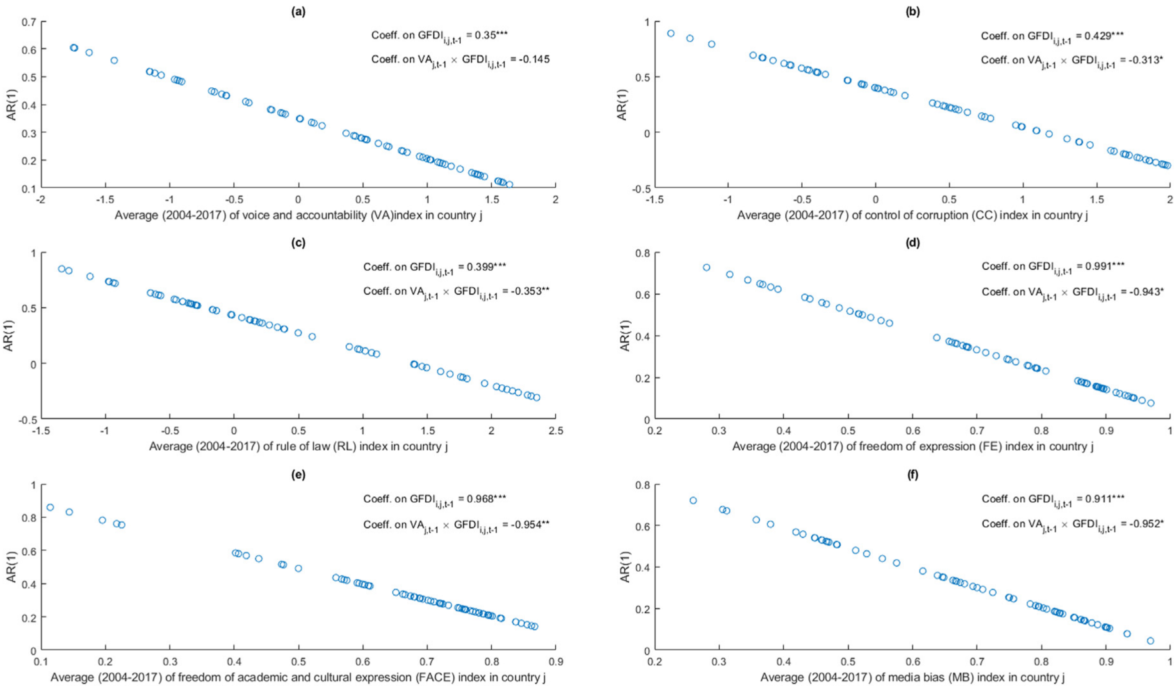

Fig. 4. Effect of information frictions on the AR(1) coefficient.

variables one at a time until the number of instruments is roughly equal to the number of cross-sections. The coefficient on $GFDI_{i,j,t-1}$ (0.349) is significant at 1% level, and the *p*-value of the Hansen test reduces to 0.375. Overall, we find the AR persistence of service firms (business service and sales, marketing & support) is higher than that of manufacturing firms, especially when we compare the AR persistence of the sales, marketing & support industry (0.8) with that of the manufacturing industry. These results are in line with our predictions. As discussed in Section 4.2, the variance of private signal, the variance of type, and the AR persistence for service firms are expected to be higher than manufacturing firms. Also, the AR persistence of the retail industry lies between the service industries and the manufacturing industry, as its profitability is subject to both "hard facts" and "soft factors."

Finally, given that the *p*-value of the Hansen test tends to become inflated with an increasing number of instruments, in Appendix Tables A7–A10, we follow Roodman (2009a,b)'s suggestion to report the results of using different lags for instruments as a robustness check. According to Table A7 and A8, there is no sign that the Hansen test is weakened at the selected lags for instruments (lag 2–4) as the *p*-values are not increasing after introducing more lags for instruments. However, in Table A9, the risk of weakening the Hansen test presences in the manufacturing, retail, and business service sub-samples. We further reduce the number of instruments by removing the most insignificant control variable one at a time until half of the control variables are removed. Table A10 shows that the coefficient on $GFDI_{i,j,t-1}$ is not sensitive to the model reduction. The Hansen tests do not reject the null in all model specifications.

6. Conclusion and policy implications

While persistent inflows of FDI are usually portrayed as good and bullish news by the media, we have pointed out in Section 3 that persistence itself, which characterizes both the ups and downs of FDI, contributes to higher volatility and is something that policymakers try to avoid. We show in this paper that some of the persistence of greenfield FDI comes from information frictions, and greenfield FDI becomes more volatile when firms are less certain about the investment environment of the destination. When firms see that other firms invest in a country, they treat it as a signal and follow. When firms see that other firms retreat from a country, they do the same. Such "herding" behavior contributes to the volatility of FDI.

We have presented a list of factors that are related to information friction. While some are not subject to changes (e.g., language), other institutional and governance factors can be improved by reforms and other policy changes. Upholding the rule of law, promoting freedom of the press, and preventing corruption in the government are some of the obvious policy implications of this paper. Indeed, numerous other studies have already pointed out the economic benefits of having those characteristics (e.g., Acemoglu et al. (2005)). Our paper points out another channel they contribute: better institutions and governance reduce information frictions, thereby avoiding drastic and persistent ups and downs in FDI.

Due to the limitation of our data, both in the sample length and coverage of countries, we can only obtain "reduced form" estimates of the model. As a result, we cannot further pin down the more structural parameters. In addition, with limited data, we cannot look at more complex interactions across economies. For example, a firm in country A may learn from the greenfield FDI in nearby country B. We look forward to follow-up studies that make use of a larger panel of data.

Data availability

The data that has been used is confidential.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A

This appendix provides the followings:

- List of economies: Table A1.
- Relationship between variance of greenfield FDI and three proxies for information frictions, economies with a variance of less than one: Fig. A1.
- Detailed proof of the social learning model.
- Descriptive statistics: Table A2 and A3.
- Detailed results: Table A4, A5 and A6.
- Robustness check of using lag 2 to 4 up to the maximum lag as instruments: Table A7, A8 and A9.
- Robustness check of reducing the number of controls in the manufacturing, retail and business sub-samples: Table A10.

Detailed proof of the social learning model

In this section, we frame the FDI as a social learning game. Each firm makes FDI to match an unobserved state (the optimal level of FDI), which is a discrete random walk process. Firms are heterogeneous in the sense that the optimal investment level is subject to a normal shock. We show that FDI is an AR process, and its persistence depends on the variances of signal, of type, and of the underlying state.

Let θ_t be the payoff relevant state with the law of motion $\theta_t = \theta_{t-1} + e_t^\theta : e_t^\theta \sim N(0, \nu^\theta)$. There is a sequence of players, $n = 1, 2, \ldots$. They sequentially make the FDI decision, and player $n = t$ is active at time t. A signal about the underlying state $s_t \sim N(\theta_t, \nu^s)$ is observed privately by player t. Investment decisions are publicly observed. For simplicity, we suppose the decision rule is given by

Table A1
List of economies.

Economies (abbreviation)					
Algeria (DZ)	Angola (AO)	Argentina (AR)	Australia (AU)	Austria (AT)	Bahrain (BH)
Belgium (BE)	Brazil (BR)	Bulgaria (BG)	Canada (CA)	Chile (CL)	China (CN)
Colombia (CO)	Costa Rica (CR)	Croatia (HR)	Czech (CZ)	Denmark (DK)	Egypt (EG)
Estonia (EE)	Finland (FI)	France (FR)	Germany (DE)	Greece (GR)	Hong Kong (HK)
Hungary (HU)	India (IN)	Indonesia (ID)	Ireland (IE)	Israel (IL)	Italy (IT)
Japan (JP)	Kazakhstan (KZ)	Kenya (KE)	Kuwait (KW)	Latvia (LV)	Lithuania (LT)*
Malaysia (MY)	Mexico (MX)	Morocco (MA)	Myanmar (MM)	Netherlands (NL)	New Zealand (NZ)
Nigeria (NG)	Norway (NO)	Panama (PA)	Peru (PE)	Philippines (PH)	Poland (PL)
Portugal (PT)	Qatar (QA)	Romania (RO)	Russia (RU)	Saudi Arabia (SA)	Serbia (RS)
Singapore (SG)	Slovakia (SK)	Slovenia (SI)*	South Africa (ZA)	South Korea (KR)	Spain (ES)
Sri Lanka (LK)	Sweden (SE)	Switzerland (CH)	Thailand (TH)	Tunisia (TN)	Turkey (TR)
UAE (AE)	Ukraine (UA)	United Kingdom (GB)	United States (US)	Vietnam (VN)	

* Lithuania and Slovenia are source economies only.

$$I_t = E^t(\theta_t) + a_t$$

where $a_t \sim N(0, v_a)$ is the type heterogeneity of players, $E^t(\cdot) := E(\cdot|s_t, h^{t-1})$ is the expectation operator of player t given a private signal and the history of FDI, $h^{t-1} = \{I_i\}_{i=1}^{t-1}$.[14] Since the type of a firm is unobserved by the other players, the investment decision does not reveal the private signal completely, although the investment is publicly observed.

We assume that given the history h^{t-1}, the public belief of state can be summarized as a normal process, $\theta_t|h^{t-1} \sim N(p_t, v_t)$. Next, we show that under this setting, $\theta_{t+1}|h^t$ is also a normal process.

Player t forms the private belief, $\theta_t|h^{t-1}, s_t$ by incorporating the signal, s_t, with the public belief, $\theta_t|h^{t-1}$. The Bayes rule implies:

$$\theta_t|s_t, h^{t-1} \sim N(\gamma_t s_t + (1-\gamma_t)p_t, (v_s^{-1} + v_t^{-1})^{-1})$$

where $\gamma_t = \frac{v_s^{-1}}{v_s^{-1}+v_t^{-1}}$.

Now, we consider how the public belief on θ_{t+1} are formed after I_t being publicly observed. It can be done in two steps: (i) deducing the private information from investment decision of firm t and update their belief about $\theta_t|h^t$; (ii) incorporating the law of motion of θ and forming the belief of $\theta_{t+1}|h^t$.

(i) *Forming public belief on θ_t after observing I_t*: With a_t unobserved, the investment is a normal process, $I_t|s_t, h^{t-1} \sim N(\gamma_t s_t + (1-\gamma_t)p_t, v_\alpha)$. Combining with the signal, $s_t|\theta_t \sim N(\theta_t, v_s)$, gives the investment conditional on the state with the signal and the type unobserved.

$$I_t|\theta_t, h^{t-1} \sim N(\gamma_t\theta_t + (1-\gamma_t)p_t, \gamma_t^2 v_s + v_\alpha)$$

[14] We may think of a_i represents the cost advantage of firm i (due to better technology or financing ability), and the firms make investment once only at $i = t$, with convex cost. All firms are risk neutral, with a discount factor, δ.The decision rule can be generated by the following optimization problem, with $i = t$:

$$\max_{I_i} E^i\{\sum_{j=1}^{\infty}\delta^j\hat{\theta}_{t+j}I_i - (const - a_iI_i + \frac{b}{2}I_i^2)\}$$

for θ_t is a unit root process, for any $j > 0, E^i\theta_{t+j} = E^i\theta_t$

$$\max_{I_i} \frac{\delta}{1-\delta}E^i\{\hat{\theta}_t\}I_i - (const - a_iI_i + \frac{b}{2}I_i^2)$$

Take b = 1, and normalize the unit of $\theta_t := \frac{1-\delta}{\delta}\hat{\theta}_t$ to absorb the constant $\frac{\delta}{1-\delta}$.a_i may also represent the profitability advantage of firm i (difference in rate of return). The decision rule can be generated by the following optimization problem, with $i = t$:

$$\max_{I_i} E^i\{\sum_{j=1}^{\infty}\delta^j(\hat{\theta}_{t+j} + \hat{a}_i)I_i - (const - b_1I_i + \frac{b_2}{2}I_i^2)\}$$

for θ_t is a unit root process, for any $j > 0, E^i\theta_{t+j} = E^i\theta_t$

$$\max_{I_i} \frac{\delta}{1-\delta}(E^i\{\hat{\theta}_t\} + \hat{a}_i)I_i - (const - b_1I_i + \frac{b_2}{2}I_i^2)$$

Take b_1 = 1, and normalize the unit of $\theta_t := \frac{1-\delta}{\delta}\hat{\theta}_t$ to absorb the constant $\frac{\delta}{1-\delta}$. Also, normalize the unit of $\hat{a}_i$ by defining $a_i := \frac{\delta}{1-\delta}\hat{a}_i - b_1$.

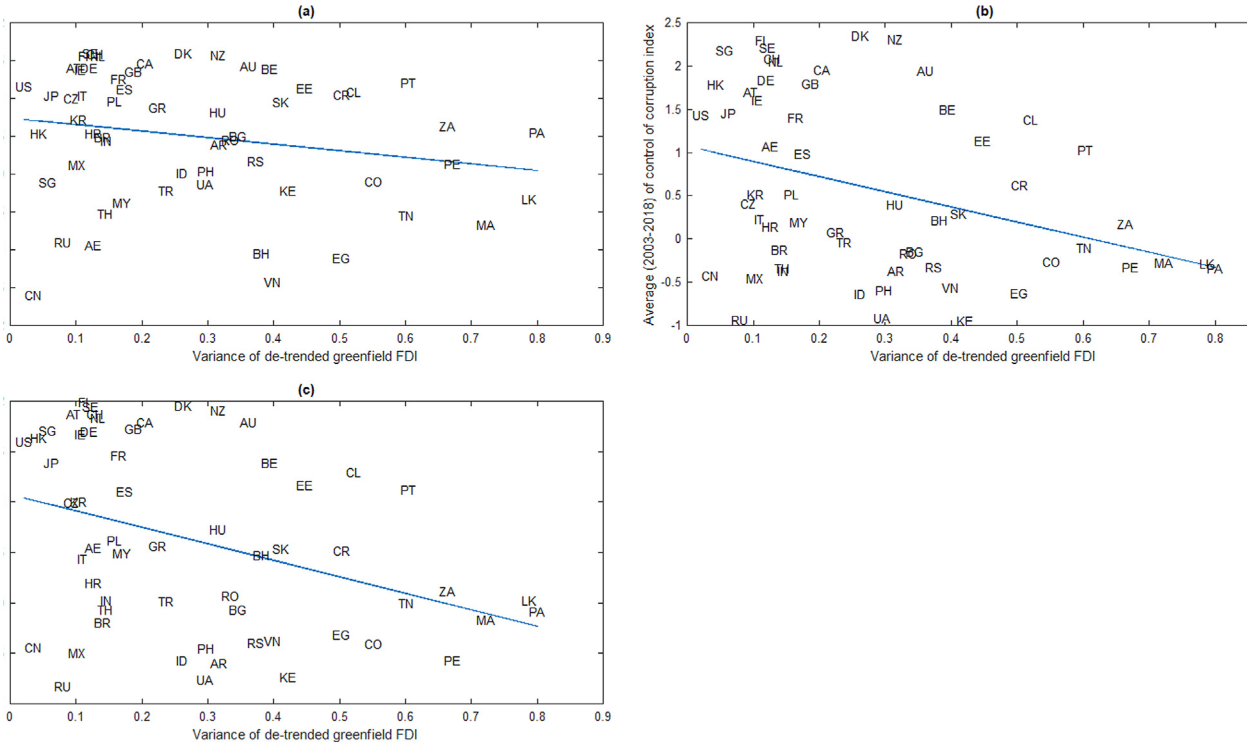

Fig. A1. Relationship between variance of greenfield FDI and information frictions, economies with a variance of less than one.

Table A2
Descriptive statistics: Pooled, between, and within.

Variable		Mean	Std. Dev.	Min	Max	Observations
GFDI	Overall	887.42	1874.02	0	59005.6	N = 7264
Millions USD	Between		1362.05	36.59	16337.79	n = 454
	Within		1288.64	−7513.72	52465.25	T = 16
GDP (Source)	Overall	4184.03	5489.63	21.85	25278.77	N = 7264
Billions USD	Between		5232.42	33	15763.76	n = 454
	Within		1677.61	−4559.12	15635.12	T = 16
GDP (Destination)	Overall	3122.88	4860.68	21.85	25278.77	N = 7264
Billions USD	Between		4551.91	33	15763.76	n = 454
	Within		1717.29	−5620.28	14573.96	T = 16
GDPcap (Source)	Overall	39380.14	14413.22	2399.82	101386.8	N = 7264
USD	Between		13227.75	4751.3	73810.39	n = 454
	Within		5755.79	11912.08	67873.97	T = 16
GDPcap (Destination)	Overall	30316.82	20240.41	1583.32	146981.8	N = 7264
USD	Between		19447.43	2726.75	122937.7	n = 454
	Within		5679.18	2848.77	58810.65	T = 16
Capital (Source)	Overall	350722.8	120874	23136.38	695455.8	N = 6810
USD	Between		119085.7	38635.62	636216.8	n = 454
	Within		21407.33	245823.8	466554.4	T = 15
Capital (Destination)	Overall	257658.9	161175.3	2089.72	695455.8	N = 6810
USD	Between		159970.2	8258.21	636216.8	n = 454
	Within		20967.13	152759.9	373490.5	T = 15

(*continued on next page*)

Table A2 (*continued*)

Variable		Mean	Std. Dev.	Min	Max	Observations
Credit (Source)	Overall	125.16	44.73	0.19	233.21	N = 7109
Percentage	Between		42.19	24.89	190.34	n = 454
	Within		14.59	60.93	188.52	T = 15.66
Credit (Destination)	Overall	93.89	52.44	3.12	233.21	N = 7128
Percentage	Between		50.43	10.39	190.34	n = 454
	Within		15.16	29.66	157.26	T = 15.7
Skill (Source)	Overall	3.28	0.44	1.83	3.97	N = 6810
Index: 1 to 4	Between		0.43	1.97	3.68	n = 454
	Within		0.09	2.79	4.11	T = 15
Skill (Destination)	Overall	3	0.55	1.33	3.97	N = 6810
Index: 1 to 4	Between		0.53	1.41	3.68	n = 454
	Within		0.12	2.5	3.82	T = 15
Inf (Source)	Overall	2.08	2.11	−2.6	48.7	N = 7264
Percentage	Between		1.51	0.26	13.03	n = 454
	Within		1.48	−11.25	37.75	T = 16
Inf (Destination)	Overall	3.72	4.09	−4.9	98.2	N = 7264
Percentage	Between		2.91	0.26	22.51	n = 454
	Within		2.88	−11.49	79.41	T = 16
Exrate	Overall	473.49	2831.84	0.00056	34798.37	N = 7264
Between countries	Between		2803.15	0.00072	30309.51	n = 454
	Within		421.75	−6339.55	5256.53	T = 16
Tax (Destination)	Overall	27.88	8.7	0	55	N = 7189
Percentage	Between		8.04	0	55	n = 454
	Within		3.27	12.88	52.88	T = 15.83
VA (Destination)	Overall	0.42	0.99	−2.23	1.8	N = 7264
Index: −2.5 to 2.5	Between		0.98	−1.73	1.64	n = 454
	Within		0.12	−0.43	1.33	T = 16
CC (Destination)	Overall	0.65	1.05	−1.67	2.47	N = 7264
Index: −2.5 to 2.5	Between		1.04	−1.33	2.34	n = 454
	Within		0.14	0.17	1.34	T = 16
RL (Destination)	Overall	0.67	0.95	−1.74	2.1	N = 7264
Index: −2.5 to 2.5	Between		0.94	−1.39	1.99	n = 454
	Within		0.12	0.17	1.17	T = 16
FE (Destination)	Overall	0.72	0.21	0.09	1	N = 7120
Index: 0 to 1	Between		0.2	0.28	0.97	n = 445
	Within		0.05	0.47	0.93	T = 16
FACE (Destination)	Overall	0.69	0.2	0.11	1	N = 7120
Index: 0 to 1	Between		0.19	0.26	0.97	n = 445
	Within		0.06	0.4	0.89	T = 16
MB (Destination)	Overall	0.64	0.21	0.11	1	N = 7120
Index: 0 to 1	Between		0.21	0.11	0.86	n = 445
	Within		0.06	0.4	0.9	T = 16
COL	Overall	0.21	0.41	0	1	N = 7168
Binary	Between		0.41	0	1	n = 448
	Within		0	0.21	0.21	T = 16
CNL	Overall	0.08	0.21	0	0.99	N = 7168
Probability	Between		0.21	0	0.99	n = 448
	Within		0	0.08	0.08	T = 16

Note: To avoid extremely small or large values of regression coefficients, we adjust the units of some variables before running the regressions.

Table A3
Descriptive statistics: percentile.

Variable	Unit	N	min	p25	p50	p75	max
GFDI	Millions USD	7264	0	115.8	320.3	869.63	59005.6
GDP (Source)	Billions USD	7264	21.85	548.87	2152.89	4112.91	25278.77
GDP (Destination)	Billions USD	7264	21.85	390.22	1200.43	3094.11	25278.77
GDPcap (Source)	USD	7264	2399.82	33203.64	39484.21	47007.67	101386.8
GDPcap (Destination)	USD	7264	1583.32	14024.96	29113.82	42738.12	146981.8
Capital (Source)	USD	6810	23136.38	323726.9	360496.1	426617.8	695455.8
Capital (Destination)	USD	6810	2089.72	114338.2	270561.2	365100.7	695455.8
Credit (Source)	Percentage	7109	0.19	90.84	122.63	162.97	233.21
Credit (Destination)	Percentage	7128	3.12	48.12	89.38	131.53	233.21
Skill (Source)	Index: 1 to 4	6810	1.83	3.03	3.42	3.64	3.97
Skill (Destination)	Index: 1 to 4	6810	1.33	2.56	3.09	3.47	3.97
Inf (Source)	Percentage	7264	−2.6	0.9	1.9	2.7	48.7
Inf (Destination)	Percentage	7264	−4.9	1.5	2.6	4.6	98.2
Exrate	Ratio	7264	0.00056	0.78	1.76	9.53	34798.37
Tax (Destination)	Percentage	7189	0	21	28	33.5	55
VA (Destination)	Index: −2.5 to 2.5	7264	−2.23	−0.17	0.57	1.3	1.8
CC(Destination)	Index: −2.5 to 2.5	7264	−1.67	−0.33	0.52	1.7	2.47
RL (Destination)	Index: −2.5 to 2.5	7264	−1.74	−0.18	0.64	1.63	2.1
FE (Destination)	Index: 0 to 1	7120	0.09	0.54	0.8	0.9	1
FACE (Destination)	Index: 0 to 1	7120	0.11	0.55	0.76	0.86	1
MB (Destination)	Index: 0 to 1	7120	0.11	0.57	0.7	0.79	1
COL	Binary	7168	0	0	0	0	1
CNL	Probability	7168	0	0	0	0.01	0.99

Note: To avoid extremely small or large values of regression coefficients, we adjust the units of some variables before running the regressions.

Table A4
Detailed results: institutional and governance indicators.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
$GFDI_{i,j,t-1}$	0.394***	0.35***	0.429***	0.399***	0.991***	0.968***	0.911***
	(0.118)	(0.109)	(0.124)	(0.12)	(0.265)	(0.245)	(0.259)
$GFDI_{i,j,t-2}$	0.065	0.052	0.024	0.036	0.047	0.047	0.037
	(0.063)	(0.051)	(0.041)	(0.035)	(0.049)	(0.051)	(0.052)
$GFDI_{i,j,t-1} \times VA_{j,t-1}$		−0.145					
		(0.082)					
$GFDI_{i,j,t-1} \times CC_{j,t-1}$			−0.313*				
			(0.13)				
$GFDI_{i,j,t-1} \times RL_{j,t-1}$				−0.353**			
				(0.132)			
$GFDI_{i,j,t-1} \times FE_{j,t-1}$					−0.943*		
					(0.386)		
$GFDI_{i,j,t-1} \times FACE_{j,t-1}$						−0.954**	
						(0.349)	
$GFDI_{i,j,t-1} \times MB_{j,t-1}$							−0.985*
							(0.485)
$VA_{j,t-1}$		16.558					
		(114.669)					
$CC_{j,t-1}$			−20.597				
			(152.152)				
$RL_{j,t-1}$				490.254			
				(266.71)			
$FE_{j,t-1}$					866.912		
					(526.063)		
$FACE_{j,t-1}$						973.286*	
						(423.027)	
$MB_{j,t-1}$							128.145
							(634.082)
$GDP_{i,t-1}$	3.598*	2.981	3.199	4.616*	3.806*	3.172*	3.874*
	(1.581)	(1.719)	(1.945)	(1.883)	(1.619)	(1.575)	(1.715)
$GDP_{j,t-1}$	3.875*	4.259*	3.889*	4.169*	4.778***	4.499***	4.748**
	(1.654)	(1.697)	(1.889)	(1.815)	(1.472)	(1.416)	(1.581)

(*continued on next page*)

Table A4 (*continued*)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
$GDPcap_{i,t-1}$	0.373	0.161	−0.619	−0.523	0.316	0.241	0.456
	(0.676)	(0.657)	(0.813)	(0.783)	(0.655)	(0.613)	(0.705)
$GDPcap_{j,t-1}$	−0.003	0.153	0.873	0.471	0.561	0.478	0.333
	(0.46)	(0.483)	(0.495)	(0.55)	(0.536)	(0.485)	(0.52)
$Credit_{i,t-1}$	0.189	0.796	0.729	0.578	−0.004	0.196	−0.268
	(1.351)	(1.513)	(1.514)	(1.724)	(1.552)	(1.525)	(1.578)
$Credit_{j,t-1}$	−3.159*	−3.113*	−2.155	−4.845**	−2.615	−2.616*	−2.674*
	(1.265)	(1.302)	(1.334)	(1.879)	(1.384)	(1.295)	(1.355)
$Skill_{i,t-1}$	−0.877	0.332	3.163	2.564	−0.243	−0.31	−0.197
	(1.928)	(2.076)	(2.779)	(2.806)	(2.041)	(1.989)	(2.197)
$Skill_{j,t-1}$	3.519	3.928	3.893	2.631	−0.178	0.66	0.274
	(2.109)	(2.213)	(2.27)	(2.665)	(2.11)	(2.021)	(2.149)
$Capital_{i,t-1}$	−0.205	−0.564	−0.527	−0.372	−0.053	−0.287	0.031
	(0.827)	(0.974)	(1.071)	(1.128)	(0.924)	(0.944)	(0.97)
$Capital_{j,t-1}$	−1.773	−1.1	−1.263	−3.557	−1.101	−1.217	0.222
	(1.003)	(1.161)	(1.325)	(1.826)	(1.13)	(1.275)	(1.145)
$Tax_{j,t-1}$	−10.986	−6.609	−3.745	2.261	−4.569	−3.89	−5.284
	(7.468)	(6.601)	(6.83)	(8.471)	(6.156)	(6.339)	(6.857)
$Inf_{i,t-1}$	9.183	6.401	14.462	6.445	9.619	7.205	8.936
	(17.882)	(18.571)	(19.266)	(22.083)	(19.191)	(18.943)	(20.213)
$Inf_{j,t-1}$	2.114	3.399	−1.465	4.683	−11.02	−7.696	−12.567
	(11.122)	(10.793)	(11.182)	(10.585)	(12.007)	(12.604)	(12.242)
$Exrate_{i,j,t-1}$	−7.82	−0.38	−0.256	−10.226	5.122	4.991	8.633
	(11.465)	(11.65)	(12.387)	(13.535)	(10.974)	(11.809)	(14.269)
Year dummy:							
2006	187.791***	187.062***	169.093***	206.204***	194.628***	189.822***	186.339***
	(50.77)	(47.69)	(42.099)	(43.583)	(43.693)	(46.173)	(44.583)
2007	103.347	119.278*	151.312*	207.219***	145.061*	147.949**	137.2*
	(55.354)	(57.634)	(65.169)	(62.645)	(56.804)	(55.614)	(57.819)
2008	500.972***	497.31***	500.415***	625.194***	518.721***	530.397***	503.216***
	(76.34)	(74.488)	(81.036)	(88.075)	(78.352)	(78.461)	(80.247)
2009	−11.701	41.801	43.363	188.347	87.572	94.455	78.734
	(92.011)	(97.026)	(115.683)	(124.619)	(100.036)	(95.59)	(109.072)
2010	−30.426	−5.116	22.968	183.006	47.864	57.607	37.48
	(72.76)	(74.924)	(94.889)	(102.485)	(77.55)	(74.731)	(83.967)
2011	30.107	17.884	16.703	171.98	45.817	50.679	39.551
	(61.712)	(65.041)	(94.691)	(104.634)	(68.179)	(66.133)	(69.705)
2012	−116.544	−138.593*	−148.038	13.995	−123.368	−101.075	−137.5*
	(62.854)	(65.702)	(81.684)	(98.877)	(67.634)	(66.373)	(69.101)
2013	1.443	−35.948	−53.646	128.331	6.161	8.818	−35.614
	(70.276)	(74.026)	(82.84)	(102.944)	(72.82)	(73.193)	(78.678)
2014	−45.993	−66.004	−82.565	103.778	−38.759	−16.001	−109.201
	(78.548)	(77.355)	(93.096)	(116.232)	(82.911)	(84.857)	(92.004)
2015	6.709	2.331	−18.353	151.123	8.719	58.235	−73.164
	(93.71)	(95.676)	(107.224)	(115.449)	(100.509)	(106.423)	(107.32)
2016	−29.265	−17.849	−14.398	159.679	−11.824	19.024	−94.723
	(99.529)	(99.211)	(124.627)	(139.436)	(104.709)	(112.28)	(112.607)
2017	−156.011	−189.507	−202.865	−1.978	−193.29	−148.714	−260.643*
	(106.702)	(100.408)	(118.668)	(141.379)	(116.05)	(122.868)	(121.074)
2018	15.595	8.025	−0.856	229.599	67.951	96.157	−52.618
	(104.216)	(108.201)	(133.916)	(162.2)	(118.549)	(121.527)	(128.959)
Constant	290.05	−365.064	−1250.988	−441.277	24.466	−121.957	174.384
	(747.663)	(849.307)	(870.017)	(1142.329)	(781.183)	(726.379)	(789.813)
Observations	6066	6066	6066	6066	5941	5941	5941
Cross sections	454	454	454	454	445	445	445
Number of instruments	76	80	80	80	80	80	80
Arellano-Bond test for AR(1) *p*-value	0.001	0	0	0	0	0	0
Arellano-Bond test for AR(2) *p*-value	0.452	0.353	0.462	0.693	0.295	0.297	0.316
Hansen test of over-identifying restrictions *p*-value	0.171	0.4	0.657	0.843	0.318	0.318	0.217

Note: *, **, and *** indicate 5%, 1%, and 0.1% level of significance respectively. Standard errors in parentheses.

Table A5
Detailed results: common language.

	(1) $COL = 0$	(2) $COL = 1$	(3) $CNL = 0$	(4) $CNL > 0$
$GFDI_{i,j,t-1}$	0.329**	0.135	0.426***	0.163
	(0.107)	(0.165)	(0.132)	(0.206)
$GFDI_{i,j,t-2}$	0.121	−0.01	0.093	−0.013
	(0.066)	(0.012)	(0.081)	(0.02)
$GDP_{i,t-1}$	3.417**	8.165*	3.888**	5.932**
	(1.304)	(3.721)	(1.51)	(2.1)
$GDP_{j,t-1}$	3.596*	11.889*	2.932	7.33*
	(1.48)	(5.75)	(1.653)	(3.112)
$GDPcap_{i,t-1}$	−0.274	−0.058	0.022	0.509
	(0.807)	(1.692)	(1.225)	(0.963)
$GDPcap_{j,t-1}$	−0.585	1.671	−0.278	0.264
	(0.499)	(1.487)	(0.623)	(0.565)
$Credit_{i,t-1}$	−0.997	1.938	−1.886	2.133
	(1.272)	(3.102)	(1.571)	(2.354)
$Credit_{j,t-1}$	−2.872*	−0.639	−3.164*	−0.921
	(1.26)	(3.717)	(1.511)	(2.269)
$Skill_{i,t-1}$	2.274	−0.99	2.475	−2.48
	(2.273)	(4.301)	(3.504)	(2.653)
$Skill_{j,t-1}$	1.7	−3.213	3.144	0.671
	(2.372)	(4.145)	(3.259)	(2.93)
$Capital_{i,t-1}$	0.171	2.554	−0.232	1.833
	(0.624)	(2.542)	(0.765)	(1.508)
$Capital_{j,t-1}$	−1.149	−1.463	−1.56	−1.985
	(0.965)	(2.369)	(1.262)	(1.432)
$Tax_{j,t-1}$	−6.251	7.223	2.191	−17.987*
	(7.096)	(17.423)	(10.525)	(9.103)
$Inf_{i,t-1}$	45.463	4.581	32.433	12.323
	(27.252)	(37.918)	(31.368)	(19.03)
$Inf_{j,t-1}$	−5.18	−8.778	−3.949	−14.406
	(9.69)	(16.763)	(17.412)	(12.196)
$Exrate_{i,j,t-1}$	−2.638	493.915**	−6.803	307.556
	(11.282)	(176.86)	(12.802)	(200.25)
Year dummy:				
2006	177.819**	86.425	176.479*	53.945
	(57.291)	(134.263)	(70.063)	(80.164)
2007	235.917***	61.442	149.716	153.948*
	(56.502)	(123.605)	(80.122)	(72.866)
2008	528.735***	382.352*	555.634***	365.002***
	(89.613)	(155.799)	(112.048)	(107.205)
2009	−25.352	114.011	−59.577	79.835
	(98.367)	(181.891)	(136.521)	(129.927)
2010	81.184	−161.811	8.565	−24.225
	(82.305)	(146.9)	(102.82)	(118.386)
2011	64.361	−75.691	86.191	−74.602
	(65.847)	(194.223)	(94.417)	(102.834)
2012	−80.744	−218.111	−111.439	−171.125
	(68.649)	(177.678)	(93.796)	(103.999)
2013	51.57	−274.405	74.917	−156.991
	(69.349)	(228.189)	(101.184)	(116.335)
2014	21.852	−379.3	−4.452	−235.726
	(81.154)	(227.208)	(113.163)	(123.492)
2015	81.871	−257.391	47.265	−201.999
	(99.553)	(266.152)	(137.623)	(132.765)
2016	141.333	−215.818	68.987	−208.858
	(108.768)	(241.499)	(153.398)	(153.133)
2017	−30.433	−403.223	−113.027	−241.076
	(109.114)	(310.832)	(145.378)	(161.827)
2018	105.213	−297.188	59.177	−124.186
	(106.063)	(289.648)	(142.785)	(170.107)
Constant	−220.14	133.052	−756.791	783.016
	(787.426)	(1837.667)	(1421.429)	(1055.285)
Observations	4801	1265	3571	2495
Cross sections	352	102	263	191
Number of instruments	106	76	76	76
Arellano-Bond test for AR(1) *p*-value	0.004	0.04	0.007	0.027
Arellano-Bond test for AR(2) *p*-value	0.866	0.589	0.519	0.88
Hansen test of over-identifying restrictions *p*-value	0.152	0.708	0.25	0.219

Note: *, **, and *** indicate 5%, 1%, and 0.1% level of significance respectively. Standard errors in parentheses.

Table A6
Detailed results: industry sub-samples.

	(1) Manufacturing	(2)	(3) Retail	(4) Business service	(5) Sales, marketing & support
	All controls	Sub-set of controls			
$GFDi_{i,j,t-1}$	0.382***	0.349**	0.565**	0.672***	0.8***
	(0.105)	(0.127)	(0.207)	(0.183)	(0.167)
$GFDi_{i,j,t-2}$	−0.022	−0.013	−0.014	0.149	−0.019
	(0.06)	(0.07)	(0.069)	(0.163)	(0.12)
$GDP_{i,t-1}$	5.54	4.589	0.232	−0.009	0.155
	(5.184)	(2.555)	(0.34)	(0.195)	(0.128)
$GDP_{j,t-1}$	2.067	6.611	0.191	0.044	0.063
	(3.443)	(3.666)	(0.326)	(0.313)	(0.124)
$GDPcap_{i,t-1}$	16.049	10.47	−6.227*	1.531	−1.515
	(25.282)	(15.677)	(2.618)	(1.913)	(1.461)
$GDPcap_{j,t-1}$	−8.475		11.733	−0.617	1.242*
	(14.417)		(6.955)	(0.891)	(0.617)
$Credit_{i,t-1}$	−9.216	−3.344	0.329	−0.062	0.174
	(9.507)	(6.625)	(0.506)	(0.758)	(0.319)
$Credit_{j,t-1}$	0.952		−1.353*	−0.388	−0.028
	(3.711)		(0.608)	(0.287)	(0.193)
$Skill_{i,t-1}$	−2.611		0.566	0.096	0.371
	(6.302)		(0.754)	(0.535)	(0.317)
$Skill_{j,t-1}$	−15.52	−5.514	−2.18	−0.054	−0.138
	(10.206)	(8.755)	(1.353)	(0.403)	(0.186)
$Capital_{i,t-1}$	−0.77		−0.127	−0.641	0.216
	(3.495)		(0.265)	(0.457)	(0.163)
$Capital_{j,t-1}$	4.738	1.319	−0.679	−0.123	−0.139
	(4.405)	(4.22)	(0.471)	(0.183)	(0.083)
$Tax_{j,t-1}$	−18.118	−12.083	5.962*	−0.383	0.729
	(26.846)	(38.872)	(2.858)	(1.324)	(0.878)
$Inf_{i,t-1}$	−66.816	−88.233	−1.618	−16.916*	2.774
	(127.805)	(95.531)	(6.687)	(7.754)	(3.873)
$Inf_{j,t-1}$	−55.064	−75.001	−8.484	−3.393	−4.049
	(30.297)	(45.512)	(6.792)	(3.693)	(2.424)
$Exrate_{i,j,t-1}$	−18.512		−365.143	−127.453	1.05
	(17.81)		(595.761)	(149.703)	(2.527)
Year dummy:					
2006	438.907	399.977	68.258*	12.18	2.274
	(246.305)	(226.52)	(34.307)	(18.942)	(12.374)
2007	132.774	−1.215	79.508	59.193*	41.262*
	(439.786)	(202.087)	(51.891)	(28.421)	(16.992)
2008	568.613	484.353	71.167*	22.111	9.079
	(397.187)	(272.632)	(31.801)	(46.583)	(15.399)
2009	62.769	56.259	142.439***	−13.707	−20.82
	(295.702)	(356.789)	(43.701)	(44.499)	(15.526)
2010	−411.668	−161.875	89.569*	−8.354	4.543
	(385.848)	(390.831)	(39.188)	(36.396)	(15.323)
2011	108.189	−90.257	22.542	−17.453	4.543
	(351.125)	(301.311)	(29.936)	(37.801)	(18.778)
2012	−168.336	−245.727	88.9*	45.459	−14.034
	(328.084)	(262.018)	(37.698)	(37.389)	(14.984)
2013	171.163	−299.581	182.277***	−52.727	−15.247
	(492.013)	(379.694)	(35.716)	(43.378)	(16.785)
2014	114.565	−310.279	60.731	−11.672	−7.904
	(585.013)	(444.188)	(41.093)	(39.809)	(16.308)
2015	−627.228	−806.539	83.248*	−53.34**	−15.739
	(378.224)	(462.966)	(39.609)	(18.455)	(18.111)
2016	−174.583	−738.913	98.884*	−65.617*	−16.697
	(769.648)	(563.767)	(45.652)	(29.713)	(22.759)
2017	−813.19	−1011.97	87.15	−25.751	−5.957
	(728.551)	(582.83)	(45.39)	(22.964)	(22.143)
2018	66.718	−452.668	55.138	−0.445	−10.793
	(411.356)	(419.855)	(47.222)	(26.676)	(24.886)
Constant	6623.767	2384.821	609.45	366.031	−124.91
	(3578.147)	(2781.79)	(492.984)	(276.596)	(150.404)
Observations	751	760	1193	1016	1620
Cross sections	55	55	87	75	120
Number of instruments	76	56	76	76	76
Arellano-Bond test for AR(1) p-value	0.001	0.003	0.014	0.045	0.004
Arellano-Bond test for AR(2) p-value	0.138	0.192	0.302	0.603	0.386
Hansen test of over-identifying restrictions p-value	0.966	0.375	0.397	0.392	0.262

Note: *, **, and *** indicate 5%, 1%, and 0.1% level of significance respectively. Standard errors in parentheses.

Note that public belief at time t is $\theta_t|h^{t-1} \sim N(p_t, v_t)$. The Bayes updating implies

$$\theta_t|I_t, h^{t-1} = \theta_t|h^t \sim N(p_{t+1}, \omega_t)$$

where $\omega_t = \left(v_t^{-1} + (\gamma_t^2 v_s + v_a)^{-1}\right)^{-1}$, and $p_{t+1} = \omega_t v_t^{-1} p_t + (1 - \omega_t v_t^{-1}) I_t$.

(ii) *Forming* $\theta_{t+1}|h^t$: With the common knowledge that $\theta_{t+1} = \theta_t + e^\theta_{t+1}$, the public belief on θ_{t+1} given the history h^t is $\theta_{t+1}|h^t \sim N(p_{t+1}, \omega_t + v_\theta)$. It shows that when the public belief of state at time t is a normal process, the public belief at time $t+1$ is also a normal process. Inductively, the public belief will always be a normal process.

Thus, given the initial value of θ_0 and the public belief $\theta_0 \sim N(p_0, v_0)$ (for consistence, we impose $p_0 = \theta_0$.), the system can be written as:

$$s_t = \theta_t + e^s_t \tag{11}$$
$$I_t = \gamma_t s_t + (1 - \gamma_t) p_t + a_t \tag{12}$$
$$p_{t+1} = \omega_t v_t^{-1} p_t + (1 - \omega_t v_t^{-1}) I_t \tag{13}$$
$$\theta_{t+1} = \theta_t + e^\theta_{t+1} \tag{14}$$
$$v_{t+1} = \left(v_t^{-1} + (\gamma_t^2 v_s + v_a)^{-1}\right)^{-1} + v_\theta \tag{15}$$

where $\gamma_t = \frac{v_s^{-1}}{v_s^{-1} + v_t^{-1}}, \omega_t = \left(v_t^{-1} + (\gamma_t^2 v_s + v_a)^{-1}\right)^{-1}$.

Solving (12) and (13) recursively shows that investment (I_t) and the mean of public belief (p_t) are AR processes. However, the AR coefficients are time-varying, making the system intractable. In the following, we simplify the analysis by showing the global convergence of variance of public belief. For any $v_t \in \mathbb{R}, \lim_{i\to\infty} v_{t+i} = v$, where v is a constant, we will directly impose the stable public belief variance as the initial variance $v_0 = v$, and show that γ_t becomes invariant under this condition.

Global convergence of variance of public belief

We show that for any initial variance of public belief, the public belief converges to a constant over time. With the definition of γ_t, Eq. (15) shows the dynamics of belief variance is

$$v_{t+1} = \left(v_t^{-1} + \left(\left(\frac{v_s^{-1}}{v_s^{-1} + v_t^{-1}}\right)^2 v_s + v_a\right)^{-1}\right)^{-1} + v_\theta.$$

The stable belief variance is the fixed point of

$$f(v) = \left(v^{-1} + \left(\left(\frac{v_s^{-1}}{v_s^{-1} + v^{-1}}\right)^2 v_s + v_a\right)^{-1}\right)^{-1} + v_\theta$$

where f is a continuous function on $v \in [0, \infty)$, with $f(0) = v_\theta$ and $\lim_{v\to\infty} f(v) = v_s + v_a + v_\theta > 0$. The Brouwer fixed-point theorem guarantees the existence of a fixed point. Note that $\forall v \in [0, \infty) : f\prime(v) > 0, f(0) = v_\theta > 0$, and the existence of the fixed point makes sure the global convergence and the uniqueness of the fixed point: $\exists v \in [v_\theta, v_s + v_a + v_\theta] : f(v) = v$.

FDI and mean of public belief as ARIMA process

By imposing the fixed point as the initial belief variance: $v_t = v; \gamma_t = \gamma; \omega_t = \omega$, the system (11)–(15) becomes

$$s_t = \theta_t + e^s_t \tag{16}$$
$$I_t = \gamma s_t + (1 - \gamma) p_t + a_t \tag{17}$$
$$p_{t+1} = \omega v^{-1} p_t + (1 - \omega v^{-1}) I_t \tag{18}$$
$$\theta_{t+1} = \theta_t + e^\theta_{t+1} \tag{19}$$

where v is the fixed point of $f(v) = \left(v^{-1} + (\gamma^2 v_s + v_a)^{-1}\right)^{-1} + v_\theta$, and $\gamma = \frac{v_s^{-1}}{v_s^{-1} + v^{-1}}, \omega = \left(v^{-1} + (\gamma^2 v_s + v_a)^{-1}\right)^{-1}$.

The above system yields the following AR process:

$$I_t = \gamma\theta_t + (1 - \gamma)(1 - \mu)\sum_{i=0}^{\infty} \mu^i I_{t-1} + \epsilon^I_t \tag{20}$$
$$p_t = (1 - \mu)\gamma\theta_{t-1} + (1 - \gamma(1 - \mu)) p_{t-1} + \epsilon^p_t \tag{21}$$
$$\theta_{t+1} = \theta_t + e^\theta_{t+1} \tag{22}$$

where $\epsilon^I_t = \gamma e^s_t + a_t, \epsilon^p_t = (1 - \mu)\gamma e^s_{t-1} + a_{t-1}, \mu = \omega v^{-1}$.

Eq. (20) shows that after controlling for θ, FDI is essentially an AR(1) process. It can be rewritten as:

$$I_t = \gamma(\theta_t - \mu\theta_{t-1}) + (1 - \gamma(1 - \mu)) I_{t-1} + \epsilon^I_t - \mu\epsilon^I_{t-1} \tag{23}$$

where $\epsilon^I_t = \gamma e^s_t + a_t$, and $(1 - \gamma(1 - \mu)) \in (0, 1)$. First differencing (23) yields:

Table A7
Robustness check: institutional and governance indicators.

Instrument lag	2–4	2–5	2–6	2–7	2–8	2–9	2–10	2–11	2–12	2–13	2–14
					Proxy for information frictions: *VA*						
Number of instruments	80	96	112	128	144	160	176	192	208	224	239
$GFDI_{i,j,t-1}$	0.35***	0.191	0.146	0.172	0.191	0.181	0.194*	0.223**	0.196*	0.188**	0.15*
	(0.109)	(0.123)	(0.12)	(0.105)	(0.098)	(0.094)	(0.084)	(0.082)	(0.081)	(0.072)	(0.073)
$GFDI_{i,j,t-2}$	0.052	0.056	0.052	0.056	0.063	0.064	0.064	0.059	0.06	0.064	0.074
	(0.051)	(0.05)	(0.057)	(0.058)	(0.059)	(0.057)	(0.062)	(0.063)	(0.062)	(0.062)	(0.064)
$VA_{j,t-1} \times GFDI_{i,j,t-1}$	−0.145	−0.212**	−0.226**	−0.156*	−0.121	−0.132	−0.137*	−0.134	−0.18*	−0.174*	−0.165*
	(0.082)	(0.077)	(0.088)	(0.075)	(0.071)	(0.071)	(0.069)	(0.07)	(0.072)	(0.074)	(0.077)
Arellano-Bond test for AR(1) *p*-value	0	0.001	0.002	0	0	0	0	0	0	0	0
Arellano-Bond test for AR(2) *p*-value	0.353	0.885	1	0.97	0.966	0.982	0.96	0.808	0.898	0.973	0.765
Hansen test of over-identifying restrictions *p*-value	0.4	0.052	0.042	0.076	0.147	0.199	0.054	0.07	0.032	0.005	0.001
Cross sections	454	454	454	454	454	454	454	454	454	454	454
					Proxy for information frictions: *CC*						
Number of instruments	80	96	112	128	144	160	176	192	208	224	239
$GFDI_{i,j,t-1}$	0.429***	0.352**	0.289*	0.274**	0.289**	0.274**	0.288***	0.312***	0.308***	0.302***	0.267***
	(0.124)	(0.126)	(0.115)	(0.099)	(0.095)	(0.091)	(0.081)	(0.074)	(0.069)	(0.063)	(0.065)
$GFDI_{i,j,t-2}$	0.024	0.027	0.027	0.041	0.048	0.053	0.055	0.051	0.046	0.051	0.059
	(0.041)	(0.047)	(0.053)	(0.057)	(0.057)	(0.056)	(0.061)	(0.062)	(0.059)	(0.06)	(0.061)
$CC_{j,t-1} \times GFDI_{i,j,t-1}$	−0.313*	−0.344***	−0.346***	−0.265**	−0.226*	−0.219*	−0.218*	−0.208*	−0.268**	−0.257**	−0.25**
	(0.13)	(0.097)	(0.096)	(0.096)	(0.094)	(0.096)	(0.096)	(0.098)	(0.086)	(0.089)	(0.086)
Arellano-Bond test for AR(1) *p*-value	0	0	0	0	0	0	0	0	0	0	0
Arellano-Bond test for AR(2) *p*-value	0.462	0.758	0.974	0.993	0.938	0.964	0.996	0.841	0.928	0.976	0.806
Hansen test of over-identifying restrictions *p*-value	0.657	0.154	0.157	0.172	0.14	0.208	0.034	0.025	0.02	0.001	0
Cross sections	454	454	454	454	454	454	454	454	454	454	454
					Proxy for information frictions: *RL*						
Number of instruments	80	96	112	128	144	160	176	192	208	224	239
$GFDI_{i,j,t-1}$	0.399***	0.308*	0.253*	0.241*	0.247**	0.227*	0.245**	0.277***	0.28***	0.274***	0.249***
	(0.12)	(0.121)	(0.115)	(0.099)	(0.096)	(0.09)	(0.084)	(0.078)	(0.072)	(0.067)	(0.069)
$GFDI_{i,j,t-2}$	0.036	0.032	0.034	0.047	0.054	0.061	0.062	0.06	0.055	0.059	0.067
	(0.035)	(0.044)	(0.054)	(0.056)	(0.057)	(0.057)	(0.061)	(0.062)	(0.061)	(0.062)	(0.064)
$RL_{j,t-1} \times GFDI_{i,j,t-1}$	−0.353**	−0.386***	−0.349**	−0.271**	−0.223*	−0.207*	−0.194*	−0.187*	−0.254**	−0.24*	−0.239**
	(0.132)	(0.106)	(0.114)	(0.101)	(0.097)	(0.095)	(0.096)	(0.095)	(0.092)	(0.097)	(0.092)
Arellano-Bond test for AR(1) *p*-value	0	0	0	0	0	0	0	0	0	0	0
Arellano-Bond test for AR(2) *p*-value	0.693	0.964	0.811	0.785	0.844	0.725	0.809	0.975	0.895	0.854	0.672
Hansen test of over-identifying restrictions *p*-value	0.843	0.286	0.093	0.148	0.132	0.18	0.044	0.042	0.027	0.005	0.004
Cross sections	454	454	454	454	454	454	454	454	454	454	454
					Proxy for information frictions: *FE*						
Number of instruments	80	96	112	128	144	160	176	192	208	224	239
$GFDI_{i,j,t-1}$	0.991***	1.009***	0.957***	0.734***	0.641**	0.607**	0.637***	0.655***	0.779***	0.743***	0.633**
	(0.265)	(0.27)	(0.297)	(0.231)	(0.205)	(0.201)	(0.194)	(0.19)	(0.204)	(0.199)	(0.2)
$GFDI_{i,j,t-2}$	0.047	0.06	0.056	0.064	0.068	0.072	0.072	0.07	0.072	0.075	0.082
	(0.049)	(0.052)	(0.055)	(0.057)	(0.059)	(0.057)	(0.063)	(0.063)	(0.063)	(0.062)	(0.065)
$FE_{j,t-1} \times GFDI_{i,j,t-1}$	−0.943*	−1.22**	−1.162**	−0.816*	−0.678*	−0.624*	−0.637*	−0.617*	−0.843**	−0.817*	−0.685*
	(0.386)	(0.392)	(0.442)	(0.347)	(0.308)	(0.305)	(0.296)	(0.296)	(0.328)	(0.32)	(0.323)
Arellano-Bond test for AR(1) *p*-value	0	0.001	0.001	0	0	0	0	0	0	0	0
Arellano-Bond test for AR(2) *p*-value	0.295	0.833	0.855	0.924	0.977	0.983	0.931	0.789	0.882	0.986	0.831
Hansen test of over-identifying restrictions *p*-value	0.318	0.065	0.09	0.154	0.222	0.268	0.09	0.059	0.02	0.005	0.004

Table A7 (*continued*)

Instrument lag	2–4	2–5	2–6	2–7	2–8	2–9	2–10	2–11	2–12	2–13	2–14
Cross sections	445	445	445	445	445	445	445	445	445	445	445
Proxy for information frictions: *FACE*											
Number of instruments	80	96	112	128	144	160	176	192	208	224	239
$GFDI_{i,j,t-1}$	0.968***	0.945***	0.866**	0.731***	0.668***	0.663***	0.682***	0.654***	0.76***	0.726***	0.624***
	(0.245)	(0.258)	(0.28)	(0.225)	(0.198)	(0.204)	(0.19)	(0.184)	(0.196)	(0.193)	(0.195)
$GFDI_{i,j,t-2}$	0.047	0.063	0.061	0.065	0.065	0.071	0.072	0.07	0.074	0.076	0.083
	(0.051)	(0.051)	(0.055)	(0.055)	(0.056)	(0.055)	(0.061)	(0.062)	(0.062)	(0.061)	(0.064)
$FACE_{j,t-1} \times GFDI_{i,j,t-1}$	−0.954**	−1.165**	−1.058*	−0.835*	−0.738*	−0.733*	−0.731*	−0.614*	−0.814**	−0.783*	−0.662*
	(0.349)	(0.393)	(0.429)	(0.34)	(0.299)	(0.315)	(0.297)	(0.284)	(0.314)	(0.309)	(0.311)
Arellano-Bond test for AR(1) *p*-value	0	0.001	0.001	0	0	0	0	0	0	0	0
Arellano-Bond test for AR(2) *p*-value	0.297	0.825	0.853	0.877	0.891	0.952	0.888	0.714	0.794	0.867	0.942
Hansen test of over-identifying restrictions *p*-value	0.318	0.066	0.084	0.139	0.238	0.267	0.095	0.043	0.022	0.007	0.005
Cross sections	445	445	445	445	445	445	445	445	445	445	445
Proxy for information frictions: *MB*											
Number of instruments	80	96	112	128	144	160	176	192	208	224	239
$GFDI_{i,j,t-1}$	0.911***	0.916***	0.96***	0.769***	0.618***	0.568**	0.569***	0.563***	0.6***	0.554***	0.472**
	(0.259)	(0.245)	(0.259)	(0.204)	(0.182)	(0.182)	(0.171)	(0.17)	(0.164)	(0.166)	(0.158)
$GFDI_{i,j,t-2}$	0.037	0.048	0.041	0.05	0.059	0.062	0.066	0.066	0.07	0.075	0.083
	(0.052)	(0.053)	(0.055)	(0.055)	(0.061)	(0.06)	(0.066)	(0.065)	(0.065)	(0.064)	(0.066)
$MB_{j,t-1} \times GFDI_{i,j,t-1}$	−0.985*	−1.318**	−1.469**	−1.074**	−0.771*	−0.664*	−0.613*	−0.526	−0.613*	−0.564	−0.476
	(0.485)	(0.448)	(0.501)	(0.389)	(0.329)	(0.314)	(0.289)	(0.296)	(0.301)	(0.316)	(0.301)
Arellano-Bond test for AR(1) *p*-value	0	0.004	0.005	0.001	0	0	0	0	0	0	0
Arellano-Bond test for AR(2) *p*-value	0.316	0.841	0.904	0.898	0.938	0.938	0.864	0.712	0.783	0.89	0.888
Hansen test of over-identifying restrictions *p*-value	0.217	0.017	0.017	0.045	0.106	0.121	0.036	0.029	0.007	0.001	0.002
Cross sections	445	445	445	445	445	445	445	445	445	445	445

Note: *, **, and *** indicate 5%, 1%, and 0.1% level of significance respectively. Standard errors in parentheses.

Table A8
Robustness check: common language.

Instrument lag	2–4	2–5	2–6	2–7	2–8	2–9	2–10	2–11	2–12	2–13	2–14
					Proxy for information frictions: *COL* = 0						
Number of instruments	76	91	106	121	136	151	166	181	196	211	225
$GFDI_{i,j,t-1}$	0.419**	0.332**	0.329**	0.325**	0.323**	0.325**	0.344**	0.374***	0.368***	0.357***	0.333**
	(0.132)	(0.111)	(0.107)	(0.108)	(0.108)	(0.115)	(0.119)	(0.115)	(0.112)	(0.112)	(0.11)
$GFDI_{i,j,t-2}$	0.097	0.126	0.121	0.124	0.122	0.125	0.122	0.124	0.121	0.123	0.134
	(0.081)	(0.065)	(0.066)	(0.068)	(0.07)	(0.075)	(0.079)	(0.086)	(0.083)	(0.084)	(0.081)
Arellano-Bond test for AR(1) *p*-value	0.005	0.005	0.004	0.004	0.004	0.005	0.006	0.006	0.005	0.006	0.006
Arellano-Bond test for AR(2) *p*-value	0.532	0.897	0.866	0.903	0.898	0.919	0.853	0.8	0.79	0.834	0.963
Hansen test of over-identifying restrictions *p*-value	0.052	0.08	0.152	0.156	0.111	0.092	0.063	0.016	0.022	0.009	0.003
Cross sections	352	352	352	352	352	352	352	352	352	352	352
					Proxy for information frictions: *COL* = 1						
Number of instruments	76	91	106	121	136	151	166	181	196	211	225
$GFDI_{i,j,t-1}$	0.135	0.145	0.14	0.167	0.146	0.138	0.156	0.153	0.155	0.147	0.077
	(0.165)	(0.112)	(0.11)	(0.115)	(0.104)	(0.109)	(0.105)	(0.107)	(0.105)	(0.1)	(0.09)
$GFDI_{i,j,t-2}$	−0.01	−0.014	−0.015	−0.016	−0.017	−0.013	−0.014	−0.016	−0.018	−0.021	−0.018
	(0.012)	(0.013)	(0.013)	(0.012)	(0.011)	(0.012)	(0.012)	(0.011)	(0.011)	(0.012)	(0.011)
Arellano-Bond test for AR(1) *p*-value	0.04	0.011	0.012	0.01	0.009	0.011	0.008	0.008	0.008	0.008	0.008
Arellano-Bond test for AR(2) *p*-value	0.589	0.567	0.564	0.655	0.588	0.538	0.61	0.619	0.637	0.632	0.38
Hansen test of over-identifying restrictions *p*-value	0.708	0.469	0.511	0.898	0.994	0.999	1	1	1	1	1
Cross sections	102	102	102	102	102	102	102	102	102	102	102
					Proxy for information frictions: *CNL* = 0						
Number of instruments	76	91	106	121	136	151	166	181	196	211	225
$GFDI_{i,j,t-1}$	0.426***	0.366**	0.364**	0.337**	0.335**	0.326**	0.332**	0.357***	0.354***	0.339**	0.331**
	(0.132)	(0.117)	(0.118)	(0.11)	(0.11)	(0.118)	(0.117)	(0.11)	(0.111)	(0.109)	(0.111)
$GFDI_{i,j,t-2}$	0.093	0.112	0.11	0.125	0.119	0.119	0.128	0.132	0.13	0.134	0.135
	(0.081)	(0.071)	(0.075)	(0.077)	(0.079)	(0.083)	(0.082)	(0.086)	(0.085)	(0.086)	(0.085)
Arellano-Bond test for AR(1) *p*-value	0.007	0.007	0.006	0.007	0.006	0.007	0.008	0.008	0.007	0.008	0.007
Arellano-Bond test for AR(2) *p*-value	0.519	0.738	0.73	0.914	0.882	0.911	0.955	0.92	0.915	0.981	0.991
Hansen test of over-identifying restrictions *p*-value	0.25	0.26	0.267	0.153	0.081	0.073	0.057	0.038	0.074	0.035	0.027
Cross sections	263	263	263	263	263	263	263	263	263	263	263
					Proxy for information frictions: *CNL* > 0						
Number of instruments	76	91	106	121	136	151	166	181	196	211	225
$GFDI_{i,j,t-1}$	0.163	0.225	0.18	0.196	0.166	0.162	0.153	0.151	0.141	0.14	0.068
	(0.206)	(0.121)	(0.093)	(0.102)	(0.089)	(0.085)	(0.083)	(0.083)	(0.08)	(0.082)	(0.076)
$GFDI_{i,j,t-2}$	−0.013	−0.019	−0.017	−0.012	−0.012	−0.01	−0.01	−0.009	−0.009	−0.01	−0.007
	(0.02)	(0.018)	(0.018)	(0.016)	(0.015)	(0.015)	(0.015)	(0.014)	(0.014)	(0.014)	(0.014)
Arellano-Bond test for AR(1) *p*-value	0.027	0	0	0	0	0	0	0	0	0	0
Arellano-Bond test for AR(2) *p*-value	0.88	0.939	0.918	0.944	0.833	0.801	0.756	0.741	0.706	0.71	0.411
Hansen test of over-identifying restrictions *p*-value	0.219	0.1	0.008	0.003	0.012	0.018	0.036	0.06	0.2	0.568	0.834
Cross sections	191	191	191	191	191	191	191	191	191	191	191

Note: *, **, and *** indicate 5%, 1%, and 0.1% level of significance respectively. Standard errors in parentheses.

Table A9
Robustness check: industry sub-samples.

Instrument lag	2–4	2–5	2–6	2–7	2–8	2–9	2–10	2–11	2–12	2–13	2–14
						Manufacturing (sub-set of controls)					
Number of instruments	56	66	76	86	96	106	116	126	136	146	155
GFDI_{i,j,t-1}	0.349**	0.336*	0.3*	0.292*	0.253*	0.235	0.214	0.27	0.31*	0.206	0.188
	(0.127)	(0.133)	(0.136)	(0.127)	(0.117)	(0.132)	(0.146)	(0.152)	(0.149)	(0.13)	(0.11)
GFDI_{i,j,t-2}	−0.013	0.003	−0.008	−0.008	0.004	0.003	0.013	−0.01	−0.025	0.011	0.032
	(0.07)	(0.055)	(0.062)	(0.068)	(0.054)	(0.056)	(0.062)	(0.067)	(0.061)	(0.056)	(0.046)
Arellano-Bond test for AR(1) in first differences	0.003	0.002	0.003	0.002	0.002	0.004	0.007	0.007	0.002	0.004	0.005
Arellano-Bond test for AR(2) in first differences	0.192	0.188	0.221	0.178	0.255	0.371	0.413	0.298	0.203	0.45	0.564
Hansen test of over-identifying restrictions *p*-value	0.375	0.775	0.981	0.995	1	1	1	1	1	1	1
Cross sections	55	55	55	55	55	55	55	55	55	55	55
						Retail					
Number of instruments	76	91	106	121	136	151	166	181	196	211	225
$GFDI_{i,j,t-1}$	0.565**	0.428**	0.398**	0.433**	0.38**	0.403**	0.428**	0.388**	0.381**	0.377**	0.384**
	(0.207)	(0.15)	(0.141)	(0.143)	(0.143)	(0.133)	(0.137)	(0.132)	(0.129)	(0.121)	(0.137)
$GFDI_{i,j,t-2}$	−0.014	0.061	0.07	0.044	0.071	0.039	0.039	0.056	0.046	0.039	0.053
	(0.069)	(0.065)	(0.065)	(0.059)	(0.057)	(0.048)	(0.048)	(0.052)	(0.052)	(0.049)	(0.052)
Arellano-Bond test for AR(1) *p*-value	0.014	0.014	0.012	0.008	0.009	0.006	0.007	0.01	0.009	0.006	0.009
Arellano-Bond test for AR(2) *p*-value	0.302	0.718	0.813	0.592	0.824	0.565	0.538	0.696	0.633	0.584	0.689
Hansen test of over-identifying restrictions *p*-value	0.397	0.537	0.925	0.995	0.999	1	1	1	1	1	1
Cross sections	87	87	87	87	87	87	87	87	87	87	87
						Business service					
Number of instruments	76	91	106	121	136	151	166	181	196	211	225
$GFDI_{i,j,t-1}$	0.672***	0.69***	0.663***	0.63***	0.666***	0.69***	0.6***	0.516***	0.437***	0.454***	0.444***
	(0.183)	(0.168)	(0.117)	(0.072)	(0.076)	(0.075)	(0.07)	(0.07)	(0.1)	(0.089)	(0.087)
$GFDI_{i,j,t-2}$	0.149	0.119	0.126	0.13	0.109	0.085	0.116	0.155	0.185	0.177	0.198*
	(0.163)	(0.15)	(0.133)	(0.105)	(0.106)	(0.103)	(0.102)	(0.104)	(0.102)	(0.099)	(0.089)
Arellano-Bond test for AR(1) *p*-value	0.045	0.028	0.015	0.011	0.01	0.007	0.007	0.007	0.011	0.007	0.006
Arellano-Bond test for AR(2) *p*-value	0.603	0.491	0.468	0.456	0.383	0.305	0.415	0.595	0.821	0.744	0.84
Hansen test of over-identifying restrictions *p*-value	0.392	0.954	0.99	0.999	1	1	1	1	1	1	1
Cross sections	75	75	75	75	75	75	75	75	75	75	75
						Sales, marketing & support					
Number of instruments	76	91	106	121	136	151	166	181	196	211	225
$GFDI_{i,j,t-1}$	0.8***	0.806***	0.705***	0.667***	0.681***	0.621***	0.613***	0.57***	0.554***	0.552***	0.543***
	(0.167)	(0.153)	(0.148)	(0.125)	(0.135)	(0.128)	(0.121)	(0.102)	(0.098)	(0.099)	(0.099)
$GFDI_{i,j,t-2}$	−0.019	−0.018	0.001	0.014	0	0.025	0.031	0.047	0.051	0.055	0.059
	(0.12)	(0.117)	(0.131)	(0.121)	(0.132)	(0.13)	(0.125)	(0.12)	(0.116)	(0.115)	(0.115)
Arellano-Bond test for AR(1) *p*-value	0.004	0.003	0.004	0.003	0.003	0.004	0.003	0.002	0.002	0.002	0.002
Arellano-Bond test for AR(2) *p*-value	0.386	0.377	0.486	0.513	0.487	0.593	0.602	0.677	0.699	0.714	0.738
Hansen test of over-identifying restrictions *p*-value	0.262	0.228	0.255	0.505	0.64	0.867	0.988	0.999	1	1	1
Cross sections	120	120	120	120	120	120	120	120	120	120	120

Note: *, **, and *** indicate 5%, 1%, and 0.1% level of significance respectively. Standard errors in parentheses.

Table A10
Robustness check: manufacturing, retail and business service sub-samples, reducing the number of controls.

Instrument lag				2–4				
Number of controls	14	13	12	11	10	9	8	7
				Manufacturing[a]				
Number of instruments						56	52	48
$GFDI_{i,j,t-1}$						0.349**	0.337*	0.268
						(0.127)	(0.136)	(0.152)
$GFDI_{i,j,t-2}$						−0.013	−0.013	−0.004
						(0.07)	(0.07)	(0.068)
Arellano-Bond test for AR(1) *p*-value						0.003	0.004	0.006
Arellano-Bond test for AR(2) *p*-value						0.192	0.213	0.293
Hansen test of over-identifying restrictions p-value						0.375	0.318	0.207
Cross sections						55	55	55
				Retail				
Number of instruments	76	72	68	64	60	56	52	48
$GFDI_{i,j,t-1}$	0.565**	0.521*	0.544*	0.519	0.558*	0.546*	0.603	0.626
	(0.207)	(0.231)	(0.24)	(0.27)	(0.264)	(0.279)	(0.316)	(0.323)
$GFDI_{i,j,t-2}$	−0.014	−0.01	−0.003	0	−0.016	−0.024	−0.039	−0.049
	(0.069)	(0.068)	(0.066)	(0.074)	(0.077)	(0.081)	(0.097)	(0.1)
Arellano-Bond test for AR(1) p-value	0.014	0.02	0.018	0.032	0.021	0.03	0.039	0.037
Arellano-Bond test for AR(2) p-value	0.302	0.328	0.324	0.4	0.318	0.334	0.339	0.313
Hansen test of over-identifying restrictions p-value	0.397	0.389	0.458	0.345	0.239	0.281	0.263	0.171
Cross sections	87	87	87	87	87	87	87	87
				Business service				
Number of instruments	76	72	68	64	60	56	52	48
$GFDI_{i,j,t-1}$	0.672***	0.72***	0.679**	0.691**	0.714***	0.719***	0.705***	0.7***
	(0.183)	(0.201)	(0.226)	(0.236)	(0.178)	(0.167)	(0.183)	(0.186)
$GFDI_{i,j,t-2}$	0.149	0.115	0.129	0.118	0.119	0.118	0.124	0.119
	(0.163)	(0.18)	(0.202)	(0.205)	(0.168)	(0.156)	(0.16)	(0.157)
Arellano-Bond test for AR(1) p-value	0.045	0.047	0.063	0.064	0.033	0.028	0.035	0.035
Arellano-Bond test for AR(2) p-value	0.603	0.526	0.592	0.568	0.497	0.476	0.513	0.5
Hansen test of over-identifying restrictions p-value	0.392	0.394	0.251	0.264	0.292	0.382	0.724	0.662
Cross sections	75	75	75	75	75	75	75	75

Note: *, **, and *** indicate 5%, 1%, and 0.1% level of significance respectively. Standard errors in parentheses.
[a] The manufacturing sub-sample starts from 9 controls because the number of controls has been reduced to 9 in Table 4.

$$\Delta I_t = (1 - \gamma(1-\mu))\Delta I_{t-1} + \epsilon_t^{\Delta I} \tag{24}$$

where $\epsilon_t^{\Delta I} = \gamma e_t^{\theta} - \gamma\mu e_{t-1}^{\theta} + \gamma\Delta e_t^s + \Delta a_t - \mu\gamma\Delta e_{t-1}^s - \mu\Delta a_{t-1}$.

Rewriting Eq. (21) yields the following error correction process:

$$\Delta p_t = -(1-\mu)\gamma(p_{t-1} - \theta_{t-1}) + \epsilon_t^p.$$

Since $-(1-\mu)\gamma < 0$, the mean of public belief adjusts according to its lagged deviation from the true state.

Variance of FDI

Since I_t is nonstationary, we study the variance of the first-differenced FDI. Using the lag operator $L : x_{t-1} = Lx_t$, the first-differenced FDI can be expressed as:

$$\Delta I_t = (1-\xi L)^{-1}\{(1-\mu L)\gamma e_t^{\theta} + (1-(1+\mu)L + \mu L^2)\epsilon_t^I\}$$

where $\xi = 1 - \gamma(1-\mu)$. $\xi \in (0,1)$:

$$\Delta I_t = \sum_{i=0}^{\infty}(\xi L)^i\{(1-\mu L)\gamma e_t^{\theta} + (1-(1+\mu)L + \mu L^2)\epsilon_t^I\}$$

Since all shocks are i.i.d, all the correlation terms are gone. The variance of ΔI_t is

$$\begin{aligned} Var(\Delta I_t) = & \left(1 + \sum_{i=0}^{\infty}\xi^{2i}(\xi-\mu)^2\right)\gamma^2 v_\theta \\ & + \left(1 + (\xi-(1+\mu))^2 + \sum_{i=0}^{\infty}\xi^{2i}(\xi^2 - (1+\mu)\xi + \mu)^2\right)Var(\epsilon_t^I) \\ & = \left(1 + \tfrac{(\xi-\mu)^2}{1-\xi^2}\right)\gamma^2 v_\theta \\ & + \left(1 + (\xi-(1+\mu))^2 + \tfrac{(\xi^2-(1+\mu)\xi+\mu)^2}{1-\xi^2}\right)Var(\epsilon_t^I) \end{aligned}$$

where $Var(\epsilon_t^I) = \gamma^2 v_s + v_a$.

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