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Outward foreign direct greenfield investments and firms predicted long-term stock volatility levels and connectedness. Evidence from China

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ABSTRACT

The paper offers an initial effort to unfold the effect of outward foreign direct greenfield investments (OFDGIs) on firms' long-term stock return volatility levels and connectedness. Within a sample of Chinese firms, in a GARCH-MIDAS model, we offer evidence that OFDGIs investments will reduce firms' long-term stock return volatility. We also introduced a measure of firms' stock return volatility connectedness and studied OFDGIs' effect on firms' dependence on other firms' risks. Implications for theory and practice are discussed.

1. Introduction

Outward foreign direct greenfield investments (OFDGIs) are foreign direct investments (FDIs) in which a firm creates a subsidiary in a foreign country and establishes its operations from the ground up. Because of their relevance to a country growth, OFDGIs at the firm level are experiencing increasing momentum, particularly in emerging markets such as China (Dong et al., 2022). At the same time, scholars widely studied both the determinants and consequences of OFDGIs (for a review, see Paul and Benito, 2018). As for the consequences of OFDGIs, particularly for performance, studies have considered OFDGIs' impact on firms' risks proxied by the risk of stock crashes. OFDGIs are intended to reduce that risk due to improved governance and higher transparency (Liu et al., 2021). Meanwhile, other studies have shown that OFDGIs negatively influence firms' risks measured in terms of stock volatility. Because OFDGIs increase agency costs and information asymmetry, they induce accounting distortions that increase the risk of downsizing (Wang et al., 2019), specifically as a result of firms' stock volatility (Wang, 2017).

Such conflicting results appear puzzling given those studies' common theoretical basis of agency theory and asymmetric information as well as the correlation between firms' stock return volatility and risk of stock crashes (Cao et al., 2022). The specific ways in which scholars calculate firms' stock volatility can explain such puzzling results. In particular, total stock volatility has two components. Whereas short-term volatility depends on the daily, noisy release of new information, long-term volatility is more related to the firms' fundamental characteristics. Therefore, if OFDGIs are to improve a firm's long-term governance structure (Liu et al., 2021), their effects on a firm's volatility can be best captured by analyzing long-term volatility. Beyond that, considering that OFDGIs im-

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prove firms' governance structure and that better governance is important to maintaining and restoring trust in corporations, OFDGIs contribute to limiting firms' exposure to risk of financial contagion (Demiris et al., 2014).

Against that background, in our research we examined the relatively unknown interdependencies of firms' volatility. Such unknowability induces uncertainty about the connections between firms with and without OFDGIs, whereas understanding those connections can help both firms to reduce unknown risks in their overseas investment strategies choices and policymakers to selectively stimulate OFDGIs in firms. Policymakers can achieve the dual goal of having a more open society while preserving the financial market's stability, which is necessary to sustain a country's development. We attempted to clarify that dynamic by estimating the connectedness between the volatility of firms with and without OFDGIs and thereby overcome the problems faced in past research seeking to link OFDGIs in estimating the volatility of firms.

Our research question was as follows: Do OFDGIs influence firms' predicted long-term stock return volatility (hereafter "long-term volatility") and connectedness? To provide answer that question, using a generalized autoregressive conditional heteroskedasticity-mixed-data sampling (MIDAS-GARCH) model we tested the effect of OFDGIs on firms' long-term volatility in a sample of firms on the Shanghai and Shenzhen Stock Exchanges. Our results first show that firms with OFDGIs have significantly lower long-term volatility than firms without such investments. Second, OFDGIs increase firms' connectedness to other firms based on long-term volatility more than firms without such investments. However, because firms with OFDGIs have lower volatility, their presence in a market, coupled with their connections with other firms, can create a cushion against volatility transfer, which mitigates financial contagion and enhances the stability of financial markets.

2. Method

We collected data about OFDGIs in the FDI market compiled by FDI Intelligence, the most comprehensive source of project-level, cross-border greenfield investments available due to covering all countries and sectors worldwide (Dong et al., 2021). By matching the firms in the FDI market with Chinese firms listed on the Shanghai and Shenzhen Stock Exchanges, we formed an initial sample of 811 listed firms with OFDGIs from 2004 to 2018. We next excluded firms listed after 2004 and firms labeled "*ST," "S," "ST," and "SST", all of which denote abnormal operating conditions. Our sample was thus reduced to 199 unique firms: 128 on the Shanghai Stock Exchange and 71 on the Shenzhen Stock Exchange. We collected daily stock prices and firm-year financial accounting data from the China Stock Market & Accounting Research Database. After we applied propensity score matching (see Section P.0 of the Supplementary Materials), the sample comprised 100 firms, 50 of which were included in the treatment group and 50 in the control group. In both groups, 25 + 25 firms were listed on the Shanghai Stock Exchange (S1), while 25 + 25 were listed on the Shenzhen Stock Exchange (S2).

We subsequently analyzed 364,500 firm-year observations from 2004 to 2018. For each sampled firm, we defined r as the stock price at time i of firm j and computed the log return as follows:

$$r_i^j = \log\left(P_i^j\right) - \log\left(P_{i-1}^j\right) \tag{1}$$

To capture each firm's long-term volatility, we adopted a GARCH-MIDAS model (Engle et al., 2013). We assumed that r could be specified as:

$$r_{i,t}^j = \sqrt{\tau_{i,t}^j \cdot g_{i,t}^j} \cdot \varepsilon_{i,t}^j \ \forall\, i = 1, \ldots, N_t \tag{2}$$

and

$$\sigma_{i,t}^j = \sqrt{\tau_{i,t}^j \cdot g_{i,t}^j} \tag{3}$$

in which r is the log return of firm j on day i of year t, τ is the long-run volatility varying daily according to a rolling annual frequency t, g is the short-term volatility varying by each day i in year t (composed of N_t days), ε is an error term with no mean or unit variance, and σ is the volatility of the log return of firm j. In Eq. (2), we supposed that the mean of the log returns was approximately equal to 0. For details see Section P.1 of the Supplementary Materials.

To filter out the macroeconomic constituents of volatility, we regressed each firm's long-term volatility on macroeconomic variables. In particular, we fit regressions of the form:

$$\tau_{i,t}^j = \beta_0 + B\Theta_{i,t} + \epsilon_{i,t}^j \tag{4}$$

in which $\tau_{i,t}^j$ is the firm's long-term stock volatility (see A2,a of the Supplementary Materials), B is a vector of regression coefficients, Θ is a vector of macroeconomic observed on day i of year t, and ϵ is an error term satisfying the traditional hypothesis in the regression model. For each regression in Eq. (4), we calculated the R^2 (Rao, 1973), which reflects the proportion of variability in firms' long-term volatility explained by the macroeconomic source of risk.

Following Liu et al. (2012) and Morelli (2022), we estimated the cross-sectional interdependence (i.e., connectedness) in volatility of the sampled firms using the array of residuals from the regression in Eq. (4), $\Xi = \{\xi_i^j\}$, with

$$\xi_i^j = \eta_0 + \sum_{\substack{\forall c_{,i}=1; \\ i \neq j}} \eta_{c_{,i}} \xi_i^{c_{,i}} + \epsilon_i^j \tag{5}$$

in which $E(\epsilon_i^j) = 0$, $Var(\epsilon_i^j) = \kappa_j^2$, and $E(\xi_z \epsilon_i^j) = 0$ for all $j \neq z$. To estimate the precision matrix C we used the non-paranormal SKEPTIC, which removes the strong assumption of the multivariate Gaussian distribution of the considered matrix (see Section P.2 of the Supplementary Materials). Last, given the shrinkage parameter λ, for occurrences $c_{.i}$, with $i \neq j$, in the concentration matrix $\hat{C}$ in Equation (A.6) of the Supplementary Materials that were equal to 1, the following regression was run:

$$\tau_{i,t}^j = \vartheta_0 + B\Theta_{i,t} + \sum_{\substack{\forall c_{,i}=1; \\ i \neq j}} \beta_{c_{,i}} \tau_{i,t}^{c_{,i}} + \epsilon_{i,t}^j \tag{6}$$

To capture the dependence of a firm's long-term volatility on other firms' volatilities, we calculated the difference between the R^2 from regressions with the specification in Eq. (6) and R^2 from the corresponding values in regressions in Eq. (4). The difference in R^2 was subsequently normalized over the R^2 value calculated in regressions defined in Eq. (4)—that is, $\Delta R^2\%$. The latter measure reflects the variation in the proportion of variability explained by the dependence of a firm's long-term volatility on other firms' risk (e.g., see Schmeling, 2009). In particular, the larger the $\Delta R^2\%$, the more important a firm's connectedness with other firms' risk based on long-term volatility. Because R^2 increased with the number of predictors, we mitigated that problem by considering the Adjusted R^2 in regression with the specification in Eqs. (4) and (6). The proposed method is implemented in R (see Section P.6 of the Supplementary Materials).

3. Empirical analysis

Table 1 reports the summary statistics of the log returns of sampled firms in S1 and S2 for the treatment and control groups.

Different firms had negative skewness of the log returns, which signals that the overall asset returns were asymmetric and subject to extreme losses to a greater extent than abnormal gains. The high kurtosis for some firms indicates that the distribution of returns was far from Gaussian.

3.1. Firms' long-term volatility and OFDGIs

We used a GARCH-MIDAS model to capture the sampled firms' long-term volatility. In our robust model selection, we employed the Model Confidence Set (MCS) procedure based on out-of-sample volatility forecasts in an out-of-sample period spanning from December 31, 2015, to December 31, 2018. The squared log returns were our proxy of choice for the volatility realized. Once we identified the best model, we re-estimated the model for each day using a rolling window of 3645 days in the sample period spanning from January 1, 2004, to December 31, 2018. The best model for S1 and S2 was most often the T-Stud asymmetric model (50%), whereas the Norm symmetric model was least often the best model for S1 and S2 (4% and 8%, respectively). Those results reflect the intrinsic characteristics of firms' log returns as shown in Table 1, particularly cross-variations in skewness and kurtosis.

Fig. 1 shows the correlations between the volatility series. The two distributions of the volatility correlations in the OFDGI group and the entire sample in S1 and S2 were very negatively skewed, with 75% of correlations exceeding 0.338 and 0.398, respectively, and 0.384 and 0.404, also respectively. The higher weight on the right tail of the distribution suggests that the companies were more

Table 1a
Statistics in the treatment group.

	S1						S2					
Year	Min.	Max.	*M*	*SD*	Skew	Kurtosis	Min.	Max.	*M*	*SD*	Skew	Kurtosis
2004	−0.106	0.096	−0.001	0.022	0.186	2.779	−0.104	0.097	−0.001	0.023	0.063	1.547
2005	−0.106	0.097	0.000	0.023	0.064	2.464	−0.107	0.097	0.000	0.025	0.055	2.156
2006	−0.106	0.097	0.004	0.027	0.133	2.155	−0.106	0.096	0.003	0.028	−0.014	1.853
2007	−0.106	0.097	0.004	0.038	−0.182	0.661	−0.106	0.096	0.004	0.041	−0.205	0.455
2008	−0.106	0.097	−0.004	0.041	−0.128	0.227	−0.107	0.096	−0.004	0.043	−0.169	0.097
2009	−0.106	0.097	0.003	0.031	−0.049	1.278	−0.359	0.096	0.004	0.034	−0.282	3.018
2010	−0.105	0.096	0.000	0.025	−0.043	1.714	−0.106	0.096	0.000	0.028	0.087	1.825
2011	−0.106	0.096	−0.001	0.021	0.141	1.976	−0.105	0.096	−0.002	0.023	0.130	2.154
2012	−0.105	0.096	0.000	0.020	0.424	2.901	−0.105	0.096	0.000	0.022	0.203	2.554
2013	−0.106	0.096	0.000	0.022	0.275	2.679	−0.106	0.096	0.000	0.025	0.263	2.622
2014	−0.106	0.097	0.001	0.020	0.556	4.183	−0.106	0.097	0.002	0.025	0.532	3.178
2015	−0.106	0.096	0.001	0.038	−0.385	1.432	−0.107	0.096	0.001	0.042	−0.357	0.851
2016	−0.106	0.096	0.000	0.024	−0.576	4.518	−0.106	0.096	0.000	0.026	−0.477	4.102
2017	−0.105	0.096	0.000	0.019	0.264	4.093	−0.105	0.097	0.000	0.021	0.210	4.665
2018	−0.106	0.096	−0.001	0.022	−0.362	3.449	−0.106	0.096	−0.002	0.023	−0.429	3.966

Table 1b
Statistics in the control group.

	S1						S2					
Year	Min.	Max.	*M*	*SD*	Skew	Kurtosis	Min.	Max.	*M*	*SD*	Skew	Kurtosis
2004	−0.105	0.096	0.000	0.022	0.129	2.262	−0.106	0.096	−0.001	0.022	0.048	2.216
2005	−0.141	0.096	0.000	0.022	0.057	2.323	−0.107	0.096	0.000	0.024	−0.151	2.555
2006	−0.106	0.096	0.002	0.025	−0.049	2.389	−0.107	0.097	0.004	0.029	0.113	2.087
2007	−0.106	0.096	0.004	0.038	−0.288	0.772	−0.106	0.096	0.004	0.040	−0.272	0.523
2008	−0.106	0.097	−0.004	0.042	−0.168	0.225	−0.106	0.097	−0.004	0.043	−0.170	0.134
2009	−0.106	0.096	0.003	0.032	−0.134	1.283	−0.106	0.097	0.003	0.032	−0.148	1.165
2010	−0.106	0.096	0.000	0.027	−0.031	1.889	−0.106	0.096	0.000	0.026	−0.083	1.686
2011	−0.106	0.096	−0.001	0.024	0.014	2.192	−0.106	0.096	−0.002	0.021	−0.128	2.158
2012	−0.106	0.096	0.000	0.022	−0.018	2.582	−0.099	0.097	0.000	0.021	0.250	2.160
2013	−0.106	0.097	0.000	0.023	0.199	2.877	−0.106	0.097	0.000	0.022	0.188	3.516
2014	−0.106	0.097	0.002	0.023	0.383	3.681	−0.106	0.097	0.002	0.021	0.513	4.243
2015	−0.106	0.096	0.001	0.045	−0.361	0.512	−0.106	0.096	0.001	0.041	−0.369	1.053
2016	−0.106	0.096	−0.001	0.027	−0.601	3.910	−0.106	0.096	−0.001	0.026	−0.508	3.869
2017	−0.106	0.097	0.000	0.020	0.203	5.120	−0.105	0.096	0.000	0.019	0.140	4.836
2018	−0.106	0.096	−0.002	0.023	−0.400	3.887	−0.106	0.098	−0.002	0.022	−0.349	4.394

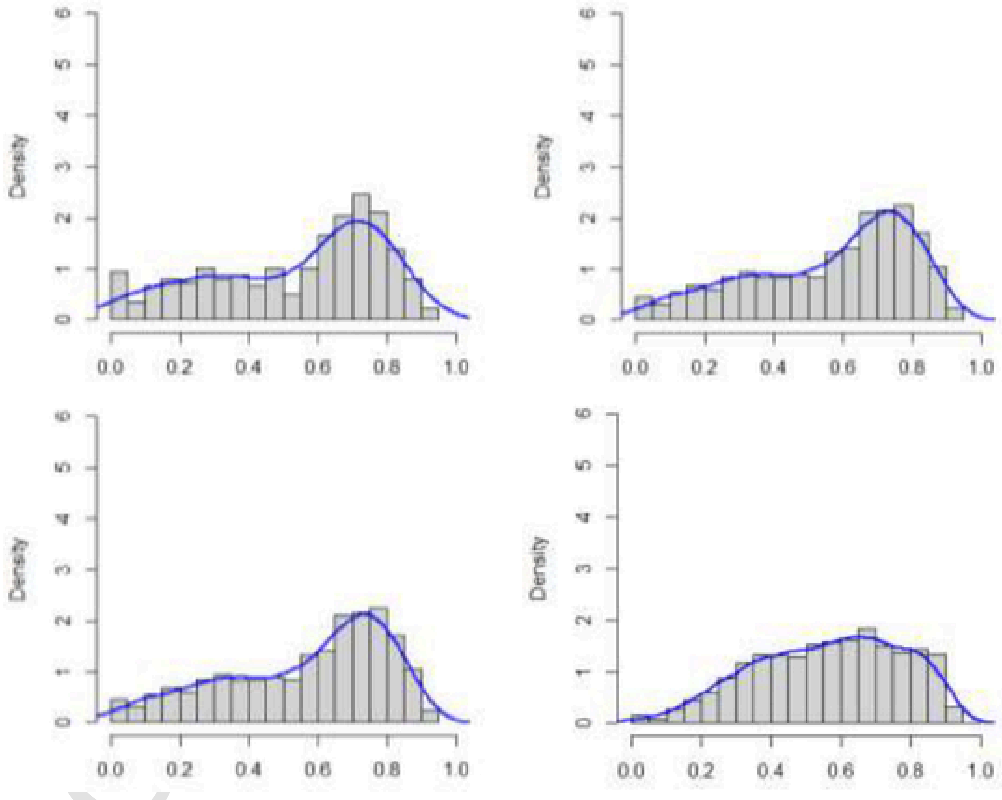

Fig. 1. Histograms of the distribution of the volatility correlations considering firms with OFDGIs (left) and the entire sample (right) in S1 (upper) and S2 (lower). The related Epanechnikov kernel density is also displayed.

connected in terms of volatility than returns. Therefore, systemic risk was more likely to arise from connections based on volatility. Moreover, when firms without any OFDGIs were included in the sample, the correlation distribution becomes more right skewed.

We ran a GARCH-MIDAS model for each sampled firm, with estimation parameters that are provided in Section P.3 of the Supplementary Materials. Long-term volatilities were recorded and used in a regression model to test whether firms with OFDGIs differed from firms without those investments. While maintaining the considered interdependencies between firms' volatility, we introduced a new variable, *Post*, which assumed, for each paired firm, the value of 0 when the firm in the treatment group first reported the OFDGIs and, at the same time, negative and positive values for the years before and after periods around the OFDGI events (e.g., −2, −1, 0, 1, 2). After the mean (*M*) and standard deviation (*SD*) of firms' long-term volatility with and without OFDGIs were calculated, the following regression model was introduced:

Table 2
Long-term volatility before and after OFDGIs event.

	S1	S2
*Post** OFDGIs	−0.0024**	−0.0012**
	(0.0001)	(0.0002)
Constant	0.022	0.056
	(0.030)	(0.047)
Control	Yes	Yes
FE year	Yes	Yes
Observations	54,226	51,264
R^2	0.05	0.03
Mean difference before	*−0.026*	*−0.030*
Mean difference after	*−0.030*	*−0.035*
Paired *t*-test	*21.70***	*16.13***

$$\widehat{\sigma}^{j}_{i,t} = \beta_0 + \beta_1 Post * OFDGI + B\Theta_{i,t} + \varepsilon^{j}_{i,t} \tag{7}$$

in which the control variables for macroeconomic sources of risk and the error term are the same as modeled in Eq. (4). Macroeconomic components in $\Theta_{i,t}$ were the debt-to-GDP (*DtG*), GDP growth (*GDPg*), inflation (*INFL*), industrial production level (*IP*), dollar–RMB exchange rate return (*CNYU*), bank credit (*CREDIT*), and realized stock market volatility (σ_M) (Girardin and Joyeux, 2013). To control for macroeconomic components at the international level, we added world GDP growth (*WGDPg*), change in the world uncertainty index (WUI), and the Chicago Board Options Exchange Volatility Index (*VIX*) (Jardet et al., 2023).

Table 2 shows the results. Control variables, omitted from Table 2, were generally non-significant given sampled firms' exposure to the same macroeconomic sources of risk. The interaction term, by contrast, was significant and negative. The comparison of the mean difference in volatility between firms before and after an OFDGI increased in the period after compared with the period before as well. Thus, our empirical estimates provide evidence that firms with OFDGIs have lower long-term volatility than firms without such investments (see also Section P.5 of the Supplementary Materials).

3.2. Firms' connectedness based on long-term volatility and OFDGIs

Eq. (4) was estimated for S1 and S2. On average, with the specification in Eq. (4), R^2 was equal to 0.871 (0.838) for OFDGIs and 0.859 (0.875) for all sampled organizations in S1 (S2). Those values indicate that, on average, 14% of the variability in firms' long-term volatility was unexplained by macroeconomic sources of risk. For details see Section P.4 of the Supplementary Materials.

Considering those results, we next derived a partial correlation network using non-paranormal SKEPTIC and residuals from Eq. (4). In that procedure, we first calculated Spearman's correlation matrix and subsequently implemented the Graphical Least Absolute Shrinkage and Selection Operator (GLASSO) procedure as in Equation (A.6). After that, we estimated regressions defined in Eq. (6). For each regression, ΔR^2% was evaluated according to the shrinkage parameter λ. We let λ vary in the interval [0, 0.3], divided into 3000 subintervals.

Firms with OFDGIs, just as firms without OFDGIs, tend to experience significant exposure to macroeconomic conditions. At the same time, the long-term volatility of firms with OFDGIs seems to be connected to other firms' risk to a degree, measured by ΔR^2%, which ranged from 14.92% in S1 to 16.39% in S2. The network effect was captured by considering standard measures of connected nodes and eigenvector centrality, which in S1 and S2 had average values of 11 and 15, respectively, and 0.543 and 0.631, also respectively, for firms with OFDGIs, as shown in Table 2 and Fig. 2.

OFDGIs do not sever or even significantly reduce the risk-related connections between firms with such investments and other firms in the market compared with firms without OFDGIs. However, because of the reduced long-term volatility of firms with OFDGIs, connections with firms with OFDGIs tend to produce a smoothing effect on the risk transfer between one firm and another, thereby limiting financial contagion and the correlated emergence of systemic risks at the market level. Such an effect was more pronounced in S2 than in S1 because firms with OFDGIs tend to have an enlarged centrality in the volatility network, as depicted in Table 3 and Fig. 2.

4. Concluding remarks

In our study, we have introduced a novel method of estimating the effect of OFDGIs on a firm's long-term volatility, along with the correlation of that volatility with the volatility of other firms. Following the proposed method, we have provided evidence that OFDGIs reduce not only a firm's long-term volatility but also the connectedness with other firms' risks. Moreover, given evidence that systemic risk is also likely to arise from volatility-based connections, firms with OFDGIs in a financial market characterized by low long-term volatility and moderate connectedness with other firms represent a potential risk due to correlated risks, which creates a cushion against financial contagion that may induce systemic risks. Our findings thus suggest that, as globalization advances, firms can reduce long-term volatility by distributing their overseas investment strategies. Beyond that, we provide a perspective for national governments facing the dilemma of increasing market openness while maintaining financial market stability, for we have

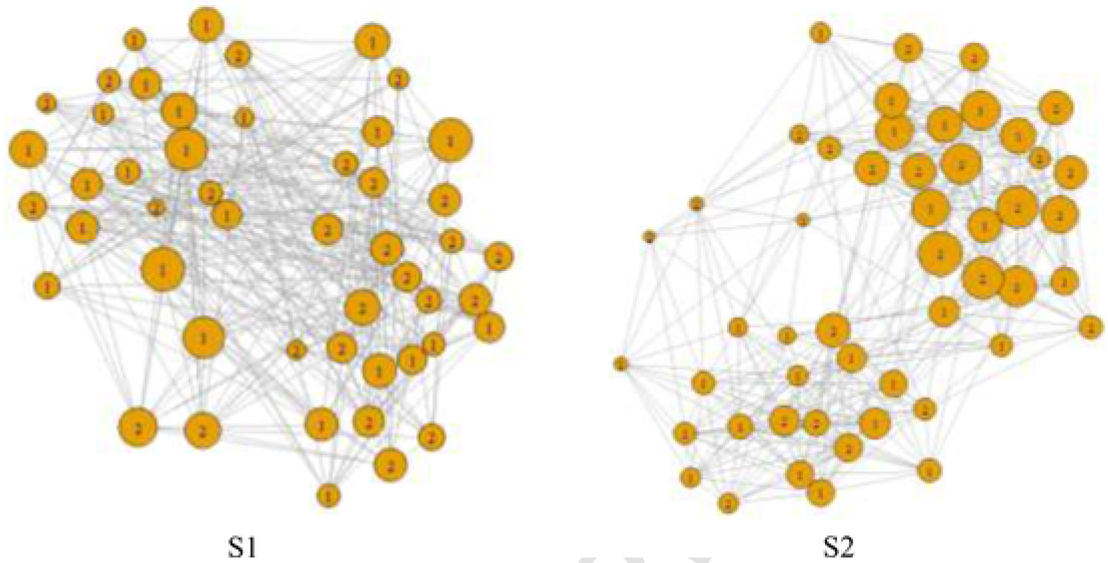

Fig. 2. Volatility networks in S1 and S2 that include firms with OFDGIs, labeled "2," and no-OFDGIs, labeled "1." Node size is based on a firm's eigenvector centrality in the volatility network. Graphs are produced over a value of λ that is equal to 0.0883 and to 0.0812. We found those values considering the value of λ that induces a volatility network with a growing explanatory power compared with the previous state.

Table 3
Firms' long-term volatility dependence on network.

	S1				S2			
	With OFDGI		Without OFDGI		With OFDGI		Without OFDGI	
	M	*SD*	*M*	*SD*	*M*	*SD*	*M*	*SD*
a) R^2 in Eq. (4)	0.871	0.060	0.838	0.071	0.859	0.055	0.875	0.060
b) R^2 in Eq. (6)	0.995	0.004	0.996	0.003	0.996	0.003	0.996	0.003
ΔR^2%: [b − a] / a	*14.66%*	*0.095*	*19.85%*	*0.110*	*16.36%*	*0.087*	*14.68%*	*0.079*
c) Number of connected nodes (%)	*10.96 (22)*	*1.791*	*12.56 (25)*	*2.181*	*15.84 (31)*	*3.484*	*15.36 (30)*	*2.736*
d) Eigenvector centrality	*0.543*	*0.130*	*0.645*	*0.180*	*0.651*	*0.210*	*0.596*	*0.179*

shown that stimulating firms' OFDGIs can improve the stability of financial markets. Incidentally, investors can use the proposed model to predict a firm's long-term volatility interdependence on other firms' risks and use such estimates in tailoring their portfolios.

CRediT authorship contribution statement

Gianluca Vagnani : Conceptualization, Methodology, Writing – original draft. **Jinhuan Tian :** Conceptualization, Data curation, Writing – review & editing. **Yan Dong :** Conceptualization, Writing – review & editing, Supervision.

Declaration of Competing Interest

Authors declare that they have no conflict of interest.

Data availability

Data will be made available on request.

Supplementary materials

Supplementary material associated with this article can be found, in the online version, at doi:10.1016/j.frl.2023.104505.

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