Foreign Investment and Corporate Social Responsibility in an Emerging Market: Impacts and Mechanisms*

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Abstract

We examine the causal effect and underlying mechanisms of foreign investment on social norms in an emerging market. Increased foreign investment in Chinese firms under the Shanghai and Shenzhen Stock Connect programs increases firms' environmental and social (ES) performance. To isolate underlying mechanisms, we develop an instrumental-variable approach and find causal evidence that supports two theories: foreign investors influence firms to improve ES performance and firms enhance ES performance to signal trustworthiness to investors. Improved ES performance and increased foreign shareholding are therefore self-reinforcing: long-run changes exceed short-run by about 80%. Short-run influence effects are somewhat larger than signalling effects, while both contribute fairly equally to long-run dynamics. Foreign investment can play an important and lasting role in convergence of social norms across countries via either mechanism.

Keywords: corporate social responsibility, foreign investment, social norms, emerging markets

JEL Classifications: M14, F36, F15, G15, F21

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1 Introduction

Economic convergence across countries and foreign capital's role in facilitating it are central concerns in economics. Research has demonstrated that foreign investment in emerging markets can promote economic convergence by enhancing targeted firms' efficiency (Matthias Arnold and Javorcik, 2009), financial condition, and export capabilities (Wang and Wang, 2015).[1] Conversely, foreign divestment has been shown to reduce firm efficiency (Javorcik and Poelhekke, 2017). Beyond market mechanisms, foreign capital flows may impact emerging markets through non-market channels, such as externalities and cultural changes, although these areas have been less studied.[2] For externalities, Brucal, Javorcik and Love (2019) finds that foreign investment reduces the energy intensity of plants, while divestment increases it. For cultural changes, Tang and Zhang (2021) shows that foreign affiliates employ more women and appoint more female managers, leading to a positive spillover effect on female employment within industry and city.[3]

This paper contributes to these few results on non-market convergence. We examine the influence of foreign investment, via stock holdings, on firms' corporate social responsibility (CSR) performance in an emerging economy. The contribution is two-fold. First, although previous studies have examined how investors influence firms' CSR performance, these consider almost exclusively intra-country investing or investing between advanced economies and therefore are not directly relevant to cross-country convergence. Assessing foreign investment's role in facilitating CSR is important in understanding non-market mechanisms for cross-country convergence because it has been shown to exert outsized influence on market outcomes in emerging markets. Foreign investment can exert more pressure on firm performance in an emerging market than domestic investment (Ferreira and Matos, 2008) and foreign investment improves corporate governance in countries where it is weak, especially if the source country has strong protections (Aggarwal, Erel, Ferreira and Matos, 2011). We examine whether this outsized influence carries over to non-market outcomes.

Second, previous literature identifies two possible mechanisms by which investment could affect CSR: firms may invest in CSR as a quality signal to attract investors and investors may directly influence firms to enhance their CSR practices. However, these stud-

[1] Wang and Wang (2015) finds that while foreign acquisitions lead to productivity improvements in target firms, it does not offer additional productivity gains compared to domestic acquisitions.

[2] Trade liberalization can also have non-market effects. Exporters reduce emissions intensity in response to liberalization (Cherniwchan, Copeland and Taylor, 2017). Foreign trade reforms are associated with improved corporate transparency in industries that rely more on external financing (Tong and Wei, 2014).

[3] Alfaro, Kalemli-Ozcan and Volosovych (2008) shows that institutional quality is crucial for poor countries to attract foreign investment from wealthy countries.

ies examine each mechanism in isolation even though they may occur simultaneously. We develop a method to disentangle these mechanisms and quantify their individual contributions in the context of foreign investment in an emerging market.[4] Isolating and quantifying these mechanisms is crucial for understanding the pathways through which cross-county convergence can occur. If the influence mechanism plays a role, foreign investors from developed countries directly shape CSR performance in emerging markets. If the signaling mechanism is at play, foreign investors exert influence only indirectly. Additionally, since these mechanisms are mutually reinforcing, isolating them allows us to quantify the long-term effects and their persistence in response to an exogenous increase in either.

To identify the causal effect of foreign investment on CSR, we leverage the relaxation of capital controls—a policy more common in emerging markets than in advanced ones. We focus on the Shanghai and Shenzhen Connect programs, which expanded Hong Kong/foreign (HKF) investment in China, known as "northbound shareholdings."[5] This is an attractive setting in which to test the effects of foreign investment on CSR in an emerging market. Entering a Connect program was based entirely on inclusion in stock indexes, which depended on market capitalization and stock trading volumes — factors not directly related to a firm's ES performance. We use a difference-in-differences (DD) approach, with firms joining the Connect program as the treatment group and those not as the control group.

Joining the Connect program has a positive impact on firms' Environmental and Social (ES) performance, two important components of CSR.[6] ES ratings increased 16.3% in the first year and 11.5% per year in subsequent years for firms joining the program relative to those not. The effects are heterogeneous. Private-owned enterprises (POEs) experienced the fastest rise in ES rating (12.3% per year). Ratings for state-owned enterprises (SOEs) also trended up but at a slower pace (6.9% per year). Ratings for foreign-owned enterprises (FOEs) did not significantly change, perhaps because foreign influence predated the Connect program. We then include the initial cohort of firms in the Shenzhen Connect program using methods robust to staggered DD estimation. The effects on ES

[4]We focus on the signalling and influence theories, as they are the most prominent, but this does not preclude other possible explanations.

[5]Cheng, Jiang, Kong and Vigne (2024) also examines the effect of foreign investment on CSR using the Connect program. Their study differs in that it utilizes only the Shanghai Connect program in a staggered difference-in-differences (DD) estimation, which may lead to biased estimates, and it relies on contemporaneous CSR measures that could be influenced by the firm's inclusion in the Connect program or have been subject to conflicts of interest or firm influence. The paper also does not address underlying mechanisms.

[6]Following Dyck, Lins, Roth and Wagner (2019) and He, Kahraman and Lowry (2023a), we focus on the environmental and social sub-ratings and construct an ES rating with equal weights. All results hold if we also include the governance sub-rating of ESG. These results are available upon request.

performance are similar to those for the Shanghai Connect program alone.

The ES increases likely reflect actual improvement, as the ratings are derived from tangible, measurable outcomes. Moreover, the ratings were assigned retroactively many years later, eliminating the possibility that ES ratings directly influenced a stock's inclusion in a Connect program, that firms artificially manipulated their performance to influence the ratings, or that conflicts of interest for the rating agency distorted ratings. Inclusion in the Connect program also significantly affects independent, direct measures of environmental outcomes: Connect firms gradually reduced their carbon emissions and filed more applications for "green" patents relative to non-Connect firms after joining – evidence that the effects are not due to "greenwashing". Since being in the Connect programs depended on inclusion in stock indexes, index inclusion itself may have increased ES performance.[7] To address this, we exclude firms added to the index when the Connect program begins and the results remain. The retroactive ES measures are also unrelated to future stock performance – evidence that foreign investment response to ES performance is not confounded by firm financial performance.

Having found significant increases in ES performance, we identify underlying mechanisms. Previous literature identifies two potential ways in which investments may influence CSR performance: firm signalling and investor influence. The signaling theory (Lins, Servaes and Tamayo, 2017) argues that firms invest in ES as a signal to investors of their trustworthiness in order to maintain investor confidence in times of crisis. An extension of this argument is that investors may proactively invest more in such firms to protect themselves in the event of future possible crises. In the context of capital controls, foreign investors face a knowledge gap about domestic firms when controls are initially loosened, and firms may increase ES activities to signal trustworthiness and reduce asymmetric information.[8] The influence theory (Ferreira and Matos, 2008; Aggarwal, Erel, Ferreira and Matos, 2011; Ferrell, Liang and Renneboog, 2016; Liang and Renneboog, 2017; Dyck, Lins, Roth and Wagner, 2019; Chen, Dong and Lin, 2020; Bisetti, She and Zaldokas, 2023) argues that foreign investors exert pressure on firms to invest in ES performance because investors intrinsically value it. In the context of the Connect program, either or both of these theories could apply. We substantiate that foreign investors care more about ES performance than domestic investors in China. This means that increased

[7]Studies of the effect of index inclusion on ES performance have mixed results. Chen, Dong and Lin (2020) find that increases in institutional ownership improve CSR performance while Cheong, Choi, Ha and Oh (2023) find that inclusion in the MSCI Emerging Market and China indexes increases emissions intensity.

[8]This is consistent with Cingano and Pinotti (2016), which finds that high-trust regions and countries exhibit larger value-added and export shares in industries that require more interpersonal trust.

foreign investment under the Connect program could both increase the signaling value of ES investments and increase foreign-investor influence on ES performance.

To identify the causal role of signaling, we use the change in firms' environmental performance under a major regulatory change as an instrument for ES ratings. As evidence that the regulatory change is exogenous, we show that it has no direct effect on firms' stock prices. Any direct effect on northbound shareholding is not large enough to affect market prices and foreign investors' responses to CSR are not confounded by firm financial performance. Foreign investors reward a one percent rise in ES ratings with increased holdings of 2.0 basis points a year later. The average annual increase in ES ratings before the Connect programs would lead to an 18.1% increase in average northbound shareholdings. To identify the causal role of influence, we use a quadratic function of the elapsed time since joining a Connect program as an instrument for northbound shareholding. We provide evidence that elapsed time has nonlinear effects on ES ratings for Connect firms, but not for non-Connect firms. A one percentage point increase in northbound shareholdings increases ES ratings in the following year by 22.3%.

These findings are consistent with a role for both mechanisms and suggest that firm ES performance and foreign investment are self-reinforcing — an exogenous increase in either will lead to long-term effects that are 80% greater than short-run (i.e., in the absence of feedback between the mechanisms). Comparing the short-run causal effects of the signalling and influence mechanisms, we find that the latter has a 12% greater effect on ES performance. Including the feedback dynamics, we find that the mechanisms have very similar effects on ES performance in the long run.

Our results contribute to three strands of literature. The first is the few papers on the role of foreign investment in cross-country convergence of non-market outcomes. There are papers that provide causal empirical evidence of the effect of investment on CSR performance but these have focused mainly on effects within advanced economies or pooled samples of advanced and emerging economies without distinguishing which investors and target firms originate from.[9] There are a few exceptions that examine effects across developed and emerging markets. Besides Brucal, Javorcik and Love (2019) and Tang and Zhang (2021), Kim, Sung and Wei (2011) examines how disparity between ownership and control rights in an investor's source country affects their choice of a target firm's disparity in an emerging market. Cai, Lu, Wu and Yu (2016) document how foreign multinational investments in China are influenced by the severity of China's environmental protections

[9] These include Ferreira and Matos (2008), Hong and Kacperczyk (2009), Aggarwal, Erel, Ferreira and Matos (2011), Chava (2014), Dimson, Karakaş and Li (2015), McCahery, Sautner and Starks (2016), Ferrell, Liang and Renneboog (2016), Liang and Renneboog (2017), Krueger, Sautner and Starks (2020), Chen, Dong and Lin (2020), and Azar, Duro, Kadach and Ormazabal (2021).

vis-à-vis the strength of protections in the multinational's home country.

The second strand of literature examines the underlying mechanisms for investment's influence on firms' CSR performance. We contribute to this area by examining the simultaneous influence of both the signalling and influence theories of foreign investment on CSR performance. For the signalling theory our results complement Lins, Servaes and Tamayo (2017), which finds that firms with better CSR scores outperform during crises of trust. We find that improvements in ES performance increase foreign shareholdings even in the absence of crises, perhaps in anticipation of them occurring in the future or as a signal of other aspects of trustworthiness. For the influence theory our results are consistent with Aggarwal, Erel, Ferreira and Matos (2011), Dyck, Lins, Roth and Wagner (2019), and Chen, Dong and Lin (2020), which find that higher foreign ownership increases future ES performance consistent with foreign investors valuing ES performance more than domestic investors.

The third strand of literature is studies that examine the development of China's financial system and its role in economic growth.[10] Ma, Rogers and Zhou (2021) analyze stock market performance and investment after the Shanghai Connect program begins. We complement this by showing significant improvements in ES performance from the Connect programs. Giannetti, Liao and Yu (2015) find that hiring directors with foreign experience significantly improves firm performance because of their ability in corporate governance and exposure to foreign markets. Relatedly, we find that HKF investors influence domestic firms' behaviors by reshaping their ES activities. Li, Brockman and Zurbruegg (2015) find that Chinese firms dual-listed in mainland China and Hong Kong improve corporate governance due to stricter listing rules, stronger investor protection, and foreign investors' information access. Similarly, we find that firms strengthen their ES performance after exposure to HKF investors. Finally, northbound trading under the Connect program makes the stock market more informative (Chen, Wang and Zhu, 2019; Lundblad, Shi, Zhang and Zhang, 2022; Bian, Chan, Han and Shi, 2023; He, Wang and Zhu, 2023b). Our findings show that the Connect firms increase their ES activities to overcome information asymmetry and signal trustworthiness to foreign investors.

The remainder of the paper is organized as follows. Section 2 discusses the institutional background. Section 3 reports the data source and sample selection. Section 4 explains the empirical strategy and Section 5 presents the results. Section 6 provides evidence for the two main mechanisms and Section 7 concludes.

[10] Allen, Qian and Gu (2017), Carpenter and Whitelaw (2017), Song and Xiong (2018), Allen, Qian and Qian (2019a), and He and Wei (2022) provide surveys.

2 Institutional Background

Since its Economic Reform and Opening in 1978, China has managed its capital flows following a learning-by-doing approach. Promoting foreign direct investment has been a part of its development strategy as it facilitates access to foreign management expertise, foreign technology, and export markets. China has frequently fine-tuned restrictions on investment flows but has generally tightly restricted them. In 1992, shortly after the Shanghai Stock Exchange (SSE) launched in December 1990 and the Shenzhen Stock Exchange (SZSE) in April 1991, a special market was established for foreign investment in domestically-listed shares, commonly termed the B-share market. These shares are of companies incorporated in mainland China, denominated in Renminbi (RMB), and traded on the SSE in US dollars or the SZSE in Hong Kong dollars. The initial intention of the B-share market was for foreign investors to invest using foreign currency. However, as a practical matter, it was difficult because it required foreign investors to deposit foreign currency in a domestic bank account and trade through a domestic broker. Although the B-share market was extended to domestic investors in February 2001, uptake remained low.[11]

The Qualified Foreign Institutional Investor (QFII) program was introduced in 2002, allowing foreign institutional investors to invest in SSE- and SZSE-listed firms. The China Securities Regulatory Commission (CSRC) granted a license, required for trading, to institutions based on their reputation and financial soundness. Once licensed, foreign investors could trade subject to capital controls and maximum trading quotas, which varied by investor. Over two decades, the quotas and license requirements were steadily eased. In 2019, the CSRC announced simplified rules and, in 2020, canceled the quotas. As of October 2022, the CSRC had approved 726 foreign investors for the QFII program.

The Shanghai and Shenzhen Connect programs were further moves to relax restrictions on foreign investors participating in the Chinese stock market. The Shanghai Connect program was launched in November 2014, and the Shenzhen program in December 2016. The programs allowed two-way trading: HKF investors could trade A-share stocks of eligible firms on the SSE and SZSE through the Stock Exchange of Hong Kong (HKEX), and investors from mainland China could trade eligible stocks on the HKEX through the SSE or SZSE. Northbound trading – that conducted by HKF investors – was open to all eligible individual and institutional investors.[12]

[11] Additional B-share issuance ceased when the QFII program was established in 2002. By the end of 2022, only 44 (42) firms were listed on the SSE (SZSE) B-share markets.

[12] Eligibility depended on information technology capability and risk management procedures specified by the exchange or clearing house. For specifics on eligibility see https://www.hkex.com.hk/Services/

The SZSE and SSE instituted other initiatives concerning CSR, but their starting times do not coincide with the Connect programs. In 2006, the SZSE published an initiative urging all its listed firms to become actively involved in CSR, establish a system to promote CSR activities, and disclose information related to CSR activities. Since then, the SZSE has periodically inspected and assessed how listed firms perform on CSR. In 2008, the SSE launched a campaign encouraging listed firms to disclose environmental assessments in their annual reports and requiring them to disclose an environmental incident if it would affect their stock price or if an environmental authority lists them as a seriously polluting enterprise. In 2018, the CSRC mandated all listed firms (not just those in the Connect program) to provide ESG information in their annual reports (we show that the Connect program affected ES ratings prior to this, ruling out better availability of CSR information in 2018 as a confounding factor).

3 Data

3.1 Sample selection of Connect firms

Our data spans the years 2009 to 2021 – five years before the beginning of the Shanghai Connect program and five years after the Shenzhen Connect program commenced. Our data include information on firms' ES ratings and financial performance. Since the launch of the Connect programs, their respective selection criteria have remained the same. The Shanghai Connect program includes SSE 180 Index and SSE 380 Index constituents and dual-listed firms on the SSE and HKEX, excluding those not traded in RMB or under "special treatment" (ST).[13] The Shenzhen Connect program includes the SZSE Component Index and Small/Mid-Cap Innovation Index constituents (except those with market capitalization below 6 billion RMB or under ST). Once a stock is removed from these indexes it can be sold, but not bought, through the Connect program. We include all Connect stocks that are never dual-listed because these may have already been exposed to foreign investors before the Connect programs. Therefore, the sample of Connect firms is determined by the criteria for inclusion in these indexes. Importantly for identification, index construction depends on financial characteristics (market capitalization and trading volume) unrelated to firms' ES ratings (details are in Appendix A.1). Each index is

Clearing/Securities/Overview/Clearing-Services?sc_lang=en.

[13]Some shares are placed under ST by SSE or SZSE (e.g., those of firms subject to possible delisting or which have been suspended by SSE or SZSE). For details, refer to the SSE Listing Rules at http://www.sse.com.cn/lawandrules/sserules/listing/stock/ and the SZSE Listing Rules at http://www.szse.cn/lawrules/index.html.

re-constituted twice a year. This means that firms not only enter a program at different times, but also some firms exit a program at different times.[14]

Due to possible heterogeneous treatment effects over time, we first focus on the initial cohort (stocks available to HKF investors on the program's first day) of the Shanghai Connect.[15] We then extend the analysis by adding the initial cohort of the Shenzhen Connect program using methods robust to staggered DD. When forced to use annual data, as we must with ES data, we treat firms entering a program in the last quarter of a year as if they enter the next year.[16] Since the first firms entered the Shanghai Connect program in November 2014 and the Shenzhen Connect program in December 2016, we measure the programs as beginning in 2015 and 2017, respectively.

3.2 Bloomberg ESG database

We obtain proprietary ESG ratings and three sub-ratings from Bloomberg, which began publishing them for listed firms in 2020. Bloomberg used historical data to provide retroactive ratings back to 2007, a year after the SZSE's initiative to promote CSR activities in annual reports.[17] The ratings are based on over 600 company-reported and derived indicators (Appendix A.2 has details). The environmental (ENV) sub-rating includes measures of the emissions and waste produced during the firm's operations, including air quality, wastewater, energy use, and material use, and general environmental impacts, such as climate change and ecological and biodiversity impact. The social (SOC) sub-rating focuses on firms' actions toward their employees, clients, and partners regarding diversity, ethics, health, safety, and human capital. The governance (GOV) sub-rating considers the accounting oversight and corporate governance of board members and executives, including composition, diversity, compensation, independence, nomination, and tenure. The ESG rating is an equal-weighted average of the three sub-ratings. Following Dyck, Lins, Roth and Wagner (2019) and He, Kahraman and Lowry (2023a), we focus on environmental and social sub-ratings and construct an ES rating using a simple average of the two.[18] The Bloomberg ESG database covers more than 11,800 companies

[14] If a firm enters a program more than once, we include only the period with the longest duration.

[15] In Appendix B.2, we incorporate all Connect firms that entered between 2015 and 2017 and examine the effects of the Connect program using the staggered and stacked methods, following Cengiz, Dube, Lindner and Zipperer (2019) for the latter. Our main results remain similar. We are unable to implement the procedure in Callaway and Sant'Anna (2021) because of the large number of fixed effects required.

[16] The results are robust to assigning based on the latter half of the year (available upon request).

[17] Berg, Fabisik and Sautner (2020) document that some vendors may retroactively update ESG ratings to better predict future firm performance. In Appendix A.3, we replicate their analysis and find no significant correlation between Bloomberg ES ratings and subsequent stock returns.

[18] All results are robust to using the ESG score instead (results available upon request).

worldwide, comprising 88% of global equity market capitalization.[19] As of the end of 2021, 1,549 Chinese firms listed on the SSE or SZSE had ever been rated.

The main challenges in ESG data are the need for more disclosure and standardization. Reporting ESG data is generally not mandatory and there is no common disclosure framework. Berg, Koelbel and Rigobon (2022) compare six prominent ESG ratings and find a large dispersion across them. How aspects of ESG are measured contributes 56% of this divergence, while what aspects are included contributes another 38%. To address these challenges, Bloomberg captures ESG data from company reports, annual general meetings, press releases, policy documents, websites, and other publicly-available documents. Moreover, Bloomberg employs quantitative data standardized to be consistent in units across firms (e.g., the share of women employed instead of the absolute number of women to measure gender equality) to make the data comparable across companies and time.

We divide the sample into two groups: firms joining a Connect program for at least two years versus firms joining for less than two years or not at all.[20] We refer throughout the paper to the former as Connect firms and the latter as non-Connect firms.

3.3 Financial variables

We control for an extensive array of variables measuring the firms' financial position and market performance, which we obtain from China Stock Market & Accounting Research Database (CSMAR).[21] We construct financial variables following Allen, Qian, Tu and Yu (2019b) and Ma, Rogers and Zhou (2021). Combining the ES ratings data with the firm financial data yields 430 firms in 2013, just before the Shanghai Connect began.

Table 1 reports summary statistics of the ES ratings and financial variables prior to 2014 - before the Shanghai Connect program launched in November 2014 (Appendix A.5 provides descriptions of the variables). Connect and non-Connect firms have similar ENV sub-ratings, but lower SOC sub-ratings and ES ratings. Connect firms are larger, more profitable, more leveraged, and experience less insider trading. ES ratings may vary systematically based on these attributes; however, our estimation compares relative ES ratings before versus after the Connect program, so this does not invalidate the

[19] For more details, refer to https://www.bloomberg.com/professional/dataset/global-environmental-social-governance-data/.

[20] We test robustness to one- and three-year duration, and the results are very similar (results available upon request).

[21] CSMAR is a widely-used database for public-firm information in China similar to CRSP and Compustat.

identification approach.[22] The two groups do not differ in age, proportion of SOEs, sales growth, or cash flows.

Table 1
SUMMARY STATISTICS PRIOR TO CONNECT PROGRAMS

	Connect Firms			Non-Connect Firms			Difference	
	obs	mean	sd	obs	mean	sd	diff	t
ES	1083	5.71	4.76	731	6.97	5.61	-1.26***	(-4.99)
ENV	1083	3.23	5.82	731	3.55	4.89	-0.32	(-1.26)
SOC	1083	8.39	5.17	731	10.68	7.72	-2.28***	(-7.00)
Log(assets)	1083	23.05	1.18	731	22.07	1.11	0.99***	(18.10)
Log(revenue)	1083	22.49	1.28	731	21.47	1.32	1.02***	(16.38)
Log(market cap)	1076	16.22	0.87	725	15.34	0.77	0.88***	(22.38)
Log(cap expenditure)	1083	19.73	1.68	731	18.83	1.58	0.90***	(11.61)
ROA	1083	0.06	0.05	731	0.04	0.04	0.02***	(8.81)
Growth rate of sales	1071	0.52	4.05	726	0.38	3.21	0.13	(0.78)
Age	1083	15.44	4.26	731	15.27	4.84	0.17	(0.75)
Tobin's Q	1076	1.91	1.31	724	1.76	0.93	0.15**	(2.83)
Profit to assets ratio	1083	0.08	0.05	731	0.06	0.05	0.02***	(8.87)
Cash flow to assets ratio	1083	0.17	0.12	731	0.17	0.14	-0.01	(-1.06)
Leverage ratio	1083	0.50	0.18	731	0.46	0.21	0.05***	(4.80)
SOE	1083	0.60	0.49	731	0.61	0.49	-0.01	(-0.34)
POE	1083	0.36	0.43	730	0.36	0.48	0.01	(0.11)
FOE	1083	0.03	0.26	731	0.03	0.23	0.01	(0.09)
QFII share	1083	0.30	0.74	731	0.23	0.64	0.06*	(2.54)
Insider trade	1083	0.01	0.06	731	0.07	0.16	-0.06***	(-9.49)
Turnover rate	1076	1.22	0.89	725	1.53	1.03	-0.31***	(-6.59)
Average daily return	1076	0.00	0.01	725	0.00	0.01	0.00	(0.16)
SD of daily return	1076	0.03	0.02	725	0.03	0.01	-0.00	(-1.67)
Log(total emissions)	1289	13.33	1.24	2528	11.90	1.12	1.42***	(34.52)
Log(production emissions)	1289	11.94	1.25	2528	10.52	1.12	1.42***	(34.41)
"Green" patents	998	7.69	19.18	2431	2.31	6.53	5.38***	(8.65)

Data on firms in sample from 2009 to 2013 (before the Connect programs begin). Sample contains 238 Connect and 192 non-Connect firms. ES ratings (**ES**) and environmental (**ENV**), and social (**SOC**) sub-ratings from Bloomberg and financial variables following Allen, Qian, Tu and Yu (2019b) and Ma, Rogers and Zhou (2021) based on CSMAR data. Connect firms include the initial cohort of firms in the Shanghai Connect that remain in the program for at least two years, while non-Connect firms join for less than two years or not at all.

[22]Given that some characteristics of Connect and non-Connect firms are statistically different before the commencement of the program, we also employ the estimation method proposed by Callaway and Sant'Anna (2021) which utilizes stabilized inverse-probability weighting. As demonstrated in Figure B.3 of Appendix B.3, the results are robust.

3.4 Other CSR outcomes

We examine how the Shanghai Connect program affects two direct measures of ES: carbon emissions and "green" patent applications. Since firm-level carbon emissions data is not available until 2018, we use industry-level emissions and assign emissions to each firm based on the fraction of their revenue in each industry.[23] Emissions include production, energy generation, waste disposal, and land industrialization. China's State Intellectual Property Office collects the patent data. Following criteria established by the World Intellectual Property Organization, we classify a patent as "green" if it concerns products or designs that provide environmental benefits (e.g., waste technology, wind power, geothermal energy, solar energy, tidal energy, or biomass). This data has broader coverage than that of the ES ratings. For this analysis, we include all firms on the SSE and SZSE for which we have data, since we aim to see if the Connect program affects these primary, underlying outcomes.

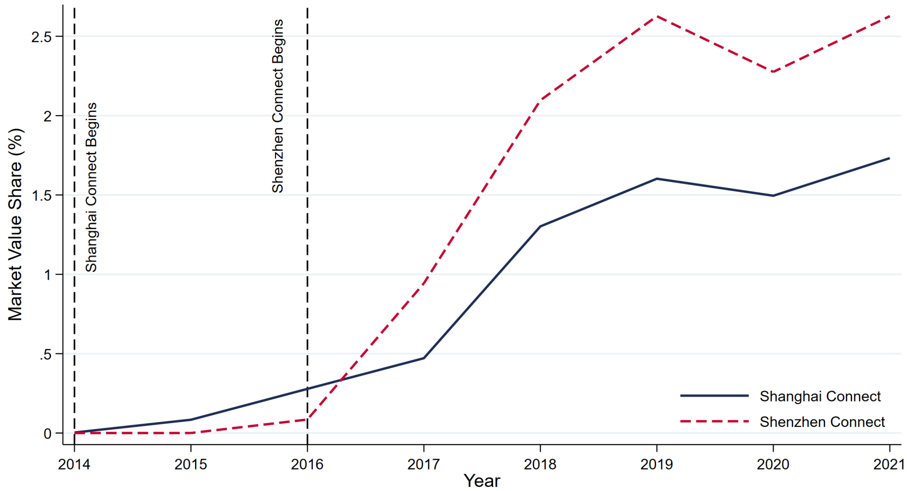
4 Estimation Approach

4.1 Identification and event study

We first confirm that the Connect programs affect trading volume. In Figure 1, the blue solid line shows the year-end market value share held by HKF investors through the Shanghai Connect as a fraction of total SSE market capitalization. In the first three years, the market value share increased slowly but steadily, then accelerated in 2018 and 2019, reaching 1.6% by the end of 2021. The dashed red line shows the fraction of SZSE market capitalization held by HKF investors through the Shenzhen Connect. It reached 2.6% by 2021. Although these represent small fractions of total shareholding, HKF investors may play an out-sized role relative to domestic investors because foreign investors are more influential – strongly predicting future stock returns (Jones, Shi, Zhang and Zhang, 2020; Lundblad, Shi, Zhang and Zhang, 2022; He, Wang and Zhu, 2023b) and their trading volume being negatively correlated with stock volatility (Bian, Chan, Han and Shi, 2023).

We apply DD estimation to identify the causal effect of the Shanghai Connect program on ES ratings. Firms joining the Shanghai Connect on its first day and remaining in the program for at least two years comprise the treatment group. All other firms, except those joining the Shanghai Connect program after its start and Shenzhen Connect firms, comprise the control group. There are two key identifying assumptions. First, no omitted factors affect both a firm's ES rating and its inclusion in the Connect program.

[23]Data from *China Energy Statistical Yearbook*.



Note: Market value share is the year-end market value of stocks held by HKF investors through the Shanghai and Shenzhen Connect programs divided by the market capital capitalization of the SSE and SZSE respectively.

Figure 1
Market value share of HKF shareholdings through Connect programs

As discussed in Section 3.1, the criteria for inclusion depend only on a firm's market capitalization and trading volume, not characteristics directly related to ES. Moreover, Bloomberg launched their ESG ratings in 2020 and constructed them retroactively, eliminating the possibility that the ESG ratings influenced inclusion in the Connect program. It also eliminates distortions in ratings resulting from conflicts of interest for the rating agency during the sample period.

Identification also requires that Bloomberg's selection criteria for rating a firm are orthogonal to inclusion in the Connect program. Since we do not observe Bloomberg's criteria, we estimate

$$\mathbf{D}_{it}^{ES} = \beta_1 \mathbf{SC}_i + \beta_2 \mathbf{SC}_i \times \mathbf{D}_t + \gamma X_{it} + \nu_t + \epsilon_{it}, \tag{1}$$

where $\mathbf{D}_{it}^{ES}$ is a dummy variable set to one if firm i received an ESG rating in year t and zero otherwise. $\mathbf{D}_t$ is an indicator variable set to one beginning in 2015, right after the Shanghai Connect program had commenced, and zero before. $\mathbf{SC}_i$ equals one if firm i is in the initial cohort of the Shanghai Connect program, and zero otherwise. X_{it} includes time-varying controls that may affect receiving an ESG rating. These include firm financial characteristics described in Section 3.3 and various firm-characteristic-by-year fixed effects (industry-by-year, province-by-year, SOE-by-year, FOE-by-year, and "sin"-stock-by-year) to capture time-varying industry, province, SOE, FOE, and "sin"-stock unobservables that affect inclusion. The last is included because Hong and Kacperczyk (2009) find that institutional investors strategically avoid investing in "sin" (alcohol, tobacco, and gambling) stocks, and this may influence whether Bloomberg rates them. A substantial portion of northbound capital in the Connect programs flowed into these "sin" stocks, particularly alcohol, so we include the "sin"-stock-year interaction to control for this.

X_{it} also includes controls for two other channels through which listed firms are exposed to foreign investors. The first is the share of firm i in year t held by QFII investors. The second is an indicator to account for the effects of inclusion in the MSCI China Index, launched in 2018. Many institutional fund managers benchmark their returns against this index, so it is an additional channel for firms listed on the SSE and SZSE to attract foreign institutional investors' attention, even though it does not provide a new trading venue. At its initiation, the index included 136 (82) firms out of the 538 (831) firms in the Shanghai (Shenzhen) Connect programs. We include year fixed effects (ν_t) in the specification to indicate that this is a two-way fixed effects estimator, even though these are absorbed by the fixed effects interactions included in X_{it}. ϵ_{it} captures firm-specific, time-varying unobservables that affect receiving a rating. We cluster errors by firm to allow for correlation of unobservables across years within a firm.

Column 1 of Table 2 employs a probit model and uses contemporaneous values for the programs (Connect, QFII, and MSCI) and control variables and finds no significant effect from Connect status on receiving an ESG rating. Column 2 repeats the estimation using lagged control variables. Columns 3 and 4 repeat the same two specifications using a logit rather than probit. All the results are insignificant, consistent with Bloomberg choosing firms to rate independent of their inclusion in the Connect program.

The second identifying assumption is that the treatment and control groups' pre-existing time trends are parallel. To check this, we estimate an event study, normalizing the effect in year 2014 to zero

$$y_{it} = \mathbf{exp}\left[\sum_{-4\leq r\leq 4,\, r\neq -1} \beta_r \mathbf{SC}_i \times \mathbf{1}_{irt} + \beta_{-5}\mathbf{SC}_i \times \mathbf{D}_{it}^{pre,5} + \beta_5 \mathbf{SC}_i \times \mathbf{D}_{it}^{post,5} + \omega_i + \nu_t\right] + \epsilon_{it}, \quad (2)$$

where we use the ES rating and the two sub-ratings as the dependent variables. r counts the number of years since 2014. $\mathbf{1}_{irt}$ is a dummy variable set equal to one if firm i in year t is r years relative to the beginning of the program and zero otherwise. $\mathbf{D}_{it}^{pre,5}$ ($\mathbf{D}_{it}^{post,5}$) are dummy variables set equal to one if firm i in year t is five or more years before (after) the beginning of the program and zero otherwise. These capture the average effects before and after the nine-year window, respectively. $\mathbf{SC}_i$ is set to one if firm i is in the Connect program, and zero otherwise. ω_i and ν_t are firm and year fixed effects.

Table 2

REPORTING PROBABILITY BY BLOOMBERG

	(1)	(2)	(3)	(4)
$\mathbf{SC}_i$	-0.32	-0.38*	-0.52	-0.59
	(0.200)	(0.209)	(0.396)	(0.421)
$\mathbf{SC}_i \times \mathbf{D}_t$	0.39		0.90	
	(0.311)		(0.762)	
$\mathbf{SC}_i \times \mathbf{D}_{i,t-1}$		0.42		1.05
		(0.313)		(0.748)
Method	probit	probit	logit	logit
Obs	4,383	3,726	4,383	3,726
Control Variables	t	$t-1$	t	$t-1$
Province ×Year FE	Y	Y	Y	Y
Industry×Year FE	Y	Y	Y	Y
SOE×Year FE	Y	Y	Y	Y
FOE×Year FE	Y	Y	Y	Y
"Sin"-Stock×Year FE	Y	Y	Y	Y

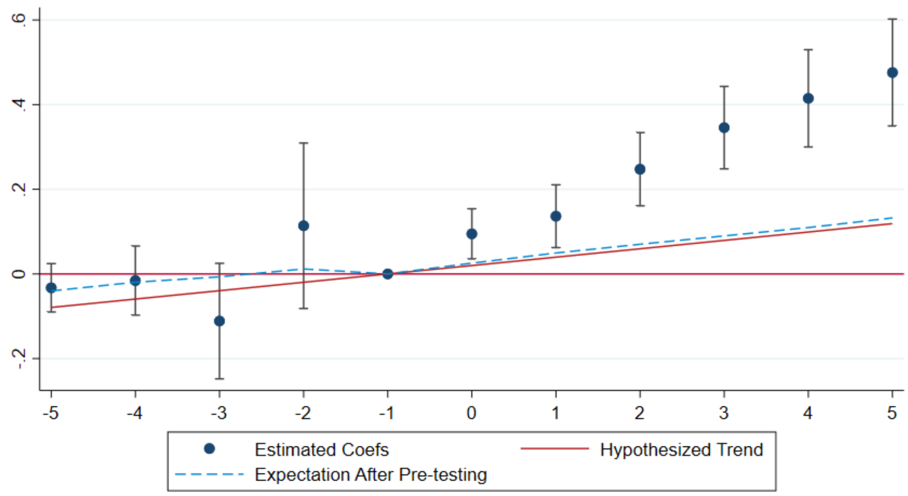
Note: Selected coefficients from estimating Equation (1) using probit and logit models. An indicator variable for whether Bloomberg includes the firm in their ESG ratings is the dependent variable. The control variables are lagged or not as shown in the bottom panel. Standard errors clustered by firm are in parentheses. $*** \ p < 0.01$, $** \ p < 0.05$, $* \ p < 0.1$.

The ES score contains zeros in the early years.[24] Silva and Tenreyro (2006), Cohn, Liu and Wardlaw (2022), and Chen and Roth (2023) show that average treatment effects using transformations, such as log-plus-one and inverse hyperbolic functions, can be biased and thus should not be interpreted as approximating a percentage effect. Instead, we apply Poisson pseudo maximum likelihood (PPML) as proposed in these studies.[25] Figure 2 plots the β_r coefficients estimated with ES as the dependent variable along with 95% confidence intervals. The pre-treatment coefficients display no obvious pattern and are not significantly different from zero, while the post-treatment coefficients are positive, increasing, and statistically significant. In Appendix A.4, we perform the same test on the ENV and SOC sub-ratings and find similar results.

A pre-trend test, the null hypothesis of which is $\beta_{-5} = \beta_{-4} = \beta_{-3} = \beta_{-2} = 0$, has an χ^2 statistic of 4.21 with a p value of 0.39. Roth (2022) argues that such a test may suffer from low power, so that the DD estimate based on it may be biased even if the test is passed. Thus, we adopt the method in that paper and calculate a trend (red-solid line in Figure 2 with a slope of 0.0198), which results in an 80% probability of rejecting the pre-trends as insignificant. The blue-dashed line represents the point estimates conditional on not

[24]From 2009 to 2014, out of 430 firms, 83, 92, 58, 5, 2, and 2 zeros are observed in each year.

[25]In Table B.1 of Appendix B.1, we employ a linear regression. The results are robust.



Note: Dots are point estimates and bars are 95% confidence intervals from the event study in Equation (2) estimated using PPML. Red-solid line is hypothetical trend estimated according to Roth (2022). Blue-dashed line represents the average point estimates conditional on not finding a significant pre-trend if the red-solid was the true line. Generated using the Stata "pretends" package.

Figure 2
Event-study estimates – ES ratings for Shanghai Connect firms

finding a significant pre-trend if the true trend was the hypothesized red line.[26] Thus, the hypothesized trend is unlikely in our case. Following Rambachan and Roth (2023), we also conduct a sensitivity analysis and find that the effect of the Connect program on ES ratings is robust even if we allow for a violation of parallel trends up to 0.3 as big as the maximal violation in the pre-treatment period (0.225), which is 3.4 times larger than the slope of the hypothesized trend.

4.2 DD specification

We employ a DD approach to estimate the Connect program's causal effect on various outcomes.[27] Since inclusion in the Connect program is orthogonal to factors influencing ES, the effect on the treatment relative to the control group is the causal effect of the

[26]The likelihood ratio of the observed pre-treatment coefficients under the hypothesized trend relative to under parallel trends is 1.07. Thus, the realization of the pre-trends is about as likely under the hypothesized as under parallel trends.

[27]We attempted to estimate a regression discontinuity specification comparing firms just above the threshold of qualifying for inclusion in the Connect program to those just below. However, because the regulators applied subjectivity in applying the weights and did not disclose them, we were not able to reconstruct the index with enough precision to implement this.

Connect program on the outcome. Our benchmark specification is given by

$$y_{it} = \mathbf{exp}\left[\left(\beta_1 + \beta_2 \mathcal{T}_t\right) \times \mathbf{SC}_i \times \mathbf{D}_t + \left(\beta_3 + \beta_4 \mathcal{T}_{it}^E\right) \mathbf{E}_{it} + \gamma' X_{it} + \omega_i + \nu_t\right] + \epsilon_{it}, \tag{3}$$

where y_{it} is the outcome of interest, including the annual ES rating and sub-ratings for firm i in year t. $\mathbf{SC}_i$ is as defined earlier – an indicator set to one if firm i is a Connect firm and zero otherwise. $\mathbf{D}_t$ is an indicator variable set to one beginning in the year 2015 (after the Connect program begins) and zero before. $\mathbf{E}_{it}$ is an indicator variable set to one in all years t after firm i exits the Connect program after having previously entered, if it does so, and zero otherwise. β_1 captures any level shift with the commencement of the program, while β_3 captures any level shift for firms leaving the program relative to being in the program.

As in Dobkin, Finkelstein, Kluender and Notowidigdo (2018), we allow for a linear trend in event time, $\mathcal{T}_t$, equal to the number of years since 2015 and zero before. $\mathcal{T}_{it}^E$ is equal to the number of years since a Connect firm exited the program, if it does so, and zero otherwise. β_2 captures the relative change in trend for Connect relative to non-Connect firms once the policy begins, and β_4 captures any change in trend for firms leaving the program relative to the trend under the program. This specification allows for the pattern observed in Figure 2 — an approximately linear trend in response to the policy.

X_{it} includes controls that may affect ES ratings including firm financial characteristics described in Section 3.3 as well as firm-characteristic-by-year fixed effects (industry-by-year, province-by-year, SOE-by-year, FOE-by-year, and "sin"-stock-by-year fixed effects) that capture time-varying industry, province, SOE, FOE, and "sin"-stock effects. Firm fixed effects (ω_i) capture time-invariant, firm-specific unobservables that affect ES ratings. We display a year fixed effect (ν_t) to indicate that this is a two-way fixed effect estimator, even though the firm-characteristic-by-year fixed effects absorb these. We again use PPML to accommodate zero values for the ES rating.

5 Results

5.1 Benchmark results

We first estimate the average policy effect across the post-policy years, allowing only a level shift in ES ratings (Column 1 of Table 3). Joining the Connect program increases a firm's ES rating by 14.1% on average post-policy.[28] When firms exit, their ES ratings do not experience a significant drop in the first year but begin declining at 7.1% per year thereafter. Column 2 is the benchmark regression. ES ratings increase 16.3% in the first year and increase by 11.5% annually thereafter. When evaluated at the mean ES rating (6.22) in 2013, the last full year without the Connect program, this equals a jump of 1.01 and an annual increase of 0.72. This compares to an average annual increase in ES ratings of 0.74 across all firms before 2013. Although the significant uptake in HKF shareholdings did not occur until a couple of years after the Connect programs began (Figure 1), the immediate increase in ES performance may have resulted from firms' desire to immediately begin signalling to build foreign investors' confidence. The annual decline upon exiting (-9.2%) equals 0.57, evaluated at the mean in 2013.

Table 3

EFFECT OF SHANGHAI CONNECT PROGRAM ON ES RATINGS AND SUB-RATINGS

	ES				**ENV**	**SOC**
	(1)	(2)	(3)	(4)	(5)	(6)
$\mathbf{SC}_i \times \mathbf{D}_t$	0.132***	0.151***	0.248***	0.141**	0.349**	0.095**
	(0.048)	(0.057)	(0.076)	(0.070)	(0.136)	(0.046)
$\mathbf{SC}_i \times \mathbf{D}_t \times \mathcal{T}_t$		0.109***	0.190***	0.118***	0.182***	0.072***
		(0.027)	(0.034)	(0.027)	(0.060)	(0.023)
$\mathbf{E}_{it}$	0.067	0.007		0.003	0.001	0.001
	(0.046)	(0.047)		(0.047)	(0.095)	(0.034)
$\mathbf{E}_{it} \times \mathcal{T}_{it}^E$	-0.074***	-0.096***		-0.100***	-0.197***	-0.027
	(0.024)	(0.025)		(0.024)	(0.060)	(0.020)
Observations	5,083	5,083	3,575	5,066	5,083	5,083
Psuedo R^2	0.451	0.453	0.467	0.455	0.634	0.397
Province ×Year FE	Y	Y	Y	Y	Y	Y
Industry×Year FE	Y	Y	Y	Y	Y	Y
SOE×Year FE	Y	Y	Y	Y	Y	Y
FOE×Year FE	Y	Y	Y	Y	Y	Y
"Sin"-Stock×Year FE	Y	Y	Y	Y	Y	Y
Firm Characteristics	Y	Y	Y	Y	Y	Y
Firm Characteristics×$\mathbf{D}_t$	N	N	N	Y	N	N

Note: Selected coefficients from estimating Equation (3) with different dependent variables. $\mathbf{SC}_i$ is an indicator set to one if firm i is the first cohort of firms in Shanghai Connect program and stays in the program at least two years and zero otherwise. $\mathbf{D}_t$ is an indicator variable set to one beginning in 2015 and zero before. $\mathbf{E}_{it}$ is an indicator variable set to one beginning in year t if firm i exits the Connect program in year t after having previously entered, and zero otherwise. $\mathcal{T}_t$ measures the number of years since 2015. $\mathcal{T}_{it}^E$ equals the number of years since a treatment firm exits either program, if it did so, and zero otherwise. Columns 1 through 4 estimate with ES rating as the dependent variable. Column 3 excludes firms that were selected into the program but later exited. Column 5 estimates with the ENV sub-rating as the dependent variable, and Column 6 with the SOC sub-rating. All columns use PPML estimation. Standard errors clustered by firm are in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

[28] We transform all PPML results to marginal effects throughout the paper.

Firms that were selected into the program but later exited may possess unobserved characteristics that influence their actions after inclusion. As shown in Column 3, the Connect program effects remain robust when we exclude these firms from the analysis. The effects on ES scores are somewhat greater for non-exiting firms. Since inclusion in the Connect program is associated with financial characteristics and because the Connect program may affect firms' financial performance, Column 4 checks robustness to controlling for changes in these characteristics around the policy by adding interactions of the financial covariates in X_{it} with D_t to the benchmark regression. This allows the covariates to have differential effects on ES ratings before versus after the Connect program begins. The results are similar to those in the benchmark specification. Columns 5 and 6 repeat the benchmark regression for the ENV and SOC sub-ratings. Although the estimates are statistically significant for both, the magnitudes are much larger for the ENV than the SOC sub-rating. The ENV sub-rating experiences an increase of 41.8% in the first year or 1.40 evaluated at the mean in 2013 (3.36). It then increases at 20.0% (0.67) per year. The SOC sub-rating increases by 10.0% (0.93) in the first year evaluated at the mean in 2013 (9.31) and it increases by 7.5% (0.70) per year thereafter. These compare to average annual increases of 0.51 for ENV and 0.99 for SOC prior to the Connect program.[29]

5.2 Heterogeneity, robustness, and validation checks

Column 1 of Table 4 distinguishes the effects of the Connect program on firms of different ownership types. The Connect program significantly affects ES ratings for SOEs and POEs, but not FOEs. This is consistent with FOEs experiencing influence from foreign investors before the Connect program began. For POEs, ES ratings increase by 15.5%, or 0.05 applying the 2013 mean rating for POEs (0.33), in the first year and then increase by 12.3% (0.041) annually. SOEs do not experience a change in the first year but do increase 6.9% per year thereafter. This equals 0.04, applying the mean rating for SOEs in 2013 (0.62). These compare to an average annual increase in ES ratings of 12.7% for POEs and 10.9% for SOEs prior to the Connect program. Our results are consistent with Hsu, Liang and Matos (2021), which finds that SOEs are responsive to environmental issues. Since inclusion in the SSE 180 or SSE 380 Indexes is necessary for being in the Connect

[29] In unreported regressions (available upon request), we re-estimate the baseline results, allowing for differential effects for "sin" versus non-"sin" stocks. The effects for non-"sin" stocks were slightly larger, and the effects for "sin" stocks insignificant. The latter could be because the northbound investments in "sin" stocks are primarily by individuals rather than institutions (we cannot separately quantify them) and individuals exert less influence, or it may result from self-selection. Investors that choose to hold "sin" stocks may care less about ES issues and thus choose to exert little influence on firms' ES activities (Dyck, Lins, Roth and Wagner, 2019).

program, the increase in ES ratings could be due to entry into the indexes themselves. To test for this, Column 2 re-estimates the benchmark regression, excluding the thirty firms that joined the two indexes in 2013 and 2014, just before the Connect program began. The results are very similar to the benchmark results.

The fraction of market value held by HKF investors increased considerably in 2018 (Figure 1) raising the question whether the main effects of the Connect program occurred then rather than at its initiation. To assess this, we carried out a placebo test with 2018 as the event threshold (i.e., setting $\mathbf{D}_t$ equal to one beginning in 2018 and adjusting $\mathcal{T}_t$ appropriately) in our benchmark sample. Column 3 shows no significant change in effects around the 2018 placebo threshold.

Bloomberg's ES ratings are retroactive and based on objective measures. However, to the extent that these measures involve some subjectivity, Connect firms may exert more effort than non-Connect firms to influence the rating agency without any actual change in objective performance. To test for this, we examine whether the Connect program affected two important environmental outcomes not included in Bloomberg's criteria (described in Section 3.4). The first independent outcome is carbon emissions. We estimate a linear version of the benchmark model (Equation 3) with the log of annual firm-level emissions as the dependent variable. Column 4 of Table 4 reports the results for total emissions, and Column 5 for production emissions. Neither declines in the first year, but emissions decline more over time (by 1.4% per year for total and 1.3% for production emissions) for Connect relative to non-Connect firms. Column 6 reports estimates with "green" patent applications in a firm-year as the dependent variable using a PPML model to account for instances of zero patents in a year. The number of patents is not affected in the first year, but does experience a 3.6% increase per year in subsequent years for Connect firms relative to non-Connect firms.

5.3 Including the Shenzhen Connect program

Examining the mechanisms behind the Connect program's effect on ES performance in the next section requires that we include data on the Shenzhen Connect program to provide sufficient time-series variation. We perform a check here to see whether the combined Shanghai and Shenzhen Connect programs affect ES ratings. To do so, we add data for the initial cohort (firms joining the first day) of the Shenzhen Connect to the initial cohort of the Shanghai Connect. This changes the estimation to a staggered DD. de Chaisemartin and d'Haultfoeuille (2020), Goodman-Bacon (2021) and Baker, Larcker and Wang (2022) show that staggered DD estimation may bias estimates because later-treated units

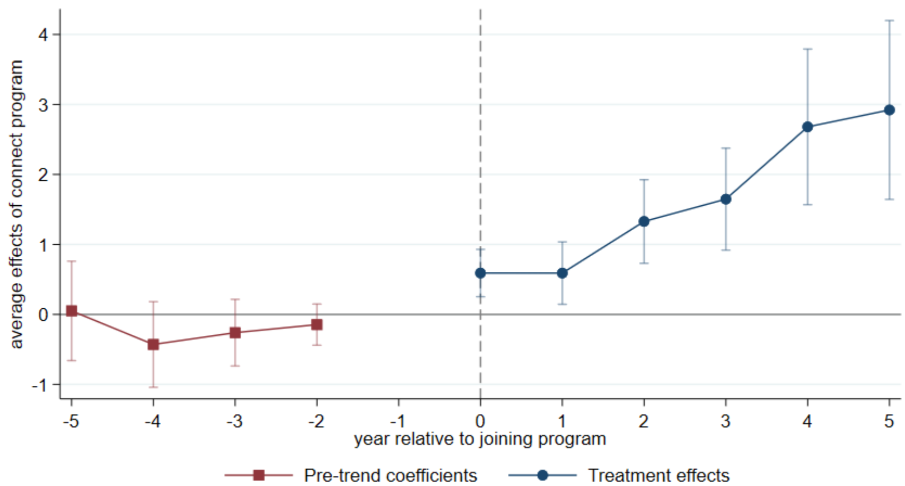
Table 4

Heterogeneity, robustness, and validation checks: effect of Shanghai Connect program on ES ratings and independent CSR measures

	ES			log (Carbon Emissions)		"Green"
	Ownership	Index	2018	Total	Production	Patents
	(1)	(2)	(3)	(4)	(5)	(6)
$SOE \times \mathbf{SC}_i \times \mathbf{D}_t$	0.081					
	(0.063)					
$POE \times \mathbf{SC}_i \times \mathbf{D}_t$	0.144*					
	(0.085)					
$FOE \times \mathbf{SC}_i \times \mathbf{D}_t$	-0.142					
	(0.205)					
$SOE \times \mathbf{SC}_i \times \mathbf{D}_t \times \mathcal{T}_t$	0.067**					
	(0.030)					
$POE \times \mathbf{SC}_i \times \mathbf{D}_t \times \mathcal{T}_t$	0.116***					
	(0.039)					
$FOE \times \mathbf{SC}_i \times \mathbf{D}_t \times \mathcal{T}_t$	0.060					
	(0.066)					
$\mathbf{SC}_i \times \mathbf{D}_t$		0.154***	-0.027	-0.014	-0.010	0.048
		(0.058)	(0.083)	(0.011)	(0.012)	(0.057)
$\mathbf{SC}_i \times \mathbf{D}_t \times \mathcal{T}_t$		0.112***	0.026	-0.014***	-0.013***	0.035**
		(0.028)	(0.024)	(0.004)	(0.004)	(0.014)
$\mathbf{E}_{it}$	0.013	0.025	0.031	0.012	-0.003	-0.028
	(0.046)	(0.050)	(0.041)	(0.017)	(0.018)	(0.060)
$\mathbf{E}_{it} \times \mathcal{T}_{it}^E$	-0.097***	-0.100***	-0.054**	0.001	0.005	-0.013
	(0.025)	(0.026)	(0.022)	(0.007)	(0.008)	(0.023)
Methodology	PPML	PPML	PPML	Linear	Linear	PPML
Observations	5,083	4,798	5,083	11,943	11,943	15,245
R^2/Psuedo R^2	0.453	0.447	0.450	0.990	0.989	0.966
Province ×Year FE	Y	Y	Y	Y	Y	Y
Industry×Year FE	Y	Y	Y	Y	Y	Y
SOE×Year FE	Y	Y	Y	Y	Y	Y
FOE×Year FE	Y	Y	Y	Y	Y	Y
"Sin"-Stock×Year FE	Y	Y	Y	Y	Y	Y
Firm Characteristics	Y	Y	Y	Y	Y	Y

Note: Selected coefficients from estimating Equation (3). $\mathbf{SC}_i$ is an indicator set to one if firm i is the first cohort of firms in Shanghai Connect program and stays in the program at least two years and zero otherwise. $\mathbf{D}_t$ is an indicator variable set to one when the Connect program begins in 2015 and zero before. $\mathbf{E}_{it}$ is an indicator variable set to one beginning in year t if firm i exits the Connect program in year t after having previously entered, and zero otherwise. $\mathcal{T}_t$ measures the number of years since 2015 and $\mathcal{T}_{it}^E$ equals the number of years since a treatment firm exits either program, if it did so, and zero otherwise. Column 1 distinguishes effects by firm ownership type (some observations are omitted because ownership type cannot be determined). Column 2 excludes firms joining SSE 180 and SSE 380 in 2013 and 2014. Column 3 estimates a placebo test with $\mathbf{D}_t$ set to one beginning in 2018 and zero before and $\mathcal{T}_{it}^E$ appropriately adjusted. Columns 4 through 6 show results with log total carbon emissions, log production carbon emissions, and number of "green"-patent applications, respectively as dependent variables. These columns include all firms with data not just those with ES ratings. Standard errors clustered by firm are in parentheses. $***\ p < 0.01$, $**\ p < 0.05$, $*\ p < 0.1$.

are compared to a combination of earlier-treated units and the control group.[30] Sun and Abraham (2021) further demonstrate that point estimates of dynamic effects under such conditions cannot be interpreted as reliable measures of "dynamic treatment effects". The recent literature (Sun and Abraham, 2021; Callaway and Sant'Anna, 2021; de Chaisemartin and d'Haultfoeuille, 2023) propose approaches to circumvent these problems. Figure 3 displays the results of applying the method in Sun and Abraham (2021) as recommended by Baker, Larcker and Wang (2022) to ES ratings. There is no discernible trend before firms join a Connect program but a significant upward trend after. In Appendix B.3, we report another method for checking the appropriateness of the staggered DD estimation, as well as checks for the ENV and SOC sub-ratings.



Note: Square and circular dots are point estimates from the generalized DD model of Sun and Abraham (2021) and bars are 95% confidence intervals based on 300 bootstrap iterations. Effect in year -1 is anchored at zero.

Figure 3
AVERAGE EFFECTS OF THE SHANGHAI AND SHENZHEN CONNECT PROGRAMS ON ES RATINGS

6 Mechanisms

In this section, we investigate why firms changed their ES activities after increased exposure to foreign investors via the Connect program. We examine the two main theories - signaling and influence - and then employ an approach to isolate their individual contributions.

[30] Roth, Sant'Anna, Bilinski and Poe (2023) and de Chaisemartin and d'Haultfoeuille (2022) provide surveys.

Lins, Servaes and Tamayo (2017) argues that firms signal trustworthiness by investing in CSR. The investment acts like insurance that pays off when investors face a crisis of confidence and the reward for being trustworthy increases markedly. In our context, domestic firms in China may signal their trustworthiness to foreign investors who face an information asymmetry. Characteristics of China's stock market provide room for such signaling. Firth, Wang and Wong (2015) document that less-transparent firms are more affected by investor sentiment, and there is evidence that transparency is low for firms traded on China's stock markets. Allen, Qian, Shan and Zhu (2021) argues that institutional deficiencies in China's stock market, such as corporate governance, delisting procedures, and IPO process, can account for the poor performance of domestically-listed firms. Song and Xiong (2018) argue that even though China has adopted accounting regulations and standards for publicly-listed firms that are similar to most developed countries, enforcement has been lax and violation penalties low. As a result, foreign investors might face greater information asymmetries about firms in China. Investments in ES activities by firms could raise their ES ratings and signal trustworthiness to foreign investors, reducing this information gap.

Alternatively, or in addition, foreign investors may directly influence domestic firms' ES activities. Dyck, Lins, Roth and Wagner (2019) provide evidence that investors, proportional to their concern with ESG performance, influence firms to improve their ESG ratings. Chen, Dong and Lin (2020) utilize the Russell Index reconstitution and find that an increase in institutional ownership improves subsequent CSR performance. Relatedly, Aggarwal, Erel, Ferreira and Matos (2011) find that a rise in institutional ownership is positively associated with better subsequent governance. Jia, Wang and Xiong (2017) show that local investors react more strongly to local analysts and foreign investors to foreign analysts. Given this, the commencement of the Connect programs opens domestic firms to the influence of foreign investors (and analysts) that may care more about ES performance than domestic.

For either of these mechanisms to be at play, it must be that foreign investors at the beginning of the Connect program care more about ES than China's domestic investors. This appears to be the case. At the Shanghai Connect's initiation in November 2014, only two investment management funds headquartered in Mainland China had joined the Principles for Responsible Investment (PRI), an international network of financial institutions supported by the United Nations and working to promote ESG factors. In contrast, foreign PRI signatories increased from 734 in 2010 to 1,384 in 2015. By 2020, there were 3,038 signatories, only 49 of which were Mainland-China-based.[31] HKF investors also

[31] As further evidence, in unreported results (available upon request) we find that the effects of the Con-

emphasize ES initiatives. About 76% of Hong Kong's institutional investors plan to allocate similar or more resources to climate risk measurement than in the previous twelve months (HKIMR, 2022).

6.1 Combining the two theories

Under the signaling theory, ES ratings should causally increase northbound shareholdings since foreign investors will reward higher ratings with increased ownership. Under the influence theory, northbound shareholdings should causally increase ES activities since greater foreign ownership leads to greater pressure on firms to increase them. These two theories can be summarized as a system of two simultaneous equations. Since the subsample used here is from 2013 to 2021, there are very few zero values for ES ratings (which we exclude) allowing a linear specification[32]

$$NBshare_{itq} = \beta_1 log\left(y_{i,t-1}\right) + \beta_2 \mathbf{N}^2_{itq} + \left(\beta_3 + \beta_4 \mathcal{T}^E_{i,t-1,q}\right)\mathbf{E}_{i,t-1,q} + \gamma' X_{i,t-1,q} + \omega_i + \nu_{tq} + \epsilon_{itq}, \quad (4a)$$

$$\log\left(y_{it}\right) = \beta_5 NBshare_{i,t-1} + \beta_6 C_i \times \mathbf{P}_{it} + \left(\beta_7 + \beta_8 \mathcal{T}^E_{i,t-1}\right)\mathbf{E}_{i,t-1} + \gamma' X_{i,t-1} + \omega_i + \nu_t + \epsilon_{it}, \quad (4b)$$

where t and q stand for year and quarter and other variables will be discussed shortly. If the signaling theory is at play, the direction of causality is from ES ratings to northbound shareholdings (Equation 4a). If the influence theory is at play, the direction of causality is from northbound shareholdings to ES ratings (Equation 4b). We lag values since we assume that signaling through northbound shareholdings takes one year and ES ratings (published annually) are reported with a year lag.

We discuss below how we deal with the different frequency in the two equations (yearly ES ratings and quarterly northbound shareholdings). y_{it} is the ES rating of firm i in year t and y_{itq} is the quarterly value (the annual value replicated across the four quarters). $NBshare_{itq}$ is the northbound share of holdings for firm i in year t and quarter q while $NBshare_{it}$ is the average annual value. X_{itq} are control variables, including year-quarter-firm financial characteristics described in Section 3.3 and province-, industry-, SOE-, FOE-, and "sin"-stock-by-year-by-quarter fixed effects. X_{it} contains the yearly averages of the firm financial characteristics and province-, industry-, SOE-, FOE-, and "sin"-stock-by-year fixed effects. The firm fixed effect (ω_i) captures time-invariant, firm-specific factors affecting the two endogenous variables. We show year (ν_t) and year-by-quarter (ν_{tq}) fixed effects, even though these are absorbed by other fixed effects to illustrate that

nect program on the ChiNext firms' ES performance are more significant than other Shenzhen Connect firms. Notably, the ChiNext firms are exclusively traded by HKF institutional investors.

[32]Most zero values occur prior to 2013. In this subsample there are only 5 firms (10 firm-year observations) out of 501 firms (4577 firm-year observations) with zero values.

this is a two-way fixed effects estimator. ϵ_{it} and ϵ_{itq} are firm-year and firm-year-quarter unobservables affecting ES ratings and northbound shareholdings respectively.

In Equation (4a), the indicator variable for firm i exiting a Connect program ($\mathbf{E}_{itq}$) is included to control for the fact that foreign investors can only sell (not buy) the firm's stock once it exits. It equals one beginning in the quarter the firm exits, if it does so, and zero otherwise. $\mathcal{T}_{itq}^{E}$ equals the number of quarters since a Connect firm exited a program, if it does so, and zero otherwise. In Equation (4b), $\mathbf{E}_{it}$ is included to control for changes in the ES rating due to a firm exiting a Connect program. It equals one beginning in the year the firm exits a program, if it does so, and zero otherwise. $\mathcal{T}_{it}^{E}$ equals the number of years since a Connect firm exited a program, if it does so, and zero otherwise.

The key coefficients of interest are β_1, which captures the effect of ES ratings on northbound shareholdings (the signaling effect), and β_5, which captures the effect of northbound shareholdings on ES ratings (the influence effect). Unless one or both of these is zero, an exogenous increase in either northbound shareholdings or ES ratings will create feedback between the two and amplify the effects. This simultaneity bias is the key challenge in estimation, which we address by using the excluded variable in each equation as an instrument.[33] To examine the causal effect of ES ratings on northbound shareholdings, we use a change in environmental regulation ($C_i \times \mathbf{P}_{it}$) as an instrument for ES ratings. To examine the causal effect of northbound shareholdings on ES ratings, we use squared duration in the Connect program ($\mathbf{N}_{itq}^2$) as an instrument for northbound shareholdings. We use a single-equation method to address the simultaneity bias in estimating the system of equations. Therefore, we discuss these variables and identification in more detail when we discuss estimating each equation.

6.2 The signaling theory

To isolate the causal effect of ES ratings on northbound shareholdings, we employ an instrument that exogenously shifts ES ratings: an environmental regulatory change that centralized environmental monitoring and inspections (the variable $C_i \times \mathbf{P}_{it}$ excluded from Equation (4a)).[34] After the policy change, provincial environmental protection departments began controlling the lower-level municipal and prefecture departments by

[33] We separately estimate equations (4a) and (4b) using ordinary least squares in Appendix B.4. The coefficients, presented in Table B.3, are of the same sign as those obtained using the 2SLS method but lower in magnitude. This indicates that the exogenous control variables are significantly correlated with the endogenous variables.

[34] This is known as *Guiding Opinions on the Pilot Program of the Reform of the Vertical Management System of Monitoring, Supervision and Law Enforcement by Provincial-Level Environmental Protection Authority*. For details, see http://www.gov.cn/zhengce/2016-09/22/content_5110853.htm.

appointing delegates to their offices and controlling their budgets. The change was implemented across all provinces except Shanxi and Xizang Autonomous Region in a staggered fashion from 2016 to 2019. Since firms' exposures to the policy are likely affected by the extent of their polluting activities, we weight firm responses by their pre-policy pollution production. $\mathbf{P}_{it}$, is an indicator equal to one if firm i's province is subject to the regulation in year t. We define regulatory exposure as

$$C_i = \frac{CE_i}{\overline{CE} + CE_i}, \tag{5}$$

where CE_i is firm i's carbon emissions described in Section 3.4 averaged over the period 2009 to 2011 (pre-policy) and $\overline{CE}$ is the average across all firms. C_i lies between zero and one and is an increasing function of firm i's pre-policy emissions intensity. β_6 in Equation (4b) captures the differential effect on the ES ratings of more intensively-polluting firms from the regulatory change.

Identification requires that the regulation affects ES ratings but affects northbound shareholdings only through its effect on ES ratings. The first condition is met as long as the policy sufficiently changes firms' environmental performance and, thereby, their ES ratings. We confirm this below. The most likely challenge to the second condition is that the policy affected firms' financial performance and thereby their stock prices; and that foreign investors are more sensitive to these stock price changes than domestic investors or that the change in financial performance directly affected investments in ES performance. To check this, we run an event study regressing the stock price of all firms traded on the SSE and SZSE in the 24 months prior to and after the policy change, with the implementation month in the firm's province normalized to zero

$$sp_{itm} = \sum_{r \neq 0} \beta_r \mathbf{P}_{irtm} + \gamma' X_{itm} + \omega_i + \nu_{tm} + \epsilon_{itm}. \tag{6}$$

sp_{itm} is the average stock price, defined as monthly total trading value divided by monthly total trading volume, for firm i in month m of year t, and $\mathbf{P}_{irtm}$ is equal to one if it is r months relative to the regulatory change. Firm fixed effects (ω_i) capture firm-specific unobservables affecting the stock price, and X_{itm} includes province-, industry-, SOE-, FOE, and "sin"-stock-by-year-by-month fixed effects. We show a year-month fixed effect (ν_{tm}) in the specification, even though this is absorbed by the other fixed effects, to illustrate that this is a two-way fixed effects estimator. Appendix B.5 plots β_r along with 95% confidence intervals. There are no significant effects around the staggered implementation dates. This suggests that the policy's effects on financial performance were not significant enough to affect stock prices. This also rules out that foreign investors are simply investing in financially successful firms and that ES improvements are a byproduct of their better financial conditions.

We estimate Equation (4a) using 2SLS. In the first stage, we include both Connect and non-Connect firms to increase the variation available for identification. We use data from 2013 onward because we use the previous years to compute the pre-policy emissions weightings for each firm. The data frequency in the first stage is annual (ES ratings), while the frequency in the second stage is quarterly (northbound shareholdings) so we employ Mixed 2SLS (M2SLS), which allows for different aggregation levels in the two stages. M2SLS produces estimates that are consistent and asymptotically normal (Dhrymes and Lleras-Muney, 2006) provided that the groupings are independent of the structural error as they are when the grouping is a primitive (in our case, grouping quarterly observations into years). The first-stage equation is

$$\log y_{it} = \theta C_i \times \mathbf{P}_{it} + \sum_{k \in \{SH,SZ\}} \left[\left(\rho_1^k + \rho_2^k \mathcal{T}_{it}^k \right) \mathbf{SC}_i^k \times \mathbf{D}_t^k \right] + \left(\beta_1 + \beta_2 \mathcal{T}_{it}^E \right) \mathbf{E}_{it} + \gamma' X_{it} + \omega_i + \nu_t + \epsilon_{it}. \qquad (7)$$

This includes the instrument, all the exogenous variables from the second-stage equation (Equation 4a) averaged at the annual level, plus an additional term in square brackets.[35] $\mathbf{SC}_i^k$ is an indicator set to one if firm i is in program k (denoted by SH for Shanghai and SZ for Shenzhen) in any year. $\mathbf{D}_t^k$ is an indicator variable set to one after Connect program k begins (2015 for Shanghai and 2017 for Shenzhen) and zero before. The terms inside the square brackets do not vary across firms within a year in the second stage and are therefore collinear with the time fixed effects in the second stage. ρ_1^k captures any level shift for the Connect relative to the non-Connect firms once the program begins.

Following Dobkin, Finkelstein, Kluender and Notowidigdo (2018), we allow different trends for the two programs by interacting $\mathbf{SC}_i^k$ with $\mathcal{T}_{it}^k$, which equals the number of years since policy k is in effect for firm i. For firms that never join a program, it equals the number of years since the Connect program began (2015 for Shanghai and 2017 for Shenzhen) and zero before. ρ_2^k captures the change in trends for Connect firms relative to non-Connect once each policy begins. Importantly, since we include province-by-year fixed effects, the regulation's impact is identified by within-province variation over time.

In the second stage (Equation 4a), we replace $\log(y_{i,t-1})$ with the fitted values from

[35] To ensure the exclusion restriction is met, the first-stage equation must include the averaged values of all the exogenous variables in the second stage. The exit indicator and trend are the average values of the quarterly measures in the second stage. The firm-year characteristics and financial control variables in the first stage are the average values of the firm-year-quarter characteristics and financial control variables in the second. The firm fixed effect remains the same and the year fixed effect is the average of the year-quarter fixed effects in the second stage. Since the second stage includes only Connect firms, $\mathbf{SC}_i^k = 1$ for all observations and the term in square brackets is collinear with the time fixed effects in the second stage.

the first stage ($\widehat{\log(y_{it})}$) lagged by one year. In doing so, we use the corresponding quarter in the previous year (e.g., the lagged fitted value for each of the four quarters in 2017 in the second stage would be the 2016 annual fitted values from the first stage). Also, since northbound shareholdings are only available while a firm is in the Connect program, the second stage only uses year-quarters in which the firm is in the Connect program (but including exits after joining).

The top panel of Column (1) in Table 5 reports the estimates of Equation (7), where only the initial cohorts of both Connect programs are used as the treated group and those joining later are dropped from the sample. ES ratings are increasing in firms' carbon emission intensity with the advent of the regulation. Since the F-statistic for the first stage is slightly below the critical value of 10 in Stock and Yogo (2005), we apply the tF critical-value function developed in Lee, McCrary, Moreira and Porter (2022). The instrument is significant at the 7.5% level. After the regulatory change, a one standard deviation (0.22) increase in emissions intensity is associated with 4.0% higher ES ratings, or 0.23 evaluated at the mean ES rating in 2013 (5.71). This estimation generates similar year-by-year predictions of the causal effect of the Connect program on ES performance as the DD estimates shown in Figure 3.[36] In Appendix B.6, we estimate Equation (7) with the ENV and SOC sub-ratings as dependent variables as a validation test of the instrument and of Bloomberg's proper measurement of E versus S elements. As expected, the regulation has a strong effect on the ENV sub-rating both statistically and in magnitude but no significant effect on the SOC sub-rating.

The bottom panel of Column (1) reports the second-stage estimates. The effect is positive and significant. A one percent increase in ES rating leads to a 2.0 basis points increase in northbound shareholding, consistent with ES ratings acting as a positive signal for foreign investors. The average annual increase in ES ratings prior to the Connect programs (11.9%) would lead to an increase of 24 basis points in northbound shareholdings which is 18.1% of the average northbound shareholdings (1.31%).

6.3 The influence theory

To isolate the effect of northbound shareholdings on ES ratings, we employ an instrument that exogenously shifts northbound shareholdings but plausibly affects ES ratings only through northbound shareholdings. This is the variable ($\mathbf{N}_{itq}^2$) excluded from Equation (4b) (the linear term is absorbed by the year-quarter fixed effects). $\mathbf{N}_{itq}$ equals the number of quarters since firm i entered the Connect program as of year t and quarter q. The

[36] The values in Figure 3 in years zero through five are 0.59, 0.59, 1.33, 1.65, 2.68, and 2.92 while those from this first-stage estimation are 0.61, 0.79, 1.68, 2.05, 2.58, and 2.72.

Table 5

IV ESTIMATION OF MECHANISMS: SYSTEM OF EQUATIONS

	Signalling Theory (1)	**Influence Theory** (2)
First-stage estimation		
	$\mathbf{ES}_{it}$	$\mathbf{NB\ share}_{itq}$
$C_i \times \mathbf{P}_{it}$	0.181***	
	(0.065)	
$\mathbf{N}^2_{itq}$		-1.74e(-5)***
		(5.51e(-6))
Obs	4,504	21,538
$\mathbf{R}^2$	0.824	0.771
F statistic	9.75	9.94
tF significance	7.50%	0.75%
Second-stage estimation		
	$\mathbf{NB\ share}_{itq}$	$\log(\mathbf{ES}_{it})$
$\log(\widehat{\mathbf{ES}_{\mathbf{i,t-1,q}}})$	0.020**	
	(0.009)	
$\widehat{\mathbf{NB\ share}}_{i,t-1}$		22.334**
		(10.269)
Obs	6,760	2,447
Province ×Year (Year-Quarter) FE	Y	Y
Industry×Year (Year-Quarter) FE	Y	Y
SOE×Year (Year-Quarter) FE	Y	Y
FOE×Year (Year-Quarter) FE	Y	Y
"Sin"-Stock×Year (Year-Quarter) FE	Y	Y
Firm Characteristics	Y	Y

Note: The first stage of Column (1) is estimated with Equation (7) and the second stage with Equation (4a). The data used in the first stage are annual and in the second stage quarterly. Lagged control variables are used in the second stage. The sample data in the first stage are from 2013 to 2021 and include both Connect and non-Connect firms in all periods. The data in the second stage are from 2017Q1 to 2021Q4 and are restricted to Connect firms in periods after they joined. The first stage of Column (2) is estimated with Equation (8) and the second stage with Equation (4b). The data used in the first stage are quarterly and those in the second stage are annual. Average annual fitted values are used in the second stage. The sample data are from 2017Q1 to 2021Q4 and include only Connect firms in periods after they joined. Standard errors clustered by firm in both stages are in parentheses. Second stage errors based on a block bootstrap by firm (1,000 iterations). $***\ p < 0.01$, $**\ p < 0.05$, $*\ p < 0.1$.

instrument is premised on the idea that northbound shareholdings exert nonlinear effects on ES ratings. For the exclusion restriction to be met, there must be no nonlinearity in ES ratings with respect to elapsed time independent of the Connect program. While this cannot be directly verified, Appendix B.7 provides suggestive evidence that this is the case. It shows that log ES ratings are nonlinear with respect to elapsed time for Connect firms but not for non-Connect firms.[37] The use of elapsed time in the program means that the sample here is biased toward firms that do not exit after joining the Connect program. As shown in Column 3 of Table 3, these firms experienced similar but somewhat greater improvements in ES performance due to the Connect program.

Both stages of the 2SLS estimation include only data while firms belong to a Connect program, so that northbound shareholdings data are available. The first-stage equation is

$$NB\ share_{itq} = \beta_1 \mathbf{N}^2_{itq} + \theta C_i \times \mathbf{P}_{itq} + \left(\beta_2 + \beta_3 \mathcal{T}^E_{itq}\right)\mathbf{E}_{itq} + \gamma' X_{itq} + \omega_i + \nu_{tq} + \epsilon_{itq}. \tag{8}$$

This includes the instrument and all the exogenous variables from the second-stage equation (4b) measured at the quarterly level.[38] The latter include the effect of the environmental policy on northbound shareholdings and the level and trend change in holdings due to a firm exiting a Connect program. X_{itq} includes firm-year-quarter financial characteristics described in Section 3.3 as well as province-, industry-, SOE-, FOE-, and "sin"-stock-by-year-quarter effects. Firm fixed effects (ω_i) capture time-persistent firm unobservables that affect northbound shareholdings. We include year-by-quarter fixed effects (ν_{tq}) to indicate that this is a two-way fixed effect estimator, even though these are absorbed by the other fixed effects. In the second-stage equation (4b), we replace $NB\ share_{i,t-1}$ with the annual average of the fitted values from the first stage lagged by one year $\widehat{NB\ share}_{i,t-1}$. Since the second stage is at the annual level we again employ M2SLS.

The top panel of Column (2) in Table 5 reports the estimates for the first-stage equation using quarterly data from 2017Q1, when HKEX began disclosing northbound shareholding for individual stocks, to 2021Q4. The coefficient of $\mathbf{N}^2_{itq}$ is negative and statistically significant. Applying the *tF* critical-value function of Lee, McCrary, Moreira and Porter (2022), the first-stage coefficient is significant at the 0.75% level. The bottom panel of Table 5 reports estimates of the second-stage equation. The sample includes only Connect firms and uses data from 2017 to 2021. For every percentage point rise in northbound shareholding in a quarter, the ES rating in the following year increases by 22.3%.

[37] Since annual data must be used for this test, we use a more parsimonious specification (log of elapsed time in the program). Using the square of elapsed time also results in insignificant effects for the non-Connect firms. The first stage of the 2SLS estimation uses quarterly data since we employ M2SLS.

[38] To ensure the exclusion restriction is met, the first-stage equation must include the non-averaged values of all the exogenous variables in the second stage. The exit indicator and trend in the second stage are the average values of the corresponding first-stage variables. The firm-year characteristics and the year fixed effects in the second stage are the average values of the firm-year-quarter characteristics and year-quarter fixed effects from the first stage respectively, and the firm fixed effects in the second stage remain the same as in the first stage.

This is an increase of 1.39 evaluated at the mean ES rating in 2013 (6.22).

6.4 Interpretation

Because we find evidence consistent with both the signaling and influence theory, an exogenous increase in either northbound shareholdings or ES ratings will have greater long- than short-run effects. We therefore quantify the relative contribution of each in the short run and long run.

The short-run effect of an increase in either northbound shareholdings or ES performance is the effect when shutting down feedback from the other mechanism. In this case, there will be a level shift equal to the short-run effect that persists thereafter. We quantify the relative short-run effects of the two mechanisms using the first and second years of firms joining the Connect program. The causal effect on ES performance in the first year of firms joining the Connect program equals 0.59 (7.5% of the average ES score of 7.91 in the year before firms join the Connect program) based on the DD estimation shown in Figure 3.[39] This is a pure signaling effect because the influence mechanism has not taken effect yet. In the absence of any influence mechanism, this effect will persist in the ensuing years.

Also, by the end of the first year, northbound shareholdings for a firm increase. We obtain a causal estimate of this (0.0037) from the predicted values of the first-stage estimation for Equation (4b). Using the coefficient from the second-stage of our 2SLS estimation (22.3), this results in an increase of 0.083 in logged ES performance by the end of the second year due to the influence effect. In the absence of any feedback from the signalling mechanism, this will persist in the ensuing years. Again, using the average ES score of 7.91 in the year before firms join the Connect program, this is an increase of 0.66 in ES performance.[40] Therefore, in the short-run, the influence mechanism is about 12% greater than the signaling mechanism.

In the presence of both mechanisms, ES performance increases more due to the feedback between the two, and the long-run effect of an exogenous increase in either northbound shareholdings or ES performance will be 80.5% greater than the short-run response. To compare the contribution of the two mechanisms in the long run, we compare the dynamics of ES performance and northbound shareholding using the 2SLS estimates from Table 5. We introduce an exogenous change to one mechanism in year zero in the

[39] Figure 3 uses data from the combined Shanghai and Shenzhen programs so that it is comparable to that used in the 2SLS estimation.

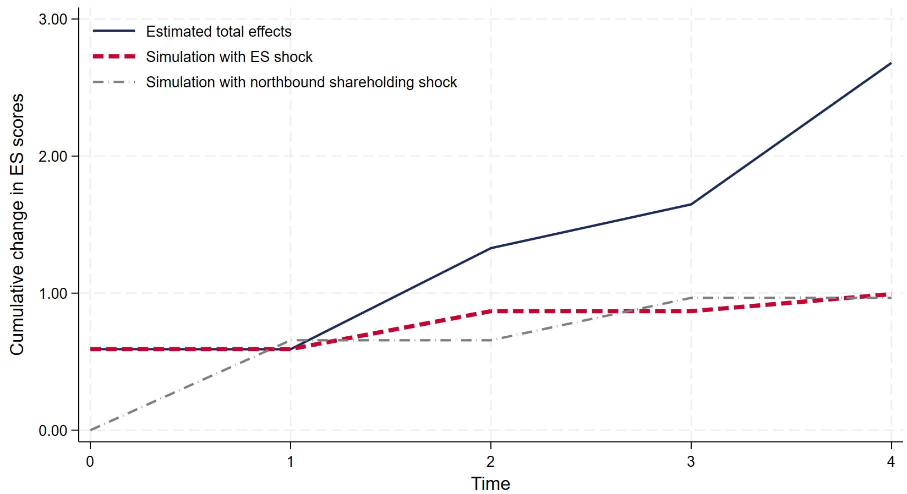
[40] This implies a total change in ES score of 0.59 + 0.66 = 1.25 in year two. This is close to the 1.33 DD estimate of the total effect in year two (Figure 3). Since our simulation does not include the influence of the control variables, these will not necessarily be identical.

absence of the other and simulate using Equations (4a) and (4b). These results can then be compared to each other and to the total effects from the DD estimation (as noted earlier, the causal effects of the Connect program on ES performance are similar using the DD estimates or the 2SLS first-stage estimates, allowing a comparison).

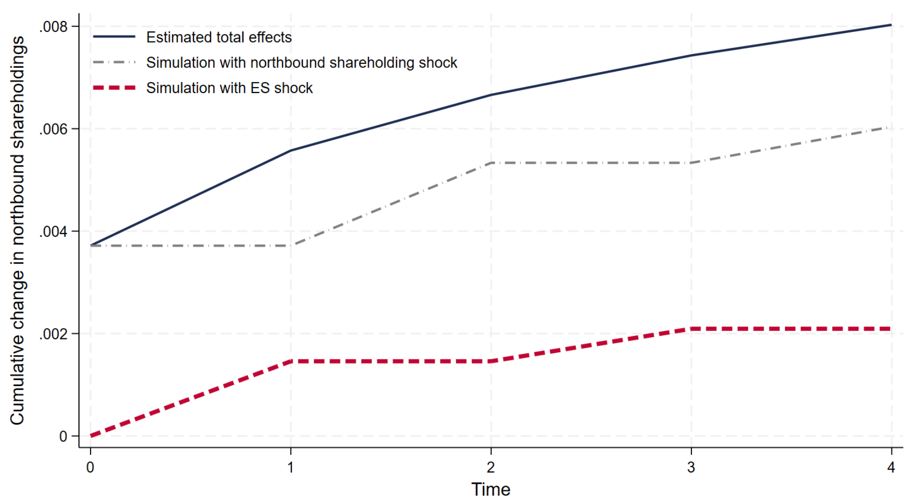
We first assess the dynamic response reflected in ES performance. For the total causal effect of the Connect program on ES performance, we utilize the DD estimates, reproduced as the blue solid line in panel (a) of Figure 4. To evaluate the dynamic contribution of the signalling mechanism, we introduce the first-year causal increase in ES performance (0.59) into Equation (4b). Since Figure 3 presents ES score levels while Equations (4a) and (4b) employ logged ES scores, we convert the increase to a percentage (7.5%) using the average ES score one year prior to firms joining the Connect program (7.91). Due to the signaling mechanism, this increase in ES performance leads to a 0.0015 increase in northbound shareholdings in the first year using our causal estimate of the signalling effect (0.02). This, in turn, drives a subsequent 3.3% increase in the ES score in the second year through the influence mechanism, applying the causal estimate of the influence effect (22.3). Applying the same procedure, ES performance increases an additional 1.5% two years later due to the feedback effects between the two mechanisms. The red, large-dashed line in panel (a) of Figure 3 displays the cumulative change in the level of ES performance relative to the average ES performance one year before the program's commencement. The increase in ES performance due to the signaling mechanism explains 65% of the total increase in year two and 37% in year four.

We assess the dynamic response to the first-year causal increase in northbound shareholdings similarly. For the total causal effect of the Connect program on northbound shareholdings relative to the year before firms join the Connect program, we utilize the first-stage results of the 2SLS estimation of Equation (4b). The resulting cumulative year-end changes for years zero through four are displayed in the blue solid line in panel (b) of Figure 4 (0.0037, 0.0056, 0.0067, 0.0074, and 0.0080).

To evaluate the dynamic contribution of the influence mechanism, we introduce the exogenous increase in northbound shareholdings (0.0037) that occurs by the end of year one into Equation (4a). Due to the influence mechanism, this increase in northbound shareholdings leads to an 8.3% increase in ES performance in the first year using our causal estimate of the influence effect (22.3). This, in turn, drives a subsequent 0.0017 increase in northbound shareholdings in the second year, applying the causal estimate of the signaling effect (0.02). Two years later, northbound shareholdings experiences an additional 0.00076 increase due to the feedback effects of the two channels. The red, large-dashed line in panel (b) of Figure 3 displays the cumulative change in the level



(a) Effects on ES scores



(b) Effects on northbound shareholding

Note: Panel (a) shows dynamic effects of the initial increase in ES scores (red, large-dashed line) and northbound shareholding (gray, small-dashed line) on ES scores based on simulations using the 2SLS estimates, compared to the total effects based on the DD estimates (blue solid line). Panel (b) shows dynamic effects of the initial increase in ES scores (red, large-dashed line) and northbound shareholding (gray, small-dashed line) on northbound shareholdings based on simulations using the 2SLS estimates, compared to the total effects based on predicted values from the first stage of Equation (4b) (blue solid line).

Figure 4
Dynamic contribution of two mechanisms to total effects

of northbound shareholdings relative to that one year before firms join the Connect program. The increase in northbound shareholding due to the influence mechanism explains 80% of the total increase in year two and 75% in year four.

We can also compare the dynamics of the two mechanisms by adding the dynamics of the other mechanism to each panel of the figure. The gray, small-dashed line in panel (a) of Figure 3 displays the effect on ES performance that occurs in years two and four due to the first-year exogenous increase in northbound shareholding. The two mechanisms have very similar contemporaneous effects; however, since the influence mechanism is delayed by one year, its effects are somewhat greater in the long run. The gray, small-dashed line in panel (b) of Figure 3 displays the effect on northbound shareholdings that occurs in years two and four due to the first-year exogenous increase in ES performance. The influence mechanism has much greater effects on northbound shareholdings than does the signaling mechanism. Although the two mechanisms experience the same increases over time due to feedback, the initial shock to northbound shareholdings is greater than the initial shock to ES performance and this persists throughout.

7 Conclusion

We find that deregulating China's financial system to allow more foreign investors in its stock market leads to increased ES performance for firms receiving foreign investments. The evidence is consistent with both foreign investors exerting influence on domestic firms to improve their ES performance and firms improving their ES activities to signal their trustworthiness to foreign investors. Thus, exogenous increases in either ES performance or foreign investment holdings will reinforce each other and amplify the long-term effects. This identifies an important channel for cross-country convergence in ES performance either through a transmission of concern with ES from the source to the target country or though efforts by firms in the target country to signal their quality.

It would be useful to obtain direct evidence of these mechanisms. For example, are the increased ES ratings valuable as a signal to foreign investors in later times of crisis? Alternatively, do firms that are more opaque by some measure benefit more from the increased ES ratings that result from foreign investment? Does ES performance increase relatively more for firms that receive investments from foreign investors that value ES relatively more? This would require a measure of the value that foreign investors place on ES. Given the feedback between the two mechanisms, it is essential to disentangle the two in order to estimate the causal effects of these direct measures. The instrumenting approach developed in this paper could be used to do so by estimating subsamples split by the direct measures.

References

Aggarwal, R., Erel, I., Ferreira, M. and Matos, P. (2011). Does governance travel around the world? evidence from institutional investors. *Journal of Financial Economics*, **100** (1), 154–181.

Alfaro, L., Kalemli-Ozcan, S. and Volosovych, V. (2008). Why doesn't capital flow from rich to poor countries? an empirical investigation. *The review of economics and statistics*, **90** (2), 347–368.

Allen, F., Qian, J., Shan, C. and Zhu, J. (2021). Dissecting the long-term performance of the chinese stock market. *Available at SSRN 2880021*.

—, Qian, J. Q. and Gu, X. (2017). An overview of china's financial system. *Annual Review of Financial Economics*, **9**, 191–231.

—, — and Qian, M. (2019a). A review of china's institutions. *Annual Review of Financial Economics*, **11**, 39–64.

—, Qian, Y., Tu, G. and Yu, F. (2019b). Entrusted loans: A close look at china's shadow banking system. *Journal of Financial Economics*, **133** (1), 18–41.

Azar, J., Duro, M., Kadach, I. and Ormazabal, G. (2021). The big three and corporate carbon emissions around the world. *Journal of Financial Economics*, **142** (2), 674–696.

Baker, A. C., Larcker, D. F. and Wang, C. C. (2022). How much should we trust staggered difference-in-differences estimates? *Journal of Financial Economics*, **144** (2), 370–395.

Berg, F., Fabisik, K. and Sautner, Z. (2020). Rewriting history ii: The (un) predictable past of esg ratings. *European Corporate Governance Institute–Finance Working Paper*, **708** (2020).

—, Koelbel, J. F. and Rigobon, R. (2022). Aggregate confusion: The divergence of esg ratings. *Review of Finance*, **26** (6), 1315–1344.

Bian, J., Chan, K., Han, B. and Shi, D. (2023). Cross-border equity flows and information transmission: Evidence from chinese stock markets. *Journal of International Financial Markets, Institutions and Money*, **84**, 101755.

Bisetti, E., She, G. and Zaldokas, A. (2023). Esg shocks in global supply chains. *Available at SSRN*.

Brucal, A., Javorcik, B. and Love, I. (2019). Good for the environment, good for business: Foreign acquisitions and energy intensity. *Journal of International Economics*, **121**, 103247.

Cai, X., Lu, Y., Wu, M. and Yu, L. (2016). Does environmental regulation drive away inbound foreign direct investment? evidence from a quasi-natural experiment in china. *Journal of development economics*, **123**, 73–85.

Callaway, B. and Sant'Anna, P. H. (2021). Difference-in-differences with multiple time periods. *Journal of Econometrics*, **225** (2), 200–230.

Carpenter, J. N. and Whitelaw, R. F. (2017). The development of china's stock market and stakes for the global economy. *Annual Review of Financial Economics*, **9**, 233–257.

Cengiz, D., Dube, A., Lindner, A. and Zipperer, B. (2019). The effect of minimum wages on low-wage jobs. *The Quarterly Journal of Economics*, **134** (3), 1405–1454.

Chava, S. (2014). Environmental externalities and cost of capital. *Management Science*, **60** (9), 2223–2247.

Chen, J. and Roth, J. (2023). Logs with Zeros? Some Problems and Solutions. *The Quarterly Journal of Economics*, p. qjad054.

Chen, K., Wang, Y. and Zhu, X. (2019). The value of information in the china's connected market. *Available at SSRN 3395141*.

Chen, T., Dong, H. and Lin, C. (2020). Institutional shareholders and corporate social responsibility. *Journal of Financial Economics*, **135** (2), 483–504.

Cheng, X., Jiang, X., Kong, D. and Vigne, S. (2024). Shifting stakeholders logics: Foreign institutional ownership and corporate social responsibility. *Journal of Business Ethics*.

Cheong, C., Choi, J., Ha, S. and Oh, J. Y. J. (2023). Does foreign institutional capital promote green growth for emerging market firms? *Available at SSRN 4288880*.

Cherniwchan, J., Copeland, B. R. and Taylor, M. S. (2017). Trade and the environment: New methods, measurements, and results. *Annual Review of Economics*, **9**, 59–85.

Cingano, F. and Pinotti, P. (2016). Trust, firm organization, and the pattern of comparative advantage. *Journal of International Economics*, **100**, 1–13.

Cohn, J. B., Liu, Z. and Wardlaw, M. I. (2022). Count (and count-like) data in finance. *Journal of Financial Economics*, **146** (2), 529–551.

de Chaisemartin, C. and d'Haultfoeuille, X. (2022). Two-way fixed effects and differences-in-differences with heterogeneous treatment effects: A survey. *Working Paper*.

— and — (2023). Difference-in-differences estimators of intertemporal treatment effects. *Working Paper*.

— and d'Haultfoeuille, X. (2020). Two-way fixed effects estimators with heterogeneous treatment effects. *American Economic Review*, **110** (9), 2964–2996.

Dhrymes, P. J. and Lleras-Muney, A. (2006). Estimation of models with grouped and ungrouped data by means of "2sls". *Journal of Econometrics*, **133** (1), 1–29.

Dimson, E., Karakaş, O. and Li, X. (2015). Active ownership. *The Review of Financial Studies*, **28** (12), 3225–3268.

Dobkin, C., Finkelstein, A., Kluender, R. and Notowidigdo, M. J. (2018). The economic consequences of hospital admissions. *American Economic Review*, **108** (2), 308–52.

Dyck, A., Lins, K. V., Roth, L. and Wagner, H. F. (2019). Do institutional investors drive corporate social responsibility? international evidence. *Journal of Financial Economics*, **131** (3), 693–714.

Ferreira, M. A. and Matos, P. (2008). The colors of investors' money: The role of institutional investors around the world. *Journal of Financial Economics*, **88** (3), 499–533.

Ferrell, A., Liang, H. and Renneboog, L. (2016). Socially responsible firms. *Journal of Financial Economics*, **122** (3), 585–606.

Firth, M., Wang, K. and Wong, S. M. (2015). Corporate transparency and the impact of investor sentiment on stock prices. *Management Science*, **61** (7), 1630–1647.

Giannetti, M., Liao, G. and Yu, X. (2015). The brain gain of corporate boards: Evidence from china. *The Journal of Finance*, **70** (4), 1629–1682.

Goodman-Bacon, A. (2021). Difference-in-differences with variation in treatment timing. *Journal of Econometrics*, **225** (2), 254–277.

He, Y. E., Kahraman, B. and Lowry, M. (2023a). ES Risks and Shareholder Voice. *The Review of Financial Studies*, **36** (12), 4824–4863.

He, Z., Wang, Y. and Zhu, X. (2023b). Homemade foreign trading. *University of Chicago, Becker Friedman Institute for Economics Working Paper 2022-170*.

— and Wei, W. (2022). *China's Financial System and Economy: A Review*. Working Paper 30324, National Bureau of Economic Research.

HKIMR (2022). *Climate Risk Measurement The existing landscape and developments in Hong Kong's financial services industry*. Tech. rep., HKIMR.

Hong, H. and Kacperczyk, M. (2009). The price of sin: The effects of social norms on markets. *Journal of Financial Economics*, **93** (1), 15–36.

Hsu, P.-H., Liang, H. and Matos, P. (2021). Leviathan inc. and corporate environmental engagement. *Management Science*, **69** (12), 7719–7758.

Javorcik, B. and Poelhekke, S. (2017). Former Foreign Affiliates: Cast Out and Outperformed? *Journal of the European Economic Association*, **15** (3), 501–539.

Jia, C., Wang, Y. and Xiong, W. (2017). Market segmentation and differential reactions of local and foreign investors to analyst recommendations. *The Review of Financial Studies*, **30** (9), 2972–3008.

Jones, C. M., Shi, D., Zhang, X. and Zhang, X. (2020). Understanding retail investors: evidence from china. *Available at SSRN 3628809*.

Kim, W., Sung, T. and Wei, S.-J. (2011). Does corporate governance risk at home affect investment choices abroad? *Journal of International Economics*, **85** (1), 25–41.

Krueger, P., Sautner, Z. and Starks, L. T. (2020). The importance of climate risks for institutional investors. *The Review of Financial Studies*, **33** (3), 1067–1111.

Lee, D. S., McCrary, J., Moreira, M. J. and Porter, J. (2022). Valid t-ratio inference for iv. *American Economic Review*, **112** (10), 3260–90.

Li, S., Brockman, P. and Zurbruegg, R. (2015). Cross-listing, firm-specific information, and corporate governance: Evidence from chinese a-shares and h-shares. *Journal of Corporate Finance*, **32**, 347–362.

Liang, H. and Renneboog, L. (2017). On the foundations of corporate social responsibility. *The Journal of Finance*, **72** (2), 853–910.

Lins, K. V., Servaes, H. and Tamayo, A. (2017). Social capital, trust, and firm performance: The value of corporate social responsibility during the financial crisis. *The Journal of Finance*, **72** (4), 1785–1824.

Lundblad, C. T., Shi, D., Zhang, X. and Zhang, Z. (2022). Are foreign investors informed? trading experiences of foreign investors in china. *Trading Experiences of Foreign Investors in China (Feb 19, 2022)*.

Ma, C., Rogers, J. H. and Zhou, S. (2021). The effect of the china connect. *Available at SSRN 3432134*.

Matthias Arnold, J. and Javorcik, B. S. (2009). Gifted kids or pushy parents? foreign direct investment and plant productivity in indonesia. *Journal of International Economics*, **79** (1), 42–53.

McCahery, J. A., Sautner, Z. and Starks, L. T. (2016). Behind the scenes: The corporate governance preferences of institutional investors. *The Journal of Finance*, **71** (6), 2905–2932.

Rambachan, A. and Roth, J. (2023). A More Credible Approach to Parallel Trends. *The Review of Economic Studies*, **90** (5), 2555–2591.

Roth, J. (2022). Pretest with caution: Event-study estimates after testing for parallel trends. *American Economic Review: Insights*, **4** (3), 305–322.

—, Sant'Anna, P. H., Bilinski, A. and Poe, J. (2023). What's trending in difference-in-differences? a synthesis of the recent econometrics literature. *Journal of Econometrics*, **235** (2), 2218–2244.

Silva, J. S. and Tenreyro, S. (2006). The log of gravity. *The Review of Economics and Statistics*, **88** (4), 641–658.

Song, Z. and Xiong, W. (2018). Risks in china's financial system. *Annual Review of Financial Economics*, **10**, 261–286.

Stock, J. H. and Yogo, M. (2005). Testing for weak instruments in linear iv regression. In D. W. K. Andrews and J. H. Stock (eds.), *Identification and Inference for Econometric Models: Essays in Honor of Thomas Rothenberg*, Cambridge University Press, p. 80–108.

Sun, L. and Abraham, S. (2021). Estimating dynamic treatment effects in event studies with heterogeneous treatment effects. *Journal of Econometrics*, **225** (2), 175–199.

Tang, H. and Zhang, Y. (2021). Do multinationals transfer culture? evidence on female employment in china. *Journal of International Economics*, **133**, 103518.

Tong, H. and Wei, S.-J. (2014). Does trade globalization induce or inhibit corporate transparency? unbundling the growth potential and product market competition channels. *Journal of International Economics*, **94** (2), 358–370.

Wang, J. and Wang, X. (2015). Benefits of foreign ownership: Evidence from foreign direct investment in china. *Journal of International Economics*, **97** (2), 325–338.

A Data

A.1 Construction of SSE and SZSE stock indexes

The SSE 180 Index is constructed as follows. After excluding stocks listed for less than one quarter or under ST, all remaining are assigned an aggregate rank which equals the sum of their ranks on market capitalization and trading volume during the past year. To make the index representative of industry composition in the entire market, a quota for the number of firms in each industry is calculated by multiplying 180 by the market value share of all stocks in the industry divided by the total market value of all stocks. Firms are then selected into the index by their aggregate rank within each industry and subject to the quota. The SSE 380 index is constructed similarly, except stocks paying no dividends in the previous five years or for more than five years cumulatively are excluded.

For the SZSE Component Index, stocks listed less than a half year, under ST, or with market capitalization in the top 1% are excluded. All remaining stocks are sorted based on their aggregate rank, which equals the sum of their ranks on market capitalization and trading volume during the previous half year. After filtering out those in the bottom 10% of this aggregate rank, the top 500 stocks are selected based on their market capitalization ranking but subject to the same industry representation as in the aggregate market. After removing the SZSE Component Index constituents from the SZSE 1000 Index, which adopts the same method of construction as the SZSE Component Index, the remaining 500 stocks are selected as the SZSE Small/Mid-Cap Innovation Index constituents, again subject to the same industry representation as in the aggregate market.

A.2 Bloomberg ESG data

Proprietary ESG ratings and three sub-ratings are provided by Bloomberg, which began publishing in 2020. The ratings are based on over 600 company-reported and derived key performance indicators. In particular

1. Environment

    - Air Quality: Air Quality Disclosure Score, Nitrogen Oxide Emissions, VOC Emissions, Carbon Monoxide Emissions, Particulate Emissions, Sulphur Dioxide/Sulphur Oxide Emissions
    - Climate Change: Climate Change Disclosure Score, Emissions Reduction Initiatives, Climate Change Policy, Climate Change Opportunities Discussed,

Risks of Climate Change Discussed, Direct CO2 Emissions, Indirect CO2 Emissions, ODS Emissions, GHG Scope 1/2/3, Scope 2 Market Based GHG Emissions, Scope of Disclosure, Carbon per Unit of Production

- Ecological & Biodiversity Impacts: Ecological & Biodiversity Impacts Disclosure Score, Biodiversity Policy, Number of Environmental Fines, Environmental Fines (Amount), Number of Significant Environmental Fines, Amount of Significant Environmental Fines
- Energy: Energy Disclosure Score, Energy Efficiency Policy, Total Energy Consumption, Renewable Energy Use, Electricity Used, Fuel Used - Coal/Lignite, Fuel Used - Natural Gas, Fuel Used - Crude Oil/Diesel, Self Generated Renewable Electricity, Energy Per Unit of Production
- Materials & Waste: Materials & Waste Disclosure Score, Waste Reduction Policy, Hazardous Waste, Total Waste, Waste Recycled, Raw Materials Used, % Recycled Materials, Waste Sent to Landfills, Percentage Raw Material from Sustainable Sources
- Supply Chain: Supply Chain Disclosure Score, Environmental Supply Chain Management
- Water: Water Disclosure Score, Water Policy, Total Water Discharged, Water per Unit of Production, Total Water Withdrawal, Water Consumption

2. Social

- Community & Customers: Community & Customers Disclosure Score, Human Rights Policy, Policy Against Child Labor, Quality Assurance and Recall Policy, Consumer Data Protection Policy, Community Spending, Number of Customer Complaints, Total Corporate Foundation and Other Giving
- Diversity: Diversity Disclosure Score, Equal Opportunity Policy, Gender Pay Gap Breakout, % Women in Management, % Women in Workforce, % Minorities in Management, % Minorities in Workforce, % Disabled in Workforce, Percentage Gender Pay Gap for Senior Management, Percentage Gender Pay Gap Mid & Other Management, Percentage Gender Pay Gap Employees Ex Management, % Gender Pay Gap Total Employment Including Management, % Women in Middle and or Other Management
- Ethics & Compliance: Ethics & Compliance Disclosure Score, Business Ethics Policy, Anti-Bribery Ethics Policy, Political Donations

- Health & Safety: Health & Safety Disclosure Score, Health and Safety Policy, Fatalities - Contractors, Fatalities - Employees, Fatalities - Total, Lost Time Incident Rate, Total Recordable Incident Rate, Lost Time Incident Rate - Contractors, Total Recordable Incident Rate - Contractors, Total Recordable Incident Rate - Workforce, Lost Time Incident Rate - Workforce
- Human Capital: Human Capital Disclosure Score, Training Policy, Fair Remuneration Policy, Number of Employees - CSR, Employee Turnover %, % Employees Unionized, Employee Training Cost, Total Hours Spent by Firm - Employee Training, Number of Contractors
- Supply Chain: Supply Chain Disclosure Score, Social Supply Chain Management, Number of Suppliers Audited, Number of Supplier Audits Conducted, Number Supplier Facilities Audited, Percentage of Suppliers in Non-Compliance, Percentage Suppliers Audited

3. Governance

   - Audit Risk & Oversight: Audit Risk & Oversight Disclosure Score, Audit Committee Meetings, Years Auditor Employed, Size of Audit Committee, Number of Independent Directors on Audit Committee, Audit Committee Meeting Attendance Percentage
   - Board Composition: Board Composition Disclosure Score, Company Conducts Board Evaluations, Size of the Board, Number of Board Meetings for the Year, Board Meeting Attendance %, Number of Executives / Company Managers, Number of Non-Executive Directors on Board
   - Compensation: Compensation Disclosure Score, Company Has Executive Share Ownership Guidelines, Director Share Ownership Guidelines, Size of Compensation Committee, Number of Independent Directors on Compensation Committee, Number of Compensation Committee Meetings, Compensation Committee Meeting Attendance %
   - Diversity: Diversity Disclosure Score, Board Age Limit, Number of Female Executives, Number of Women on Board, Age of the Youngest Director, Age of the Oldest Director
   - Independence: Independence Disclosure Score, Number of Independent Directors
   - Nominations & Governance Oversight: Nominations & Governance Oversight Disclosure Score, Size of Nomination Committee, Number of Independent Di-

rectors on Nomination Committee, Number of Nomination Committee Meetings, Nomination Committee Meeting Attendance Percentage

- Sustainability Governance: Sustainability Governance Disclosure Score, Verification Type, Employee CSR Training
- Tenure: Tenure Disclosure Score, Board Duration (Years)

A.3 Bloomberg ES ratings and stock returns

Berg, Fabisik and Sautner (2020) shows that some vendors may revise ESG scores retrospectively, making them more predictive of future corporate performance. Following that paper, we test the correlation between future stock returns and Bloomberg ES ratings:

$$\mathbf{SR}_{it} = \alpha \mathbf{ES}_{i,t-1} + \gamma' X_{it} + \omega_i + \nu_t + \epsilon_{it} \tag{A1}$$

Here, $\mathbf{SR}_{it}$ is the stock return and $\mathbf{ES}_{it}$ is the annual ES rating of firm i in year t. X_{it} includes controls that may affect ES ratings including firm financial characteristics described in Section 3.3 as well as firm-characteristic-by-year fixed effects (industry-by-year, province-by-year, SOE-by-year, FOE-by-year, and "sin"-stock-by-year fixed effects) that capture time-varying industry, province, SOE, FOE, and "sin"-stock effects. Firm fixed effects (ω_i) capture time-invariant, firm-specific unobservables that affect stock returns. We display a year fixed effect (ν_t) to indicate that this is a two-way fixed effect estimator, even though the firm-characteristic-by-year fixed effects absorb these.

Table A.1 presents the estimated results for Equation (A1). In Columns 1 and 2, the estimation is performed on the full sample. The analysis reveals that the coefficients for both the lagged and two-period lagged ES ratings are not significant. In Columns 3 and 4, the analysis is replicated using the same sample of firms as in our benchmark regression, confirming the robustness of the results. Finally, Columns 5 and 6 use the subsample employed in our mechanisms test (from 2017 to 2021). The findings remain consistent.

A.4 Pre-trend tests for sub-ratings

Using Equation (2), we test the pre-trend for the ENV and SOC sub-ratings. As shown in Figures A.1, the pre-trends for the Shanghai Connect firms are similar to those of the non-Connect firms for both sub-ratings.

Table A.1

CORRELATION BETWEEN BLOOMBERG ES RATINGS AND STOCK RETURNS

	(1)	(2)	(3)	(4)	(5)	(6)
$\mathbf{ES}_{i,t-1}$	0.049		0.112		-0.069	
	(0.061)		(0.077)		(0.086)	
$\mathbf{ES}_{i,t-2}$		-0.028		0.031		-0.142
		(0.073)		(0.091)		(0.109)
Observations	9,271	8,159	5,083	4,616	4,881	4,624
R^2	0.734	0.740	0.790	0.797	0.795	0.791
Province ×Year FE	Y	Y	Y	Y	Y	Y
Industry×Year FE	Y	Y	Y	Y	Y	Y
SOE×Year FE	Y	Y	Y	Y	Y	Y
FOE×Year FE	Y	Y	Y	Y	Y	Y
"Sin"-Stock×Year FE	Y	Y	Y	Y	Y	Y
Firm Characteristics	Y	Y	Y	Y	Y	Y

Note: Selected coefficients from estimating Equation (A1). The dependent variable is stock returns, defined as the percent change in the year-end stock price. **ES** is the annual ES rating. X_{it} includes controls that may affect ES ratings including firm financial characteristics described in Section 3.3 as well as firm-characteristic-by-year fixed effects (industry-by-year, province-by-year, SOE-by-year, FOE-by-year, and "sin"-stock-by-year fixed effects) that capture time-varying industry, province, SOE, FOE, and "sin"-stock effects. Columns 1 and 2 estimate with the full sample, Columns 3 and 4 estimate with the subsample used in our benchmark regression, and Columns 5 and 6 estimate with the subsample between 2017 and 2021. Standard errors clustered by firm are in parentheses. $*** p < 0.01$, $** p < 0.05$, $* p < 0.1$.

A.5 Variable definitions

- ROA: Net income divided by book value of total assets at quarter end. Source: CSMAR.
- Growth rate of sales: The firm's year-over-year change in sales. Source: CSMAR.
- Market capitalization: The firm's closing price at month end multiplied by its month-end share outstanding divided by the aggregated market capitalization of the Chinese domestic stock market (SSE and SZSE as applicable). Source: CSMAR.
- Tobin's Q: The book value of total assets minus the book value of equity plus the market value of equity scaled by the book value of total assets at each year-end. Source: CSMAR.
- Cash flow to assets ratio: Cash and cash equivalents divided by the book value of total assets measured at year-end. Source: CSMAR.
- Leverage ratio: book value of debt divided by the book value of total assets measured at year-end. Source: CSMAR.

- SOE: A dummy variable equal to one if a firm's ultimate owner or blockholder is a government related entity, and zero otherwise. Source: CSMAR, WIND.
- POE: A dummy variable equals to one if a firm's ultimate owner or blockholder is an individual or other non-government related entity, and zero otherwise. Source: CSMAR, WIND.
- FOE: A dummy variable equal to one if a firm's ultimate owner or blockholder is a foreign/HMT related entity, and zero otherwise. Source: CSMAR, WIND.
- QFII share: QFII share (%) The fraction of shares hold by qualified investor institutional investors (QFII) at year-end. Source: CSMAR.
- Insider trade: insider selling as a percentage of the firm's market capitalization on day t. Source: CSMAR.
- Turnover rate: Average daily turnover over the past 12 months. Turnover is defined as trading volume (in shares) divided by total shares outstanding. Source: CSMAR
- Average daily return: Average daily return over the past 12 months. Source: CSMAR.
- SD of daily return: Standard deviation of daily stock return. Source: CSMAR.

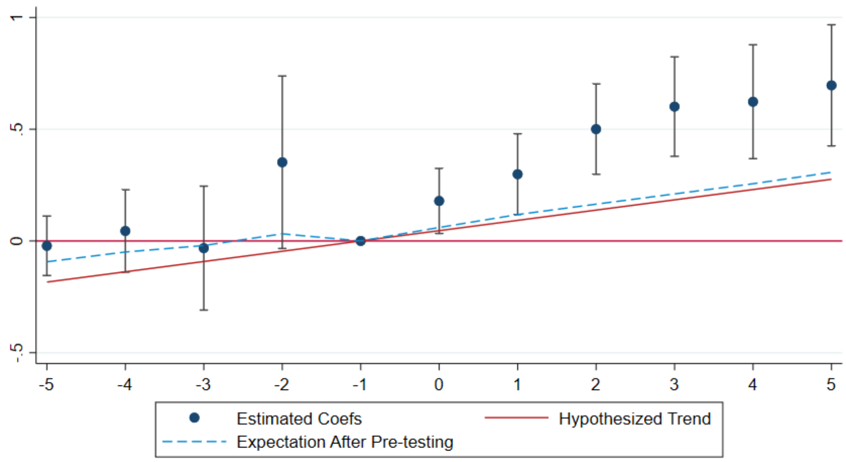
B Additional Tests

B.1 Test with ES level using linear regression

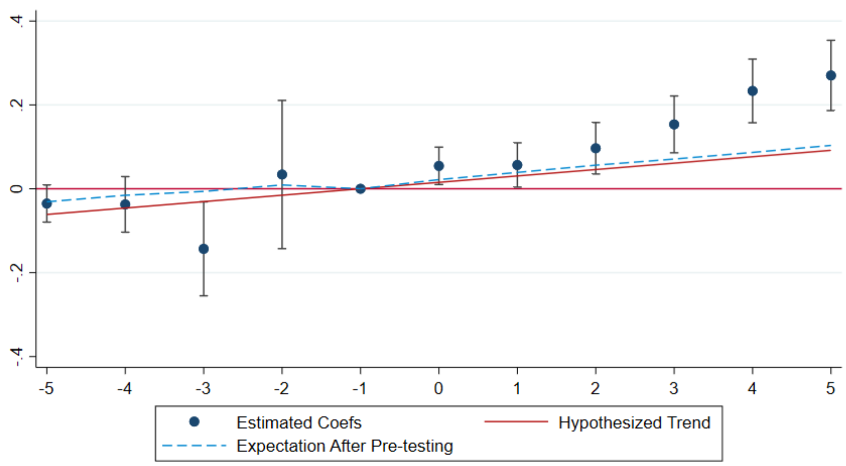
In Table B.1, we replicate the benchmark specification and robustness checks with the levels of ES rating and ENV and SOC sub-ratings, using a linear OLS regression.

B.2 Staggered and stacked estimation with all cohorts of the Shanghai and Shenzhen Connect programs

In this section, we pool all Connect firms of the Shanghai and Shenzhen programs together to estimate the causal effect of the Connect programs on various outcomes. We employ DD estimation with Connect firms as the treatment group and all other (non-Connect) firms traded on the exchange as the control group. Since inclusion in the Connect program is orthogonal to factors affecting ESG, the effect on the treatment relative



(a) ENV sub-rating



(b) SOC sub-rating

Note: Dots are point estimates and bars are 95% confidence intervals from the event study in Equation (2) estimated using PPML. Red-solid line is hypothetical trend estimated according to Roth (2022). Blue-dashed line represents the average point estimates conditional on not finding a significant pre-trend if the red-solid was the true line. Generated using the Stata "pretends" package.

Figure A.1
Event-study estimates for sub-ratings for Shanghai Connect program

to the control group is the causal effect of the Connect program on the outcome. We employ a parametric DD approach to allow for a differential time trend prior to the policy implementation relative to after

$$\begin{aligned} y_{ijt} &= \sum_{k\in\{SH,SZ\}} \left[\beta_0^k \mathbf{SC}_i^k \mathcal{T}_t^{2009} + \left(\beta_1^k + \beta_2^k \mathcal{T}_{it}^k + \left(\beta_3^k + \beta_4^k \mathcal{T}_{it}^k\right)\mathbf{SC}_i^k\right)\mathbf{D}_{it}^k\right] \\ &\quad + \left(\beta_5 + \beta_6 \mathcal{T}_{it}^E\right)\mathbf{E}_{it} + \gamma' X_{it} + \nu_{jt} + \alpha_i + \epsilon_{ijt}, \end{aligned} \tag{A1}$$

Table B.1

Effect of Shanghai Connect program on ES ratings and sub-ratings — linear estimation

	ES					ENV	SOC
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
$\mathbf{SC}_i \times \mathbf{D}_t$	1.061**	0.792	0.087		0.652	0.849	0.731
	(0.463)	(0.484)	(0.552)		(0.493)	(0.665)	(0.541)
$\mathbf{SC}_i \times \mathbf{D}_t \times \mathcal{T}_t$		0.837***	0.892***		0.778***	0.953***	0.711***
		(0.245)	(0.244)		(0.253)	(0.353)	(0.236)
$\mathbf{SC}_i \times \mathbf{D}_t \times SOE_i$				0.219			
				(0.544)			
$\mathbf{SC}_i \times \mathbf{D}_t \times POE_i$				1.097			
				(0.809)			
$\mathbf{SC}_i \times \mathbf{D}_t \times FOE_i$				-1.320			
				(2.605)			
$\mathbf{SC}_i \times \mathbf{D}_t \times \mathcal{T}_t \times SOE_i$				0.507*			
				(0.287)			
$\mathbf{SC}_i \times \mathbf{D}_t \times \mathcal{T}_t \times POE_i$				1.189***			
				(0.409)			
$\mathbf{SC}_i \times \mathbf{D}_t \times \mathcal{T}_t \times FOE_i$				1.213*			
				(0.671)			
$\mathbf{E}_{it}$	0.645	0.085	0.246	0.074	0.361	0.177	-0.013
	(0.547)	(0.569)	(0.568)	(0.562)	(0.602)	(0.889)	(0.454)
$\mathbf{E}_{it} \times \mathcal{T}_{it}^E$	-0.563**	-0.763***	-0.753***	-0.800***	-0.785***	-1.211***	-0.279
	(0.257)	(0.261)	(0.257)	(0.264)	(0.273)	(0.392)	(0.272)
Observations	5,083	5,083	5,083	5,083	4,815	5,083	5,083
R^2	0.809	0.813	0.816	0.814	0.816	0.742	0.852
Province ×Year FE	Y	Y	Y	Y	Y	Y	Y
Industry×Year FE	Y	Y	Y	Y	Y	Y	Y
SOE×Year FE	Y	Y	Y	Y	Y	Y	Y
FOE×Year FE	Y	Y	Y	Y	Y	Y	Y
"Sin"-Stock×Year FE	Y	Y	Y	Y	Y	Y	Y
Firm Char	Y	Y	Y	Y	Y	Y	Y
Firm Char×$\mathbf{D}_t$	N	N	Y	N	N	N	N

Note: Selected coefficients from estimating a linear version of Equation (3) with different dependent variables. $\mathbf{SC}_i$ is an indicator set to one if firm i is the first cohort of firms in Shanghai Connect program and stays in the program at least two years and zero otherwise. $\mathbf{D}_t$ is an indicator variable set to one beginning in 2015 and zero before. $\mathbf{E}_{it}$ is an indicator variable set to one beginning in yer t if firm i exits the Connect program in year t after having previously entered, and zero otherwise. $\mathcal{T}_t$ measures the number of years since 2015. $\mathcal{T}_{it}^E$ equals the number of years since a treatment firm exits either program, if it did so, and zero otherwise. Columns 1 through 5 estimate with ES rating as the dependent variable, Column 6 with the ENV sub-rating, and Column 7 with the SOC sub-rating. All columns use OLS regressions. Standard errors clustered by firm are in parentheses. $***\ p < 0.01$, $**\ p < 0.05$, $*\ p < 0.1$.

where y_{ijt} is the outcome of interest including the annual ESG rating and sub-ratings for firm i in industry j in year t. $\mathbf{SC}_i^k$ is as defined earlier – an indicator set to one if firm i is in program k in any year. $\mathbf{D}_{it}^k$ is an indicator variable set to one if policy k is in effect for firm i in year t. For non-Connect firms, this is set to one after the Connect programs begin (2015 for Shanghai and 2017 for Shenzhen) and zero before. For Connect firms this equals one beginning in the year they join the Connect program and zero before. $\mathbf{E}_i$ is an indicator variable set to one in all years t after firm i exits a Connect program after having previously entered. β_1^k captures any level shift with the commencement of program k while β_3^k captures any level shift for the Connect relative to the non-Connect firms. β_5 captures any level shift for firms leaving either program relative to being in the program.

$\mathcal{T}_{it}^{2009}$ is equal to the number of years since 2009. $\mathcal{T}_{it}^{k}$ is equal to the number of years since policy k is in effect for firm i. For firms that never join a program, it equals the number of years since the Connect program began (2015 for Shanghai and 2017 for Shenzhen) and zero before. For firms that join a program it equals the number of years since they joined and zero otherwise. $\mathcal{T}_{it}^{E}$ is equal to the number of years since a Connect firm exited program k, if it does so, and zero otherwise. β_0^k captures any differential time trend for Connect firms under program k over the entire sample period (the industry-by-year fixed effects capture the baseline trends). β_2^k captures any change in trend when policy k begins while β_4^k captures the relative change in trend for Connect firms once the policy begins. β_6 captures any change in trend for firms leaving either program relative to the trend under the program.

X_{it} includes controls that may affect ESG ratings. This includes province fixed effects that capture unobservables common to a province and firm financial characteristics described in Section 3.3. Industry-by-year fixed effects (ν_{jt}) capture industry-specific unobservables by year that influence ESG ratings. Firm fixed effects (α_i) capture time-invariant, firm-specific unobservables that affect ESG ratings.

This is a staggered DD estimation – effects are identified by both cross-sectional and time series variation. Cross-sectionally, some firms qualified for Connect while others did not for reasons unrelated to ESG ratings. Dynamically, the Shanghai and Shenzhen programs were implemented in different years. Additional time series variation is provided by firms entering and exiting the Connect programs at different times as they gained or lost qualification, again for reasons unrelated to their ESG ratings.

Table B.2 presents the point estimates of Equation (A1). In the staggered estimation, firms that joined the Connected program between 2015 and 2017 are selected as the treatment group, while firms that never joined or joined after 2020 serve as the control group. The sample period spans from 2009 to 2020. As shown in Columns (1) through (3), our main results from the estimation of the benchmark model are robust, with coefficients similar in scale to those in the benchmark case.

We then estimate Equation (A1) using the stacked method (Cengiz, Dube, Lindner and Zipperer, 2019). Specifically, we treat firms that joined the Connect program in a particular year as a cohort of the treatment group, while firms that never joined or joined after 2020 serve as the control group. Observations for each cohort are truncated five years before and after the event year, stacked together, and the cohort fixed effects are

Table B.2

Robustness check with all cohorts of Shanghai and Shenzhen Connect firms

	Staggered DD Estimation			Stacked DD Estimation		
	ES (1)	**ENV** (2)	**SOC** (3)	**ES** (4)	**ENV** (5)	**SOC** (6)
$\mathbf{SC}_i^{SH} \times \mathbf{D}_{it}^{SH}$	0.077	0.317**	0.003	0.044	0.225**	-0.018
	(0.058)	(0.138)	(0.046)	(0.037)	(0.090)	(0.030)
$\mathbf{SC}_i^{SH} \times \mathbf{D}_{it}^{SH} \times \mathcal{T}_{it}^{SH}$	0.084***	0.160**	0.050**	0.063***	0.105**	0.035**
	(0.029)	(0.063)	(0.024)	(0.020)	(0.045)	(0.016)
$\mathbf{SC}_i^{SZ} \times \mathbf{D}_{it}^{SZ}$	0.050	0.098	-0.002	0.022	0.064	-0.027
	(0.047)	(0.123)	(0.032)	(0.026)	(0.069)	(0.016)
$\mathbf{SC}_i^{SZ} \times \mathbf{D}_{it}^{SZ} \times \mathcal{T}_{it}^{SZ}$	0.032	0.009	0.026	0.020	-0.001	0.015
	(0.024)	(0.052)	(0.018)	(0.014)	(0.030)	(0.010)
$\mathbf{E}_{it}$	-0.063*	-0.081	-0.043*	-0.070***	-0.089**	-0.048***
	(0.036)	(0.074)	(0.025)	(0.020)	(0.042)	(0.014)
$\mathbf{E}_{it} \times \mathcal{T}_{it}^{E}$	-0.041*	-0.102*	-0.003	-0.040***	-0.092***	-0.002
	(0.024)	(0.058)	(0.017)	(0.013)	(0.033)	(0.009)
Observations	9,048	9,048	9,048	24,561	24,561	24,561
Pseudo R^2	0.450	0.598	0.374	0.446	0.595	0.367
Province ×Year FE	Y	Y	Y	Y	Y	Y
Industry×Year FE	Y	Y	Y	Y	Y	Y
SOE×Year FE	Y	Y	Y	Y	Y	Y
FOE×Year FE	Y	Y	Y	Y	Y	Y
"Sin"-Stock×Year FE	Y	Y	Y	Y	Y	Y
Firm Characteristics	Y	Y	Y	Y	Y	Y

Note: Selected coefficients from estimating Equation (A1). $\mathbf{SC}_i^k$ is an indicator set to one if firm i is in program k in any year. $\mathbf{D}_{it}^k$ is an indicator variable set to one if the policy is in effect for firm i in year t for program k. For Shanghai (Shenzhen) control firms this equals one in 2015 (2017) and later and zero otherwise. For treatment firms this equals one in the years after they join the Connect program and zero before. $\mathbf{E}_i$ is an indicator variable set to one if firm i exits either of the Connect programs in year t after having previously entered. $\mathcal{T}_{it}^k$ measures the number of years firm i has been subject to policy k. For Shanghai (Shenzhen) control firms it equals the number of years since 2015 (2017) and zero before. For treatment firms it equals the number of years since joining program k and zero before.$\mathcal{T}_{it}^E$ equals the number of years since a treatment firm exits either program if it did so and zero otherwise. In Column (4) through (6), the stacked method is applied (Cengiz, Dube, Lindner and Zipperer, 2019). All columns use PPML estimation. Standard errors clustered by firm from Column (1) through (3) and by firm by cohort from Column (4) through (6) are in parentheses. $***\ p < 0.01$, $**\ p < 0.05$, $*\ p < 0.1$.

interacted with all other fixed effects to account for repeated observations. Columns (4) through (6) in Table B.2 report these point estimates, with standard errors clustered by firm and cohort. Our main results remain robust.

B.3 Robustness checks — staggered DD estimation of Connect programs' effects using initial cohorts of Shanghai and Shenzhen programs

Here we perform additional robustness checks of the appropriateness of the staggered DD estimation using initial cohorts of both the Shanghai and Shenzhen Connect programs. Figure B.1 displays the results of applying the method proposed by de Chaisemartin and d'Haultfoeuille (2023) on the ES rating. There is no discernible trend prior to firms joining a Connect program, but a significant upward trend after the policy takes effect.

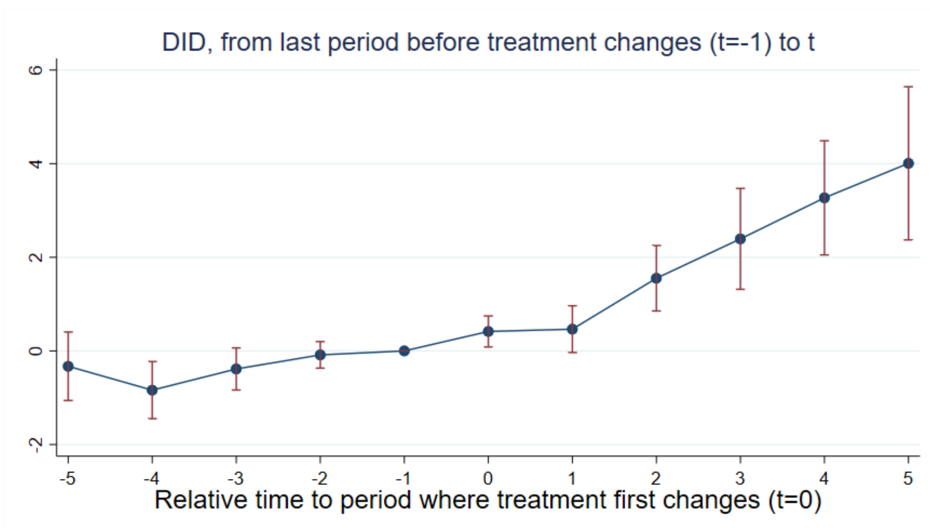
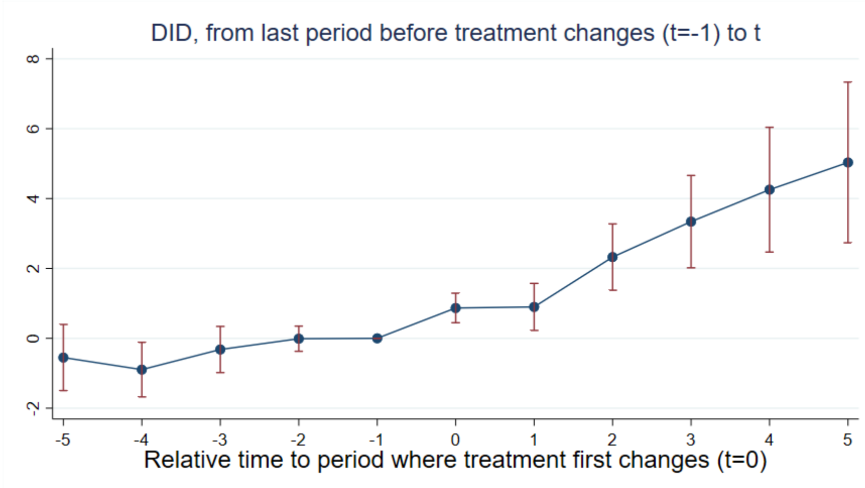


Figure B.1
Average effects for ES rating using method in de Chaisemartin and d'Haultfoeuille (2023)

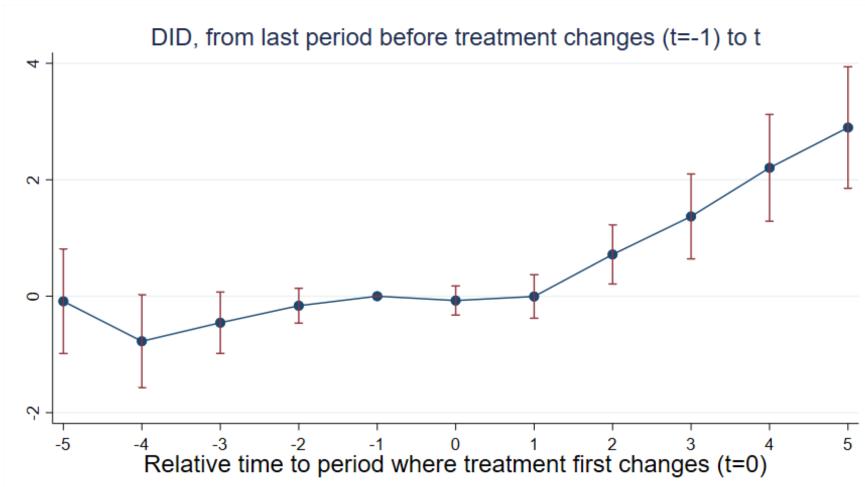
Figure B.2 applies the same method to the ENV and SOC sub-ratings. For both, there is no discernible trend prior to joining a Connect program, but a significant upward trend after the policy takes effect.

Since Table 1 shows that some characteristics of connect and unconnected firms are statistically different, we perform the estimation method as in Callaway and Sant'Anna (2021), who propose a doubly robust DD estimator based on stabilized inverse probability weighting. As shown Figure B.3, our results are robust.

Figure B.4 displays results of applying the method proposed by Sun and Abraham (2021) to the ENV and SOC sub-ratings. There is no discernible trend prior to firms joining a Connect program, but a significant upward trend after the policy takes effect.



(a) ENV sub-rating



(b) SOC sub-rating

Figure B.2
AVERAGE EFFECTS FOR SUB-RATINGS USING METHOD IN DE CHAISEMARTIN AND D'HAULTFOEUILLE (2023)

B.4 OLS estimation of mechanisms

We separately estimate equations (4a) and (4b) via ordinary least squares (OLS) using the same sample as that used in the 2SLS estimation (Table 5). The results, presented in Table B.3, indicate that the coefficients are of the same sign as those in the 2SLS estimation but are lower in magnitude. This indicates that there are significant correlations between the exogenous control variables and the endogenous variables.

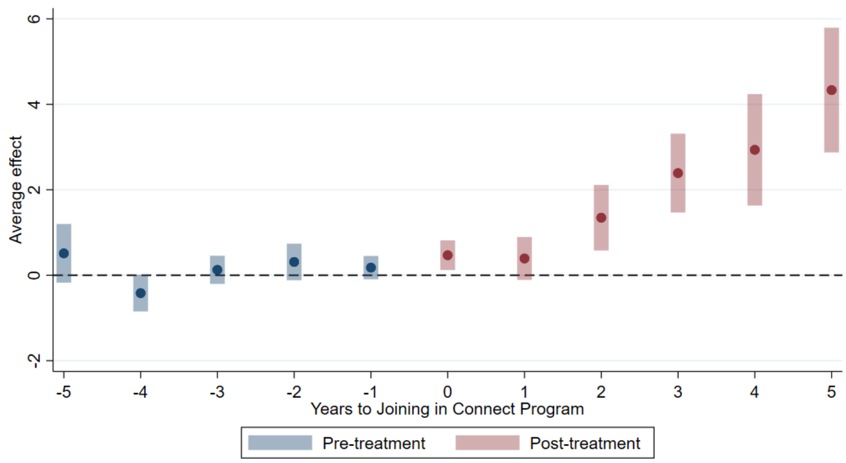


Figure B.3
AVERAGE EFFECTS FOR ES USING METHOD IN CALLAWAY AND SANT'ANNA (2021)

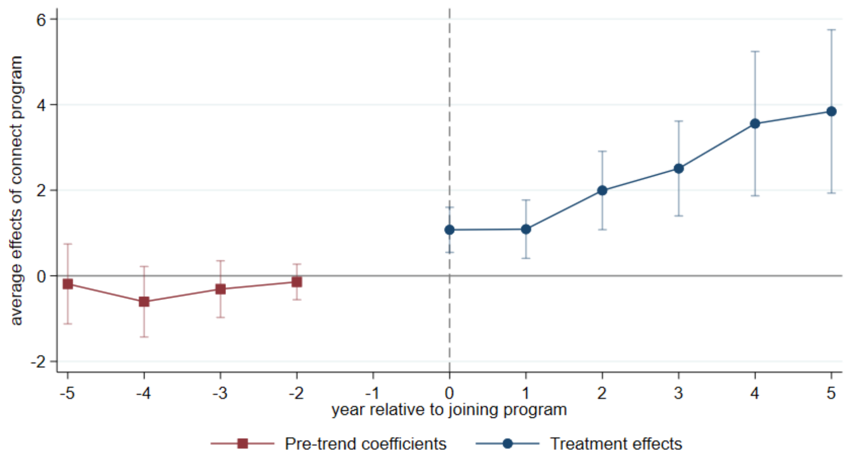
Table B.3
OLS ESTIMATION OF MECHANISMS: SYSTEM OF EQUATIONS

	NB share$_{itq}$ (1)	log(**ES**$_{it}$) (2)
log($\mathbf{ES_{i,t-1,q}}$)	0.003**	
	(0.002)	
NB share$_{i,t-1}$		2.219*
		(1.279)
Obs	6,760	2,447
R^2	0.849	0.874
Province ×Year (Year-Quarter) FE	Y	Y
Industry×Year (Year-Quarter) FE	Y	Y
SOE×Year (Year-Quarter) FE	Y	Y
FOE×Year (Year-Quarter) FE	Y	Y
"Sin"-Stock×Year (Year-Quarter) FE	Y	Y
Firm Characteristics	Y	Y

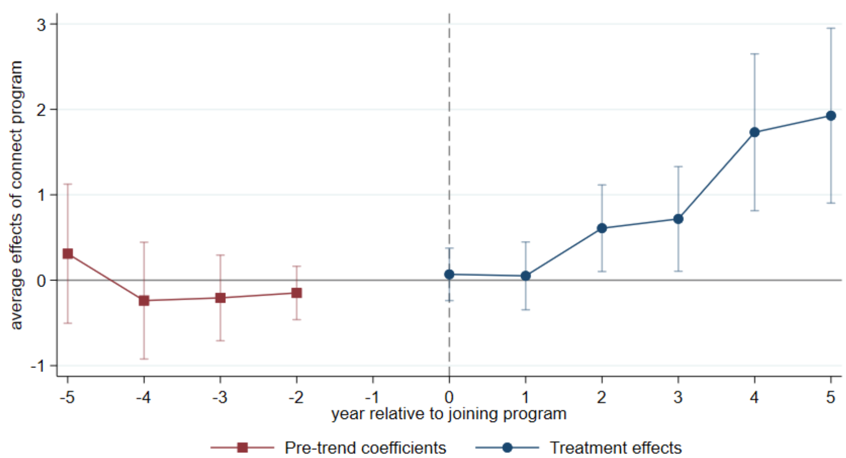
Note: Equations (4a) and (4b) estimated using OLS. The sample is the same as that used in the 2SLS estimation in Table 5 in the main text.

B.5 Event study for stock price reaction to environmental policy

Figure B.5 shows the coefficients and 95% confidence intervals for the stock-price event study in Equation (6) of the main text. Estimation uses 24 months of data before and after the environmental policy change and includes all stocks on the SSE and SZSE.



(a) ENV sub-rating

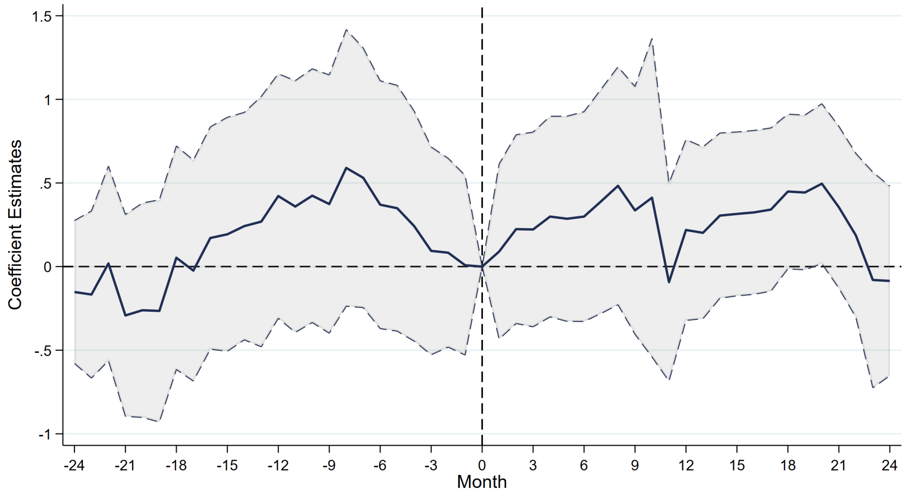


(b) SOC sub-rating

Figure B.4
AVERAGE EFFECTS FOR SUB-RATINGS USING METHOD IN SUN AND ABRAHAM (2021)

B.6 Relevance of the environmental policy instrument

In order to examine the relevance of the environmental policy, we estimate Equation (7) with the ENV and SOC sub-ratings as dependent variables. Since 743 firm-year observations out of 4,577 are zero for the ENV sub-rating, we apply PPML. The results are shown in Table B.4. As expected, the environmental regulation has a strong effect on the ENV sub-rating both statistically and in magnitude (82.2%) but no significant effect on the SOC sub-rating.



Note: Solid lines are point estimates and shaded area 95% confidence intervals from the event study in Equation (6).

Figure B.5
Event study for stock price effects from environmental policy

Table B.4
Response of ENV and SOC sub-ratings to environmental policy change

	ENV	SOC
$C_i \times \mathbf{P}_{it}$	0.600***	0.050
	(0.156)	(0.046)
Obs	4,577	4,577
Psuedo R^2	0.781	0.831
F Statistic	14.76	1.18
Province ×Year-Quarter FE	Y	Y
Industry×Year-Quarter FE	Y	Y
SOE×Year-Quarter FE	Y	Y
FOE×Year-Quarter FE	Y	Y
"Sin"-Stock ×Year-Quarter FE	Y	Y
Firm Characteristics	Y	Y

Note: Equation (7) estimated with PPML. The sample data are from 2013 to 2021 and include both Connect and non-Connect firms in all periods. $***\ p < 0.01$, $**\ p < 0.05$, $*\ p < 0.1$.

B.7 Suggestive evidence for exclusion restriction of $\mathbf{N}^2_{itq}$

This section provides suggestive evidence that the instrument $\mathbf{N}^2_{itq}$ in Section 6.3 affects ES ratings only through northbound shareholdings. Since this analysis relates elapsed time in the program to ES ratings, annual data must be used. As a result, we employ a more parsimonious nonlinear function (log of elapsed years) than the square of elapsed quarters used in our 2SLS estimation (the linear trend in ES ratings is absorbed by the year fixed effects).[41] We estimate:

$$\log \mathbf{ES}_{it} = \beta_1 \log \mathbf{N}_{it} + \left(\beta_2 + \beta_3 \mathcal{T}^{E}_{it}\right)\mathbf{E}_{it} + \gamma' X_{it} + \omega_i + \nu_t + \epsilon_{it}, \tag{A2}$$

where $\log \mathbf{ES}_{it}$ is the logarithm of annual ES rating for firm i in year t. $\mathbf{N}_{it}$ is the number of years since the Connect program began. For the Shanghai program this is the number of years since 2015 and for the Shenzhen program the number of years since 2017. $\mathbf{E}_i$ is an indicator set to one in all years t after firm i exits a Connect program, if it does so, after having previously entered and zero otherwise. $\mathcal{T}^{E}_{it}$ is equal to the number of years since a Connect firm exited a program, if it does so, and zero otherwise. X_{it} includes controls that may affect ES ratings including firm financial characteristics described in Section 3.3 as well as firm-characteristic-by-year fixed effects (industry-by-year, province-by-year, SOE-by-year, FOE-by-year, and "sin"-stock-by-year fixed effects) that capture time-varying industry, province, SOE, FOE, and "sin"-stock effects. Firm fixed effects (ω_i) capture time-invariant, firm-specific unobservables that affect ES ratings. We display a year fixed effect (ν_t) to indicate that this is a two-way fixed effect estimator, even though the firm-characteristic-by-year fixed effects absorb these. This analysis utilizes data from 2017 to 2021, consistent with the time frame used in Section 6.3.

The first two columns of Table B.5 estimate Equation (A2) for the first cohort of firms in the Shanghai Connect program. Column (1) uses the contemporaneous elapsed time, while Column (2) uses the lagged value (the 2SLS estimates employ lagged values of northbound shareholdings). Both specifications show that log ES ratings are increasing and concave in the elapsed time since firms entered the Connect program. Columns (3) and (4) repeat these estimates for the first cohort of firms in the Shenzhen Connect program. The results are similar, again showing an increasing and concave effect of elapsed time on annual ES ratings.

Columns (5) and (6) of Table B.5 estimate the following equation for non-Connect firms on the Shanghai and Shenzhen stock exchanges:

$$\log \mathbf{ES}_{it} = (\beta_{1a}\mathbf{SSE_i} + \beta_{1b}\mathbf{SZSE_i}) \times \log \mathbf{N}_{it} + \left(\beta_2 + \beta_3 \mathcal{T}^{E}_{it}\right)\mathbf{E}_{it} + \gamma' X_{it} + \omega_i + \nu_t + \epsilon_{it}, \tag{A3}$$

where $\mathbf{SSE_i}$ and $\mathbf{SZSE_i}$ are indicators distinguishing firms on the Shanghai and Shenzhen stock exchanges. Column (5) of Table B.5 estimates this equation using contemporaneous values for elapsed time ($\mathbf{N}_{it}$ is set to the number of years since 2015 for Shanghai exchange

[41] The square of elapsed years also has an insignificant effect on log ES ratings for non-Connect firms.

firms and since 2017 for Shenzhen exchange firms). β_{1a} and β_{1b} are both insignificant. Column (6) repeats this estimation using lagged elapsed time. Both coefficients are again insignificant for firms on both exchanges.

Overall, these results are consistent with log ES ratings being increasing and concave with respect to elapsed time in the program for Connect firms. In contrast, log ES ratings for non-Connect firms display no nonlinear effects with respect to elapsed time in the program. This provides suggestive evidence that elapsed time exerts nonlinear effects on log ES ratings via northbound shareholdings but not directly.

Table B.5

Suggestive evidence for exclusion restriction of $\mathbf{N}^2_{itq}$

	SSE-Connect Firms		SZSE-Connect Firms		Non-Connect firms	
	(1)	(2)	(3)	(4)	(5)	(6)
$\log \mathbf{N}_{it}$	0.149***		0.105***			
	(0.055)		(0.036)			
$\log \mathbf{N}_{i,t-1}$		0.167***		0.133***		
		(0.057)		(0.046)		
$\mathbf{SSE}_i \times \log \mathbf{N}_{it}$					-0.386	
					(0.609)	
$\mathbf{SZSE}_i \times \log \mathbf{N}_{it}$					-0.361	
					(0.308)	
$\mathbf{SSE}_i \times \log \mathbf{N}_{i,t-1}$						0.488
						(0.935)
$\mathbf{SZSE}_i \times \log \mathbf{N}_{i,t-1}$						0.131
						(0.445)
Obs	2,439	1,949	2,522	1,940	1,056	843
R^2	0.920	0.950	0.925	0.957	0.938	0.957
Province ×Year FE	Y	Y	Y	Y	Y	Y
Industry×Year FE	Y	Y	Y	Y	Y	Y
SOE×Year FE	Y	Y	Y	Y	Y	Y
FOE×Year FE	Y	Y	Y	Y	Y	Y
"Sin"-Stock×Year FE	Y	Y	Y	Y	Y	Y
Firm Characteristics	Y	Y	Y	Y	Y	Y

Note: Columns (1) through (4) estimate Equation (A2). Columns (1) and (2) include the initial cohort of Shanghai Connect firms while Columns (3) and (4) include the initial cohort of Shenzhen Connect firms. Columns (5) and (6) estimate Equation (A3) and include non-Connect firms on both the Shanghai and Shenzhen stock exchanges. All columns employ OLS estimation and use data from 2017 to 2021. Standard errors clustered at the firm level are shown in parentheses. $***\ p < 0.01$, $**\ p < 0.05$, $*\ p < 0.1$.