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

V. Brian Viard Gang Zhang

January 15, 2024

Abstract

We examine the causal effect of foreign ownership on publicly-listed firms' environmental and social (ES) performance in an emerging market. Increased foreign ownership of Chinese firms under the Shanghai and Shenzhen Stock Connect programs increases firms' ES performance. For mechanisms, we find causal evidence consistent with both foreign investors influencing firms to increase ES performance and firms improving performance to signal trustworthiness to foreign investors. Improved ES performance and increased foreign shareholding are therefore self-reinforcing, and exogenous changes in either have long-run effects that exceed short-run by about **77%**.

Keywords: corporate social responsibility, financial deregulation, social norms, emerging markets

JEL Classifications: G15, G23, G30, M14, F21

*V. Brian Viard, Cheung Kong GSB, email: brianviard@ckgsb.edu.cn; Gang Zhang, Cheung Kong GSB, email: gzhang@ckgsb.edu.cn. We thank Hongyi Chen, Joy Chen, Wei Guo, Zhao Jin, KC Kwok, Paul Luk, Chang Ma, Pedro Matos, Giorgio Valente, Li Zhao, Ling Zhong, participants to the seminar at HKIMR, and an anonymous reviewer for helpful comments and suggestions. We thank Jing Zhang for excellent research assistance. This paper was developed while Zhang visited HKIMR. Zhang gratefully acknowledges financial support from Hong Kong Institute for Monetary and Financial Research and the ASEAN Business Research Initiative.

1 Introduction

Socially responsible investing, in which investors respond positively to firms' corporate social responsibility (CSR) performance and propel firms to invest in these outcomes, represents a fast-growing portion of capital market investments (Hong and Kacperczyk, 2009; Chava, 2014; Dimson *et al.*, 2015; McCahery *et al.*, 2016; Lins *et al.*, 2017; Dyck *et al.*, 2019; Krueger *et al.*, 2020; Chen *et al.*, 2020; Azar *et al.*, 2021). Studies in this literature have focused almost entirely on advanced economies.[1] Examining the CSR performance of emerging market firms is important because in 2021 they represented 86% of the world's population (WEO, 2022) and produced two-thirds of global greenhouse gas emissions (IEA, 2021). For emerging markets, it is particularly important to examine the influence of foreign investment, as it may exert more pressure than domestic investment when interest in CSR is greater in the source country (Ferreira and Matos, 2008; Aggarwal *et al.*, 2011). If foreign investors are influential, it is also important to understand the underlying reasons to inform relevant policies.

We take advantage of loosening capital controls, a policy more common in emerging than advanced markets, to identify the causal effect of foreign investment on CSR in an emerging market.[2] We focus on the advent of the Shanghai and Shenzhen Connect programs, which expanded Hong Kong/foreign (HKF) investment in China. This is an attractive setting to test foreign ownership influence. 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.

To avoid problems arising from staggered DD estimation, we focus first on the initial cohort of Shanghai Connect firms. Joining the program has a positive causal impact on firms' Environmental and Social (ES) performance, two important components of CSR.[3] 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. These effects are heterogeneous. After the program begins, private-owned enterprises (POEs) experienced the fastest rise in ES rating (12.3% per year). ES 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

[1] An exception is Cheong *et al.* (2023), as described later.

[2] Occasionally, developed-county governments may implement capital controls to address specific economic challenges. For example, during the 2008 global financial crisis, Iceland and Cyprus temporarily imposed some capital controls and restrictions on financial transactions to stabilize their financial systems.

[3] Following Dyck *et al.* (2019) and He *et al.* (2023a), we focus on environmental and social sub-ratings and construct an ES rating with equal weights. All results hold if we also include the governance sub-rating.

significantly change, perhaps because foreign influence began prior to the Connect program. We then extend our analysis by adding the initial cohort of firms in the Shenzhen Connect program using methods robust to staggered DD. The effects on ES performance are similar to those for the Shanghai Connect program.

The ES increases likely reflect actual improvements, 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 distortions in ratings resulted from conflicts of interest for the rating agency. Inclusion in the Connect program also significantly affects independent, direct measures of environmental outcomes; evidence that the effects are not due to "greenwashing". Connect firms reduced their carbon emissions and filed more applications for "green" patents relative to non-Connect firms after joining. Since being in the Connect programs depended on inclusion in stock indexes, index inclusion itself may have increased ES performance.[4] To address this, we exclude firms added to the index when the Connect program begins and the results remain.

Having found significant effects on ES performance, we investigate possible mechanisms. We consider the two predominant theories, which are not mutually exclusive: firm signaling and investor influence. The signaling theory (Lins *et al.*, 2017) argues that firms invest in ES as a signal to investors of their trustworthiness, to maintain investor confidence in times of crisis. If so, 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. The influence theory (Aggarwal *et al.*, 2011; Dyck *et al.*, 2019; Chen *et al.*, 2020) argues that foreign investors exert pressure on firms to invest in ES performance because they intrinsically value it. In the context of the Connect program, either or both of these theories could apply. We substantiate that foreign investors in China care more about ES performance than domestic. This means that increased foreign ownership under the Connect program could both increase the signaling value of investing in ES performance and increase foreign-investor influence on ES performance.

Lins *et al.* (2017) find empirical evidence of the signaling theory by examining stock

[4]Some studies examine the effect of index inclusion on ES performance with mixed results. Chen *et al.* (2020) utilize the Russell Index reconstitution and find that firms with an exogenous increase in institutional ownership improved their CSR performance. On the contrary, Cheong *et al.* (2023) find that inclusion in the MSCI Emerging Market and China indexes increases both output and emissions of emerging-market firms, but that the latter increases more.

returns of firms with different ex-ante ES performance after the 2008 financial crisis and the Enron/Worldcom scandals. Dyck *et al.* (2019) find empirical evidence for the influence theory by examining the response of an ES index to foreign ownership. We examine the simultaneous effects of both theories.[5] To disentangle them, we take advantage of the different directions of causality: ES performance increases foreign shareholdings under the signaling theory; while under the influence theory, the reverse occurs. We identify instrumental variables that exogenously shift ES ratings and foreign ownership, respectively, to eliminate the simultaneity bias and estimate causal effects.

To identify the role of signaling, we use the change in firms' environmental performance under a major regulatory change as an instrument for ES ratings. We provide evidence that this instrument is relevant and strong, and find that 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 a 18.1% increase in average northbound shareholdings. To identify the role of influence, we use a quadratic function of the elapsed time since joining a Connect program as an exogenous shock to northbound shareholding. We provide evidence that elapsed time has nonlinear effects on ES ratings for Connect firms, but not for non-Connect firms, consistent with nonlinear effects of foreign investors on ES performance over time. A one percentage point increase in northbound shares increases ES ratings in the following year by 22.3%. These findings are consistent with a role for both mechanisms and suggest that firms' investments in ES performance and foreign ownership are self-reinforcing — an exogenous increase in either will lead to long-term effects that are 77% greater than short-run.

Our results contribute to three strands of literature. First, we specifically add to previous findings on why firms invest in ES performance. One rationale is that firms do so to signal trustworthiness to foreign investors. Our results complement Lins *et al.* (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. An alternative rationale is that foreign investors value ES performance more than domestic investors and exert pressure on domestic firms to improve. Consistent with Aggarwal *et al.* (2011), Dyck *et al.* (2019), and Chen *et al.* (2020), we find that higher foreign ownership increases future ES performance. We contribute to this strand of literature by examining the simultaneous influence of both theories. Since

[5] To increase the time-series variation in the data, we combine data from the Shanghai and Shenzhen Connect programs in the mechanism analysis.

the two are self-reinforcing, accounting for both allows quantification of the long-run effects, inclusive of feedback, of an exogenous increase in either ES ratings or northbound shareholdings.

The second strand of literature investigates the effects of financial liberalization and deregulation on economic growth.[6] Empirical findings vary with country characteristics. Countries with stronger institutions, more-developed financial markets, and higher initial incomes are more likely to obtain larger capital inflows, higher investment and growth, and lower volatility of both consumption and capital inflows (King and Levine, 1993; Jayaratne and Strahan, 1996; Rajan and Zingales, 1998; Beck *et al.*, 2000; Ranciere *et al.*, 2008; Levchenko *et al.*, 2009; Gennaioli *et al.*, 2014; Broner and Ventura, 2016). Our paper documents an additional channel by which foreign capital affects real activity and influences the domestic market's social norms. Although China is usually viewed as an economy with weak institutions and less-developed financial markets, we find significant improvement in ES performance after the Connect programs commence.

The third strand of literature is studies that examine the development of China's financial system and its role in economic growth.[7] He and Wei (2022) identify three channels by which China's stock market supports its real economy: price information, liquidity from share pledging, and current account liberalization. Ma *et al.* (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 *et al.* (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 *et al.* (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 *et al.*, 2019; Lundblad *et al.*, 2022; Bian *et al.*, 2023; He *et al.*, 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

[6]See Levine (2005), Prasad *et al.* (2007), Obstfeld (2009), and Kose *et al.* (2010) for thorough surveys.

[7]Allen *et al.* (2017), Carpenter and Whitelaw (2017), Song and Xiong (2018), Allen *et al.* (2019a), and He and Wei (2022) provide thorough surveys.

explains the empirical strategy and Section 5 presents the results. Section 6 provides evidence for two main mechanisms and Section 7 concludes.

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.[8]

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

[8] 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.

SSE or SZSE. Northbound trading – that conducted by HKF investors – was open to all eligible individual and institutional investors.[9]

The SZSE and SSE instituted other initiatives concerning CSR, but their starting times did 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.

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).[10] 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 trad-

[9]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/Clearing/Securities/Overview/Clearing-Services?sc_lang=en.

[10]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.

ing volume) unrelated to firms' ES ratings (details are in Appendix A.1). Each index is 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.[11]

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. 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.[12] 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. 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 *et al.* (2019) and He *et al.* (2023a), we focus on environmental and social sub-ratings and construct an ES rating using a simple average of the two.[13] The Bloomberg ESG database covers more than 11,800 companies worldwide, comprising 88% of global equity market capitalization.[14] As of the end of 2021, 1,549 Chinese firms listed on the SSE or SZSE had ever been rated.

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

[12] The results are robust to assigning based on the latter half of the year.

[13] All results are robust to using the ESG score instead.

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

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 *et al.* (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). Thus, the data is 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.[15] 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).[16] We construct financial variables following Allen *et al.* (2019b) and Ma *et al.* (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. 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 identification approach. The two groups do not differ in age, proportion of SOEs, sales growth, or cash flows.

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

[15] We test robustness to one- and three-year duration, and the results are very similar.

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

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 *et al.* (2019b) and Ma *et al.* (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.

available until 2018, we use industry-level emissions and assign emissions to each firm based on the fraction of their revenue in each industry.[17] 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, geother-

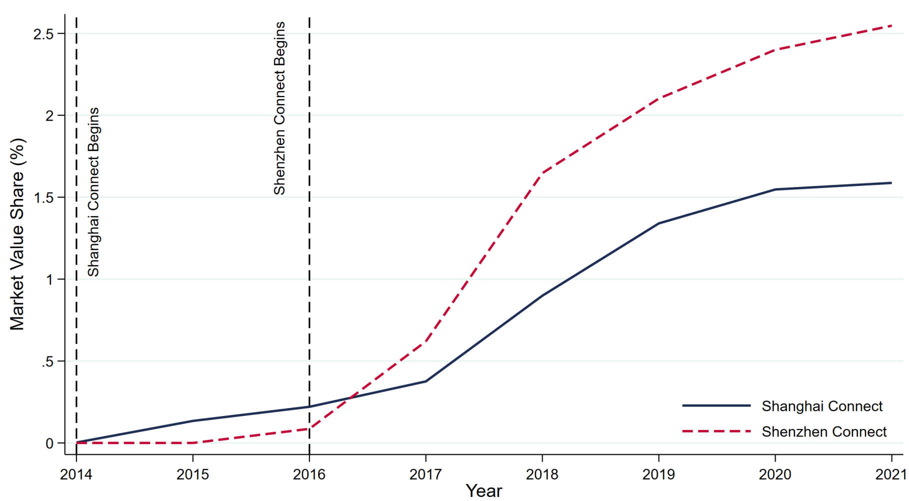
[17]Data from *China Energy Statistical Yearbook*.

mal 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

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 trading volume, HKF investors may play an out-sized role relative to domestic investors because foreign investors are more influential – strongly predicting future stock returns (Jones *et al.*, 2020; Lundblad *et al.*, 2022; He *et al.*, 2023b) and their trading volume being negatively correlated with stock volatility (Bian *et al.*, 2023).



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 total market capital capitalization of the SSE and SZSE respectively.

Figure 1
Market value share of HKF shareholdings through Connect programs

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. 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 the ESG ratings retroactively. This eliminates 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. Such conflicts have occurred in other settings: Bolton *et al.* (2012) argue that bond rating agencies inflated ratings to compete in rating-shopping prior to the subprime mortgage crisis.

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, Appendix A.3 shows the results of estimating

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

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) show 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 by Morgan Stanley Capital International. 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 A.1 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

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

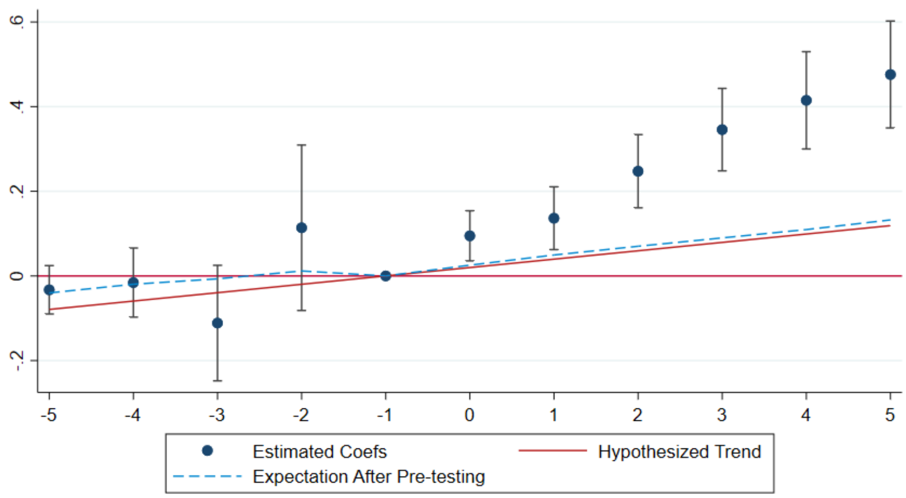
where we use the ES rating and the two sub-ratings as the dependent variables. r counts the number of years since 2014. $\mathbf{1}_{irt}$ is a dummy variable set equal to one if firm i in year t is r years relative to the beginning of the program and zero otherwise. $\mathbf{D}_{it}^{pre,5}$ ($\mathbf{D}_{it}^{post,5}$) 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.

The ES score contains zeros in the early years.[18] Silva and Tenreyro (2006), Cohn *et al.* (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.[19] Figure 2 plots the β_r coefficients estimated with ES as the dependent variable along with 95% confidence

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

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

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.



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

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 finding a significant pre-trend if the true trend was the hypothesized red line.[20] 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.

[20] 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.

4.2 Econometric specification

We employ a DD approach to estimate the Connect program's causal effect on various outcomes. 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 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 *et al.* (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 2). Joining the Connect program increases a firm's ES rating by 14.1% on average post-policy.[21] When firms exit, their ES ratings do not experience a 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. The effect upon exiting (-9.2%) equals 0.57, evaluated at the mean in 2013. These results indicate that the Connect program led to increased ES ratings for firms, and that these increases began reversing if a firm left the program.

Since inclusion in the Connect program is associated with financial characteristics, Column 3 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 after the Connect program begins. The results are similar to those in the benchmark specification. Columns 4 and 5 repeat the benchmark regressions 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.[22]

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

[22] In unreported regressions, 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 were 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 *et al.*, 2019).

Table 2
Effect of Shanghai Connect program on ES ratings and sub-ratings

	ES			ENV	SOC
	(1)	(2)	(3)	(4)	(5)
$\mathbf{SC}_i \times \mathbf{D}_t$	0.132***	0.151***	0.141**	0.349**	0.095**
	(0.048)	(0.057)	(0.070)	(0.136)	(0.046)
$\mathbf{SC}_i \times \mathbf{D}_t \times \mathcal{T}_t$		0.109***	0.118***	0.182***	0.072***
		(0.027)	(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	5,066	5,083	5,083
Psuedo R^2	0.451	0.453	0.455	0.634	0.397
Province ×Year FE	Y	Y	Y	Y	Y
Industry×Year FE	Y	Y	Y	Y	Y
SOE×Year FE	Y	Y	Y	Y	Y
FOE×Year FE	Y	Y	Y	Y	Y
"Sin"-Stock×Year FE	Y	Y	Y	Y	Y
Firm Characteristics	Y	Y	Y	Y	Y
Firm Characteristics×$\mathbf{D}_t$	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 3 estimate with ES rating as the dependent variable, Column 4 with the ENV sub-rating, and Column 5 with the SOC sub-rating. All columns use PPML estimation. Standard errors clustered by firm are in parentheses. $***$ $p < 0.01$, $**$ $p < 0.05$, $*$ $p < 0.1$.

5.2 Heterogeneity, robustness, and validation checks

Column 1 of Table 3 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 *et al.* (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 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.

Bloomberg's ES ratings are 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. The first independent outcome is carbon emissions, as described in Section 3.4. We estimate a linear version of the benchmark model (Equation 3) with the log of annual firm-level emissions as the dependent variable. Column 3 reports the results for total emissions, and Column 4 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 5 reports estimates with applications of "green" patents, as described in Section 3.4, in a firm-year as the dependent variable. In the year the Connect program commences, treatment firms increase "green" invention patents by 3.5 (0.34 standard deviations) relative to non-Connect firms. In subsequent years, Connect firms increase the number of patents by 2.7 (0.26 standard deviations) per year more than non-Connect firms.

5.3 Including the Shenzhen Connect program

Our examination of 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 on 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 *et al.* (2022) show that staggered DD estimation may bias estimates because later-treated units are compared to a combination of earlier-treated units and the control group, potentially resulting in signs opposite of the true average effect.[23] 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 lit-

[23] Roth *et al.* (2023) and de Chaisemartin and d'Haultfoeuille (2022) provide thorough surveys.

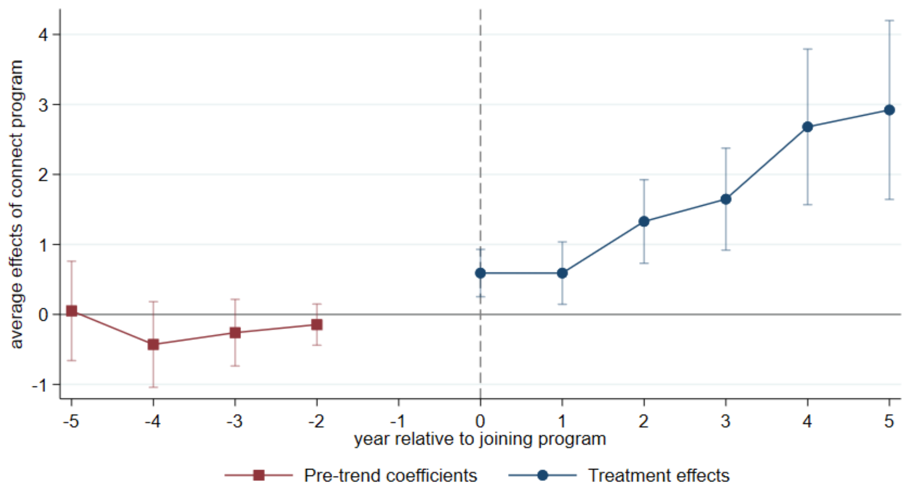
Table 3

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

	ES		log (Carbon Emissions)		"Green"
	Ownership	Index	Total	Production	Patents
	(1)	(2)	(3)	(4)	(5)
$SOE \times \mathbf{SC}_i \times \mathbf{D}_t$	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***	-0.005	-0.010	3.479**
		(0.058)	(0.011)	(0.012)	(1.458)
$\mathbf{SC}_i \times \mathbf{D}_t \times \mathcal{T}_t$		0.112***	-0.014***	-0.013***	2.742**
		(0.028)	(0.004)	(0.004)	(1.280)
$\mathbf{E}_{it}$	0.013	0.025	0.012	-0.003	-4.749
	(0.046)	(0.050)	(0.017)	(0.018)	(4.321)
$\mathbf{E}_{it} \times \mathcal{T}_{it}^E$	-0.097***	-0.100***	0.001	0.005	-3.105
	(0.025)	(0.026)	(0.007)	(0.008)	(1.975)
Methodology	PPML	PPML	Linear	Linear	Linear
Observations	5,083	4,798	11,943	11,943	12,298
R^2/Psuedo R^2	0.453	0.447	0.990	0.989	0.729
Province ×Year FE	Y	Y	Y	Y	Y
Industry×Year FE	Y	Y	Y	Y	Y
SOE×Year FE	Y	Y	Y	Y	Y
FOE×Year FE	Y	Y	Y	Y	Y
"Sin"-Stock×Year FE	Y	Y	Y	Y	Y
Firm Characteristics	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. Columns 3 through 5 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. $***\ p < 0.01$, $**\ p < 0.05$, $*\ p < 0.1$.

erature (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 *et al.* (2022) to ES ratings. There is no discernible trend before firms join a Connect program but a significant upward trend after the policy takes effect. In Appendix B.2, 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 period -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 through the Connect program. We examine the two main theories: signaling and influence.

Lins *et al.* (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, such as during the Enron/World-com fraud scandals or the subprime mortgage crisis. These arguments can be applied to domestic firms in China, who may signal their trustworthiness to foreign investors who face an information asymmetry. Characteristics of China's stock market provide room for such signaling. Firth *et al.* (2015) document that firms with lower transparency are more affected by investor sentiment, and there is evidence that transparency is low for firms traded on China's stock markets. Allen *et al.* (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 penalties for violations low. Due to these, foreign investors might face greater information asymmetries and uncertainty 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 *et al.* (2019) provide evidence that investors, according to their concern with ESG performance, influence firms to improve their ESG ratings. Chen *et al.* (2020) utilize the Russell Index reconstitution and find that firms with an exogenous increase in institutional ownership improve their subsequent CSR performance. Relatedly, Aggarwal *et al.* (2011) find that a rise in institutional ownership is positively associated with better subsequent governance. Jia *et al.* (2017) show that local investors react more strongly to revisions from 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 industry 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 time of the Connect program's initiation 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 and incorporate them into investment practices. 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.[24] HKF investors also 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).

[24]As further evidence, in unreported results we find that the effects of the Connect 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.

6.1 Combining the two theories

Under the signaling theory, ES ratings should causally increase northbound shares 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 here is from 2013 to 2021, there are very few zero values for ES ratings (which we exclude) allowing a linear specification[25]

$$\begin{aligned} NBshare_{itq} &= \beta_1 log\left(y_{i,t-1}\right) + \beta_2 \mathbf{N}^2_{itq} + \left(\beta_3 + \beta_4 \mathcal{T}^E_{i,t-1,q}\right)\mathbf{E}_{i,t-1,q} + \gamma' X_{i,t-1,q} + \omega_i + \nu_{tq} + \epsilon_{itq}, \quad (4a) \\ \log\left(y_{it}\right) &= \beta_5 NBshare_{i,t-1} + \beta_6 C_i \times \mathbf{P}_{it} + \left(\beta_7 + \beta_8 \mathcal{T}^E_{i,t-1}\right)\mathbf{E}_{i,t-1} + \gamma' X_{i,t-1} + \omega_i + \nu_t + \epsilon_{it}, \quad (4b) \end{aligned}$$

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 shares (Equation 4a). If the influence theory is at play, the direction of causality is from northbound shares to ES ratings (Equation 4b). We lag values since we assume that signaling through northbound shares takes one year and ES ratings (published only annually) are reported with a year lag.

The frequency of data differs in the two equations (yearly for ES ratings and quarterly for northbound shares). We discuss below how we deal with this. 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 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 shares 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 is set equal to one beginning in the quarter the firm exits, if it does so, and zero otherwise. $\mathcal{T}^E_{itq}$ is equal to the number of quarters since a Connect firm exited

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

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 is set equal to one beginning in the year the firm exits a program, if it does so, and zero otherwise. $\mathcal{T}_{it}^{E}$ is equal to 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 shares (the signaling effect), and β_5, which captures the effect of northbound shares on ES ratings (the influence effect). Unless one or both of these is zero, an exogenous increase in either northbound share or ES ratings (for example, due to the Connect program) 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. To examine the causal effect of ES ratings on northbound shares, we use a change in environmental regulation ($C_i \times \mathbf{P}_{it}$) as an instrument for ES ratings and test how foreign ownership responds to ES ratings. To examine the causal effect of northbound shares on ES ratings, we use squared duration in the Connect program ($\mathbf{N}_{itq}^2$) as an instrument for northbound shares and test how the ES ratings respond to a change in northbound shareholding. 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 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)).[26] After the policy change, provincial environmental protection departments began controlling the lower-level municipal and prefecture departments by 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.

[26]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.

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 pollution-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 shares 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 the power of the instrument 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. 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.3 plots β_r along with 95% confidence intervals. There are no significant effects on stock prices around the staggered implementation dates. This suggests that the direct effects of the policy were not significant enough to affect stock prices and, therefore, deferentially affect shares held by foreign and domestic investors.

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 earlier 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 shares). We, therefore, 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

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

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.[27] $\mathbf{SC}_i^k$ 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. $\mathbf{D}_t$ is an indicator variable set to one after the Connect program 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 *et al.* (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 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 shares 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 (including exits after joining).

The top panel of Column (1) in Table 4 reports the estimates of Equation (7), where

[27] 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 firms that are in a Connect program, $\mathbf{SC}_i^k = 1$ for all observations and the term in square brackets is collinear with the time fixed effects in the second stage.

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 *et al.* (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). In Appendix B.4, 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 shares 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 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.5 provides suggestive evidence that this is the case. The appendix shows that log ES ratings are nonlinear with respect to elapsed time for firms in the Connect program but not for those outside the program.[28]

Both stages of the 2SLS estimation include only data while firms belong to a Connect

[28]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.

Table 4

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
Second-stage estimation		
	$\mathbf{NB\ share}_{itq}$	$\mathbf{ES}_{it}$
$\log(\widehat{\mathbf{ES}_{\mathbf{i,t-1,q}}})$	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 includes 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). $***\ p < 0.01$, $**\ p < 0.05$, $*\ p < 0.1$.

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.[29] 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 shares. We include year-by-quarter fixed effects (ν_{tq}) in the specification 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 4 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 *et al.* (2022), the first-stage coefficient is significant at the 0.75% level. The bottom panel of Table 4 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%. This is an increase of 1.39 evaluated at the mean ES rating in 2013 (6.22). This is consistent with foreign investors influencing firms' ES ratings.

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. An exogenous one percent increase in ES ratings increases northbound shareholding in the next year by 0.02%, while an exogenous one percent increase in northbound shareholding increases ES ratings in the next year by 22.3%. Accounting for feedback between the two, the long-run effect of an exogenous increase in either will be 76.6% higher than the first-year response.

[29]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.

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.

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 sub-samples split by the direct measures.

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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 Reporting probability by Bloomberg

To test whether the selection criteria for Bloomberg to produce an ESG rating for a firm are orthogonal to inclusion in the Stock Connect programs, we estimate Equation (1). Table A.1 reports the estimates.

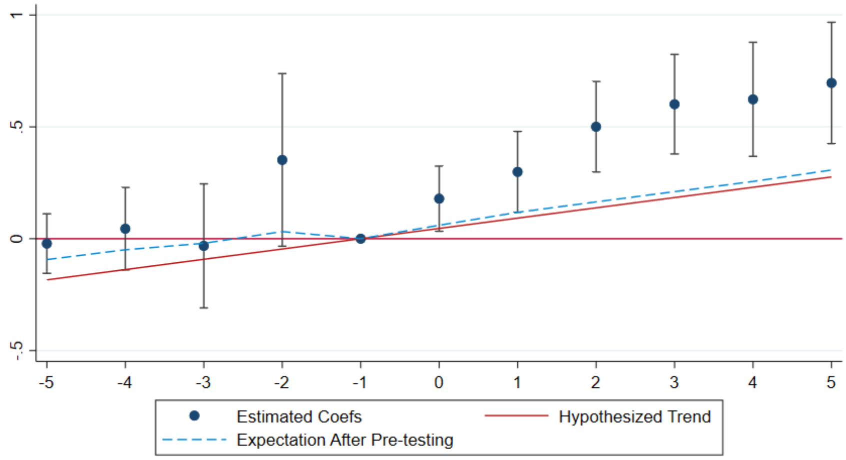
Table A.1
REPORTING PROBABILITY BY BLOOMBERG

	(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

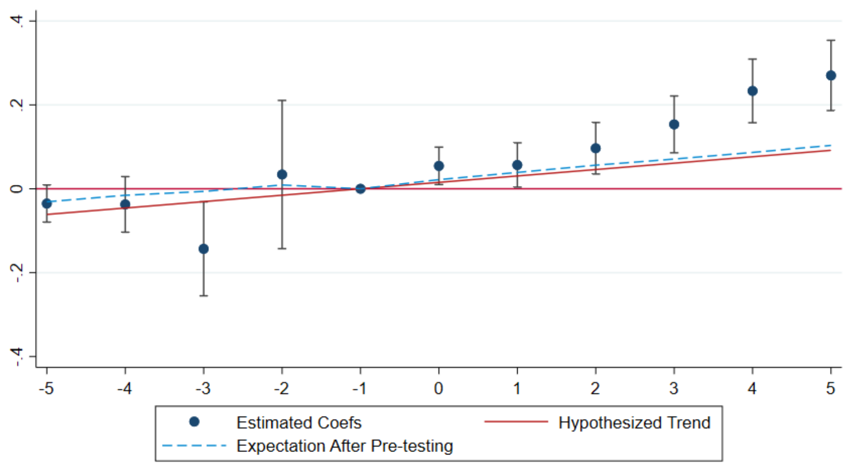
Note: Selected coefficients from estimating Equation (1) using probit and logit models. An indicator variable for whether Bloomberg includes the firm in their ESG ratings is the dependent variable. The control variables are lagged or not as shown in the bottom panel. Standard errors clustered by firm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

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.



(a) ENV sub-rating



(b) SOC sub-rating

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

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.

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 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 3 estimate with ES rating as the dependent variable, Column 4 with the ENV sub-rating, and Column 5 with the SOC sub-rating. All columns use OLS regressions. Standard errors clustered by firm are in parentheses. $*** \, p < 0.01$, $** \, p < 0.05$, $* \, p < 0.1$.

B.2 Robustness checks — staggered DD estimation of Connect programs' effects

Here we perform additional robustness checks of the appropriateness of the staggered DD estimation. 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.

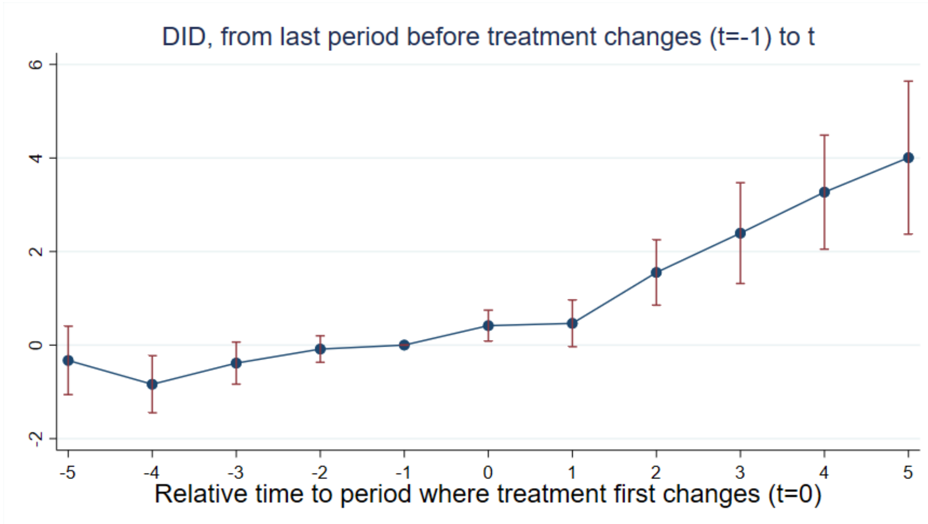


Figure B.1
AVERAGE EFFECTS FOR ES RATING USING METHOD IN DE CHAISEMARTIN AND D'HAULTFOEUILLE (2023)

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.

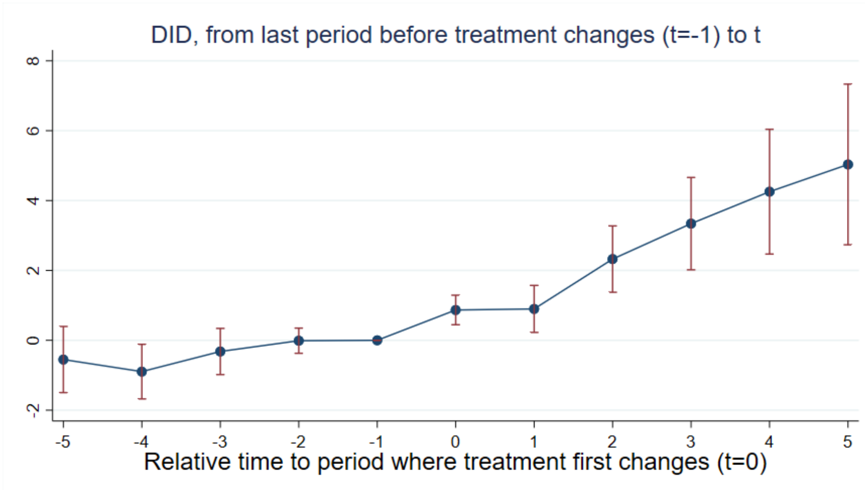
Figure B.3 displays results of applying the method proposed by Sun and Abraham (2021) to the ENV and SOC sub-ratings. There is no discernible trend prior to firms joining a Connect program, but a significant upward trend after the policy takes effect.

B.3 Event study for stock price reaction to environmental policy

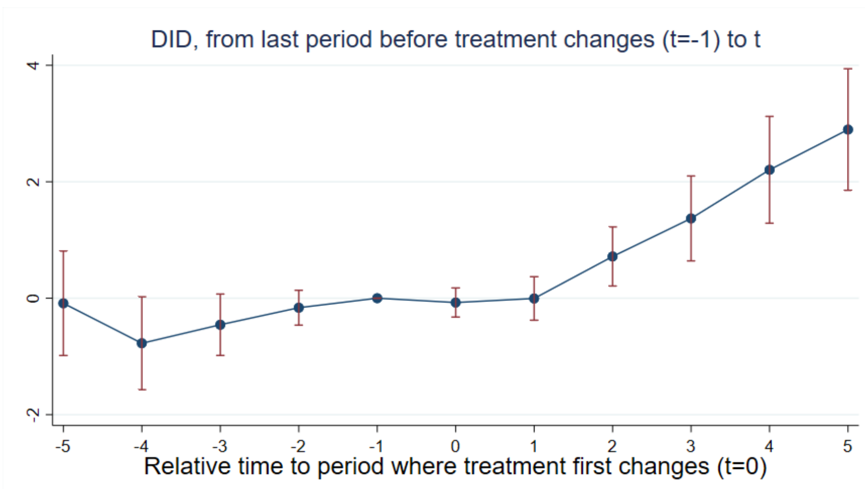
Figure B.4 shows the coefficients and 95% confidence intervals for the stock-price event study in Equation (6) of the main text. Estimation uses 24 months of data before and after the environmental policy change and includes all stocks on the SSE and SZSE.

B.4 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.2. 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.



(a) ENV sub-rating

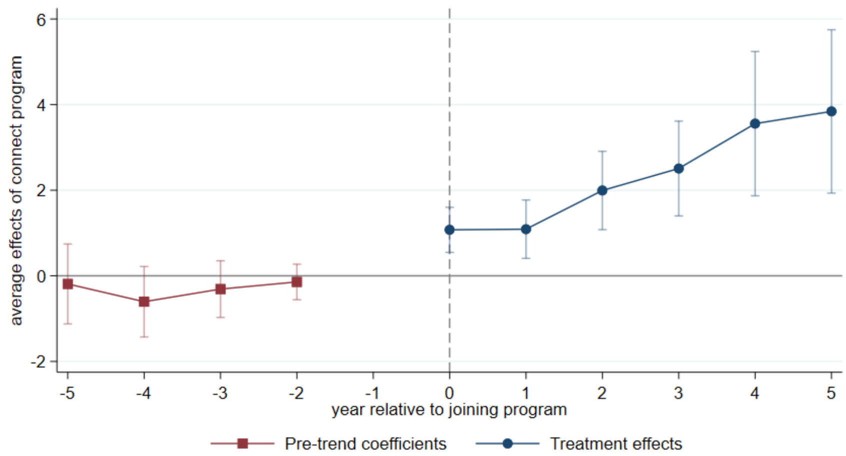


(b) SOC sub-rating

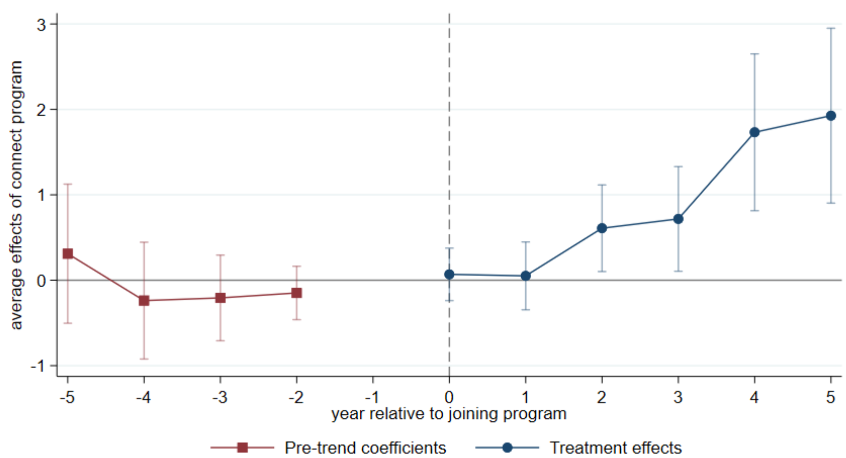
Figure B.2
AVERAGE EFFECTS FOR SUB-RATINGS USING METHOD IN DE CHAISEMARTIN AND D'HAULTFOEUILLE (2023)

B.5 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



(a) ENV sub-rating



(b) SOC sub-rating

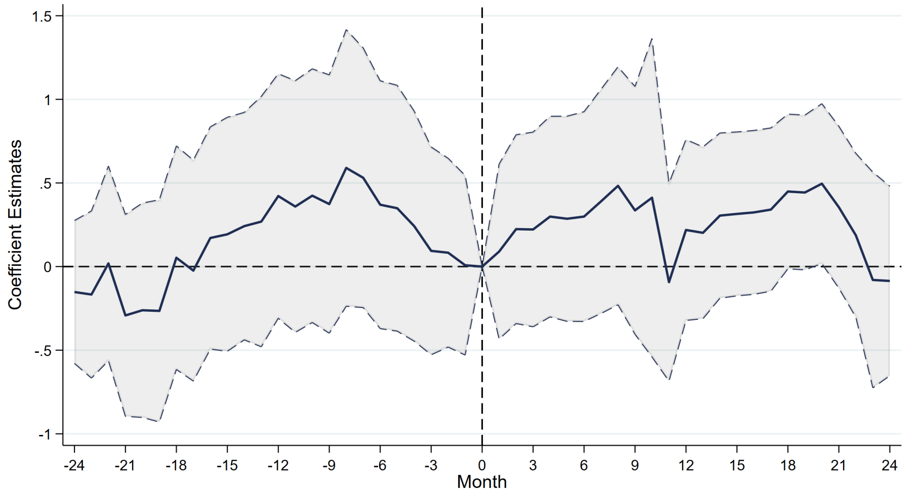
Figure B.3
AVERAGE EFFECTS FOR SUB-RATINGS USING METHOD IN SUN AND ABRAHAM (2021)

year fixed effects).[30] We estimate:

$$\log \mathbf{ES}_{it} = \beta_1 \log \mathbf{N}_{it} + \left(\beta_2 + \beta_3 \mathcal{T}^E_{it}\right)\mathbf{E}_{it} + \gamma' X_{it} + \omega_i + \nu_t + \epsilon_{it}, \tag{A1}$$

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

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



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

Figure B.4
Event study for stock price effects from environmental policy

Table B.2
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. $***\ p < 0.01$, $**\ p < 0.05$, $*\ p < 0.1$.

it does so, after having previously entered and zero otherwise. $\mathcal{T}_{it}^{E}$ 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.3 estimate Equation (A1) 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.3 estimate the following equation for non-Connect firms on the Shanghai and Shenzhen stock exchanges:

$$\log \mathbf{ES}_{it} = (\beta_{1a}\mathbf{SSE_i} + \beta_{1b}\mathbf{SZSE_i}) \times \log \mathbf{N}_{it} + \left(\beta_2 + \beta_3 \mathcal{T}_{it}^E\right)\mathbf{E}_{it} + \gamma' X_{it} + \omega_i + \nu_t + \epsilon_{it}, \qquad \text{(A2)}$$

where $\mathbf{SSE_i}$ and $\mathbf{SZSE_i}$ are indicators distinguishing firms on the Shanghai and Shenzhen stock exchanges. Column (5) of Table B.3 estimates this equation using contemporaneous values for elapsed time ($\mathbf{N}_{it}$ is set to the number of years since 2015 for Shanghai exchange firms and number of years 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 otherwise.

Table B.3

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 (A1). 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 (A2) 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. $***\ p < 0.01$, $**\ p < 0.05$, $*\ p < 0.1$.