Financial Deregulation and ESG: Impacts and Mechanisms*

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Abstract

We examine the causal effect of financial deregulation on publicly-listed firms' ESG performance in a developing economy. Increased foreign ownership of Chinese firms under the Shanghai and Shenzhen Stock Connect programs increases firms' ESG ratings; and improvements spill over to non-participating firms upstream through the value chain. For mechanisms, we find evidence consistent with both influence from foreign investors to increase ESG ratings and firms improving ESG ratings to signal trustworthiness to foreign investors. ESG rating improvements and foreign shareholding increases are therefore self-reinforcing, and exogenous changes in either have long-run effects that are about 13.4% greater than short-run effects.

Keywords: financial deregulation, ESG, social norms, emerging markets

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

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1 Introduction

Opening up a country's capital account is a major policy change and there has been significant debate about the effects it has on many outcomes, including capital inflows, investment levels, economic growth and the volatility of capital inflows and economic growth (Obstfeld, 1994; Rajan and Zingales, 1998; Levine, 2005; Kose *et al.*, 2010; Broner and Ventura, 2016). However, little attention has been paid to the effect of capital loosening on firms' environmental, social, and governance (ESG) activities despite significant evidence that institutional investors respond positively to firms' ESG activities and institutional investors propel firms to invest in ESG activities (Hong and Kacperczyk, 2009; Chava, 2014; Lins *et al.*, 2017; Dyck *et al.*, 2019; Chen *et al.*, 2020). Studies that relate ESG and investing have focused almost entirely on countries without capital controls (an exception is Dyck *et al.* (2019)). It is important to examine the influence of investments on ESG in the presence of capital controls because if capital is not freely mobile across national boundaries it could prevent investors from acting on their beliefs or firms influencing investors.

We address this gap by examining what happens to firms' ESG performance when a country loosens its capital controls. We examine two of China's moves to open its capital account: the Shanghai and Shenzhen Connect programs. These programs allowed Hong Kong/foreign (HKF) investors to invest in a subset of firms publicly listed on the Shanghai Stock Exchange (SSE) and the Shenzhen Stock Exchange (SZSE).[1] To identify the causal effect of the Connect programs on ESG ratings, we use a difference-in-differences (DD) approach with firms joining a Connect program as the treatment group and those not joining as the control group. We find that the Connect programs had a positive causal impact on firms' ESG ratings. After the Shanghai program commences, Connect firms do not experience an immediate increase in ESG ratings relative to non-Connect firms, but their ratings increase at a faster pace (1.3% per year). The Shenzhen Connect program leads to both an immediate (4.6%) and a faster rate (2.0% per year) of increase for Connect relative to non-Connect firms. Firms that later exit either program (for reasons unrelated to ESG ratings) reduce their ESG ratings by 2.8% in the first year, which then decline by 2.0% per year thereafter. There are spillovers from increased ESG ratings within the value chain. Non-Connect firms upstream of a Connect firm in a value chain experience an increase in ESG ratings after its downstream partner enters the program but before it does so.

The ESG increases likely reflect actual ESG improvements as the ratings are derived

[1] See He *et al.* (2023b) for a survey of the Connect programs' effect on stock prices and foreign investment.

from tangible, measurable outcomes. In addition, we find significant effects on environmental outcomes not measured in the ESG ratings - evidence that the estimated effects are not due to firms' influencing the rating agency without making real ESG changes. Connect firms in both programs begin filing more applications for "green" patents and firms in the Shenzhen program reduce their total carbon emissions over time after joining the Connect program.

Since we find significant effects on ESG ratings, we investigate possible mechanisms. We consider the two predominant theories for ESG improvements which are not mutually exclusive: signalling and investor influence. The signalling theory (Lins *et al.*, 2017) argues that firms invest in ESG as a signal to investors of their trustworthiness in order to protect their stock value in times of crisis. Because of this protection, investors are more willing to invest in firms with high ESG performance. In the context of capital controls, foreign investors face a knowledge gap about domestic firms when controls are initially loosened and firms may increase ESG activities to signal trustworthiness and reduce the asymmetric information. The influence theory (Dyck *et al.*, 2019) argues that foreign investors exert influence on firms to invest in ESG activities because they intrinsically value ESG outcomes. In the context of the Connect program, either or both of these theories could be at play. We substantiate that foreign investors in China care more about ESG ratings than do domestic investors. This means that increased foreign ownership under the Connect program could increase the value of investing in ESG as a signal and could also increase foreign-investor influence on ESG ratings.

To assess the role of these respective theories, we take advantage of the difference in the direction of influence under the two. If ESG ratings are a positive signal to investors then ESG ratings drive foreign stock ownership; while, if investors influence ESG activities, foreign stock ownership drives ESG ratings. Our approach is to identify instruments that exogenously shift ESG ratings and foreign ownership respectively and then assess its influence on the other variable. We find that ESG ratings drive foreign stock ownership with an elasticity of 3.2, consistent with ESG as a positive signal to investors, and that foreign stock ownership drives ESG ratings with an elasticity of 0.037, consistent with foreign pressure acting to increase ESG ratings. That is, both are at play. This means that the effects are self-reinforcing and that the long-run effect of an exogenous increase in either is greater than the short-run effect by about 13.4%.

To obtain the causal effects, the DD estimation requires two key identifying assumptions. First, no omitted factors affect both a firm's ESG ratings and its inclusion in a Connect program. ESG ratings were constructed retroactively and became available only in 2020 - after the initiation of both Connect programs. This eliminates the possibility that the ESG ratings directly influenced the inclusion of a stock in a Connect program. Moreover, the criteria for entering the Connect program depend entirely on market capitalization and stock trading volumes of firms, factors not directly related to firm's ESG performance. We confirm empirically that inclusion in a Connect program is independent of receiving an ESG rating.

The second identifying assumption is that the pre-existing trends in ESG ratings are parallel for the treatment and control groups. This assumption holds for the Shanghai Connect program but not for Shenzhen. For the latter, ratings for Connect firms are increasing faster than for non-Connect firms pre-policy. We address this in three ways. First, we employ a parametric DD estimation approach (Dobkin *et al.*, 2018) and allow for a differential time trend prior to policy implementation relative to after. Second, we apply the generalized method of De Chaisemartin and d'Haultfoeuille (2022) which estimates the instantaneous and dynamic effects after treatment allowing for non-parallel pre-policy trends. The method produces estimates similar to the baseline. Third, we perform robustness checks based on Rambachan and Roth (2023) that allows for non-parallel trends and find that the estimates remain significant under fairly broad deviations of trends between the treatment and control groups.

To investigate the mechanisms for increased ESG performance, we first document that ESG ratings are of greater concern to foreign than domestic investors in China and show that ESG ratings increase more under the Connect program for shares held predominantly, or only, by institutional rather than individual investors. This is important since it is difficult for individual investors to coordinate sufficiently that they can influence firms ESG ratings. We contrast the ESG ratings of firms on the main board (available to all investors) with those in the SZSE ChiNext board (available only to foreign institutional investors) and those included in the MSCI China Index, a benchmark frequently used by institutional investors. We find that the effects of the Connect programs are greater for these institutionally-favored Connect stocks than other Connect stocks.

To investigate the possible role of the two main mechanisms, we take advantage of the direction of causality. To test the influence theory, we use the elapsed time since joining the Connect program as an exogenous shock to northbound shareholding and then examine how northbound shares affect future ESG ratings. We provide evidence that elapsed time is a valid and strong instrument and find that a one percentage point increase in northbound shares increases ESG ratings in the following year by 3.2%. To test the signalling theory, we use the change in firms' environmental performance due to a major regulatory change as an instrument for ESG ratings and see whether foreign investors reward ESG performance. We provide evidence that this instrument is relevant and strong and find that a one percent rise in ESG ratings leads northbound investors to increase their holdings by 3.7 basis points a year later. These findings provide support for both theories and suggest that firms' investments in ESG activity and foreign ownership are self-reinforcing and will lead to greater long- than short-run effects.

Our paper relates to three strands of literature. The first investigates the effects of financial liberalization on economic growth, (surveys are Levine (2005), Prasad *et al.* (2007), Obstfeld (2009), Kose *et al.* (2010)). The primary variables of interest are capital inflows, investment levels, GDP growth, and volatility of capital inflows and GDP growth. 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 (e.g., Alfaro *et al.* (2008), Bonfiglioli (2008), Ranciere *et al.* (2008), Levchenko *et al.* (2009), Bacchetta *et al.* (2012), Gennaioli *et al.* (2014), Broner and Ventura (2016)). Our paper documents an additional channel by which foreign capital can affect real activity and influence 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 ESG ratings and related outcomes after the Connect programs commence. Given previous results, an even larger effect of financial liberalization on ESG activities would be expected in countries with stronger institutions and more-developed financial markets.

The second strand of literature investigates how investors interact with firms regarding ESG/CSR activities. The empirical literature finds that norm-constrained institutions, such as pension funds, are more likely to avoid holding stocks in certain industries with environmental or CSR concerns (e.g., Hong and Kacperczyk (2009), Chava (2014), Starks *et al.* (2017), Nofsinger *et al.* (2019), Chen *et al.* (2020)). Our paper contributes to this literature in three ways. First, most of the literature focuses on advanced economies with more developed financial markets, whereas we study the role of foreign capital in influencing ESG activities in a less-developed market. Second, we test for both the signalling mechanism, as documented in Lins *et al.* (2017), and the influence mechanism, as argued in Dyck *et al.* (2019), and find both channels at work generating a self-reinforcing cycle between foreign capital and firm's activities. Third, we find foreign capital influences domestic firms' ESG activities through the value chain from firms to suppliers.

The third strand of literature are studies that examine the development of China's financial system and its role in economic growth (surveys are Allen *et al.* (2017), Carpenter and Whitelaw (2017), Song and Xiong (2018), Allen *et al.* (2019a), He and Wei (2022)). 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. Our paper contributes to the third channel by documenting the impacts of the Connect programs on improving firms' ESG ratings. Ma *et al.* (2021) analyze market performance and investment after the introduction of the Shanghai Connect program. We complement this by showing significant improvements in ESG ratings from both the Shanghai and Shenzhen 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 foreign market exposure. Relatedly, we find that HKF investors influence domestic firms' behaviors by reshaping their ESG activities. Li *et al.* (2015) find that A-share (mainland Chinese firms traded on the Shanghai and Shenzhen exchanges) firms being dual-listed improves corporate governance due to stricter listing rules, stronger investor protection, and foreign investors' information access. Similarly, we find that firms strengthen their ESG activities after exposure to HKF investors. Moreover, northbound trading makes the stock market more informative (e.g., Chen *et al.* (2019), Lundblad *et al.* (2022), Bian *et al.* (2023), and He *et al.* (2023a)). Our findings show that the Connect firms improve their ESG activity to signal trustworthiness to foreign investors.

2 Institutional Background

Since its Economic Reform and Opening in 1978, China has managed its capital flows following a cautious learning-by-doing approach, aiming to propel strong economic growth while minimizing risk. Promoting foreign direct investment has been an important 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 kept a tight rein on them. In 1992, shortly after the launch of the Shanghai Stock Exchange (SSE) in December 1990 and 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 on 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 for foreign investors to do so because it required depositing the foreign currency in a domestic bank account and trading through a domestic broker. Although the B-share market was extended to domestic investors in February 2001, uptake remained low.[2]

The Qualified Foreign Institutional Investor (QFII) program was introduced in 2002 allowing foreign institutional investors to invest in firms listed on the SSE and SZSE. The China Securities Regulatory Commission (CSRC) granted a license, required for trading, based on the reputation and financial soundness of the institution. 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 attempts to relax restrictions on foreign investors participating in the Chinese stock market. The Shanghai Connect program was launched in November 2014 and the Shenzhen program in December 2016. The programs allowed two-way trading: HKF investors could trade A-share stocks of eligible firms on the SSE and SZSE through the Stock Exchange of Hong Kong (HKEX) and investors from mainland China could trade eligible stocks on the HKEX through the SSE or SZSE. Northbound trading - that conducted by the HKF investors - was open to all eligible individual and institutional investors.[3] SSE shares eligible for northbound trading included all SSE 180 Index and SSE 380 Index constituents and firms dual-listed on the SSE and HKEX (excluding those not traded in RMB or those under "special treatment" (ST)).[4] Similar selection criteria were adopted by the SZSE. Eligible stocks were SZSE Component Index and Small/Mid-Cap Innovation Index constituents, along with dual-listed firms (except those not traded in RMB or under ST).

In 2006, the SZSE published an initiative urging all listed firms (not just those in the Connect program) to become actively involved in corporate social responsibility (CSR), establish a system to promote CSR activities, and to disclose information related to CSR activities. Since then, the SZSE has periodically inspected and assessed how listed firms performed 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 they are listed by an en-

[2]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 market.

[3]Eligibility depended on information technology capability and risk management procedures as 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.

[4]Some shares are placed under "special treatment" 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.

vironmental authority as a seriously-polluting enterprise. In 2018, the CSRC mandated all listed firms to provide ESG information in their annual reports.

3 Data

3.1 Sample selection of Connect firms

Our data spans the years 2007 to 2021 - seven years before the beginning of the Shanghai Connect program and five years after the Shenzhen Connect program commenced. Our data includes information on firms' ESG ratings and firm financial control variables. In order to ensure enough data to identify effects, we exclude firms that enter a Connect program in 2019 or later. 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 ST. The Shenzhen Connect program includes 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 any of these indexes it can be sold, but not bought, through the Connect program. We include all program stocks that are never dual-listed because dual-listed stocks may have already been exposed to foreign investors before the introduction of the Connect programs.

Our sample of Connect firms is therefore determined by the criteria for firms to be included in these indexes. Importantly for identification, the construction of these indexes is orthogonal to firms' ESG ratings. First, consider the SSE 180 index. After excluding stocks listed for less than one quarter or under ST, all remaining are sorted based on a summation of their ranks on market capitalization and trade 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 rank within each industry and subject to the quota. The SSE 380 index is constructed similarly, except that 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 combined rank on market capitalization and trade volume during the previous half year. After filtering out those ranked in the bottom 10%, the top 500 stocks are selected based on the market capitalization ranking but subject to the same industry representation as in the aggregate market. After removing the SZSE Component Index constituents from SZSE 1000 Index, which adopts the same method of construction to construct 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.

Each index is re-evaluated 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.[5] As a result, we employ a staggered DD method to analyze the effects of the Connect programs on ESG performance. When forced to use annual data, as we must with ESG data, we treat firms entering a program in the second half of a year as if they enter the next year. 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 ESG ratings for listed firms in 2020. Although compiled in 2020, Bloomberg used historical data to provide retroactive ratings back to 2007, a year after the SZSE's initiative to promote social responsibility activities in annual reports. The ratings are based on over 600 company-reported and derived indicators (Appendix A.1 has details). The environmental (ENV) sub-rating includes measures of the emissions and waste produced during the firm's operations, including air quality, waste water, energy use, and material use and general impacts on the environment, such as climate change and ecological and biodiversity impact. The social sub-rating (SOC) focuses on firms' actions with respect to 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. The Bloomberg ESG database covers more than 11,800 companies worldwide, comprising 88% of global equity market capitalization.[6] As of the end of 2021, 1,549 Chinese firms listed on the SSE or SZSE had ever been rated.

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

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

The main challenges in ESG data are lack of disclosure and standardization. Reporting ESG data is generally not mandatory and no common framework is used by companies for disclosure. As a result, ESG information can be sparse, incomplete, untimely, and non-standardized. Berg *et al.* (2022) compare six prominent ESG rating agencies and find a large dispersion across their ratings. 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, company-reported data is comparable across time and companies.

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.[7] We refer throughout the paper to the former group as Connect firms and the latter group 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).[8] We construct financial variables following Allen *et al.* (2019b) and Ma *et al.* (2021). After combining the ESG ratings data with the firm financial data there are 685 firms in 2013, just before the Shanghai Connect began.

Table 1 reports summary statistics of the ESG ratings and financial variables prior to 2014, the year the first Connect program was launched. Since the ESG rating and its sub-ratings are unit-less and lie between 0 and 100, we use the natural logarithm of the rating plus one in our estimates. Connect firms have on average 2% higher ESG ratings although the difference is statistically significant at only the 10% level, 13% lower environmental sub-ratings, similar social sub-ratings, and 2% higher governance sub-ratings. Thus, ESG ratings and sub-ratings differ across the treatment and control groups before the programs. This is likely due to the selection criteria of the SSE and SZSE indexes, which determine inclusion in the Connect programs. Connect firms are younger, larger, more profitable, and have higher market evaluations; and ESG ratings may vary system-

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

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

atically based on these attributes. Our estimation compares relative ESG ratings before versus after the Connect program so that the fact that Connect firms have different ESG ratings before the program commences does not invalidate the identification approach. The two groups do not differ in the proportion of state-own enterprises, sales growth rate, or leverage ratio.

Table 1
SUMMARY STATISTICS PRIOR TO CONNECT PROGRAMS

	Connect Firms			Non-Connect Firms			Difference	
	obs	mean	sd	obs	mean	sd	diff	t
log(1 + **ESG**)	2799	2.96	0.23	942	2.94	0.22	0.02*	(2.33)
log(1 + **ENV**)	2777	0.71	0.90	918	0.84	0.96	-0.13***	(-3.59)
log(1 + **SOC**)	2799	1.80	1.02	942	1.87	1.11	-0.07	(-1.83)
log(1 + **GOV**)	2799	3.85	0.19	942	3.83	0.17	0.02**	(2.67)
log(assets)	2799	22.59	1.20	942	21.99	1.09	0.60***	(14.22)
log(revenue)	2799	22.08	1.35	942	21.44	1.28	0.64***	(13.11)
log(stock price)	2781	2.68	0.70	935	2.37	0.61	0.31***	(12.84)
log(market cap)	2781	16.04	0.89	935	15.34	0.78	0.71***	(23.01)
log(cap expenditure)	2798	19.37	1.65	942	18.8	1.57	0.57***	(9.52)
ROA	2799	0.07	0.06	942	0.04	0.04	0.02***	(13.80)
growth rate of sales	2782	0.99	20.91	935	0.36	2.95	0.63	(1.55)
age	2799	13.84	4.77	942	14.73	4.76	-0.89***	(-4.96)
Tobin's Q	2781	2.03	1.39	934	1.76	0.91	0.28***	(6.97)
% change in debt	2677	0.42	2.00	909	0.27	0.69	0.15***	(3.37)
cash to assets ratio	2799	0.19	0.14	942	0.17	0.13	0.02***	(4.86)
SOE	2799	0.60	0.49	942	0.61	0.49	-0.01	(-0.34)
cash flow to assets ratio	2797	-0.01	0.14	941	-0.01	0.13	0.00	(0.26)
leverage ratio	2799	0.47	0.20	942	0.47	0.2	0.00	(0.02)
QFII share	2799	0.30	0.74	942	0.23	0.64	0.06*	(2.54)
turnover rate	2781	1.26	0.92	935	1.56	1.01	-0.30***	(-8.01)
average daily return	2781	0.00	0.01	935	0	0.01	0.00	(0.35)
sd of daily return	2781	0.03	0.03	935	0.03	0.03	-0.00	(-1.04)

Data on firms in sample from 2007 to 2013 (before the Connect programs began). Our sample contains 192 non-Connect and 493 Connect firms. ESG ratings (**ESG**) and environmental (**ENV**), social (**SOC**), and governance (**GOV**) sub-ratings from Bloomberg and financial variables following Allen *et al.* (2019b) and Ma *et al.* (2021) based on CSMAR data. Connect firms join a program for at least two years while non-Connect firms join for less than two years or not at all.

3.4 Other outcomes

We examine how the Connect programs affect two environmental outcomes not included in deriving ESG ratings: carbon emissions and "green" patent applications. Since firm-level carbon emissions data is not available until 2018, we use industry-level emissions and we assign emissions to each firm based on the fraction of their revenue in each industry.[9] The patent data is collected by China's State Intellectual Property Office. Following criteria established by the World Intellectual Property Organization (WIPO), we classify a patent as "green" if it concerns products or designs that provide environmental benefits (e.g., waste technology, wind power, geothermal energy, solar energy, tidal energy, or biomass). This data has broader coverage than that for ESG ratings. 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 outcomes independent of the ESG ratings.

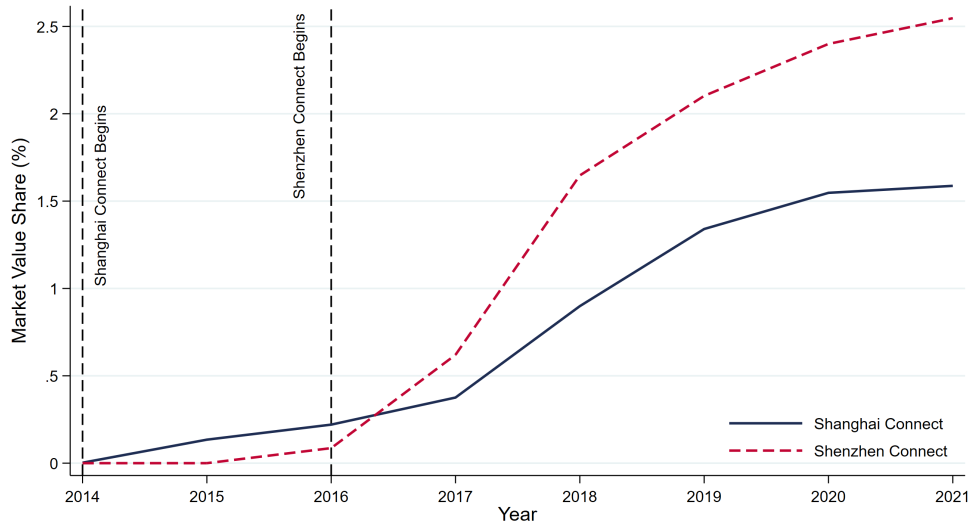
4 Estimation Approach

4.1 Identification

We first confirm that the Connect programs have an effect on trading volume. In Figure 1, the blue solid line shows the year-end market value share held by HKF investors through the Shanghai program as a fraction of total SSE market capitalization. In the first three years, the market value share increased steadily but slowly, then accelerated in 2018 and 2019, reaching 1.6% by the end of 2021. The dashed red line shows the same for the fraction held by HKF investors through the Shenzhen program as a fraction of total SZSE market capitalization. This increases gradually prior to 2017 and then increases more rapidly to 2.6% by 2021.

We apply DD estimation to identify the causal effect of the Connect programs on ESG ratings. Firms that join a program for at least two years comprise the treatment group while all other firms on the exchange comprise the control group. Since firms join the Connect programs at different times, we employ staggered DD estimation. There are two key identifying assumptions. First, there are no omitted factors that affect both a firm's ESG rating and its inclusion in a Connect program. As discussed in Section 3.1, the criteria for a firm entering the Connect program depend only on its market capitalization and trade volume, not characteristics related to ESG. Moreover, Bloomberg launched their ESG ratings in 2020 and constructed the ESG ratings retroactively. This eliminates the possibility that the ESG ratings themselves influenced factors related to 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. For example, Bolton *et al.* (2012) argue that bond rating agencies inflated

[9] Data from *China Energy Yearbook*. Includes emissions from production, energy generation, waste disposal, and land industrialization.



Note: The 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

ratings to compete in rating-shopping prior to the sub-prime mortgage crisis.

Identification also requires that the selection criteria for Bloomberg to produce an ESG rating for a firm are orthogonal to inclusion in the Connect programs. Since we do not observe Bloomberg's criteria for including a firm, Appendix A.2 shows the results of estimating:

$$\mathbf{D}_{ijt}^{ESG} = \sum_{k \in \{SH,SZ\}} \left(\beta_1^k + \beta_2^k \mathbf{SC}_i^k\right)\mathbf{D}_{it}^k + \theta \mathbf{D}_{it}^{QFII} + \left(\rho_1 + \rho_2 \mathbf{MS}_i\right)\mathbf{D}_{it}^{MS} + \gamma X_{it} + \nu_{jt} + \epsilon_{ijt} \tag{1}$$

where $\mathbf{D}_{ijt}^{ESG}$ is a dummy variable set to one if firm i in industry j received an ESG rating in year t. $\mathbf{D}_{it}^k$ is an indicator variable set to one if program k ("SH" for Shanghai and "SZ" for Shenzhen) had commenced for firm i in year t. For Connect firms this is set to one beginning in the year they joined the program and zero otherwise. For non-Connect firms, this is set to one after program k commences (2015 for Shanghai and 2017 for Shenzhen) and zero otherwise. $\mathbf{SC}_i^k$ is set equal to one if firm i is a Connect firm on exchange k in any year and zero otherwise. We control for two other channels through which listed firms have exposure to foreign investors. $\mathbf{D}_{it}^{QFII}$ is a dummy variable set equal to one if any QFII investors hold shares of firm i in year t. $\mathbf{MS}_i$ equals one if firm i is included in the MSCI China Index in any year and zero otherwise; and $\mathbf{D}_{it}^{MS}$ equals one if firm i is included in the MSCI China Index in year t and zero otherwise.

X_{it} includes controls that may affect receiving an ESG rating including province fixed effects and firm financial characteristics described in Section 3.3. Industry-by-year fixed effects (ν_{jt}) capture industry-specific unobservables by year that influence receiving an ESG rating. ϵ_{ijt} 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.

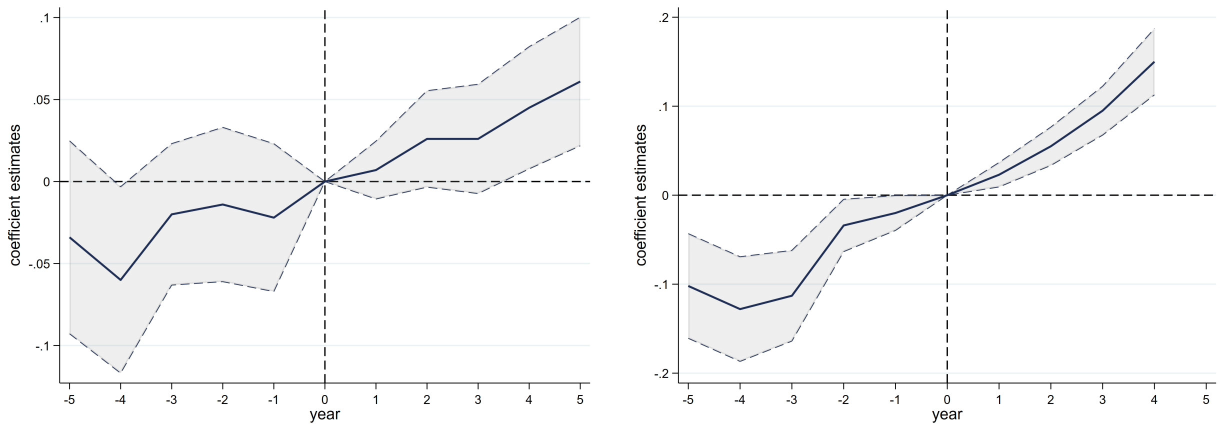
We employ a probit model to accommodate the discrete nature of the dependent variable. Column 1 of Table A.1 uses contemporaneous values for the programs (Connect, QFII, and MS) and control variables and finds no significant effect from Connect status on receiving an ESG rating. Column 2 repeats the estimation using lagged control variables. Column 3 uses lagged program but contemporaneous control variables while Column 4 uses lagged values for both. All the results are insignificant, consistent with Bloomberg choosing firms to rate independent of their inclusion in the Connect programs. On the other hand, whether any QFII fund holds a firm's stock and selection into the MSCI China Index are positively associated with the probability that Bloomberg rates the firm.

The second identifying assumption is that pre-existing time trends are parallel for the treatment and control groups. To check this, we estimate event studies separately for the Shanghai and Shenzhen Connect programs ($k \in \{SH, SZ\}$):

$$y_{ijt} = \sum_{r \neq 0} \left(\beta_{1r}^{k} + \beta_{2r}^{k} \mathbf{SC}_{i}^{k}\right) \mathbf{1}_{irt}^{k} + \sum_{r>0} \beta_{3r}^{k} \mathbf{EX}_{irt}^{k} + \gamma' X_{it} + \nu_{jt} + \alpha_{i} + \epsilon_{it}, \tag{2}$$

with the ESG measures as the dependent variable. r counts the number of years before or after a firm joins a Connect program (if it does) normalized to zero in the year it joined. If a firm never joins a program, we normalize r to zero in the year in which the most firms join the program (the initial years – 2015 for Shanghai and 2017 for Shenzhen). $\mathbf{1}_{irt}^{k}$ is a dummy variable set equal to one if firm i in year t is r years relative to entering program k (or for firms not joining if it is r years relative to the program's beginning). $\mathbf{SC}_{i}^{k}$ is set to one if firm i is in program k in any year. $\mathbf{EX}_{irt}^{k}$ is an indicator variable set to one beginning in year t if firm i exits the Connect program k in year r after having entered it. X_{it} includes controls that may affect the rating including province fixed effects and firm financial characteristics described in Section 3.3. Industry-by-year fixed effects (ν_{jt}) capture industry-specific unobservables by year that influence the ESG rating. Firm fixed effects (α_{i}) capture time-persistent firm unobservables that affect the rating.

Panel (a) of Figure 2 plots the β_{2r}^{SH} coefficients estimated using $\log(1 + \mathbf{ESG})$ for each year along with 95% confidence intervals. The overall ESG ratings follow similar trends for control and treatment groups in the years prior to the commencement of the Shanghai Connect program. Afterward, the ratings for the Connect (treatment) group increase faster than those for the non-Connect (control) group. Appendix A.3 displays similar patterns for the environmental ($\log(1+\mathbf{ENV})$), social ($\log(1+\mathbf{SOC})$), and governance ($\log(1+\mathbf{GOV})$) sub-ratings for firms on the SSE.



(a) Shanghai Connect Program

(b) Shenzhen Connect Program

Note: Solid lines are point estimates and dashed lines 95% confidence intervals from the event study in Equation (2).

Figure 2
EVENT-STUDY ESTIMATES FOR ESG RATINGS FOR CONNECT PROGRAMS

Panel (b) of Figure 2 provides an analogous graph using the overall ESG rating for the Shenzhen Connect program. The graph shows that the parallel trends assumption does not hold. The treatment group's ratings are increasing faster than the control group. Appendix A.3 displays event studies for each of the three sub-ratings, which show that the violation of the parallel trends assumption is due to the environmental and governance sub-ratings but not the social sub-rating. Because of this, we employ a parametric DD estimation approach (Dobkin *et al.*, 2018) and allow for a differential time trend prior to policy implementation relative to after. This requires an additional assumption which is that the difference in trends is linear. We also apply the generalized method of De Chaisemartin and d'Haultfoeuille (2022) and the robust inference methods of Rambachan and Roth (2023) as robustness checks of our results. We now describe the parametric DD specification in detail.

4.2 Econometric specification

To estimate the causal effect of the Connect programs on various outcomes we employ DD estimation with Connect firms as the treatment group and all other (non-Connect) firms traded on the exchange as the control group. Since inclusion in the Connect program is orthogonal to factors affecting ESG, the effect on the treatment relative to the control group is the causal effect of the Connect program on the outcome. Because of the violation of the parallel trends assumption for the Shenzhen Connect program, we employ a parametric DD approach to allow for a differential time trend prior to the policy implementation relative to after

$$\begin{aligned} y_{ijt} &= \sum_{k \in \{SH,SZ\}} \Big[\beta_0^k \mathbf{SC}_i^k \mathcal{T}_t^{2007} + \Big(\beta_1^k + \beta_2^k \mathcal{T}_{it}^k + \Big(\beta_3^k + \beta_4^k \mathcal{T}_{it}^k\Big)\mathbf{SC}_i^k\Big)\mathbf{D}_{it}^k\Big] \\ &\qquad + \Big(\beta_5 + \beta_6 \mathcal{T}_{it}^E\Big)\mathbf{E}_{it} + \gamma' X_{it} + \nu_{jt} + \alpha_i + \epsilon_{ijt}, \end{aligned} \tag{3}$$

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

$\mathcal{T}_{it}^{2007}$ is equal to the number of years since 2007. $\mathcal{T}_{it}^k$ is equal to the number of years since policy k is in effect for firm i. For firms that never join a program, it equals the number of years since the Connect program began (2015 for Shanghai and 2017 for Shenzhen) and zero before. For firms that join a program it equals the number of years since they joined and zero otherwise. $\mathcal{T}_{it}^E$ is equal to the number of years since a Connect firm exited program k, if it does so, and zero otherwise. β_0^k captures any differential time trend for Connect firms under program k over the entire sample period (the industry-by-year fixed effects capture the baseline trends). β_2^k captures any change in trend when policy k begins while β_4^k captures the relative change in trend for Connect firms once the policy begins. β_6 captures any change in trend for firms leaving either program relative to the trend under the program.

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

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

5 Results

5.1 Benchmark results

Column 1 of Table 2 shows the coefficients of interest in estimating Equation (3) with $\log(1+\mathbf{ESG})$ as the dependent variable.[10] Although unreported, β_0^{SH} is insignificant and β_0^{SZ} is significant and indicates a trend of 1.2% per year for the SZSE. This is consistent with Figure 2 which shows no differential time trend for control versus treatment firms on the SSE prior to the Connect program but a gradual trend for the SZSE. After the Shanghai Connect commences, treatment firms do not experience a significant change in ESG ratings relative to control firms in the first year but their ESG ratings start increasing at a faster pace (1.3% per year). The Shenzhen Connect program leads to both an increase in the first year (4.6%) and a faster rate of increase over time (2.0% per year) for treatment relative to control firms. Firms that exit either program suffer a drop of 2.8% in their ESG rating in the first year of exit after which it declines by 2.0% per year. These results indicate that the Connect programs led to increases in ESG ratings for firms and that these increases started reversing if a firm left a program.

Columns 2, 3, and 4 of Table 2 estimate the same specification with the three sub-ratings as dependent variables. The environmental and social sub-ratings are significantly affected by both Connect programs while the governance sub-rating is not. However, the governance sub-rating is affected when a firm leaves either program.

5.2 Robustness to differences in trends

Since the pre-policy trends in ESG ratings for the Shenzhen Connect program are not parallel for the treatment and control groups, we perform two robustness checks. First, we apply the generalized method of De Chaisemartin and d'Haultfoeuille (2022) to esti-

[10] In Appendix B.1, we show that these results are robust to using levels rather than logged values.

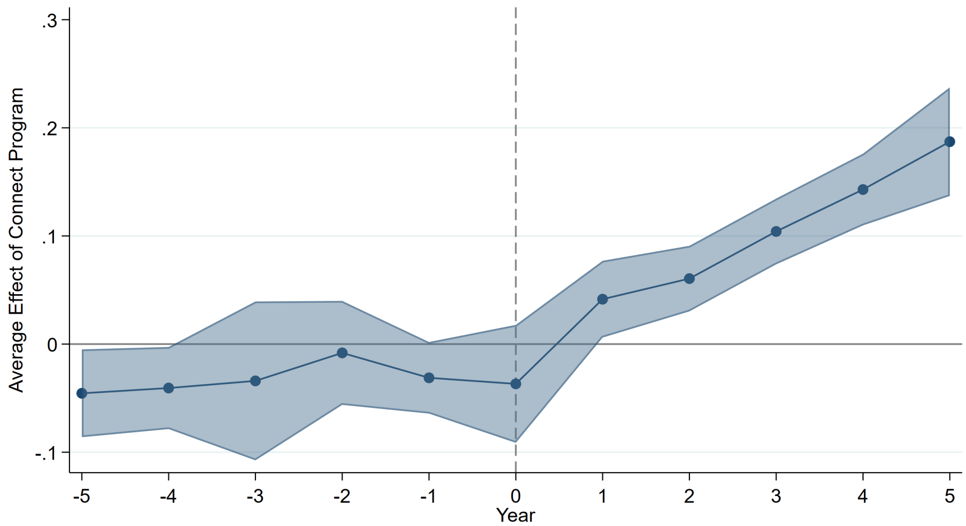
Table 2
Effects of Connect programs on ESG ratings and sub-ratings

	log(1 + **ESG**)	log(1 + **ENV**)	log(1 + **SOC**)	log(1 + **GOV**)
Shanghai Connect				
Level Change ($\mathbf{D}_{it}^{SH} \times \mathbf{SC}_i^{SH}$)	0.012	0.121	0.076	0.006
	(0.024)	(0.096)	(0.067)	(0.025)
Slope Change ($\mathbf{D}_{it}^{SH} \times \mathbf{SC}_i^{SH} \times \mathcal{T}_{it}^{SH}$)	0.013**	0.088***	0.076***	-0.006
	(0.006)	(0.034)	(0.024)	(0.005)
Shenzhen Connect				
Level Change ($\mathbf{D}_{it}^{SZ} \times \mathbf{SC}_i^{SZ}$)	0.046**	0.222**	0.029	0.031*
	(0.019)	(0.103)	(0.058)	(0.019)
Slope Change ($\mathbf{D}_{it}^{SZ} \times \mathbf{SC}_i^{SZ} \times \mathcal{T}_{it}^{SZ}$)	0.020***	0.172***	0.045**	-0.005
	(0.006)	(0.036)	(0.022)	(0.005)
Disconnecting				
Level Change ($\mathbf{E}_{it}$)	-0.028**	-0.097	0.009	-0.025***
	(0.011)	(0.069)	(0.030)	(0.009)
Slope Change ($\mathbf{E}_{it} \times \mathcal{T}_{it}^{E}$)	-0.020***	-0.101**	-0.025	-0.008
	(0.005)	(0.044)	(0.016)	(0.005)
Obs	10,180	10,071	10,180	10,180
R^2	0.837	0.722	0.686	0.825
Firm FE	Y	Y	Y	Y
Province FE	Y	Y	Y	Y
Industry×Year FE	Y	Y	Y	Y
Firm Characteristics	Y	Y	Y	Y

Note: Selected coefficients from estimating Equation (3). $\mathbf{SC}_i^k$ is an indicator set to one if firm i is in program k in any year. $\mathbf{D}_{it}^k$ is an indicator variable set to one if the policy is in effect for firm i in year t for program k. For Shanghai (Shenzhen) control firms this equals one in 2015 (2017) and later and zero otherwise. For treatment firms this equals one in the years after they join the Connect program and zero before. $\mathbf{E}_i$ is an indicator variable set to one if firm i exits either of the Connect programs in year t after having previously entered. $\mathcal{T}_{it}^k$ measures the number of years firm i has been subject to policy k. For Shanghai (Shenzhen) control firms it equals the number of years since 2015 (2017) and zero before. For treatment firms it equals the number of years since joining program k and zero before.$\mathcal{T}_{it}^E$ equals the number of years since a treatment firm exits either program if it did so and zero otherwise. The number of observations for the environmental sub-rating is slightly lower due to missing values. Standard errors clustered by firm are in parentheses. $***\ p < 0.01$, $**\ p < 0.05$, $*\ p < 0.1$.

mate instantaneous and dynamic effects after treatment. Their method requires only the weaker assumption that all control groups follow the same trend period-by-period over the sample period. Besides allowing for different pre-policy trends for treatment and control groups, the method allows for staggered event times and heterogeneous treatment effects across groups. Allowing for level and slope changes, as in our benchmark model, is a special case of their more general model.

Figure 3 displays the average point estimates of their method pooling the data for both Connect programs. While there is no instantaneous change in ESG ratings when firms join a Connect program, there are long-lasting dynamic effects equal to about an average increase of 2.9% per year relative to non-Connect firms. These results are not too different from the benchmark results averaged across the two Connect programs (a slope change of 1.3% per year for the Shanghai Connect and an instantaneous increase of 4.6% and slope change of 2.0% per year for the Shenzhen Connect program). These estimates differ because they weight treatment groups differently depending on when in the sequence they are treated whereas the baseline results weight them equally.



Note: Solid line are point estimates from the generalized DD model of De Chaisemartin and d'Haultfoeuille (2022) and shaded areas are 95% confidence intervals based on 100 bootstrap iterations.

Figure 3
Average effects of the Connect programs on ESG ratings - Robustness Check

Second, we apply the robust inference method of Rambachan and Roth (2023). This method relaxes the assumption of precisely parallel trends and instead bound the maximum difference between the treatment and control group trends.[11] Appendix B.2 shows the 95% confidence intervals for the treatment effect (assuming only a level shift rather than a level and slope change) for different values of M - a parameter governing by how much the treatment and control trends can vary from each other between successive periods post-policy. Panel A shows the analysis for the Shanghai program for values of M ranging from 0.8 to 1.2. The 95% confidence interval for the treatment effect is above zero for values of 1.0 or below. This means that treatment and control group trends can vary by up to 100% period-by-period for the treatment effect to be positive. Panel B shows the

[11] This robustness test does not allow for staggered implementation of the policy. We therefore use 2014 for Shanghai and 2016 for Shenzhen as reference years since this is just before the first, and largest, cohorts joined the two respective Connect programs. Also, the method does not allow for level and slope changes due to the treatment so we analyze only a level shift.

analysis for the Shenzhen program with M values ranging from 0 to 0.10. As expected based on the pre-trends shown in Figure 2, the maximum M value that ensures a 95% confidence interval that exceeds zero is lower (only up to 0.07) than it is for Shanghai. That is, relative trends can vary up to 7% in successive periods to ensure a 95% confidence interval that exceeds zero. As a benchmark for these results, the β_0^{SH} estimated from Equation (3) is insignificant and β_0^{SZ} indicates a trend of 1.2% per year.

5.3 Spillover effects in the value chain

ESG improvements by a firm may require changes by firms upstream or downstream of it in the value chain. We therefore examine whether a firm being included in a Connect program influences the ESG ratings of other firms in its value chain. We are not aware of other papers that examine these spillovers although Cao *et al.* (2019) find that competitors of firms that implement ESG/CSR measures are more likely to also implement them. We add to the benchmark specification in Equation (3) a dummy variable ($\mathbf{D}_{it}^{partner}$) to identify a firm i that has not yet joined a Connect program or never does but is a partner of a firm that has joined a Connect program. This variable is set equal to one beginning in the year that its partner joins a Connect program and zero before.

We set this dummy variable using the following procedure. The value chain of all firms listed on the SSE and SZSE is unavailable; however, firms must disclose the names of buyers in their initial public offering (IPO) prospectus.[12] Using the names of buyers disclosed in IPO prospectuses, we identify all value-chain pairs in which both firms are in the ESG database. Since we wish to see whether a partner firm is affected by a focal firm joining the Connect program first, we ignore all pairs in which the firms join Connect programs in the same year. Of the remaining 85 pairs, we set $\mathbf{D}_{it}^{partner}$ equal to one for the firm that joins latest but beginning in the year that its partner joins the Connect program. Given that there is often a time lag between the IPO and our sample period, this will be a noisy measure of these relationships and bias against finding an effect. This is also a selective sample as it only includes firms that are large enough that both the focal firm and its partner have an ESG rating.

Column 1 of Table 3 reports the estimates and reveals a significant increase in the ESG ratings of 10.9% for partner firms. This is an increase when the partner firm has not yet joined the Connect program but the focal firm has. It provides evidence that the effects of ESG improvements can be transmitted along the value chain. The effects on partner firms are much greater than the baseline effects, perhaps because these firms are

[12]In annual reports, firms are required to disclose the size of sales with their top five buyers. However, the name of the buyer is not mandatory. In practice, many firms choose not to reveal such information.

larger than the average Connect firm. We replace $\mathbf{D}_{it}^{partner}$ with two dummy variables to distinguish whether firm i is a supplier or buyer of the Connect firm. We replace $\mathbf{D}_{it}^{partner}$ with $\mathbf{D}_{it}^{supplier}$ if the firm that IPOed joins the Connect program after the firm listed as a buyer in the prospectus. We instead replace $\mathbf{D}_{it}^{partner}$ with D_{it}^{buyer} if the firm listed as a buyer in the prospectus joins after the firm that IPOed. The improvement is transmitted from a Connect firm upstream to suppliers but not downstream to buyers (Column 2). This is consistent with firms having more incentive to influence or have more leverage over their suppliers than their buyers.

5.4 Are ESG increases the result of manipulation?

Inclusion in a Connect program increases firms' ESG ratings. As explained earlier, Bloomberg's ESG ratings are based on objective measures. However, to the extent that these measures involve some amount of subjectivity, Connect firms may exert more effort to influence Bloomberg's ratings than non-Connect firms without any actual change in objective performance. In this subsection, we examine whether the Connect program had any effect on two important environmental outcomes that are not included in Bloomberg's criteria. If these outcomes are significantly affected by inclusion in the Connect program this would be suggestive evidence that influencing Bloomberg's ESG ratings do not explain the significant effects found earlier.

The first independent outcome we assess is carbon emissions as described in Section 3.4. We estimate the benchmark model (Equation 3) with the log of annual firm-level emissions as the dependent variable. Column 3 of Table 3 reports the results. Carbon emissions do not decline in the first year for Connect relative to non-Connect firms, but the emissions decline gradually over time (by 0.5% per year for Shanghai and 0.8% for the Shenzhen). Columns 4 and 5 of Table 3 reports estimates using the benchmark model (Equation 3) with applications of "green" patents in a firm-year as the dependent variable (as described in Section 3.4). There are two main types of patents granted in China. Invention patents involve the development of a fundamental technology while design patents alter the function or appearance of an existing technology. In the year the Shanghai Connect commences, treatment firms experience a significant increase in the number of patent applications relative to non-Connect firms, by 3.9 more patents for the invention and by 3.4 for design patents. These effects persist over time with no significant trend. In the year the Shenzhen Connect program commences, patent applications by Connect firms increase for both types relative to non-Connect firms (3.3 for invention and 2.8 for design patents) but the effects taper off within 2.0 and 2.8 years for the respective patent

Table 3

Spillover effects and effects on outcomes not included in ESG ratings

	$\log(1+\mathbf{ESG})$		Carbon Emissions	"Green" Patent Applications Invention	Design
	(1)	(2)	(3)	(4)	(5)
$D_{it}^{partner}$	0.109**				
	(0.050)				
$D_{it}^{supplier}$		0.125**			
		(0.053)			
D_{it}^{buyer}		-0.007			
		(0.048)			
$\mathbf{D}_{it}^{SH} \times \mathbf{SC}_i^{SH}$	0.012	0.012	-0.018	3.943***	3.391***
	(0.024)	(0.024)	(0.014)	(1.379)	(1.194)
$\mathbf{D}_{it}^{SH} \times \mathbf{SC}_i^{SH} \times \mathcal{T}_{it}^{SH}$	0.014**	0.014**	-0.005*	0.394	0.297
	(0.006)	(0.006)	(0.003)	(0.363)	(0.289)
$\mathbf{D}_{it}^{SZ} \times \mathbf{SC}_i^{SZ}$	0.045**	0.045**	-0.005	3.343**	2.816***
	(0.019)	(0.019)	(0.010)	(1.370)	(0.801)
$\mathbf{D}_{it}^{SZ} \times \mathbf{SC}_i^{SZ} \times \mathcal{T}_{it}^{SZ}$	0.020***	0.020***	-0.008***	-1.664**	-0.992*
	(0.006)	(0.006)	(0.003)	(0.795)	(0.536)
$\mathbf{E}_{it}$	-0.028**	-0.028**	-0.011	-3.126**	-2.409**
	(0.011)	(0.011)	(0.007)	(1.569)	(1.061)
$\mathbf{E}_{it} \times \mathcal{T}_{it}^{E}$	-0.020***	-0.020***	0.002	-0.863**	-0.238
	(0.005)	(0.005)	(0.003)	(0.412)	(0.313)
Obs	10,180	10,180	19,628	25,597	25,597
R^2	0.838	0.838	0.992	0.561	0.658
Firm Characteristics	Y	Y	Y	Y	Y
Firm FE	Y	Y	Y	Y	Y
Province FE	Y	Y	Y	Y	Y
Industry × Year FE	Y	Y	Y	Y	Y

Note: Column 1 shows selected coefficients from estimating Equation (3) allowing for a level shift for partners after a focal firm joins a Connect program. $D_{it}^{partner}$ is a dummy variable set equal to one if firm i is a partner of a firm that is part of the Connect (either Shanghai or Shenzhen) in year t, and zero otherwise. Only cases where the partner never joins a Connect program or enters later than the focal firm are considered. Column 2 replaces $D_{it}^{partner}$ with $\mathbf{D}_{it}^{supplier}$ ($\mathbf{D}_{it}^{buyer}$) which are set equal to one if firm i is a supplier (buyer) of a Connect firm in year t, and zero otherwise. Columns 3 through 5 show selected coefficients from estimating Equation (3) with log carbon emissions, number of "green" invention patent applications, and "green" design patent applications respectively as dependent variables. These columns include all firms with data not just those with ESG ratings. The remaining variables are as described in Table 2. Standard errors clustered by firm are in parentheses. $***\ p < 0.01$, $**\ p < 0.05$, $*\ p < 0.1$.

types.

6 Mechanisms

In this section, we investigate why firms changed their ESG activities after increased exposure to foreign investors through the Connect program. We examine the two main theories: the influence theory and the signalling theory.

Dyck *et al.* (2019) provide evidence that investors influence firms to improve their ESG ratings according to their concern with ESG activities. Based on data from 41 countries, foreign institutional shareholders from countries with strong E&S (environmental and social) performance in their home country propel firms in the destination countries to improve their E&S performance. Allen *et al.* (2019a) and Song and Xiong (2018) document that China's stock market is dominated by retail investors. Jia *et al.* (2017) show that in response to analyst recommendations, local (foreign) investors react more strongly to revisions from local (foreign) analysts. Given this result, the commencement of the Connect programs opens domestic firms to the influence of foreign investors that may care more about ESG activities than domestic investors.

Lins *et al.* (2017) argues that firms signal trustworthiness by investing in corporate social responsibility (CSR). Investing in CSR acts like insurance that pays off when investors face a crisis of confidence and the reward for being trustworthy increases markedly. This would occur when there is a crisis of trust, such as during the Enron/Worldcom fraud scandal or the subprime mortgage crisis. These arguments can be applied to domestic firms in China signalling their trustworthiness to foreign investors who face an information asymmetry. 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. Firth *et al.* (2015) document that firms with low transparency are more affected by investor sentiment than those with high and there is evidence that transparency is low for firms traded on China's stock markets. Song and Xiong (2018) argue that even though China has adopted accounting regulations and standards for publicly-listed firms similar to most developed countries, enforcement has been lax and penalties for violations low. Due to these, foreign investors might face uncertainty and information asymmetries about firms in China before the Connect programs. Subsequent investments in ESG activities by firms could raise their ESG ratings and signal trustworthiness to foreign investors, reducing this information gap.

Before examining the two theories, we perform two preliminary checks. We first show that foreign investors care more about ESG than do domestic investors. We then show that northbound shareholdings affect ESG ratings more for stocks that are eligible for trading only by, or more likely to be held by, institutional investors. This is consistent with both theories. Institutional investors are more likely to exert influence on firms to improve their ESG ratings given the difficulty of individual investors coordinating their activities. At the same time, ESG ratings could act as a signal to both institutional and individual investors.

We then provide evidence on whether the two theories are at play. Under the influence theory, northbound shares should causally increase ESG ratings since greater foreign ownership leads to greater pressure on firms to increase their ESG ratings. Under the signalling theory, ESG ratings should causally increase northbound shares since foreign investors will reward higher ratings with increased ownership of the stocks. Our approach is to use instruments that isolate the causal effects in each direction. To examine the causal effect of northbound shares on ESG ratings, we use duration in the Connect program as an instrument for northbound shares and test how the ESG rating responds to a change in northbound shareholding. To examine the causal effect of ESG ratings on northbound shares, we use a change in environmental regulation as an instrument for ESG ratings and test how foreign ownership responded to ESG ratings.

6.1 Do foreign investors care more about ESG?

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 ESG than do China's domestic investors. This appears to be the case. At the time the Shanghai Connect program was launched 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, the number of 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.

6.2 Effects for institutional versus individual ownership

Although ESG ratings could be influenced by either individual or institutional investors, the influence from institutional investors is likely to be greater given the difficulty for individual investors to coordinate. To test whether this is the case, we see whether there are differential effects for a subset of Connect firms whose stocks are restricted to institutional investors and firms whose stocks are part of an index used as a benchmark by institutional investors.

We examine the differential effects on stocks listed on the ChiNext board of the SZSE which was launched on 30 October 2009.[13] Of HKF investors, only institutions can trade the stocks on this board (both individual and institutional domestic investors can trade them).[14] Sixty-five out of the 356 stocks in the Shenzhen Connect program in 2017 were on the ChiNext board. We add a dummy variable $\mathbf{D}_i^{ChiNext}$, set equal to one if firm i is listed on the ChiNext board and zero otherwise, to the benchmark specification (Equation 3). Column 1 of Table 4 reports the estimates. The ESG ratings for firms on the ChiNext board rose 13.3% on average after entering the Connect program, dominating the baseline level shift induced by the Shenzhen Connect program.[15] There is no differential trend change for firms on the ChiNext board when joining a Connect program and the baseline trend remains.

Next, we consider the introduction of the MSCI China Index in 2018 by Morgan Stanley Capital International (162 firms were in the MSCI Index in 2018 out of a total of 1,547 firms in both Connect programs). Many institutional fund managers benchmark their returns against this index. This is a channel for firms listed on the SSE and SZSE to attract foreign institutional investors' attention, even though the Index does not provide a new trading venue. Column 2 of Table 4 allows for a level and a trend shift due to the MSCI program by adding $\mathbf{MS}_{it}$ (an indicator set equal to one if firm i was included in the MSCI China Index in year t and zero otherwise) and an interaction of it with $\mathcal{T}_{it}^{MS}$ (a time trend beginning when the firm was included in the MSCI and zero before). Inclusion in the MSCI index increases ESG ratings in the first year the firm is included in the index by 2.9% and an additional 1.1% per year thereafter. The baseline effects of the Shenzhen program remain similar to that in the benchmark results, while the effects of the Shanghai Connect program are dominated by the MSCI firms. These exercises suggest that effects on ESG ratings in response to the Connect program are greater for institutional than individual investors.

Hong and Kacperczyk (2009) show that institutional investors strategically avoid investing in "sin" (alcohol, tobacco, and gambling) stocks. A substantial portion of northbound capital in the Connect programs flowed into these "sin" stocks, particularly the alcohol industry. Therefore, we want to see if the effect of the Connect programs on ESG ratings is even stronger for non-"sin" stocks. To do so, we use the classification in Hong and Kacperczyk (2009) to identify twenty "sin" stocks with ESG ratings. Column 3 of Ta-

[13] The SSE exchange has a similar STAR board but it began on July 22, 2019 and thus does not offer enough data for this estimation.

[14] This board contains stocks that focus on innovative and fast-growing science and technology firms and enjoy less stringent listing standards than the main board. Thus, the higher ESG ratings for these stocks could indicate differential effects for high-technology firms. Our results using the MSCI index are therefore critical as corroborating evidence.

[15] In unreported results, such dominance exists across all sub-ratings.

Table 4

DIFFERENTIAL EFFECTS OF CONNECT PROGRAMS ON INSTITUTIONAL INVESTORS

	(1)	(2)	(3)
$\mathbf{D}_i^{ChiNext} \times \mathbf{D}_{it}^{SZ} \times \mathbf{SC}_i^{SZ}$	0.133***		
	(0.040)		
$\mathbf{D}_i^{ChiNext} \times \mathbf{D}_{it}^{SZ} \times \mathbf{SC}_i^{SZ} \times \mathcal{T}_{it}^{SZ}$	0.023		
	(0.014)		
$\mathbf{MS}_{it}$		0.029***	
		(0.010)	
$\mathbf{MS}_{it} \times \mathcal{T}_{it}^{MS}$		0.011**	
		(0.006)	
$\mathbf{D}_{it}^{SH} \times \mathbf{SC}_i^{SH}$	0.008	0.016	0.019
	(0.024)	(0.024)	(0.024)
$\mathbf{D}_{it}^{SH} \times \mathbf{SC}_i^{SH} \times \mathcal{T}_{it}^{SH}$	0.012*	0.009	0.013**
	(0.006)	(0.006)	(0.006)
$\mathbf{D}_{it}^{SZ} \times \mathbf{SC}_i^{SZ}$	0.014	0.048**	0.049**
	(0.024)	(0.020)	(0.020)
$\mathbf{D}_{it}^{SZ} \times \mathbf{SC}_i^{SZ} \times \mathcal{T}_{it}^{SZ}$	0.015**	0.015**	0.020**
	(0.007)	(0.006)	(0.006)
$\mathbf{E}_{it}$	-0.028**	-0.023**	-0.026**
	(0.011)	(0.011)	(0.011)
$\mathbf{E}_{it} \times \mathcal{T}_{it}^{E}$	-0.020***	-0.016***	-0.020***
	(0.005)	(0.005)	(0.005)
Obs	10,180	10,180	9,948
R^2	0.838	0.838	0.838
Firm Characteristics	Y	Y	Y
Firm FE	Y	Y	Y
Province FE	Y	Y	Y
Industry × Year FE	Y	Y	Y

Note: Column 1 shows selected coefficients from estimating Equation (3) but adding a level and trend shift for ChiNext firms. $\mathbf{D}_i^{ChiNext}$ is a dummy variable set equal to one if firm i is listed on the ChiNext board and zero otherwise. Column 2 shows selected coefficients from estimating Equation (3) but adding a level and trend shift for inclusion in the MSCI index. $\mathbf{MS}_{it}$ is a dummy variable set equal to one if firm i is included in the MSCI index in year t and zero otherwise. $\mathcal{T}_{it}^{MS}$ is the number of year since a firm is selected into the MSCI index and zero before. In Column 3, we exclude all "sin" stocks. Standard errors clustered by firm are in parentheses. $***\ p < 0.01$, $**\ p < 0.05$, $*\ p < 0.1$.

ble 4 re-estimates the benchmark model dropping them. The results are not substantially different than the baseline results perhaps because there are very few "sin" stocks.[16]

[16] 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) or it may be a result of self-selection. Investors that choose to hold "sin" stocks may care less about ESG issues and thus choose to exert little influence on firms' ESG activities (Dyck *et al.*, 2019).

6.3 The influence theory

If the influence theory is at play in the increased ESG ratings then the direction of causality is from northbound shares to ESG ratings. To provide suggestive evidence of whether the influence theory is at work we employ an instrument which exogenously shifts northbound shares but affects ESG ratings only though northbound shares. Since it takes time for HKF investors to accumulate shares of Connect firms, we use the number of quarters since the firm enters the Connect program as an instrument for northbound shareholding. To be a valid instrument, this must not directly affect ESG ratings. It is necessary therefore that this instrument does not capture a time trend since ESG ratings may trend over time. This is a firm-specific instrument since firms enter the Connect program at different times and therefore is not the same as a general time trend. Moreover, our specification includes industry-by-year fixed effects that will absorb any year-specific factors that affect ESG ratings. Therefore, this instrument captures firm-specific deviations from a general time trend vis-à-vis the firm's entry into a Connect program.

We employ two-stage least squares (2SLS) to implement the estimation. We first regress the share of market value held by northbound investors of the stock of firm i in industry j in year t and quarter q on the number of quarters since the firm entered a Connect program as

$$NB\ share_{ijtq} = \beta_0 + \beta_1 \mathbf{N}_{itq} + \beta_2 \mathbf{N}_{itq}^2 + \gamma' X_{itq} + \nu_{jt} + \alpha_i + \epsilon_{itq} \tag{4}$$

where $\mathbf{N}_{itq}$ is the number of quarters since firm i entered the Connect program as of year t and quarter q, X_{itq} includes controls that may affect the northbound share including province fixed effects and firm quarterly financial characteristics described in Section 3.3. Industry-by-year fixed effects (ν_{jt}) capture industry-specific unobservables by year that influence the northbound share. Firm fixed effects (α_i) capture time-persistent firm unobservables that affect the northbound share.

Second-stage estimation is at the annual level since ESG ratings are available annually. We therefore employ Mixed 2SLS (M2SLS) which allows for different levels of aggregation 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 second-stage equation is

$$y_{ijt} = \beta_0 + \beta_1 \widehat{NB\ share}_{i,t-1} + \gamma' X_{i,t-1} + \nu_{jt} + \alpha_i + \epsilon_{it} \tag{5}$$

where y_{ijt} is the annual ESG rating ($\log(1 + \mathbf{ESG})$) for a firm i in industry j in year t. For

Table 5
RESPONSE OF ESG RATINGS TO NORTHBOUND SHARE

First-stage estimation

	N_{iq}	N_{iq}^2	Obs	R^2	**F** Statistic
	1.63e-3***	-2.69e-5***	19,437	0.756	40.1
	(1.89e-4)	(5.59e-6)			

Second-stage estimation

	$\log(1+\textbf{ESG})$	$\log(1+\textbf{ENV})$	$\log(1+\textbf{SOC})$	$\log(1+\textbf{GOV})$
$\widehat{NB\,share}_{i,t-1}$	3.191***	17.024*	1.222	2.804***
	(1.257)	(9.163)	(3.031)	(0.686)
Obs	2,706	2,690	2,706	2,706
R^2	0.916	0.848	0.891	0.946
Firm FE	Y	Y	Y	Y
Province FE	Y	Y	Y	Y
Industry×Year FE	Y	Y	Y	Y
Firm Characteristics	Y	Y	Y	Y

Note: The first stage is estimated with Equation (4) and the second stage with Equation (5). 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. Standard errors clustered by firm in both stages are in parentheses. Second stage based on a block bootstrap by firm (1,000 iterations). $***\ p < 0.01$, $**\ p < 0.05$, $*\ p < 0.1$.

the independent variables, we use lagged values because ESG ratings are reported with a year lag. $\widehat{NB\,share}_{i,t-1}$ is the annual average of the fitted values from the first stage lagged by one year, $X_{i,t-1}$ are the annual average of the same set of controls variables in the first-stage lagged by one year. Industry-by-year fixed effects (ν_{jt}) capture industry-specific unobservables by year that influence ESG ratings. Firm fixed effects (α_i) capture time-persistent firm unobservables that affect ESG ratings.[17]

The top panel of Table 5 reports the estimates for the first-stage equation using quarterly data from 2017Q1, when HKEX began disclosing northbound shareholding for individual stocks, to 2021Q4. The coefficient of N_{itq} is positive and statistically significant while the squared term is negative and statistically significant. This implies that northbound shareholding is increasing and concave over the duration of the sample period.[18] The F-statistic for the first stage is above the critical value of 10 (Staiger and Stock, 1997)

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

[18] The trend does not decline until the 31st quarter after the first firms join a Connect program, which is after the sample period ends.

indicating a strong instrument.

The bottom of Table 5 reports the 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 the northbound shareholding, the ESG rating in the following year increases by 3.2%. This result is consistent with foreign investors influencing firms' ESG ratings. The results for the sub-ratings indicate that the environmental sub-rating is the biggest contributor followed by the governance sub-rating.

6.4 The signalling theory

If the signalling theory is at play in the increased ESG ratings then the direction of causality is from ESG ratings to northbound shares. To provide suggestive evidence for whether the signalling theory is at work we employ an instrument that exogenously shifts ESG ratings: an environmental regulatory change which significantly centralized environmental monitoring and inspections.[19] 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 change are likely affected by the extent of their polluting activities we weight firm responses by their pre-policy pollution production.

Identification requires that the policy change affects ESG ratings but affects northbound shares only through its effect on ESG ratings. The first condition is met as long as the centralization of environmental monitoring and inspections changed firms environmental performance sufficiently and thereby their ESG ratings. The most likely challenge to the second condition is that the environmental policy affected firms' financial performance and therefore 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

$$sp_{ijptm} = \sum_{r \neq 0} \beta_r \mathbf{1}_{prtm} + \nu_{jtm} + \alpha_i + \epsilon_{itm}. \tag{6}$$

where sp_{ijptm} is the average stock price, defined as the ratio of monthly total trading value

[19]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.

over monthly total trading volume, for firm i in industry j and province p in month m of year t, $\mathbf{1}_{prtm}$ is equal to one if it is r months before or after the event, and ν_{jtm} are industry-by-year-by-month fixed effects. Appendix B.3 plots β_r along with 95% confidence intervals. The results show that there were 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 employ 2SLS to implement the estimation. Since we wish to estimate the causal effect of ESG ratings on northbound shares we restrict the sample to stocks for which northbound share data are available - only firms that were part of a Connect program at some point. We use data only from 2013 onward because we use the earlier years to compute the pre-policy emissions weightings for each firm. In the first stage we use the policy change as an instrument for ESG ratings by adding to the benchmark model a dummy variable for the policy implementation and interacting it with the firm's emissions intensity as

$$\begin{aligned} y_{ijpt} &= (\theta_1 + \theta_2 \times C_i)\mathbf{1}_{pt} + \sum_{k\in\{SH,SZ\}} \left[\beta_0^k \mathbf{SC}_i^k \mathcal{T}_t^{2013} + \left(\beta_1^k + \beta_2^k \mathcal{T}_{it}^k + \left(\beta_3^k + \beta_4^k \mathcal{T}_{it}^k\right)\mathbf{SC}_i^k\right)\mathbf{D}_{it}^k\right] \\ &\quad + \left(\beta_5 + \beta_6 \mathcal{T}_{it}^E\right)\mathbf{E}_{it} + \gamma' X_{it} + \nu_{jt} + \alpha_i + \epsilon_{ijt}, \qquad (7) \end{aligned}$$

where y_{ijpt} is the annual ESG rating for firm i in industry j and province p in year t and $\mathbf{SC}_i^k$, $\mathbf{D}_{it}^k$, $\mathcal{T}_{it}^k$, X_{it}, $\mathbf{E}_{it}$, and $\mathcal{T}_{it}^E$ are defined as in Equation (3). Importantly, recall that X_{it} includes province fixed effects which means the impact of the policy is identified by within-province variation over time. $\mathcal{T}_t^{2013}$ is set to zero in 2013 and increases by one in each year to control for any differential pre-policy trend for Connect relative to non-Connect firms. $\mathbf{1}_{pt}$ is an indicator set equal to one in all years after the province p adopts the environmental policy and zero before. C_i equals $1 - 1/(1 + Carbon\ \ Emission_i)$ where $Carbon\ \ Emission_i$ is the carbon emissions discussed in Section 3.4 averaged over the pre-policy period (2010 to 2012). C_i lies between zero and one and is an increasing function of firm i's pre-policy pollution production intensity. θ_1 captures the baseline effect of the environmental policy change on firms' ESG ratings while θ_2 captures the differential effect on more intensively-polluting firms. All other parameters serve a similar role as in the benchmark regression (Equation 3).

In the second stage, we take the fitted values from the first stage and regress the northbound shareholding on the one-year lagged fitted value and control variables. We lag values since we assume that ESG ratings (which are published only annually) take a year to influence northbound shareholdings. Northbound shares are measured at the quarterly level. Therefore, the frequency of data in the first stage is annual while the frequency of data in the second stage is quarterly and we again employ M2SLS. Since we lag values by one year in the second stage, 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 part of the Connect program, the second stage only uses years (and quarters where appropriate) in which the firm is active in the Connect program

$$\begin{aligned} NB\ share_{ijtq} &= \beta_0 + \beta_1 \log(\widehat{1+\mathbf{y}_{ijp,t-1}}) + \sum_{k\in\{SH,SZ\}} \beta_2^k \mathcal{T}_{i,t-1,q}^k \\ &\quad + \left(\beta_3 + \beta_4 \mathcal{T}_{i,t-1,q}^E\right) \mathbf{E}_{i,t-1,q} + \gamma' X_{i,t-1,q} + \nu_{jt} + \alpha_i + \epsilon_{itq}. \end{aligned} \tag{8}$$

where $\log(\widehat{1+\mathbf{y}_{ijp,t-1}})$ is the lag of the fitted value from the first stage, $X_{i,t-1,q}$ are lagged values of the same set of control variables as in the first-stage except measured at the year-quarter level. The indicator variable for firm i exiting a Connect program ($\mathbf{E}_{i,t-1,q}$) is included to control for the fact that foreign investors can only sell (not buy) the firm's stock once it exits. β_2 controls for post-policy time trends for the two programs. β_3 controls for the level shift after exit and β_4 any time trend after exit.[20] Industry-by-year fixed effects (ν_{jt}) capture industry-specific unobservables by year that influence northbound shares and α_i time-invariant, firm-specific factors that affect northbound shares.

The top panel of Table 6 reports the estimates of Equation (7). The change in environmental policy lowered ESG ratings for firms with very low carbon emissions. However, ESG ratings increased with the intensity of firms' carbon emissions. The ESG rating of a firm with average carbon emissions ($C_i = 0.925$) decreased by 0.87%. Firms with low emissions and therefore not highly exposed to the policy change experienced a decrease in ESG ratings while those with high emissions and therefore highly exposed experienced an increase of up to 20%. The cutoff in emissions intensity is $\bar{C} = 0.928$, above which firms' ESG ratings increase and below which they decline. Based on the distribution of carbon emissions in the data, roughly 33% of the firms have emissions intensities exceeding $\bar{C}$. The F-statistic for the first stage is above the critical value of 10 indicating a reasonably strong instrument.

The bottom panel of Table 6 reports the second-stage estimates. The effects are pos-

[20] To ensure the exclusion restriction is met, the first-stage equation must include the averaged values of all the exogenous variables from the second stage. The firm-year characteristics in the first-stage are the average values of the firm-year-quarter characteristics in the second stage and the firm and industry-by-year fixed effects are the same in both stages. It is unnecessary to control for $\left[\left(\beta_1^k + \beta_2^k \mathcal{T}_{it}^k + \mathbf{SC}_i^k \beta_3^k\right)\mathbf{D}_{it}^k\right]$ in the second stage since the data only include periods in which the Connect programs are active and the firm is active in the Connect program (except for later exits).

Table 6

Response of HKF shareholding to ESG ratings

First-stage estimation

	$\log(1+\mathbf{ESG})$	$\log(1+\mathbf{ENV})$	$\log(1+\mathbf{SOC})$	$\log(1+\mathbf{GOV})$
$\mathbf{1}_{pt}$	-3.002***	-8.661**	-0.236	-1.679***
	(0.575)	(3.434)	(1.126)	(0.483)
$\mathbf{1}_{pt} \times C_i$	3.236***	9.306**	0.266	1.808***
	(0.619)	(3.700)	(1.213)	(0.521)
Obs	4,748	4,691	4,748	4,748
R^2	0.878	0.753	0.819	0.880
F Stat	13.65	3.27	0.20	6.03

Second-stage estimation

	(1)	(2)	(3)	(4)
$\log(1+\widehat{\mathbf{ESG}}_{\mathbf{ijp,t-1}})$	0.037***			
	(0.015)			
$\log(1+\widehat{\mathbf{ENV}}_{\mathbf{ijp,t-1}})$		0.006**		
		(0.003)		
$\log(1+\widehat{\mathbf{SOC}}_{\mathbf{ijp,t-1}})$			0.032***	
			(0.007)	
$\log(1+\widehat{\mathbf{GOV}}_{\mathbf{ijp,t-1}})$				0.026
				(0.025)
Obs	6,718	6,673	6,718	6,718
R^2	0.838	0.838	0.839	0.838
Firm FE	Y	Y	Y	Y
Province FE	Y	Y	Y	Y
Industry×Year FE	Y	Y	Y	Y
Firm Characteristics	Y	Y	Y	Y

Note: The first stage is estimated with Equation (7) and the second stage with Equation (8). 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 had joined a Connect program. Standard errors clustered by firm in both stages are in parentheses. Second stage based on a block bootstrap by firm (1,000 iterations). *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

itive and significant. A one percent increase in ESG rating leads to a 3.7 basis point increase in northbound shareholdings consistent with ESG ratings acting as a positive signal for foreign investors. The results for sub-ratings indicate that the environmental sub-rating is the biggest contributor consistent with the policy affecting environmental performance; however, the first-stage F-statistics indicate weak instruments for the sub-ratings results.

7 Conclusion

We find that deregulating China's financial system to allow more foreign investors in its stock market leads to increased ESG activities and ratings for firms receiving foreign investments. Evidence suggests that both foreign investors exert influence on domestic firms to improve their ESG ratings and that firms improve their ESG activities to signal their trustworthiness to foreign investors. Thus, exogenous increases in either ESG ratings or foreign investment holdings will reinforce each other and amplify the effects in the long term.

It would be useful to obtain direct evidence of these mechanisms. For example, are the increased ESG 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 ESG ratings that are driven by foreign investment? Do ESG ratings increase relatively more for firms that receive investments from foreign investors that value ESG relatively more? This would require a measure of the value that foreign investors place on ESG.

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 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 Directors 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.2 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 employ the probit model to estimate Equation (1). Table A.1 reports the estimates.

A.3 Pre-trend tests

Using Equation (2), we test the pre-trend for all three sub-ratings. As shown in Figures A.1 through A.3, the pre-trends for the Shanghai Connect firms are similar to those of the non-Connect firms; while the pre-trends for the Shenzhen Connect firms are similar to those of the non-Connect firms for the environmental and governance sub-ratings but not for the social sub-rating.

Table A.1
Reporting probability by Bloomberg

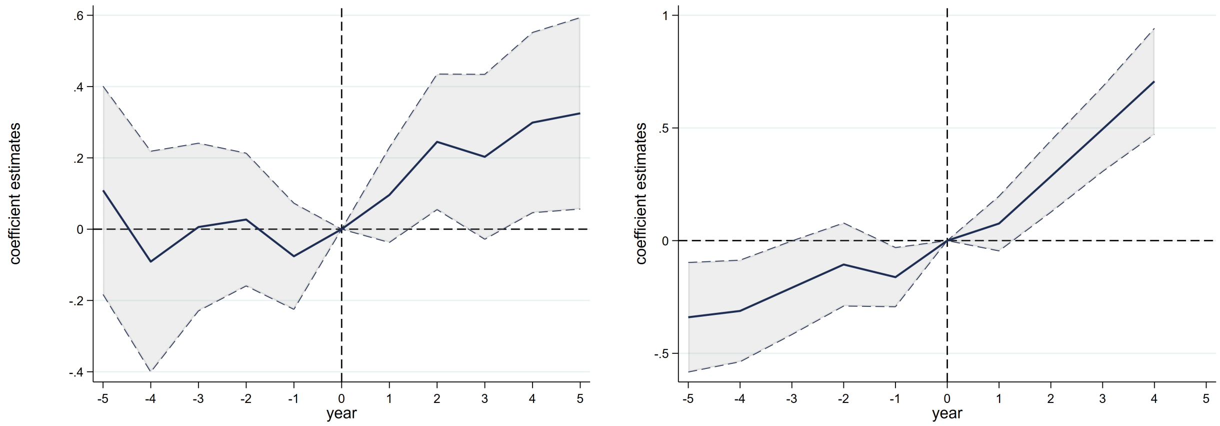
	(1)	(2)	(3)	(4)
$\mathbf{D}_{it}^{SH}$	0.35***	0.33***		
	(0.094)	(0.100)		
$\mathbf{SC}_i^{SH} \times \mathbf{D}_{it}^{SH}$	0.06	-0.02		
	(0.102)	(0.105)		
$\mathbf{D}_{it}^{SZ}$	0.26***	0.15**		
	(0.069)	(0.074)		
$\mathbf{SC}_i^{SZ} \times \mathbf{D}_{it}^{SZ}$	0.05	0.02		
	(0.072)	(0.073)		
$\mathbf{D}_{it}^{QFII}$	0.13***	0.12***		
	(0.044)	(0.040)		
$\mathbf{MS}_i \times \mathbf{D}_{it}^{MS}$	0.61***	0.48**		
	(0.234)	(0.239)		
$\mathbf{D}_{i,t-1}^{SH}$			0.35***	0.36***
			(0.089)	(0.095)
$\mathbf{SC}_i^{SH} \times \mathbf{D}_{i,t-1}^{SH}$			0.11	-0.02
			(0.101)	(0.103)
$\mathbf{D}_{i,t-1}^{SZ}$			0.32***	0.23***
			(0.067)	(0.070)
$\mathbf{SC}_i^{SZ} \times \mathbf{D}_{i,t-1}^{SZ}$			0.09	-0.02
			(0.070)	(0.072)
$\mathbf{D}_{i,t-1}^{QFII}$			0.09**	0.10**
			(0.043)	(0.047)
$\mathbf{MS}_i \times \mathbf{D}_{i,t-1}^{MS}$			0.58**	0.38
			(0.236)	(0.237)
Obs	9,570	9,478	9,570	9,570
R^2	0.844	0.726	0.692	0.828
Control Variables	t	$t-1$	t	$t-1$
Province FE	Y	Y	Y	Y
Industry×Year FE	Y	Y	Y	Y

Note: Selected coefficients from estimating Equation (1) using a probit model. An indicator variable for whether Bloomberg includes the firm in their ESG ratings is the dependent variable. Standard errors clustered by firm are in parentheses. $***\ p < 0.01$, $**\ p < 0.05$, $*\ p < 0.1$.

B Additional Tests

B.1 Robustness using ESG ratings levels

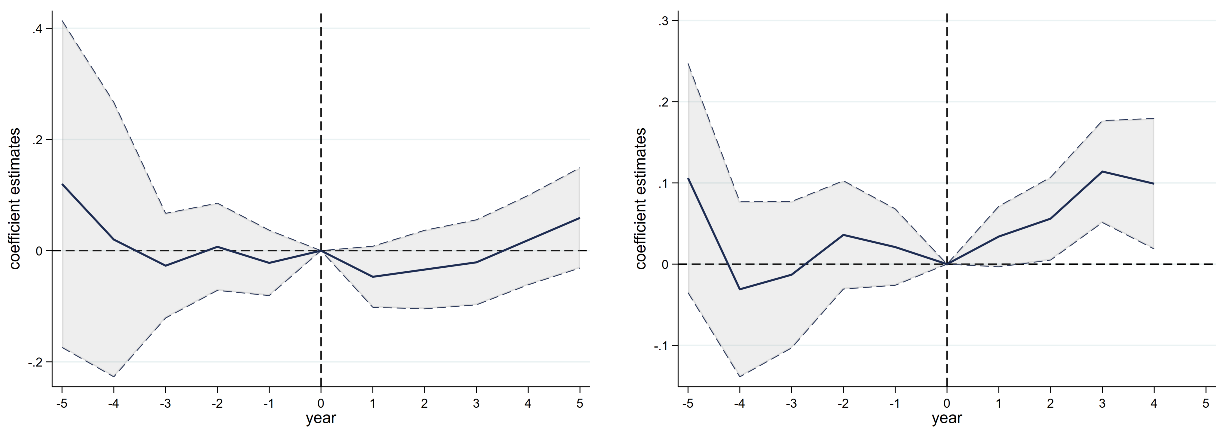
Column 1 of Table B.1 shows the results of estimating Equation (3) with **ESG** ratings levels as the dependent variable. The standard deviation of the ESG rating and its sub-ratings are respectively 4.42, 5.36, 6.41 and 8.67. The results here are robust as in the benchmark model.



(a) Shanghai Connect Program (b) Shenzhen Connect Program

Note: Solid lines are point estimates and dashed lines 95% confidence intervals from the event study in Equation (2).

Figure A.1
Event-study estimates for environmental sub-rating for Connect programs

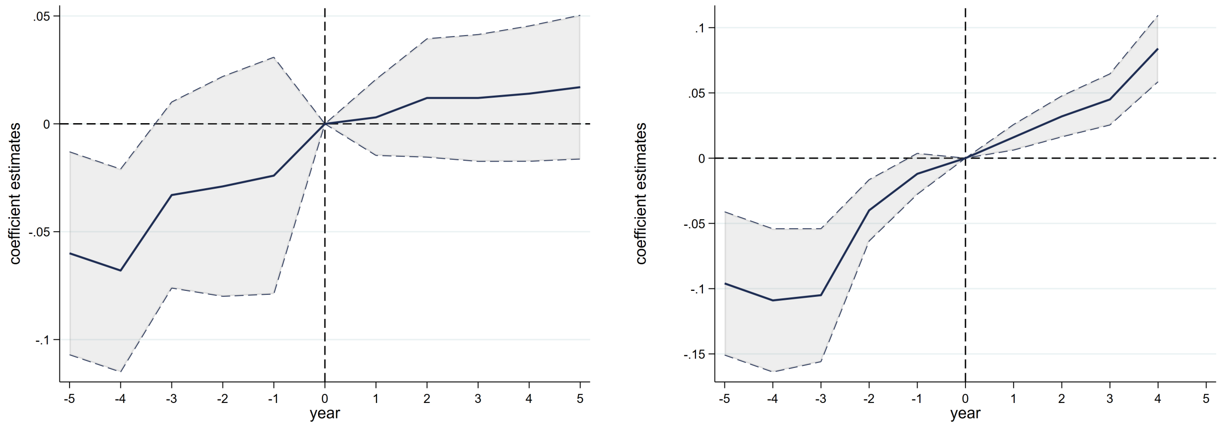


(a) Shanghai Connect Program (b) Shenzhen Connect Program

Note: Solid lines are point estimates and dashed lines 95% confidence intervals from the event study in Equation (2).

Figure A.2
Event-study estimates for social sub-rating for Connect programs

Columns 2, 3, and 4 of Table B.1 estimate the same specification with the levels of the three sub-ratings as dependent variables. The environmental and social sub-ratings are major contributors to the overall ESG rating for both programs while the governance sub-rating is not. However, the governance sub-rating does influence the effects when a firm leaves either program.



(a) Shanghai Connect Program

(b) Shenzhen Connect Program

Note: Solid lines are point estimates and dashed lines 95% confidence intervals from the event study in Equation (2).

Figure A.3
Event-study estimates for governance sub-rating for Connect programs

B.2 Robustness to differences in trends

Figure B.1 shows robustness tests for the period-by-period difference in trends for the treatment and control groups using the robust inference methods of Rambachan and Roth (2023). Panel A shows the results for the Shanghai Connect program for M values ranging from 0.8 to 1.2 while Panel B shows the results for the Shenzhen Connect program for M values ranging from 0 to 1.0.

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

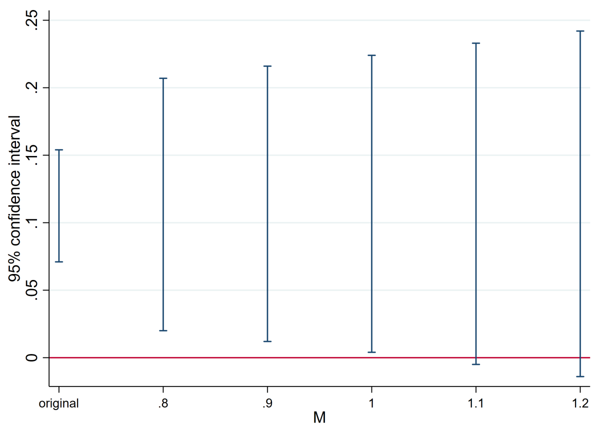
Figure B.2 shows the coefficients and 95% confidence intervals for the stock-price event study in Equation (6) of the main text. Estimation uses 24 months of data before and after the environmental policy change and includes all stocks on the SSE and SZSE.

Table B.1

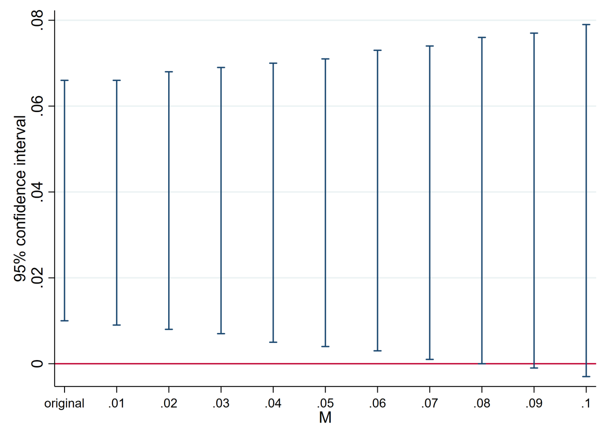
Benchmark model with ESG ratings levels

	ESG	**ENV**	**SOC**	**GOV**
$\mathbf{D}_{it}^{SH} \times \mathbf{SC}_{i}^{SH}$	0.352	0.564	0.081	0.561
	(0.550)	(0.757)	(0.520)	(1.293)
$\mathbf{D}_{it}^{SH} \times \mathbf{SC}_{i}^{SH} \times \mathcal{T}_{it}^{SH}$	0.583***	1.225***	0.722***	-0.174
	(0.167)	(0.286)	(0.166)	(0.275)
$\mathbf{D}_{it}^{SZ} \times \mathbf{SC}_{i}^{SZ}$	1.089**	1.212*	0.073	1.934*
	(0.480)	(0.702)	(0.410)	(1.009)
$\mathbf{D}_{it}^{SZ} \times \mathbf{SC}_{i}^{SZ} \times \mathcal{T}_{it}^{SZ}$	0.833***	1.897***	0.745***	-0.131
	(0.173)	(0.332)	(0.182)	(0.271)
$\mathbf{E}_{it}$	-0.943***	-1.061	-0.263	-1.425***
	(0.352)	(0.668)	(0.320)	(0.507)
$\mathbf{E}_{it} \times \mathcal{T}_{it}^{E}$	-0.737***	-1.166***	-0.432***	-0.608**
	(0.159)	(0.322)	(0.161)	(0.270)
Obs	10,180	10,180	10,180	10,180
R^2	0.836	0.706	0.792	0.844
Firm FE	Y	Y	Y	Y
Province FE	Y	Y	Y	Y
Industry×Year FE	Y	Y	Y	Y

Note: Selected coefficients from estimating Equation (3) with ESG rating and sub-ratings in levels as dependent variables. $\mathbf{SC}_i^k$ is an indicator set to one if firm i is in program k in any year. $\mathbf{D}_{it}^k$ is an indicator variable set to one if the policy is in effect for firm i in year t for program k. For Shanghai (Shenzhen) control firms this equals one in 2015 (2017) and later and zero otherwise. For treatment firms this equals one in the years after they join the Connect program and zero before. $\mathbf{E}_i$ is an indicator variable set to one if firm i exits either of the Connect programs in year t after having previously entered. $\mathcal{T}_{it}^k$ measures the number of years firm i has been subject to policy k. For Shanghai (Shenzhen) control firms it equals the number of years since 2015 (2017) and zero before. For treatment firms it equals the number of years since joining program k and zero before.$\mathcal{T}_{it}^E$ equals the number of years since a treatment firm exits either program if it did so and zero otherwise. The number of observations for the environmental sub-rating is slightly lower due to missing values. Standard errors clustered by firm are in parentheses. $***\ p < 0.01$, $**\ p < 0.05$, $*\ p < 0.1$.

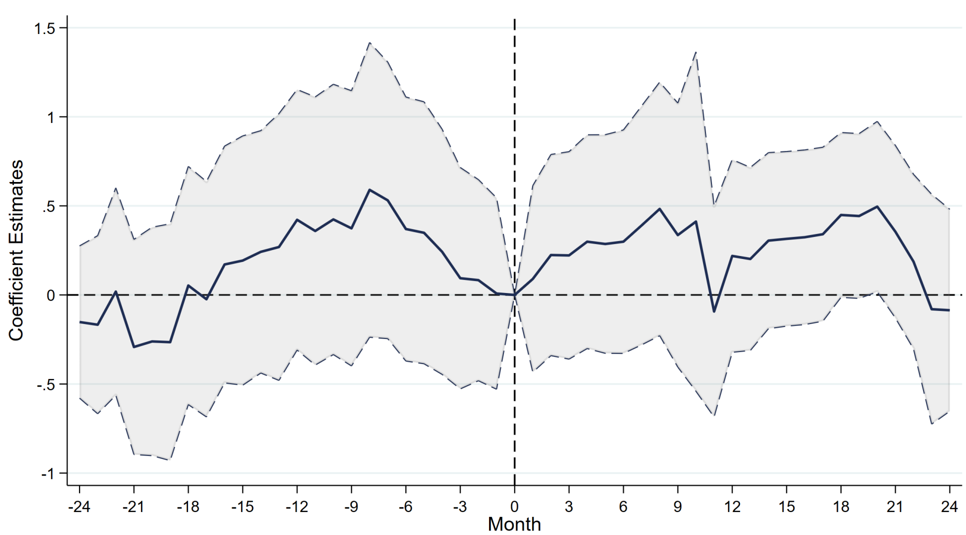


(a) Shanghai Connect Program



(b) Shenzhen Connect Program

Figure B.1
ROBUSTNESS TO PERIOD-BY-PERIOD DIFFERENCES IN TRENDS



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

Figure B.2
EVENT STUDY FOR STOCK PRICE EFFECTS FROM ENVIRONMENTAL POLICY