

Navigating Geoeconomic Risk: Evidence from U.S. Mutual Funds*

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Abstract

How do investors respond to firm-level geoeconomic shocks? U.S. export controls restrict technology sales to targeted Chinese firms, depressing the stock prices of their U.S. suppliers. We trace these shocks to domestic equity mutual funds. Funds more exposed to affected suppliers display higher volatility and lower performance. Although export controls target specific firms, they trigger portfolio-wide adjustments: funds rebalance away from affected suppliers and other U.S. exporters to China, leaving portfolios more concentrated. Specialist and high-fee funds see smaller performance declines. Affected suppliers' stock prices subsequently recover, consistent with dissipating selling pressure or higher required returns.

JEL classification: G12, F51, F38.

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1 Introduction

Geoeconomic risk—the risk that firms incur valuation losses when countries deploy economic, trade, or financial leverage for geopolitical aims—has become a first-order concern for investors (BlackRock, 2024). The stocks of multinational corporations offer international diversification benefits but may increasingly expose investors to geoeconomic shocks through these firms’ foreign operations and supply chains. Despite growing recognition of this risk (International Monetary Fund, 2025), little is known about how these shocks affect portfolio performance and how investors manage them.

We study this question in the context of U.S. domestic equity mutual funds, which account for nearly half of the \$31 trillion in assets managed by U.S. mutual funds. Although these funds are mandated to invest in U.S. equities and may appear insulated from geopolitical tensions, their stock holdings give them substantial indirect exposure to foreign markets through firms’ global supply chains (Demirci et al., 2022; Bai et al., 2022). These international links increasingly expose domestic firms to geoeconomic policies such as U.S. export controls. As a key policy tool in the ongoing U.S.-China technological rivalry, export controls restrict the sale of U.S. cutting-edge technologies to selected foreign customers. These restrictions impose costs on the U.S. firms (hereafter, affected firms) supplying these customers. The stocks of these affected firms experience negative abnormal returns around export-control announcements (Crosignani et al., 2026). This setting provides *firm-level* variation in exposure to realized geoeconomic shocks, allowing us to trace how these shocks affect investors through their portfolio holdings.

We find that firm-level geoeconomic shocks propagate to the portfolios of well-diversified mutual funds. Funds with greater exposure to affected stocks experience higher volatility and lower returns. In response, fund managers reduce holdings of affected firms, as well as stocks of other U.S. firms that export to China but are not directly affected by export controls. Fund managers also buy more lottery-like stocks and reduce holdings in the affected industry, increasing portfolio concentration. For a given level of exposure, funds run by specialists and funds charging higher fees exhibit smaller performance declines, while passive funds suffer larger declines than actively managed ones. Lastly, we analyze the effect of export controls on the stock returns of affected suppliers and document an initial stock price decline followed by a recovery—a pattern consistent with either dissipating temporary selling pressure or a discount rate shock that increases required returns.

To construct our firm-level geoeconomic shocks, we hand-collect the names of Chinese firms targeted by export controls and the corresponding announcement dates. We then use FactSet Revere supply chain data to identify their U.S. suppliers. To measure mutual funds’ exposure to export controls, we compute the share of each mutual fund’s portfolio invested in affected U.S. suppliers, using holdings from the month before the announcement. Consistent with [Crosignani et al. \(2026\)](#), we find that affected U.S. firms experience cumulative abnormal stock returns of -3.6% around export-control announcements. Abnormal returns in the ten trading days before announcements are statistically insignificant, which suggests that the market does not anticipate the timing of export controls.

Funds with greater exposure to affected stocks experience higher volatility and lower performance. The decline in performance is not explained by exposure to standard risk factors.

Comparing funds within the same investment style and month, a one-standard-deviation increase in exposure lowers 3- and 5-factor adjusted monthly alphas by 12 and 10 basis points, respectively. Because export controls are staggered over time, a standard two-way fixed effects (TWFE) model may compare newly treated funds with previously treated funds whose outcomes will reflect earlier shocks (Goodman-Bacon, 2021; Baker et al., 2022). To address this concern, we use the local projections difference-in-differences method of Dube et al. (2025), which restricts comparisons to clean control observations and allows for continuous treatment effects. Our main results hold under this alternative estimator.

We next examine how actively managed mutual funds adjust their holdings following export-control shocks. Fund managers may retain affected suppliers' stocks if they believe the price decline partly reflects temporary mispricing. Alternatively, they may sell the affected stocks if they consider them too risky or face investor pressure to reduce exposure. We find that exposed funds scale back their positions in affected stocks in the announcement month. Their trading shows no detectable change in the months before the announcement, providing no evidence of anticipatory trading.

These portfolio adjustments extend beyond directly affected stocks. First, we find that exposed funds are more likely to sell stocks of U.S. firms that export to Chinese companies not currently targeted by U.S. export controls. These sales reduce funds' exposure to China beyond directly affected suppliers, consistent with managers seeking to limit exposure to future export controls. Second, we find that funds more exposed to export controls tilt their portfolios towards lottery-like stocks. Because funds holding lottery stocks tend to attract larger inflows (Agarwal et al., 2022), this shift may reflect an attempt to offset outflows

following underperformance. Lastly, exposed funds reduce their allocation to the affected industry, increasing overall portfolio concentration.

We next explore which funds better navigate geoeconomic shocks. Traditional skills such as stock picking and market timing (Kacperczyk et al., 2014) are not associated with smaller performance declines following these shocks. By contrast, funds run by specialists managing a single investment style (Zambrana and Zapatero, 2021) experience significantly smaller performance declines than those run by generalists managing multiple styles. Funds charging higher fees also exhibit smaller performance declines, suggesting that high-fee funds may offer advantages when facing geoeconomic shocks. We then compare active and passive funds. For the same level of exposure, passive funds experience a decline in factor-adjusted returns about 2.4 to 2.9 times as large as active funds. Passive funds show no trading responses in affected stocks, consistent with their mandate to track a benchmark. Both active and passive funds experience outflows in the month following the shock. These results are consistent with portfolio discretion helping funds limit losses from geoeconomic shocks.

Lastly, we examine stock returns following export-control announcements. Affected suppliers experience an initial stock price decline. Part of this decline reflects lower expected cash flows, since affected suppliers lose sales to Chinese customers and become less profitable (Crosignani et al., 2026). With discount rates unchanged, a downward revision to expected cash flows explains the initial price decline but does not, by itself, predict a subsequent reversal (Campbell, 1991; Campbell and Vuolteenaho, 2004).¹ Our point estimates suggest

¹Negative ESG news is one such case, where the price decline is explained by downward revisions to expected cash flows rather than by changes in discount rates (Derrien et al., 2025).

that affected suppliers’ stock prices recover in a few months after the shock. The recovery is consistent with either dissipating temporary selling pressure or a discount rate shock that increases required returns. Our longer-horizon estimates are noisy and sensitive to industry controls, so we cannot distinguish between the two. The pattern of an initial decline followed by higher subsequent returns is in line with recent studies on the asset pricing implications of political and geopolitical risk (Gala et al., 2023; Sheng et al., 2025; Gonçalves et al., 2025).

Contribution to the literature. We contribute to the growing literature on geoeconomic risk (see Mohr and Trebesch (2025) for a review) by tracing how firm-level policy shocks transmit to investors’ portfolios. The theoretical literature examines how hegemons use economic policies to achieve geopolitical goals (e.g., Clayton et al., 2024, 2026; Liu et al., 2026; Thoenig, 2024; Broner et al., 2025; Liu and Yang, 2025). A complementary empirical literature documents how geoeconomic policy shocks—tariffs, sanctions, and export controls—affect firm performance, supply chains, labor markets, and macroeconomic outcomes (e.g., Fajgelbaum et al., 2020; Flaaen et al., 2020; Benguria and Saffie, 2020, 2023; Ahn and Ludema, 2020; Felbermayr et al., 2020; Crozet et al., 2021; Besedeš et al., 2021; Han et al., 2024; Crosignani et al., 2026).² Building on prior work that studies the costs of export controls on domestic exporters (Crosignani et al., 2026), we trace the effects of these shocks on domestic mutual fund performance and subsequent portfolio reallocation. Another strand of related work examines how political ideology and geopolitical alignment influence cross-border capital

²Related work develops text-based measures of policy uncertainty, political and country risk, and geoeconomic pressure (Baker et al., 2016; Caldara and Iacoviello, 2022; Hassan et al., 2019, 2024; Clayton et al., 2025). Our analysis focuses on realized policy shocks and investors’ responses.

allocation (Kempf et al., 2023; Aiyar et al., 2024; Gopinath et al., 2025). We complement this work by examining how investors reallocate their domestic portfolios in response to firm-level geoeconomic shocks.

Our work also contributes to the mutual fund literature along several dimensions. First, prior work shows that holdings of multinational firms give domestic mutual funds indirect exposure to foreign markets and can contribute to fund performance (Demirci et al., 2022; Bai et al., 2022). Our paper shows how these same holdings transmit geoeconomic shocks to domestic fund portfolios. Second, a growing literature studies how investors and fund managers respond to emerging risks, including market-wide disruptions such as the COVID-19 pandemic (Pástor and Vorsatz, 2020; Falato et al., 2021) and climate risk (Alok et al., 2020; Alekseev et al., 2022; Huynh and Xia, 2023). We extend this work to geoeconomic shocks, tracing funds' reallocations across affected stocks and the rest of their portfolios following export-control announcements. Lastly, we contribute to the literature on managerial skill and mutual fund performance (e.g., Jensen, 1968; Malkiel, 1995; Gruber, 1996; Fama and French, 2010; Berk and Green, 2004; Kacperczyk et al., 2005; Kacperczyk and Seru, 2007; Barras et al., 2010; Kacperczyk et al., 2014; Berk and Van Binsbergen, 2015; Pástor et al., 2015; Cremers et al., 2016; Zambrana and Zapatero, 2021). We show that funds run by specialists experience smaller performance declines following export-control shocks, while we find no comparable advantage for funds with stronger stock-picking or market-timing skills. Passive funds also experience larger performance declines than active funds, consistent with their benchmark-tracking mandates constraining portfolio adjustment.

Outline. The remainder of the paper proceeds as follows. Section 2 describes the institutional details and data. Section 3 explains how we capture export-control shocks, measure fund-level shock exposure, and estimate the effects of export controls on fund volatility and performance. Section 4 analyzes how funds reallocate their portfolios after export-control shocks. Section 5 discusses which fund and manager characteristics help in navigating geoeconomic shocks. Section 6 examines the relation between firms’ exposure to export controls and subsequent stock returns. Finally, Section 7 concludes.

2 Institutional Details and Data

We now provide some background on export controls (Section 2.1) and describe our data (Section 2.2).

2.1 Background on Export Controls

The Bureau of Industry and Security (BIS) of the U.S. Commerce Department has the authority to forbid U.S. firms from exporting certain technologies to designated foreign firms. To do so, the BIS includes foreign firms in the Code of Federal Regulations, Part 744, Supplement No. 4, also known as the “Entity List.” Originally meant to restrict exports to entities engaged in the production of weapons of mass destruction, the Entity List has more recently been used to curb “activities contrary to the national security or foreign policy interests of the United States.” In December 2020, the BIS introduced an additional list, called the Military End User (MEU) List, to limit exports to foreign companies that support the military efforts of China, Russia, and Venezuela. We refer to the Entity List and the

Military End User List collectively as the “BIS lists.” Finally, the BIS publishes the Unverified List (UVL) which includes entities whose legitimacy the BIS cannot promptly verify. The BIS removes an entity from the UVL once it validates the end user’s legitimacy through either a pre-license check or a post-shipment verification.

Since 2010, the BIS has used its authority numerous times, predominantly to restrict U.S. technology from being exported to a selected group of Chinese firms. We therefore focus on export controls aimed at restricting U.S. technology from these Chinese firms, which we call “Chinese targets.” For every Chinese entity on the list, we record both the announcement date of the relevant notice and its effective date, which typically falls five calendar days later. Following [Crosignani et al. \(2026\)](#), we designate the announcement date as the event date in our event study.

2.2 Data

Data on export controls are hand-collected from the Code of Federal Regulations ([ecfr.gov](#)). Specifically, we obtain information on additions and removals from the Entity List (Part 774, Supplement No. 4), the MEU list (Part 774, Supplement No. 7), and the UVL (Part 774, Supplement No. 6). Since Chinese entities represent the vast majority of the inclusions in the BIS lists, we focus only on them for consistency. Entities from other countries (e.g., Russia and Iran) have very few supply chain connections with U.S. firms. Multiple subsidiaries and aliases of the same Chinese firm are often included in the BIS lists. From a total of 1,120 Chinese entries, we find 732 unique Chinese entities: 470 corporations and 262 universities and institutions. Most targeted entities are from the Entity List, which started in 1997 but

records a surge in activity only after 2014.

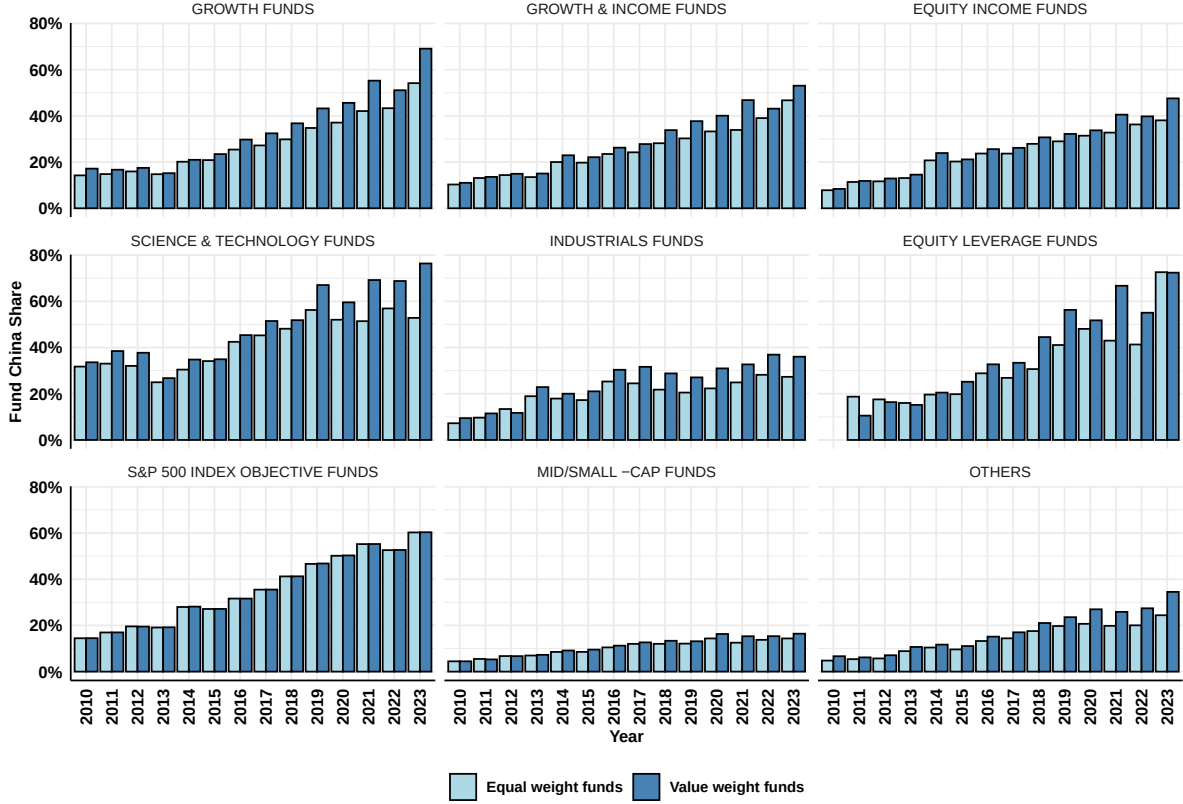
We obtain information on supply chain relations from FactSet Revere. Each relation includes the names and identifiers of both customer and supplier, along with the relation’s start and end dates. Following [Gofman et al. \(2020\)](#), we combine multiple relations with gaps shorter than 6 months into a continuous one. Using ISINs and name matching, we identify 90 Chinese firms targeted by U.S. export controls and 351 affected U.S. suppliers. Among these, 125 suppliers both maintained supply chain relations with the listed Chinese customers at the time of their inclusion in the BIS lists and were held by mutual funds during the event window.

The mutual fund data come from the CRSP Mutual Fund Database. We focus on mutual funds because they are major investors in U.S. equity markets and their holdings are observed at the fund level monthly.³ We use funds’ monthly holdings to capture the granular treatment around export-control announcements.⁴ We restrict our analysis to domestic equity funds, namely funds that invest more than 80% of their holdings in domestic equities, and include leveraged funds with an equity-to-total-net-assets (TNA) ratio below 150%. CRSP Mutual Fund Database also provides additional information at the fund class level, such as returns, share classes, TNA, fund family name, and expense ratio, among other fund characteristics. To conduct our analysis, we aggregate fund class-level information to the fund

³Mutual funds held 22% of outstanding U.S. corporate equity at year-end 2023 and 19% at year-end 2025 ([Investment Company Institute, 2026](#)). In addition, CRSP offers portfolio information at the fund level whereas Form 13F filings provide aggregate long positions across multiple funds, accounts, and strategies managed by the same adviser.

⁴The SEC requires funds to disclose holdings at least quarterly, and many funds voluntarily report monthly. 77.6% of fund reports in our sample occur monthly. As a robustness check, we replicate our main tests at the quarterly frequency (Online Appendix Tables [C.2](#) and [C.3](#)). The results are qualitatively similar.

Figure 1: Portfolio Allocations to China Exporters by Investment Style. Figure 1 displays the time series of U.S. domestic mutual funds' portfolio shares in domestic firms that export to China, broken down by funds' investment style. Fund China Share refers to the proportion of a fund's portfolio invested in firms connected to Chinese customers through supply chain relationships. The light blue bars represent the average Fund China Share calculated using an equally-weighted approach, where all funds within an investment style are given equal importance. In contrast, the darker blue bars show the average Fund China Share using a value-weighted approach, where larger funds have a greater impact on the calculation based on their size within the investment style.



level. We calculate fund size as the sum of total net asset values across share classes, while we calculate fund returns, fund flows, and expense ratios as size-weighted averages. We exclude funds with less than \$15 million in TNA and with fewer than 10 stocks in their holdings. We have a total of 5,275 domestic equity funds across 26 investment styles, of which 4,598 are active and 1,111 are passive.⁵ The fund investment style is based on the Lipper objective

⁵The sum of active and passive funds is larger than the total number of funds because some funds can change from active to passive during our sample period, or vice versa.

name provided by CRSP.

Our final sample covers the years 2010 to 2023. Figure 1 illustrates the share of domestic equity mutual fund portfolios invested in firms that export to China, broken down by fund investment style. Funds that focus on growth and technology sectors generally have higher shares of stocks linked to China. In contrast, funds that concentrate on small or micro-cap sectors tend to have a lower proportion of their portfolios invested in domestic firms that export to China.

3 Export Controls and Fund Performance

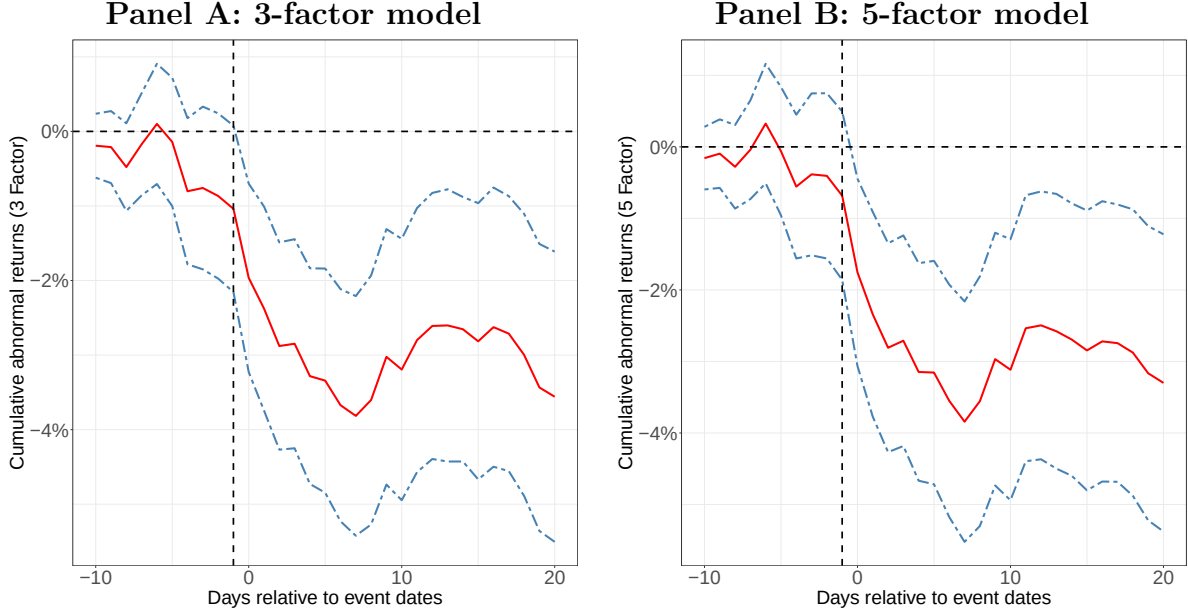
We now describe how we measure export-control shocks and funds’ exposure to such shocks (Section 3.1) and present our empirical strategy to analyze the effect of export-control shocks on fund performance (Sections 3.2).

3.1 Export-Control Shocks and Fund Exposure

Export-Control Shocks. Using FactSet Revere, we identify U.S. firms that supply goods to Chinese targets and call them “affected firms.” A U.S. firm can be affected by export controls multiple times. First, the same U.S. firm could have two distinct Chinese customers that are included in the BIS lists at different times. For example, Intel could sell to both ZTE and Huawei, which are Chinese firms that enter the BIS lists on separate occasions. Second, the same Chinese customer could appear on the BIS list multiple times, each time adding previously neglected subsidiaries.

The timing of BIS list updates is hard to anticipate: they follow no fixed schedule,

Figure 2: Cumulative Abnormal Returns around Export-Control Announcements. This figure displays the cumulative abnormal returns (CAR) of affected U.S. suppliers in a $[-10, 20]$ day window around the announcement date of the inclusion of a Chinese customer in the BIS lists. Panel A shows CARs using the Fama-French 3-factor model (Fama and French, 1993), while Panel B uses the Fama-French 5-factor model (Fama and French, 2015). The vertical axis shows cumulative abnormal returns in percentages, and the horizontal axis shows days relative to the announcement dates. The dashed vertical line represents the day before the announcement date. The solid red line represents the average CARs, and the dot-dash blue lines represent the 95% confidence intervals. This figure follows Figure 3 in Crosignani et al. (2026).



and their scope varies from a single addition to dozens of simultaneous listings, separated by stretches of a year or more with no activity. The exact timing of a firm’s exposure is therefore plausibly exogenous—unrelated to conditions at the firm or at the funds that hold it. Figure 2 shows no significant abnormal returns in the days leading up to the announcement, indicating that the market does not anticipate U.S. firms being affected by the export controls. Consistent with Crosignani et al. (2026), Figure 2 also shows that U.S. suppliers experience a -3.6% cumulative abnormal return, with most of the adjustment occurring within the first five days. This immediate stock price reaction motivates our analysis of how mutual funds respond to this geoeconomic shock.

Shock Exposure. The average equity mutual fund holds 210 stocks and is exposed to export-control shocks when it holds equity stakes in at least one U.S. firm that exports goods and services to Chinese firms targeted by export controls. Therefore, the exposure to export controls of fund i reporting in month t is measured by the share of its portfolio invested in U.S. firms affected by export controls as follows:

$$Shock\ Exposure_{i,t} = \sum_{j=1}^m \mathbb{1}(Affected)_{j,t} \times Weight_{i,j,t-1}. \quad (1)$$

where the indicator variable $\mathbb{1}(Affected)_{j,t}$ equals one if a customer of U.S. firm j is added to the BIS lists in month t and zero both before and after month t . $Weight_{i,j,t-1}$ is fund i 's portfolio weight on stock j in month $t - 1$, and m is the total number of stocks in fund i 's portfolio at time $t - 1$. $Shock\ Exposure_{i,t}$ is the continuous treatment variable of interest, measuring the aggregate exposure to export controls of fund i at time t .

Table 1 presents the summary statistics. In any given month, the likelihood of holding a newly affected stock, $\mathbb{1}(Shock\ Exposure > 0)$, is 2.2%—i.e., 2.2% of fund-month observations are treated. Funds can get treated multiple times as different Chinese firms are added to the BIS lists at different times. The shortest time span between two consecutive treatments for funds is one month, with an average of 8 months. We leave at least a one-year window between the same fund's treatment dates to ensure the current treatment does not capture the dynamics of a previous one. In the next section, we show that the effects settle after a few months. Table 1 also shows that, conditional on new export controls being imposed, the average portfolio exposure to the affected stocks, $Shock\ Exposure|_{>0}$, is 2.3% with a standard deviation of 2.5%. Meanwhile, 20.3% of assets are invested in firms that export to China. Finally, 76.6% of fund-month observations correspond to actively managed funds.

Table 1: Summary Statistics. This table presents summary statistics of fund level characteristics. *Volatility* is the monthly standard deviation of daily fund returns in percentage points. *Fund Return* is the monthly fund return in percentage points. *Alpha 3F* and *Alpha 5F* are the 3-factor and 5-factor adjusted abnormal returns, respectively. We estimate the beta coefficients at time t using the previous rolling window regression of 36 month ($t-36$ through $t-1$) on each fund over sample period. *Shock Exposure*, defined in Equation 1, equals the portfolio share invested in affected U.S. suppliers. *Shock Exposure* is strictly positive only in the month in which the Chinese customers of the affected U.S. suppliers are added to the BIS lists, and zero otherwise. $\mathbb{1}(\text{Shock Exposure} > 0)$ equals one when *Shock Exposure* is strictly positive while $\text{Shock Exposure}|_{>0}$ equals the portfolio share invested in affected U.S. suppliers conditional on *Shock Exposure* being strictly positive. *China Share* is the portfolio share invested in U.S. firms that have at least one Chinese customer. *Fund Size* is the logarithm of the fund’s total net assets (TNA). *Family Size* is the logarithm of the total net assets of the fund’s family. *Expense Ratio* is the ratio of fund operational expenses to its net assets. *Turnover Ratio* measures how frequently a mutual fund buys and sells securities within its portfolio and is computed by dividing the lesser of purchases or sales by net assets. *Age* is the logarithm of the fund age. *Past 12-Month Return* is the average fund return over the previous year. Finally, as standard in the mutual fund literature, *Fund Flow* is the percentage change in total net assets minus appreciation, $\text{Flow}_{i,t} = [TNA_{i,t} - TNA_{i,t-1}(1 + R_{i,t-1})]/TNA_{i,t-1}$. *Actively Managed Fund* is an indicator equal to one if the fund is not a passive fund, and zero otherwise. A fund is classified as passive if its CRSP index fund flag equals “D” or its name contains “index,” “idx,” or “indx.”

Statistic	Mean	St. Dev.	Obs.	p(25)	p(50)	p(75)
Volatility(%)	1.103	0.671	345,958	0.681	0.942	1.324
Fund Return (%)	0.796	5.294	345,958	-1.999	1.156	3.765
Alpha 3F(%)	-0.176	1.916	269,865	-0.960	-0.117	0.659
Alpha 5F(%)	-0.155	1.957	269,865	-0.936	-0.120	0.661
$\mathbb{1}(\text{Shock Exposure} > 0)$	0.022	0.147	345,958	0	0	0
$\text{Shock Exposure} _{>0}$	0.023	0.025	7,623	0.010	0.017	0.029
China Share	0.203	0.160	341,233	0.081	0.159	0.293
Log Fund Size	6.032	1.754	341,233	4.727	5.973	7.197
Log Family Size	11.505	2.821	341,233	9.971	11.749	14.182
Expense Ratio	0.006	0.005	341,233	0.000	0.006	0.010
Turnover Ratio	0.436	0.670	341,233	0.000	0.250	0.600
Log Fund Age	2.439	0.874	341,233	2.027	2.625	3.013
Past 12-Month Return (%)	0.982	1.295	327,948	0.205	1.003	1.728
Fund Flow	0.007	0.093	345,958	-0.013	-0.004	0.007
Actively-Managed Fund	0.766	0.424	345,958	1	1	1

Table 2 shows the distribution of funds in each investment style. Science and tech style funds have the highest exposure to export controls. On average, they invest 43.3% of their portfolios in domestic firms that export to China and, conditional on a new round of export controls, hold 8.4% of their portfolios in affected stocks. By contrast, funds in sectors with limited reliance on Chinese supply chains, such as real estate and precious metals, have low *China Share* (0.8% to 6.8%) and are never exposed to export controls over our sample period.

Table 2: Selected Statistics by Investment Style. This table presents selected summary statistics broken down by fund investment style. *Obs.* is the number of fund-month observations. *#Funds* is the total number of funds. *#Active* and *#Passive* are the number of active and passive funds, respectively. *#Ever Treat* is the number of funds that have a strictly positive exposure to export controls at any time during the sample period. *China Share* is the average portfolio share invested in U.S. firms with at least one Chinese customer. *Shock Exposure*_{|>0} is the portfolio share invested in affected U.S. suppliers conditional on being positive. *Shock Exposure* is strictly positive only in the month when the Chinese customers of the affected U.S. suppliers are added to the BIS lists and zero otherwise. The table shows sample fund styles with at least five funds in the category.

Fund Style	Obs.	#Funds	#Active	#Passive	#Ever Treat	China Share %	Shock Exposure _{>0} %
SCIENCE & TECHNOLOGY	10,318	135	110	49	92	43.30%	8.42%
S&P 500 INDEX OBJECTIVE	7,806	99	1	98	74	35.31%	1.63%
TELECOMMUNICATION	1,308	16	11	10	13	34.44%	6.66%
ALTERNATIVE LONG/SHORT EQUITY	1,660	69	61	10	36	33.93%	2.10%
GROWTH & INCOME	48,424	1,400	1,247	177	966	27.61%	2.14%
EQUITY LEVERAGE	2,645	110	92	19	31	26.74%	4.17%
GROWTH	100,914	1,923	1,727	336	1,237	26.33%	2.23%
ALTERNATIVE EQUITY MARKET NEUTRAL	286	13	12	1	3	26.03%	2.28%
EQUITY INCOME	19,662	334	314	67	237	24.48%	2.46%
ABSOLUTE RETURN	348	17	17	1	3	22.89%	2.03%
CONSUMER SERVICES	3,264	34	25	18	12	22.60%	0.77%
CAPITAL APPRECIATION	6,730	112	109	4	77	21.04%	2.09%
INDUSTRIALS	3,994	38	26	25	29	20.12%	5.81%
NATURAL RESOURCES	6,182	84	63	34	26	16.06%	2.94%
CONSUMER GOODS	2,128	19	14	11	3	15.96%	2.00%
BASIC MATERIALS	2,022	15	10	11	12	15.14%	2.76%
HEALTH/BIOTECHNOLOGY	7,680	89	70	36	30	14.83%	2.99%
MID-CAP	41,551	720	639	117	514	12.62%	1.91%
EQUITY MARKET NEUTRAL	125	16	15	1	3	12.26%	0.00%
LONG/SHORT EQUITY	208	25	22	3	6	11.66%	0.00%
DIVERSIFIED LEVERAGE	33	11	11	0	6	9.69%	0.00%
SMALL-CAP	54,905	860	769	140	592	8.21%	1.65%
REAL ESTATE	11,246	143	120	36	0	6.82%	0.00%
MICRO-CAP	2,687	50	46	4	31	6.09%	2.06%
FINANCIAL SERVICES	6,212	68	50	35	14	4.13%	2.62%
UTILITY	3,140	35	28	13	5	2.25%	1.69%
PRECIOUS METALS EQUITY	411	12	10	4	0	2.17%	0.00%
PRECIOUS METALS	53	6	5	1	0	0.83%	0.00%

3.2 Effects on Fund Volatility and Performance

To study how U.S. export controls impact funds' risk and performance, we estimate (i) standard two-way fixed effects panel regressions and (ii) local projections with clean-control restrictions to trace fund responses over time and assess pre-announcement trends.

Two-Way Fixed Effects. We start our analysis by estimating the following TWFE panel regression:

$$Y_{i,t} = \beta Shock\ Exposure_{i,t} + \boldsymbol{\gamma}' \mathbf{X}_{i,t-1} + \mu_i + \eta_t + \varepsilon_{i,t}, \quad (2)$$

where $Y_{i,t}$ is one of several outcome variables for fund i in month t , including the volatility of daily fund returns (*Volatility*), monthly returns (*Return*), and 3- and 5-factor adjusted portfolio alphas (Alpha 3F and Alpha 5F, respectively). The factor-adjusted alphas are computed as the fund's monthly excess return (net of the risk-free rate) minus the expected excess return implied by the fund's own factor loadings under the three- and five-factor models of Fama and French (1993, 2015). Loadings are estimated from a rolling 36-month window and lagged one month, so that the loadings applied to month t use only information through $t - 1$. Defined in Equation (1), the main regressor of interest (*Shock Exposure*) is equal to the portfolio share invested in U.S. firms affected by concurrent export controls. It is equal to zero otherwise. As such, the coefficient of interest, β , captures the immediate effect of export controls on fund risk and performance.

As standard in the literature (e.g., Kacperczyk and Seru, 2007), we add a set of lagged fund characteristics as control variables ($\mathbf{X}$), including the logarithms of fund size and fund family size, expense and turnover ratios, the logarithm of fund age, as well as the average return over the past year. We also include lagged dependent variables in all our specifications to control for potential autocorrelation in fund risk and returns. For a U.S. firm to be affected by export controls, it must export to Chinese firms in the first place. As a result, it is also important to control for the lagged share of a fund portfolio invested in all U.S. firms that export to China, which we call *China Share* (also in the vector $\mathbf{X}$). Otherwise, the main

regressor, *Shock Exposure*, may capture the effects of exporting to China, one of the largest and most profitable consumer markets.

While the baseline specifications include fund and time fixed effects, our preferred specifications include interactions between investment style and time fixed effects. Because funds in the same style are evaluated against similar benchmarks and draw from a similar investment universe, the comparison is, at each point in time, between funds facing the same benchmark that differ in the export-control exposure of their holdings. For instance, if funds in the aggressive growth style have high levels of both return volatility and export-control exposure, including style-time fixed effects allows us to factor out the time-varying volatility component common to funds in the same investment style. Finally, we cluster standard errors at the fund level.

The results are displayed in Table 3. Panel A shows the effect of export-control shocks on monthly volatility of daily fund returns (columns 1 to 3) and on monthly fund returns (columns 4 to 6), using different degrees of fixed effects saturation and controls. Notably, columns 3 and 6 include style-time fixed effects in addition to standard lagged fund characteristics as controls. Across specifications, higher exposure to export-control shocks leads to greater contemporaneous volatility and lower returns. Conditional on an export-control event, a one-standard-deviation increase in shock exposure (2.5%) is associated with an increase in fund volatility of 0.015 to 0.028 percentage points, corresponding to 2 to 4 percent of its standard deviation. In addition to increasing fund volatility, exposure to export-control shocks has a detrimental effect on fund returns, as shown in columns 4 to 6 of Panel A. Columns 4 to 5 show that, conditional on an export-control event, a one-standard-deviation increase in

Table 3: Performance and Exposure to Export Controls. This table presents the results of estimating Equation (2) for active funds. The dependent variables are fund volatility and returns in Panel A, and the 3- and 5-factor adjusted abnormal returns in Panel B. *Volatility* is the monthly standard deviation of daily fund returns in percentage points. *Return* is the monthly fund return in percentage points. *Alpha 3F* and *Alpha 5F* are the 3-factor and 5-factor adjusted abnormal returns, respectively. *Shock Exposure* is the portfolio share invested in affected U.S. suppliers (see Online Appendix A for the full definition). All specifications include the lagged dependent variable and *China Share*. Fund controls include fund size, family size, expense ratio, turnover ratio, age, and past return (1Y). Standard errors are clustered at the fund level. *** p<0.01, ** p<0.05, * p<0.1.

Dependent Variables :	Panel A					
	Volatility			Return		
	(1)	(2)	(3)	(4)	(5)	(6)
Shock Exposure	1.107*** (0.150)	1.031*** (0.140)	0.587*** (0.115)	-17.149*** (3.251)	-15.492*** (3.407)	-9.324*** (2.645)
Fund FE	✓	✓	✓	✓	✓	✓
Time FE	✓	✓		✓	✓	
Fund Controls		✓	✓		✓	✓
Style×Time FE			✓			✓
Observations	260,296	247,489	247,489	260,296	247,489	247,489
Adjusted R ²	0.910	0.914	0.943	0.788	0.806	0.891
Dependent Variables :	Panel B					
	Alpha 3F			Alpha 5F		
	(1)	(2)	(3)	(4)	(5)	(6)
Shock Exposure	-11.661*** (1.168)	-10.515*** (1.156)	-4.820*** (1.284)	-9.599*** (1.073)	-8.515*** (1.074)	-3.906*** (1.232)
Observations	203,894	195,659	195,659	203,894	195,659	195,659
Adjusted R ²	0.081	0.115	0.442	0.075	0.113	0.441
Fund FE	✓	✓	✓	✓	✓	✓
Time FE	✓	✓		✓	✓	
Fund Controls		✓	✓		✓	✓
Style×Time FE			✓			✓

shock exposure (2.5%) is associated with a 39 to 43 bps decline in monthly returns. Even after including fund controls and investment style-time fixed effects, as in column 6, exposure to export-control shocks retains a sizable negative effect on fund returns. Conditional on an export-control event, a one-standard-deviation increase in exposure is associated with a 23 basis point decline in monthly returns compared with peer funds within the same investment style and month.

Panel B shows the effect of export-control shocks on abnormal fund returns, namely returns adjusted for the fund’s exposure to standard equity pricing factors. Across specifications, higher exposure to export-control shocks is associated with worse fund performance. If the 3- and 5-factor models do not fully capture the exposure of a fund to time-varying risk factors, the inclusion of style-time fixed effects is more likely to guarantee that the estimated effect of *Shock Exposure* captures the effect of export controls, and not a pricing anomaly specific to the particular investment style in a given month. In addition to being statistically significant, the estimated effects are also economically meaningful. The most conservative estimates of columns 3 and 6 imply that, conditional on an export-control event, a one-standard-deviation increase in exposure is associated with a 12 basis point decline in 3 factor-adjusted monthly alphas and a 10 basis point decline in 5 factor-adjusted monthly alphas, respectively.

For ease of exposition, the controls are not shown in Table 3. Online Appendix Table C.1 displays these coefficients for the most saturated specification. Consistent with Demirci et al. (2022), we find that funds with larger holdings of U.S. firms that export to China experience better performance (see the coefficients of *China Share* in columns 3 to 4). This result indicates that U.S. exporters to China enjoy higher average returns by tapping into a large consumer market. Finally, consistent with previous studies (e.g., Kacperczyk and Seru, 2007), we find that larger funds experience lower returns and that funds that are more active in trading stocks also experience lower returns over the next month (see the coefficients of *Fund Size* and *Turnover Ratio* in columns 3 and 4).

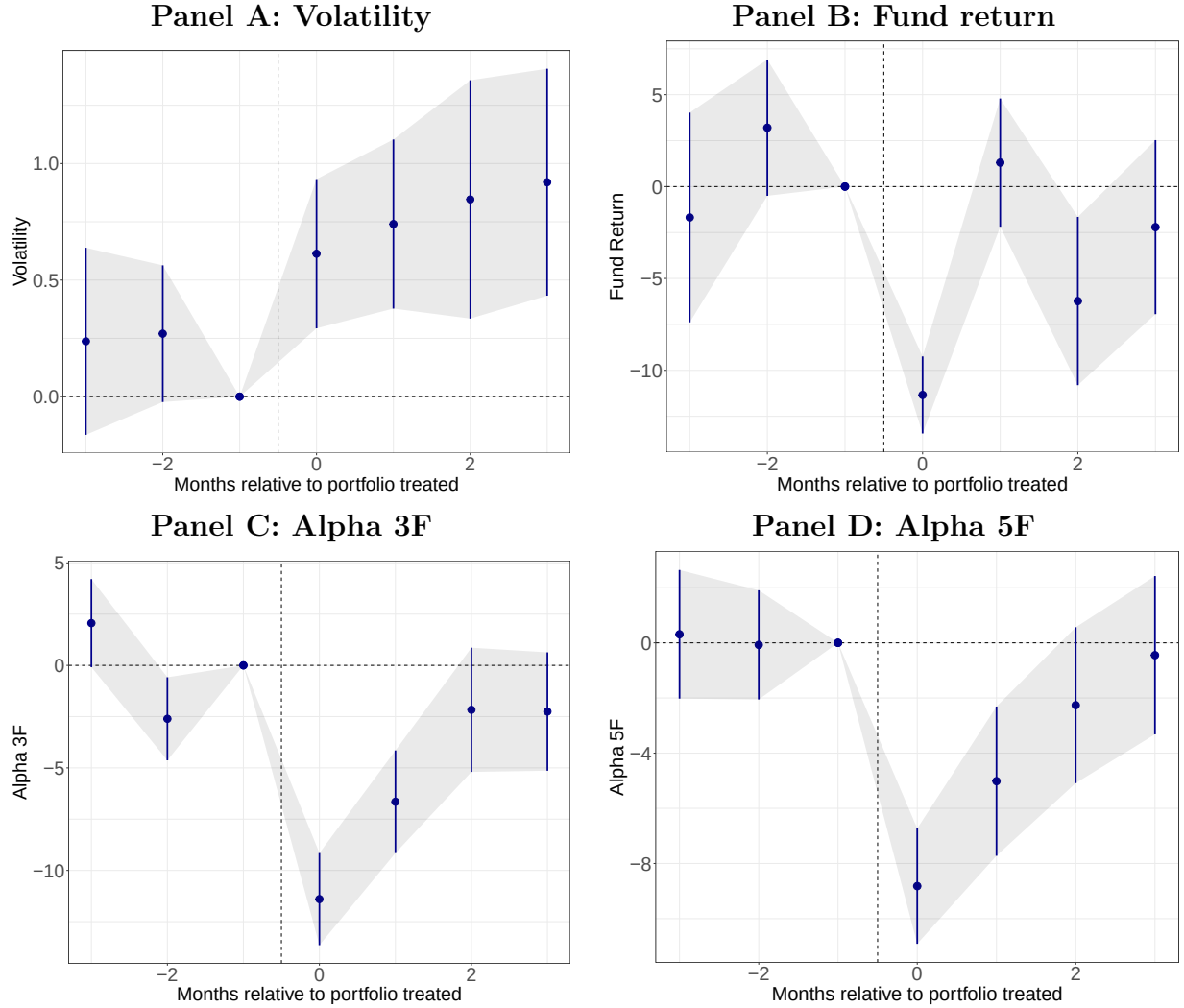
Local Projections. Our treatment is staggered over time as the BIS has enacted numerous export controls on different Chinese firms since 2010. A dynamic version of the TWFE model

in Equation (2) may yield biased estimates due to the so-called bad comparison problem (Goodman-Bacon, 2021; Baker et al., 2022). For instance, when estimating the effect of a fund treated in month t , some earlier treated funds may be used as control units (the direction of the bias is unknown). To address the bad comparison problem, we use the local projections approach developed in Dube et al. (2025), which also allows for repeated treatment and continuous treatment in a fully dynamic model.

Treated units are funds with equity holdings of U.S. firms affected by export controls introduced at time t . For funds treated at time t , we have $\Delta Shock Exposure_{it} > 0$. Control units consist of two groups: never-treated funds and not-yet-treated ones. Control units need to be similar to treated units, except that they hold assets that are not currently exposed to export controls. Since affected firms are a subset of U.S. firms that export to China, we need to control for the share of a fund portfolio invested in firms that export to China, called *China Share*. Otherwise, *Shock Exposure* may pick up the effect of holding firms that are exposed to global customer markets instead of capturing the treatment effect of exposure to export-control shocks. Furthermore, the staggered nature of treatment induces additional randomness to the exposure measure. Similar firms are treated at different times, so using not-yet-treated firms helps with identification. This approach includes in the control group funds holding firms that closely resemble the treated ones, since these firms will themselves be treated in the near future.

Finally, a given mutual fund may hold stocks affected by export controls at different times in our sample. For example, fund i could hold stock j that is affected at time t and stock k that is affected at time $t + 10$. We assume the effects of export controls stabilize after

Figure 3: Performance with Local Projections. This figure displays the dynamic coefficient estimates for horizons $k = -3, \dots, 3$ using the local projections approach of Dube et al. (2025), as presented in Equation (3). The dependent variable is the change from month $t - 1$ to month $t + k$ in monthly fund volatility (Panel A), fund return (Panel B), 3-factor-adjusted abnormal fund return (Panel C), and 5-factor-adjusted abnormal fund return (Panel D). The regressions include fund and month fixed effects and the same lagged controls as Table 3. The vertical axis shows the estimated coefficient β_k on $\Delta Shock Exposure$, and the horizontal axis shows months relative to the month in which the fund portfolio is treated. The estimate for month -1 is zero by construction because outcomes are measured as changes relative to month $t - 1$. The blue dots represent the point estimates, and the vertical bars and shaded area represent the 95% confidence intervals based on standard errors clustered at the fund level.



6 months (the horizon H). Thus, we allow treated funds to go back to the control group 6 months after treatment. Specifically, clean control units are funds that do not have holdings treated continuously from $t - 6$ to $t + k$, where k represents the horizon of the dynamic

treatment effect. For each horizon k , we estimate the following regression:

$$Y_{i,t+k} - Y_{i,t-1} = \beta_k \Delta Shock Exposure_{i,t} + \gamma' \mathbf{X}_{it} + \mu_i + \eta_t + \varepsilon_{it}. \quad (3)$$

where the treatment sample is identified by $Shock Exposure_{it} > 0$ and the controls by $Shock Exposure_{i,t+h} = 0$ for $h \geq -H$ and $h \leq k$. We include the same lagged controls as in the TWFE models. Standard errors are clustered at the fund level.

Figure 3 displays the dynamic effects of export controls on volatility, raw returns, and 3- and 5-factor adjusted returns. Following the introduction of export controls, funds more exposed to the shock experience higher volatility and lower returns. The effect on volatility builds over the first two months and remains elevated through the third month. Raw returns decline sharply in the month of the shock and again in month 2. The declines in 3- and 5-factor adjusted returns are concentrated in the month of the shock and the following month. Before treatment, the coefficients for volatility, raw returns, and 5-factor adjusted returns are statistically insignificant. For 3-factor adjusted returns, the coefficient in month -2 is negative and significant but does not represent a pre-trend (which would appear as a consistent negatively sloped line approaching the treatment month from above).

4 Portfolio Response to Export-Control Shocks

We now examine how funds respond to export controls through their trading decisions. We first study trading in stocks of newly affected U.S. suppliers, i.e., U.S. suppliers whose Chinese customers are newly targeted by export controls (Section 4.1). We then examine trading in other U.S. firms with Chinese customers (Section 4.2). Finally, we show that, after being hit by

export-control shocks, funds (i) end up with higher portfolio concentration by reducing their allocations to industries hit by export controls and (ii) tilt their portfolios toward lottery-like stocks potentially in an effort to offset earlier losses (Section 4.3).

4.1 Trading in Newly Affected U.S. Suppliers

We first examine how portfolio managers trade the newly affected stocks around export-control announcements, which we refer to as the “direct response.” Suppose that fund i holds an equity position in firm j at the beginning of the reporting month and that firm j is hit by export controls during the month. We estimate whether, and how, fund i reallocates its portfolio after stock j is affected by export controls. Because U.S. firms may be affected by export controls multiple times, we focus on the first instance in which a U.S. stock is affected. With this strategy, we identify investors’ initial trading response to export controls.

We build a fund-stock-month level panel and estimate the following specification:

$$Y_{i,j,t} = \beta Direct_{j,t} + \boldsymbol{\gamma}' \mathbf{X}_{j,t-1} + \boldsymbol{\nu}' \mathbf{Z}_{i,t-1} + \mu_i + \eta_t + \varepsilon_{i,j,t}, \quad (4)$$

where $Y_{i,j,t}$ is the trade direction of fund i in stock j at time t . More precisely, the trade direction equals one if fund i increases the number of stock j shares at time t , minus one if it reduces its holdings, and zero otherwise. In other specifications, we consider cumulative trades within a 3-month window. $Direct_{j,t}$ is an indicator variable equal to one if stock j is affected by export controls in reporting month t . We include fund-level controls (vector $\mathbf{Z}$), namely fund size, family size, fund age, expense ratio, turnover ratio, China Share, and past returns over the previous year, as well as firm-level controls (vector $\mathbf{X}$), namely firm size, firm age, book leverage, and CAPEX. All controls are lagged.

Table 4: Trading in Response to Export Controls. This table presents the results of estimating Equation (4). The dependent variables are defined as the sign of net trading in the same month (Panel A) or over a three month horizon (Panel B). *Direct* is an indicator variable equal to one in the month a stock is affected by export controls for the first time, and zero otherwise. All specifications include *China Share* as control (see Online Appendix A for the definition). Fund controls include fund size, family size, expense ratio, turnover ratio, age, and past return (1Y). Firm controls include total assets, firm age, capex, and book leverage. All controls are lagged. Standard errors are double clustered at the fund and firm level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Dependent Variables :	Panel A: Same month Trade Direction			
	(1)	(2)	(3)	(4)
Direct	−0.045*** (0.017)	−0.048*** (0.016)	−0.046*** (0.015)	−0.049*** (0.015)
Observations	25,695,130	25,695,130	25,695,130	25,695,130
Adjusted R ²	0.069	0.088	0.090	0.094
Dependent Variables :	Panel B: Within 3 months Trade Direction			
	(1)	(2)	(3)	(4)
Direct	−0.036* (0.019)	−0.041** (0.017)	−0.037** (0.017)	−0.040** (0.017)
Observations	25,694,912	25,694,912	25,694,912	25,694,912
Adjusted R ²	0.074	0.086	0.089	0.092
Fund FE	✓	✓	✓	✓
Time FE	✓			
Style×Time FE		✓	✓	
Industry×Time FE			✓	
Style×Industry×Time FE				✓
Fund Controls	✓	✓	✓	✓
Firm Controls	✓	✓	✓	✓

The baseline specification also includes fund and time fixed effects, while the most saturated specifications include fund fixed effects together with investment style-industry-time fixed effects. This specification absorbs any aggregate dynamic common to a given industry or investment style that may be more focused on cutting-edge technologies, where export control shocks are also more likely to hit, thus allowing us to more cleanly isolate a treatment effect. Standard errors are double clustered at the fund and firm levels.

Table 4 presents the results. In Panel A, the dependent variable is the direction of

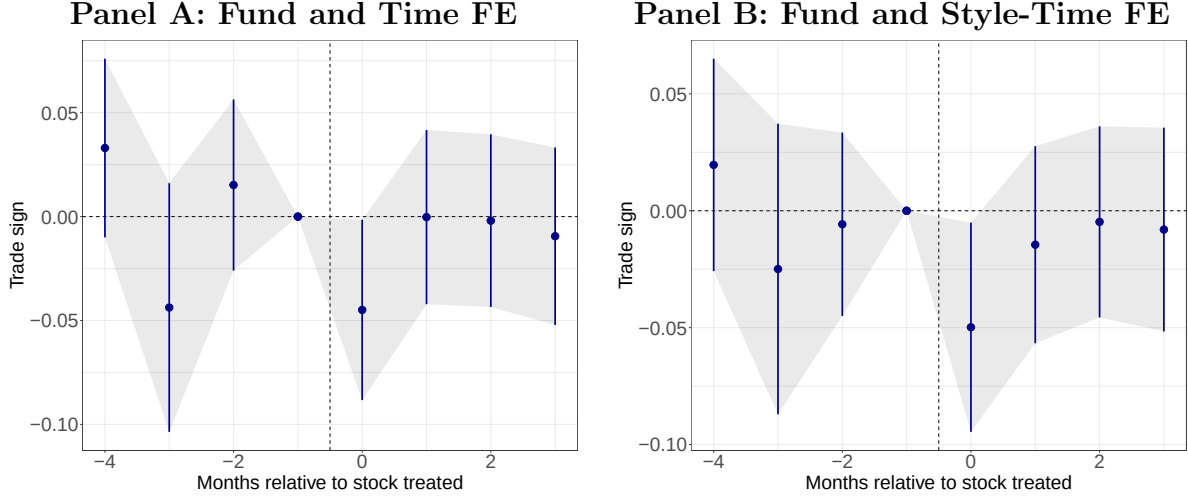
trades that occur in the same month as the export-control shock, thus capturing immediate portfolio reallocations. Panel B, by contrast, considers trades that occur within a 3-month window after the export-control shock, allowing for a slower portfolio adjustment or a complete reversal of the immediate trade. Given the panel’s high dimensionality (fund-stock-month), we progressively add fixed effects. The effect of *Direct* is negative, significant, and stable across specifications, regardless of the degree of fixed effects saturation, indicating that funds are more likely to sell affected stocks. This selling occurs immediately, as the effect is more pronounced in the same month (Panel A) than within the first three months (Panel B).⁶

As in Section 3.2, the staggered timing of export controls raises the same bad comparison concern. We address it with a dynamic local projections specification (Dube et al., 2025). This traces the coefficient β_k over $k \in -4, \dots, 3$ months around each stock’s first export-control event.⁷ Here, the control sample must satisfy the clean-control condition at both the firm and fund level. Both the held stock and the holding fund must be never-treated or not-yet-treated over the event window, using the same logic as in Section 3.2. We include the same lagged controls and fund fixed effects as in Table 4, with time fixed effects in Panel A and style-by-time fixed effects in Panel B, and double-clustered standard errors by fund and firm. Figure 4 displays the dynamic effects of export-control shocks on the trading direction of affected stocks using the local projections approach. Before a stock is first affected, funds holding it do not trade it differently from control holdings, which suggests that they do not anticipate

⁶Our results are not driven by leveraged funds, which may display outsized trading responses due to their leverage. Panel A of Online Appendix Table C.4 shows that our main results are unchanged if we remove leveraged funds from the sample.

⁷The regression equation and the formal definition of the clean-control sample are in Online Appendix B.

Figure 4: Trading Direction with Local Projections. This figure displays the coefficients β_k from the local projections described in Online Appendix B (Dube et al., 2025), for horizons $k = -4, \dots, 3$ months relative to the month in which a stock is first affected by export controls. The dependent variable is the change in trade direction from month $t - 1$ to month $t + k$, and the coefficient for month -1 is zero by construction. Panel A includes fund and month fixed effects, and Panel B includes fund and style-month fixed effects. Both panels include the same lagged controls as Table 4. The dots show point estimates, and the vertical bars and shaded area show 95% confidence intervals based on standard errors double clustered at the fund and firm levels.



export controls. Then, in the treatment month, funds are more likely to sell affected stocks. The coefficients in the subsequent months are close to zero and statistically insignificant, indicating that selling is concentrated in the treatment month.

To examine the intensity of selling decisions in affected stocks, we further analyze whether mutual funds completely liquidate their positions or only partially reduce their holdings. To capture full liquidations, we first expand the holdings data to include zero holdings, which allows us to identify stocks that funds do not hold in certain months as well as complete sell-offs. Table 5 presents the results. Columns 1 and 2 confirm our main finding that funds are more likely to sell directly affected stocks. Further, decomposing sales into partial and complete sell-offs reveals that the documented selling activity is attributable

Table 5: Trading in Response to Export Controls: Partial vs. Complete Sell. This table presents the results of estimating Equation (4). *Sell Indicator* equals one if the same month’s trading sign is negative. *Partial Sell* equals one if the same month’s trade sign is negative and sell quantity is less than previous holdings. *Complete Sell* equals one if the same month’s trade sign is negative and sell quantity is equal to the previous holdings. *Direct* is an indicator variable equal to one in the month a stock is affected by export controls for the first time, and zero otherwise. All specifications include *China Share*, fund controls, and firm controls, as in Table 4 (see Online Appendix A for variable definitions). Standard errors are double clustered at the fund and firm level. *** p<0.01, ** p<0.05, * p<0.1.

Dependent Variables:	Sell Indicator		Partial Sell		Complete Sell	
	(1)	(2)	(3)	(4)	(5)	(6)
Direct	0.022*** (0.006)	0.018*** (0.006)	0.022*** (0.006)	0.017*** (0.006)	0.000 (0.001)	0.000 (0.002)
Observations	70,744,269	70,744,250	70,744,269	70,744,250	70,744,269	70,744,250
Adjusted R ²	0.073	0.075	0.082	0.084	0.008	0.009
Fund Controls	✓	✓	✓	✓	✓	✓
Firm Controls	✓	✓	✓	✓	✓	✓
Fund FE	✓	✓	✓	✓	✓	✓
Style × Time FE	✓	✓	✓	✓	✓	✓
Industry × Time FE		✓		✓		✓

exclusively to partial reductions in holdings (columns 3 and 4), rather than to full liquidations (columns 5 and 6).

4.2 Trading in Other U.S. Firms with Chinese Customers

Having shown that investors immediately sell the stocks hit by export-control shocks, we now examine whether the same shock prompts fund managers to reassess their overall portfolio. In particular, we examine whether mutual funds that experience the export-control shock (treated funds) also sell stocks of domestic firms that export to Chinese customers *not* currently targeted by export controls. Prior studies suggest that, due to attention constraints, investors often overlook economic linkages between firms despite supply chain information being publicly available (Cohen and Frazzini, 2008). Therefore, the export-control shock may serve as a wake-up call, prompting fund managers to learn about supply-chain connections and rebalance

their portfolio accordingly.

To formally test this hypothesis, we estimate the following regression at the fund-stock-month level:

$$Y_{i,j,t} = \beta Spillover_{i,j,t} + \gamma' \mathbf{X}_{j,t-1} + \nu' \mathbf{Z}_{i,t-1} + \mu_i + \eta_{s,t} + \varepsilon_{i,j,t}. \quad (5)$$

where $Y_{i,j,t}$ is the trade direction of fund i in stock j at time t : it equals one if fund i increases the number of stock j shares at time t , minus one if it reduces its holdings, and zero otherwise. $Spillover_{i,j,t}$ is an indicator variable equal to one if firm j exports to China and is unaffected by export controls at time t , but is held by fund i , which holds stocks currently subject to export controls. The coefficient β captures whether funds experiencing an export-control shock trade stocks of other firms with Chinese customers differently from other holdings. We exclude from the sample the stocks that are ever directly affected to avoid contaminating the spillover effect with the direct effect coming from affected stocks. We include the same control variables as in Equation (4), together with fund fixed effects (μ_i) and investment style-time fixed effects ($\eta_{s,t}$), and in some specifications industry-time fixed effects.

Table 6 displays the results. Columns 1 and 2 consider the effect on trading in the same month as the export control announcement, while columns 3 and 4 estimate the effect within a 3-month window post-announcement. The coefficient on *Spillover* is only marginally significant in the baseline specification (column 1) and loses significance once we add industry-time fixed effects (column 2), providing no clear evidence that funds holding a newly affected stock reduce their holdings of other U.S. firms with Chinese customers in the announcement month. While there is no immediate effect, columns 3 and 4 estimate a delayed portfolio

Table 6: Trading in Other U.S. Firms with Chinese Customers in Response to Export Controls.

This table presents the results of estimating Equation (5) for active funds. The dependent variables reflect Trade direction, defined as the sign of net trading in the same month (columns 1 and 2) or over three month horizon (columns 3 and 4). *Spillover* is an indicator variable equal to one if firm j has Chinese customers and is not affected by export controls in month t , and fund i holds at least one U.S. supplier whose Chinese customer is newly targeted by export controls in month t . All specifications include *China Share*, fund controls, and firm controls, as in Table 4 (see Online Appendix A for variable definitions). Standard errors are double clustered at the fund and firm level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Dependent Variables :	Trade direction (same month)		Trade direction (within 3 month)	
	(1)	(2)	(3)	(4)
Spillover	-0.013* (0.008)	-0.011 (0.008)	-0.031*** (0.008)	-0.032*** (0.008)
Observations	24,578,989	24,578,989	24,578,771	24,578,771
Adjusted R ²	0.088	0.090	0.086	0.089
Fund FE	✓	✓	✓	✓
Style×Time FE	✓	✓	✓	✓
Industry×Time FE		✓		✓
Fund Controls	✓	✓	✓	✓
Firm Controls	✓	✓	✓	✓

adjustment: within the first 3 months after a new export control, funds with some direct exposure to export controls are more likely to sell the stocks of *unaffected* domestic firms that export to China. These findings suggest that fund managers need time to reassess how geoeconomic shocks may impact their portfolios going forward.⁸

Taken together, export-control shocks prompt broader portfolio rebalancing, as managers sell affected suppliers' stocks and reduce their holdings of other U.S. firms with Chinese customers.

⁸The results are robust excluding leveraged funds, as shown in Panel B of Online Appendix Table C.4.

4.3 Lottery-Stock Purchases and Portfolio Concentration

We now show that funds more exposed to export controls tilt their portfolio towards lottery-like stocks and reduce their overall allocation to the industry of the affected stocks, leading to greater portfolio concentration.

Lottery Stock Purchases. The analysis of lottery stock purchases is theoretically grounded. Concerned that posting losses might lead to future outflows, funds may respond to export controls by taking on higher risk to help offset losses (Brown et al., 1996; Schwarz, 2012). Specifically, funds' investments in lottery stocks often appear to attract larger inflows (Agarwal et al., 2022). To test whether funds hit by export controls do indeed rebalance their portfolios toward lottery stocks, we apply a similar empirical model as in Equation (5) and estimate the following regression at the fund-stock-month level:

$$Y_{i,j,t} = \beta Lottery_{i,j,t} + \boldsymbol{\gamma}' \mathbf{X}_{j,t-1} + \boldsymbol{\nu}' \mathbf{Z}_{i,t-1} + \mu_i + \eta_{s,t} + \varepsilon_{i,j,t}, \quad (6)$$

where $Y_{i,j,t}$ is the trade direction of fund i in stock j at time t . Trade direction equals one if fund i increases the number of stock j shares at time t , minus one if it reduces its holdings, and zero otherwise. $Lottery_{i,j,t}$ is an indicator variable equal to one if firm j is a lottery stock and is unaffected by export controls at time t , but it is held by fund i , which holds stocks currently subject to export controls. To identify a stock's lottery feature, we use the average of the stock's five highest daily returns in a month, following Agarwal et al. (2022). A stock is then defined as a lottery stock if its lottery feature falls in the top quartile of all stocks in that month.

Table 7: Portfolio Rebalancing in Response to Export Controls. This table presents the results of estimating Equation (6) for active funds. The dependent variables reflect Trade direction, defined as the sign of net trading in the same month (columns 1 and 2) or over a three-month horizon (columns 3 and 4). A stock’s lottery feature is the average of its five highest daily returns in a month, following Agarwal et al. (2022). A stock is a lottery stock if its lottery feature is in the top quartile of all stocks in that month. *Lottery* is an indicator variable equal to one if stock j is a lottery stock that is not affected by export controls in month t and is held by fund i , which holds stocks currently subject to export controls. All specifications include China Share, fund controls, and firm controls, as in Table 4 (see Online Appendix A for variable definitions). Standard errors are double clustered at the fund and firm level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Dependent Variables:	Trade direction (same month)		Trade direction (within 3 months)	
	(1)	(2)	(3)	(4)
Lottery	0.062*** (0.010)	0.053*** (0.010)	0.058*** (0.009)	0.047*** (0.009)
Fund FE	✓	✓	✓	✓
Style×Time FE	✓	✓	✓	✓
Industry×Time FE		✓		✓
Fund Controls	✓	✓	✓	✓
Firm Controls	✓	✓	✓	✓
Observations	24,578,989	24,578,989	24,578,771	24,578,771
Adjusted R ²	0.088	0.090	0.086	0.089

In Table 7, we show that funds more exposed to export controls immediately rebalance their portfolios in ways that are suggestive of higher risk-taking, possibly to mitigate the direct losses from export controls. Columns 1 and 2 show that funds exposed to export controls are immediately more likely to buy lottery stocks. Columns 3 and 4 show that affected funds take greater risks even three months after their exposure to export controls. These findings suggest that, after incurring losses from export controls, affected funds take on additional risk to mitigate losses and their potential effect on future outflows.

More Concentrated Portfolios. We then study whether affected funds change their overall allocations to the industry affected by export controls and how portfolio concentration and diversification change. Funds may want to maintain stable portfolios and industry concentration, substituting the affected stock with a similar firm in the same industry.

Table 8: Fund Portfolio Concentration. This table presents portfolio concentration of active funds. Δ *Affected Industry Weight* is the change in portfolio weight from the previous month in stocks belonging to the affected industry, excluding directly affected stocks. Δ *Industry Concentration* is the monthly change in the fund’s industry concentration index, defined following [Kacperczyk et al. \(2005\)](#) and multiplied by 100. Δ *Portfolio Herfindahl* is the monthly change in the fund’s portfolio Herfindahl index, computed as the sum of squared portfolio weights across all stocks held by the fund and multiplied by 100. *Shock Exposure* is strictly positive only in the month in which the Chinese customers of the affected U.S. suppliers are added to the BIS lists, and zero otherwise. All specifications include *China Share* as a control, namely the portfolio share invested in U.S. firms with at least one Chinese customer. Fund Controls include fund size, family size, expense ratio, turnover ratio, age, and past return (1Y). Standard errors are clustered at the fund level. *** p<0.01, ** p<0.05, * p<0.1.

Dependent Variables:	Δ Affected Industry Weight (1)	Δ Industry Concentration (2)	Δ Portfolio Herfindahl (3)	Δ Industry Concentration (4)	Δ Portfolio Herfindahl (5)	Δ Portfolio Herfindahl (6)
Shock Exposure	−0.687*** (0.054)	−0.729*** (0.041)	1.612*** (0.434)	1.678*** (0.520)	0.499*** (0.146)	0.510*** (0.176)
Fund Controls	✓	✓	✓	✓	✓	✓
Fund FE	✓	✓	✓	✓	✓	✓
Time FE	✓		✓		✓	
Style × Time FE		✓		✓		✓
Observations	185,120	185,120	185,120	185,120	187,732	187,732
Adjusted R ²	0.475	0.582	0.081	0.315	0.007	0.036

Alternatively, funds may rebalance away from the industry targeted by export controls, potentially increasing portfolio concentration or reducing diversification. We estimate a variation of Equation 2, where the dependent variables are: (i) the change in portfolio weight assigned to the industry of affected stocks (excluding the directly affected stocks); (ii) the change in portfolio industry concentration ([Kacperczyk et al., 2005](#)); and (iii) the change in the portfolio Herfindahl index.

The results are displayed in Table 8. The first two columns use the monthly change in the portfolio weight assigned to the affected stock’s industry, excluding the affected stock itself, as the dependent variable. Assuming funds substitute the affected stock with a firm in the same industry, we expect the coefficient on *Shock Exposure* (holdings of affected stocks)

in the affected industry weight to be positive.⁹ If the fund instead sells only the affected stock and does not change its allocations within the affected industry, we expect the coefficient to be zero. Finally, if the fund perceives the export control as delivering a negative outlook on the affected industry, we would observe a negative coefficient. Columns 1 and 2 display a negative and significant coefficient of *Shock Exposure*, suggesting that funds not only sell the affected stock but also other stocks in the same affected industry after the implementation of export controls. Next, columns 3 and 4 show that funds with higher exposure to export controls increase their industry concentration index, suggesting that portfolios become more concentrated in fewer industries. Similarly, in columns 5 and 6, the positive coefficient on *Shock Exposure* implies that funds more exposed to export controls increase their portfolio Herfindahl index, suggesting the portfolio also becomes more concentrated in fewer stocks.

5 Heterogeneity Across Funds

We have shown that export-control shocks raise fund volatility and lower performance, and that funds respond by rebalancing their portfolios. We now examine how these volatility and performance effects vary across funds, and whether manager skill helps mitigate the performance decline. We first find that specialists and high-fee funds experience smaller performance declines following export-control shocks, while market-timing or stock-picking skills do not seem to help managers (Section 5.1). We then compare the performance of active and passive funds, and find that passive funds experience a larger decline in performance

⁹That is because the affected industry weight excludes the currently affected stock. Thus, substituting the affected stock with another stock in the same industry would result in an increase in the affected industry weight.

than active funds, consistent with their limited ability to rebalance portfolios (Section 5.2).

5.1 Manager Characteristics and Performance

A large body of literature debates whether fund managers are compensated for their skills and, if so, which skills matter most for generating returns (e.g., Berk and Green, 2004; Berk and Van Binsbergen, 2015; Pástor et al., 2015). On the one hand, highly skilled managers may seamlessly adapt to new risks and generate abnormal returns across different market conditions. On the other hand, existing skills may not translate effectively to emerging risks. An intense focus on generating abnormal returns could lead to skills tailored to existing risk factors, which may become less effective when the investment environment shifts significantly. Hence, it is an empirical question whether more skilled managers can better adapt to emerging geoeconomic risk.

We use four measures of manager skills in our analysis. First, following Kacperczyk et al. (2014), we measure skills based on managers' market timing and stock picking abilities. Market timing skills are measured by the extent to which changes in a fund's holdings co-move with the systematic returns of individual stocks. Stock picking skills are instead measured by the extent to which changes in a fund's holdings co-move with the idiosyncratic returns of individual stocks. For each fund, we compute a trailing 24-month moving average of its market timing and stock picking skills. We define high market timing (stock picking) skill as being in the top quartile of all funds in market timing (stock picking) ability within the same year. Second, we examine whether specialist funds and high-fee funds respond differently to export controls. The former captures the idea that specialists may have an advantage in

navigating emerging risks, while the latter simply uses fees as a proxy for skill. Specifically, following [Zambrana and Zapatero \(2021\)](#), we classify a fund as specialist if its manager focuses on a single investment style, and we define high-fee funds as those charging fees above the median of funds in the same investment style and year.

For each measure of skill, we estimate the following panel regression:

$$Y_{i,t} = \beta_1 Shock\ Exposure_{i,t} + \beta_2 Skill_{i,t} + \beta_3 Shock\ Exposure_{i,t} \times Skill_{i,t} + \gamma' \mathbf{X}_{i,t-1} + \mu_i + \eta_{s,t} + \varepsilon_{i,t}, \quad (7)$$

where $Y_{i,t}$ is one of several outcome variables for fund i in month t , $Skill_{i,t}$ is one of the measures of skill: high market timing, high stock picking, specialist, and high fee. $\mathbf{X}_{i,t-1}$ is a vector of lagged controls as in Equation (2), while μ_i and $\eta_{s,t}$ are fund and style-time fixed effects, respectively. The coefficient of interest, β_3 , indicates whether funds with better skills display a different outcome relative to other funds for a given exposure to export-control shocks.

We first examine whether, conditional on similar exposure to export controls, managers with better skills exhibit smaller declines in performance. Table 9 presents the results, with each column interacting *Shock Exposure* with a different skill measure. In Panel A, the coefficient on *Shock Exposure* is negative and significant across all four columns, confirming that export controls lower factor-adjusted fund performance. Columns 1 and 2 show that the interactions between *Shock Exposure* and market-timing or stock-picking skill are insignificant. Columns 3 and 4 show that the interactions between *Shock Exposure* and specialist or high-fee status are positive and significant, indicating that these funds experience smaller performance

Table 9: Heterogeneity of Performance and Exposure to Export Controls: Manager Skills. This table presents the results of estimating Equation (7) for active funds. The dependent variable is the 3-factor adjusted abnormal fund return in Panel A and the 5-factor adjusted abnormal fund return in Panel B. *Shock Exposure* is the portfolio share invested in affected U.S. suppliers. Each column interacts *Shock Exposure* with a different measure of manager skill. *Market Timing* and *Stock Picking* are dummy indicators equal to one if the fund's market-timing or stock-picking skill, respectively, is in the top quartile of all funds in the year, based on the moving average of the fund's past 24-month skill measure, following [Kacperczyk et al. \(2014\)](#). *Specialist* is a dummy indicator equal to one if the fund management team has at least one specialist fund manager, where a manager is defined as a specialist if they oversee only one investment style in a given quarter, following [Zambrana and Zapatero \(2021\)](#). *High Fee* is a dummy indicator equal to one if the fund's fee is above the median fee of funds in the same investment style and year. All specifications include the lagged dependent variable, *China Share*, and fund controls, as in Table 3 (see Online Appendix A for variable definitions). Standard errors are clustered at the fund level. *** p<0.01, ** p<0.05, * p<0.1.

	Panel A: Alpha 3F			
	Market Timing (1)	Stock Picking (2)	Specialist (3)	High Fee (4)
Shock Exposure	−3.833*** (1.169)	−5.692*** (1.337)	−5.679*** (1.290)	−7.003*** (1.633)
Skill	0.017 (0.012)	−0.008 (0.011)	0.001 (0.013)	0.037** (0.017)
Shock Exposure × Skill	−3.544 (2.466)	3.845 (2.422)	5.141*** (1.831)	4.189*** (1.524)
Observations	195,659	195,659	195,659	195,659
Adjusted R^2	0.442	0.442	0.442	0.442
	Panel B: Alpha 5F			
	Market Timing (1)	Stock Picking (2)	Specialist (3)	High Fee (4)
Shock Exposure	−3.092*** (1.161)	−4.800*** (1.258)	−4.795*** (1.235)	−5.743*** (1.562)
Skill	0.002 (0.012)	−0.004 (0.011)	−0.005 (0.014)	0.037** (0.017)
Shock Exposure × Skill	−2.913 (2.352)	3.941 (2.465)	5.320*** (1.764)	3.524** (1.554)
Observations	195,659	195,659	195,659	195,659
Adjusted R^2	0.441	0.441	0.441	0.441
Fund Controls	✓	✓	✓	✓
Fund FE	✓	✓	✓	✓
Style×Time FE	✓	✓	✓	✓

declines following export controls. Panel B shows a similar pattern for the 5-factor adjusted return. The market-timing and stock-picking interactions remain insignificant. The specialist and high-fee interactions, by contrast, remain positive and significant. Overall, we find little evidence that market-timing or stock-picking skills help managers limit the performance effects of geoeconomic risk, while specialist and high-fee funds consistently mitigate performance declines following exposure to export controls.

5.2 Passive Funds

We now document that active funds seem to be able to better navigate export-control shocks compared with passive funds, consistent with discretion in portfolio management being valuable when geoeconomic shocks materialize. Specifically, passive funds often have an investment mandate to track a benchmark index as closely as possible. To do so, they hold the constituent stocks or a representative sample of them. As a result, passive funds have limited ability to adjust their holdings in response to good or bad news about individual stocks. Their demand for benchmark constituents is therefore highly inelastic (Pavlova and Sikorskaya, 2023). In contrast, active fund managers charge higher fees and employ discretion in stock selection to outperform their benchmarks (Elton et al., 2003).

Table 10 reports estimates of Equation (7) on the pooled sample of active and passive funds, with the Passive indicator in place of the skill measure. The coefficient on *Shock Exposure* captures the effect of exposure for active funds, and the coefficient on the interaction term captures the differential effect for passive funds. Panel A shows the effects on volatility and raw returns, while Panel B shows the effects on 3- and 5-factor adjusted returns. Our

Table 10: Active versus Passive Funds: Performance and Exposure to Export Controls. This table presents the results of estimating Equation (7) on the pooled sample of active and passive funds, with the Passive indicator in place of the skill measure. In Panel A, the dependent variables are fund volatility (columns 1 and 2) and fund return (columns 3 and 4). In Panel B, the dependent variables are the 3-factor adjusted abnormal fund return (columns 1 and 2) and the 5-factor adjusted abnormal fund return (columns 3 and 4). *Volatility* is the monthly standard deviation of daily fund returns in percentage points. *Return* is the monthly fund return in percentage points. *Alpha 3F* and *Alpha 5F* are the 3-factor and 5-factor adjusted abnormal returns, respectively. *Shock Exposure* is the portfolio share invested in affected U.S. suppliers (see Appendix A for the full definition). Passive is a dummy indicator equal to one if the CRSP index fund flag is “D” or the fund name contains “index,” “idx,” or “indx.” All specifications include the lagged dependent variable, *China Share*, and fund controls, as in Table 3 (see Online Appendix A for variable definitions). Standard errors are clustered at the fund level. *** p<0.01, ** p<0.05, * p<0.1.

Dependent Variables :	Panel A			
	Volatility		Return	
	(1)	(2)	(3)	(4)
Shock Exposure	0.963*** (0.135)	0.408*** (0.106)	−14.218*** (3.197)	−8.315*** (2.458)
Passive	0.008 (0.008)	0.005 (0.006)	−0.064*** (0.018)	−0.032** (0.013)
Shock Exposure × Passive	−0.405** (0.177)	−0.073 (0.125)	−3.669 (3.186)	−5.341** (2.230)
Observations	325,047	325,047	325,047	325,047
Adjusted R ²	0.911	0.945	0.797	0.891
Dependent Variables :	Panel B			
	Alpha 3F		Alpha 5F	
	(1)	(2)	(3)	(4)
Shock Exposure	−9.671*** (1.126)	−4.229*** (1.214)	−7.715*** (1.063)	−3.247*** (1.185)
Passive	−0.076* (0.041)	−0.024 (0.025)	−0.064 (0.047)	−0.010 (0.029)
Shock Exposure × Passive	−6.139*** (1.850)	−5.981*** (1.560)	−5.948*** (1.717)	−6.256*** (1.444)
Observations	255,733	255,733	255,733	255,733
Adjusted R ²	0.104	0.467	0.104	0.468
Fund Controls	✓	✓	✓	✓
Fund FE	✓	✓	✓	✓
Time FE	✓		✓	
Style×Time FE		✓		✓

preferred specifications in columns 2 and 4 include style-time fixed effects and fund controls. In Panel A, the interaction term for volatility is negative but significant only without style-time fixed effects (column 1). In Panel B, the interaction term is negative and significant for both measures of abnormal returns in all specifications. In sum, with a similar level of shock exposure, passive funds experience a larger decline in performance than active funds. The differential effect is economically large. In the preferred specifications, the interaction coefficient is about 1.5 times the coefficient on *Shock Exposure* for 3-factor adjusted alphas and about twice as large for 5-factor adjusted alphas. Summing the two coefficients, the total decline in alphas for passive funds is 2.4 to 2.9 times the decline for active funds with the same exposure.

Table 11 reports estimates of Equation (2) for Sharpe ratios and fund flows, estimated separately for active funds (Panel A) and passive funds (Panel B). For both groups, exposure to export-control shocks lowers Sharpe ratios (columns 1 and 2). Neither group experiences significant flows in the month of the shock (columns 3 and 4), but both experience outflows in the following month (columns 5 and 6), consistent with investors withdrawing capital after the performance decline.

Finally, we confirm that passive funds barely reallocate their portfolios following export-control shocks. Specifically, we analyze passive funds' trading behavior following export-control shocks. Online Appendix Table C.5 shows that passive funds do not trade affected stocks in response to export controls, consistent with their mandate to track a benchmark with minimal tracking error. This lack of trading matches the inelastic demand of benchmarked investors documented by Pavlova and Sikorskaya (2023).

Table 11: Additional Fund-Level Outcomes: Sharpe Ratio and Flows. This table presents the results of estimating Equation (2) for active and passive funds, separately. The dependent variables are the fund’s Sharpe ratio, concurrent fund flows and lead fund flows. *Sharpe Ratio* is a market-adjusted Sharpe ratio, defined as the fund’s monthly CAPM alpha divided by *Volatility*, the monthly standard deviation of daily fund returns. Shock Exposure is the portfolio share invested in affected U.S. suppliers. All specifications include the lagged dependent variable, *China Share*, and fund controls, as in Table 3 (see Appendix A for variable definitions). Standard errors are clustered at the fund level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Dependent Variables :	Panel A: Active Funds					
	Sharpe Ratio		Flows		Lead Flows	
	(1)	(2)	(3)	(4)	(5)	(6)
Shock Exposure	−7.581*** (0.986)	−3.127*** (1.060)	−0.057 (0.067)	−0.076 (0.070)	−0.078** (0.039)	−0.079* (0.044)
Observations	195,972	195,972	247,851	247,851	247,113	247,113
Adjusted R ²	0.160	0.487	0.080	0.103	0.072	0.094
Dependent Variables :	Panel B: Passive Funds					
	Sharpe Ratio		Flows		Lead Flows	
	(1)	(2)	(3)	(4)	(5)	(6)
Shock Exposure	−9.433*** (1.310)	−5.668*** (1.445)	0.096 (0.133)	0.022 (0.129)	−0.159** (0.066)	−0.133** (0.067)
Observations	59,761	59,761	77,196	77,196	77,096	77,096
Adjusted R ²	0.172	0.605	0.099	0.145	0.090	0.135
Fund FE	✓	✓	✓	✓	✓	✓
Time FE	✓		✓		✓	
Style×Time FE		✓		✓		✓
Fund Controls	✓	✓	✓	✓	✓	✓

6 Export Controls and Stock Returns

Having established how fund managers trade in response to export controls, we next show that affected suppliers’ stock prices recover following the initial decline documented in Figure 2. This recovery is consistent with either the unwinding of temporary selling pressure or higher returns compensating investors for bearing greater geoeconomic risk.

Export controls can affect stock prices through expected cash flows and required returns. By restricting firms’ sales to targeted Chinese customers, export controls can reduce affected suppliers’ expected cash flows (cash flow shock) and raise the returns investors require

to hold their stocks (discount rate shock). As discussed in [Campbell and Vuolteenaho \(2004\)](#) a negative cash flow shock would lower current prices without changing subsequent expected returns—provided that the news is fully incorporated and required returns remain unchanged.¹⁰ Mutual fund selling at the time of the shock may also push prices below fundamentals and lead to a subsequent recovery as selling pressure dissipates (temporary price pressure). Lastly, if investors incorporate the adverse cash-flow implications of export controls gradually, prices may display an initial price decline followed by a continued negative drift, akin to post-earnings-announcement drift (PEAD).¹¹

Our empirical analysis leverages a stock-month level panel.¹² For each horizon $h \in \{0, 1, 3, 6, 12\}$ months, we estimate the following specification:

$$CAR_{j,[t,t+h]} = \beta_h Affected_{j,t} + \gamma'_h \mathbf{X}_{j,t} + \mu_j + \eta_t + \varepsilon_{j,t}, \quad (8)$$

where $CAR_{j,[t,t+h]}$ is the cumulative excess return of stock j from month t to month $t + h$, computed as the sum of its monthly returns net of the risk-free rate. The window includes the shock month, so $h = 0$ captures the return in that month. $Affected_{j,t}$ is an indicator that equals one if a customer of U.S. firm j is added to the BIS Entity List in month t , and zero otherwise. The coefficient β_h captures the difference in cumulative excess returns between stocks affected in month t and those not affected in that month, from the month of the shock

¹⁰For example, export controls may reveal greater exposure to systematic geoeconomic risk, leading investors to require higher returns to hold affected stocks ([Pastor and Veronesi, 2012](#); [Pástor and Veronesi, 2013](#); [Gala et al., 2023](#); [Sheng et al., 2025](#); [Gonçalves et al., 2025](#)).

¹¹The post-earnings-announcement drift, initially documented in [Ball and Brown \(1968\)](#) has been attributed to many factors, including a delayed response to information by investors ([Bernard and Thomas, 1989](#)), investor inattention ([DellaVigna and Pollet, 2009](#)), and poor liquidity conditions ([Sadka, 2006](#)).

¹²Online Appendix D reports complementary calendar-time portfolio sorts. A long-short portfolio buying suppliers affected during the prior year and shorting other stocks earns positive factor-adjusted returns.

through month $t + h$, conditional on the controls and fixed effects.

We add a set of firm characteristics as control variables ($\mathbf{X}$), namely firm size, book-to-market ratio, investment, momentum, and profitability (Hou et al., 2020). Because affected firms in our sample supply Chinese customers, we also control for *Firm China Share*, the share of a firm’s disclosed customers that are Chinese in month t . Otherwise, *Affected* may capture return differences associated with exporting to China more generally. The baseline specification includes firm and month fixed effects. Firm fixed effects absorb persistent differences in average returns across stocks, and time fixed effects absorb market-wide return movements. We double-cluster standard errors at the firm and month levels.

Table 12 shows an initial decline followed by a recovery in affected stocks’ relative returns. The excess return of affected firms is 2.7 percentage points lower than that of unaffected firms in the month (column 1). The decline continues into the following month. The estimated cumulative excess return difference through month $t + 1$ is -3.1 percentage points and is statistically significant (column 2). The point estimates subsequently become less negative and eventually turn positive. The estimated difference through month $t + 3$ is -1.1 percentage points and is statistically indistinguishable from zero (column 3). Through month $t + 6$, the estimated difference is 5.1 percentage points, significant at the 5% level (column 4), and through month $t + 12$ it is 6.9 percentage points, although the coefficient is not statistically significant (column 5). Replacing month fixed effects with industry-month fixed effects yields a similar initial decline, but smaller positive coefficient estimates that are statistically indistinguishable from zero at six- and twelve-month horizons (Table C.6). This alternative specification compares affected suppliers with their industry peers, thus absorbing

Table 12: Cumulative Excess Returns Following Export-Control Exposure. This table reports panel regressions of cumulative excess stock returns on firms' exposure to export controls. The dependent variable is the cumulative excess return from the exposure month t through month $t + h$, computed as the sum of monthly excess returns over the window. The window is month t alone (column 1), months t to $t + 1$ (column 2), months t to $t + 3$ (column 3), months t to $t + 6$ (column 4), and months t to $t + 12$ (column 5). Excess returns are monthly stock returns minus the risk-free rate, expressed in percentage points. *Affected* is an indicator variable equal to one if a customer of U.S. firm is added to the BIS list in month t . *Firm China Share* is the share of a firm's disclosed customers that are Chinese in month t . The remaining controls are lagged. *Size* is the logarithm of market capitalization at the end of the previous quarter. *B/M* is the logarithm of book equity divided by market capitalization at the end of month $t - 1$. Book equity is stockholders' equity plus deferred taxes and investment tax credit minus preferred stock, from the most recent fiscal quarter ending at least four months before month t (Hou et al., 2020). *Investment* is the logarithm of one plus the year-over-year growth in total assets of the same fiscal quarter. *Profitability* is operating income before depreciation scaled by lagged total assets in the previous quarter. *Momentum* is the average monthly stock return from month $t - 12$ to month $t - 1$, in percentage points. Standard errors, reported in parentheses, are double clustered at the firm and time levels. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Dependent Variable:	Cumulative Excess Return				
Window (months):	[t] (1)	[$t, t + 1$] (2)	[$t, t + 3$] (3)	[$t, t + 6$] (4)	[$t, t + 12$] (5)
Affected	-2.656** (1.070)	-3.053*** (0.653)	-1.067 (1.624)	5.074** (2.072)	6.936 (5.183)
Firm China Share	-0.030 (0.624)	0.902 (1.135)	1.922 (2.054)	2.957 (2.979)	0.675 (4.645)
Size	-0.001 (0.401)	-2.818*** (0.416)	-8.006*** (0.590)	-15.254*** (0.863)	-29.121*** (1.367)
B/M	1.425*** (0.187)	1.430*** (0.242)	1.345*** (0.327)	1.430*** (0.453)	2.167*** (0.713)
Investment	-1.125*** (0.220)	-1.341*** (0.299)	-1.713*** (0.452)	-2.384*** (0.670)	-2.826*** (1.066)
Momentum	-0.076** (0.033)	-0.096** (0.044)	-0.150*** (0.057)	-0.223*** (0.068)	-0.401*** (0.116)
Profitability	7.905*** (1.523)	18.539*** (2.790)	30.412*** (4.419)	31.457*** (5.452)	28.152*** (7.242)
Firm FE	✓	✓	✓	✓	✓
Time FE	✓	✓	✓	✓	✓
Observations	592,123	592,123	585,881	568,921	529,554
Adjusted R-squared	0.135	0.156	0.195	0.251	0.349

common industry return movements, including any industry-wide response to export controls.

In sum, the evidence of longer-horizon outperformance is therefore weaker when affected suppliers are compared with their industry peers.

Taken together, the point estimates suggest an initial stock price decline followed by a

recovery, although the longer-horizon estimates are imprecise and sensitive to industry controls. This pattern is consistent with either a discount rate shock that increases required returns or temporary price pressure, but does not allow us to distinguish between their respective roles. Our findings of a contemporaneous decline followed by higher subsequent returns in the context of a firm-level shock are consistent with the literature on aggregate geopolitical risk. Specifically, [Gala et al. \(2023\)](#) identifies a global political risk factor that commands a positive premium in international equity markets. [Sheng et al. \(2025\)](#) documents a negative contemporaneous relation between trade war risk and market returns alongside a positive relation with future market returns, and [Gonçalves et al. \(2025\)](#) finds that a geopolitical threat index is priced in the cross-section of equity returns.¹³

7 Conclusion

As tensions between the U.S. and China intensify, geoeconomic risk has become a central concern for asset managers. Despite their focus on U.S. stocks, domestic equity mutual funds are not fully insulated from geopolitical frictions. Many of their largest holdings are high-technology firms, such as semiconductor and advanced computing companies, that have driven recent U.S. stock market upturns. These firms also sit at the heart of global technology supply chains and are directly exposed to U.S.–China tensions. We focus on export controls, the primary policy instrument in the technological rivalry between the two countries. Designed to restrict targeted Chinese firms’ access to U.S. technology, export

¹³Relatedly, [Florackis et al. \(2023\)](#) documents that firms with high exposure to cybersecurity risk earn higher returns on average, but these stocks exhibit lower returns during cyber attack events.

controls negatively affect the U.S. suppliers exporting to these Chinese firms. Domestic equity mutual funds with greater exposure to such affected stocks experience higher volatility and lower returns following these policy shocks. When we examine cross-sectional differences in managers' ability to navigate geoeconomic shocks, we find that fund managers that specialize in a single investment style (specialists) and funds that charge higher fees can mitigate the negative effects of export-control shocks on fund performance.

Next, we examine how investors respond to geoeconomic shocks and find that active funds rebalance away not only from directly affected firms but also from firms indirectly exposed to the geoeconomic shock. At the same time, funds with greater exposure to export-control shocks take on more risk, suggesting that managers have incentives to offset performance shortfalls. This reallocation increases portfolio concentration. We also find that firms affected by geoeconomic shocks display an immediate decline in stock prices followed by a reversal.

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Online Appendix

A Variable Definitions

Variable Name	Description
Volatility	monthly standard deviation of daily fund returns in percentage points.
Fund return	the fund's total net asset value (TNA)-weighted average monthly net return across its share classes, in percentage points.
Alpha 3F	3-factor-adjusted abnormal fund returns. We estimate the beta coefficients at time t using the previous rolling window regression of 36 months ($t-36$ through $t-1$) on each fund over the sample period.
Alpha 5F	5-factor-adjusted abnormal fund returns. We estimate the beta coefficients at time t using a 36-month rolling regression ($t-36$ through $t-1$) for each fund over the sample period.
Shock Exposure	Portfolio share invested in affected U.S. suppliers, measured with the fund's portfolio weights in the previous month (Equation 1). Exposure is strictly positive only in the month in which the Chinese customers of the affected U.S. suppliers are added to the BIS lists, and zero otherwise.
China Share	portfolio share invested in U.S. firms that have at least one Chinese customer.
Fund size	logarithm of the fund's total net assets (TNA).
Family size	logarithm of the total net assets of the fund's family.
Expense ratio	ratio of fund operational expenses to its net assets.
Turnover ratio	how frequently a mutual fund buys and sells securities within its portfolio and is computed by dividing the lesser of purchases or sales by net assets.
Trade direction	trade sign of the net trading for a particular stock. If the net quantity change is positive, the trade direction is 1. If the net quantity change is negative, the trade direction is -1.
Direct	Dummy indicator if the firm is first treated by the export control at time t
Spillover	Dummy indicator if firm j has Chinese customers and is not affected by export controls in month t , and fund i holds at least one U.S. supplier whose Chinese customer is newly targeted by export controls in month t .

Continued on next page

Table A.1 – *Continued from previous page*

Variable	Description
Lottery stock	Dummy indicator if the MAX5 returns (the average of five highest daily returns within a month) of the stock are in the top quartile among all the stocks in the same month.
Affected industry weight	Fund's portfolio weight invested in stocks belonging to the same (Fama-French) industry as a directly affected stock, excluding the directly affected stock itself: $AffectInd_{i,t} = \sum_{k \in Ind(j)} w_{i,k,t}$, where j is the directly affected stock and k ranges over its industry peers that are not themselves currently affected. Table 8 reports the regression of its month-over-month change, $\Delta AffectInd_{i,t} = AffectInd_{i,t} - AffectInd_{i,t-1}$.
Industry concentration index (ICI)	Fund's portfolio concentration across industries, following Kacperczyk et al. (2005): $ICI_{i,t} = \sum_j (w_{i,j,t} - w_{m,j,t})^2$, where $w_{i,j,t}$ is fund i 's portfolio weight invested in industry j (Fama-French classification) at time t , and $w_{m,j,t}$ is industry j 's value-weighted market share at time t . Table 8 reports the regression of its month-over-month change, scaled by 100: $\Delta ICI_{i,t} \times 100$.
Portfolio Herfindahl index	Fund's portfolio concentration across individual stocks, $HHI_{i,t} = \sum_k w_{i,k,t}^2$, the sum of squared portfolio weights across all stocks k held by fund i at time t . Table 8 reports the regression of its month-over-month change, scaled by 100: $\Delta HHI_{i,t} \times 100$.
Passive fund	Dummy indicator if the CRSP index fund flag is "D" or the names of the funds contain "index," "idx," or "indx."
Active fund	Dummy indicator equal to one minus the Passive fund indicator.
Market timing skills	Indicator variable equal to one if the moving average of the last two years of the market timing skill is in the top quartile in a given year. We measure funds' market timing skills based on how funds' holdings of each stock co-move with the market component of the stock returns, following Kacperczyk et al. (2014). Specifically, for fund i and time t , $Timing_{i,t} = \sum_{j=1}^{N_j} (w_{i,j,t} - w_{m,j,t}) \times (\beta_{j,t} R_{m,t+1})$. To estimate the stock market beta t , we use the rolling window of past 24 months.

Continued on next page

Table A.1 – *Continued from previous page*

Variable	Description
Stock picking skills	Indicator variable equal to one if the moving average of the last two years of the stock picking skill is in the top quartile in a given year. We measure funds' stock-picking skills based on how funds' holdings of each stock comove with the idiosyncratic component of the stock returns, following Kacperczyk et al. (2014) . Specifically, for fund i and time t , $Stock\ picking_{i,t} = \sum_{j=1}^{N_j} (w_{i,j,t} - w_{m,j,t}) \times (R_{j,t+1} - \beta_{j,t} R_{m,t+1})$. To estimate the stock market beta t , we use the rolling window of past 24 months.
Specialist Funds	Indicator variable equal to one if the fund management team has at least one specialist fund manager. A fund manager is a specialist if the manager oversees only one investment style in a particular quarter, following Zambrana and Zapatero (2021) .
High Fee Funds	Indicator variable equal to one if the fund fee is above the median of funds in the same investment style and year.
Age	logarithm of the fund age.
Past Return (1Y)	average fund return over the previous year.
Flow	percentage change in total net assets minus appreciation, $Flow_{i,t} = [TNA_{i,t} - TNA_{i,t-1}(1 + R_{i,t-1})]/TNA_{i,t-1}$.
Sharpe Ratio	a fund's monthly CAPM alpha divided by volatility.
Assets	firm's total assets in \$ million (at).
Firm age	number of years since the firm's IPO.
Book leverage	firm's ratio of total debt to total assets (dlttq+dlcq)/atq.
CAPEX	firm's capital expenditures (capx) divided by lagged assets.

B Local Projections for Trading Direction

For each horizon k , we estimate

$$Y_{i,j,t+k} - Y_{i,j,t-1} = \beta_k \Delta Direct_{j,t} + \gamma' \mathbf{X}_{i,j,t-1} + \mu_i + \eta_t + \varepsilon_{i,j,t},$$

where $Y_{i,j,t}$ is defined as in Equation (4) and $\Delta Direct_{j,t}$ equals one in the month stock j is first affected by export controls and zero otherwise. A stock-fund-month observation is a clean control if (i) at the firm level, stock j is not affected by export controls, and does not become affected, at any point in $[t - 6, t + k]$, and (ii) at the fund level, fund i 's own overall export-control exposure (as defined in Section 3.2) is likewise unchanged over $[t - 6, t + k]$. Observations must satisfy both (i) and (ii), or belong to the treated sample (stock j in its first event month, held by a fund satisfying condition (ii)), to enter the regression.

C Additional Tables

Table C.1: Performance and Exposure: Showing Controls. This table presents the results of estimating Equation (2) for active funds. The dependent variables are fund volatility, returns, and the 3- and 5-factor adjusted abnormal returns. *Volatility* is the monthly standard deviation of daily fund returns in percentage points. *Return* is the monthly fund return in percentage points. *Alpha 3F* and *Alpha 5F* are the 3-factor and 5-factor adjusted abnormal returns, respectively. *Shock Exposure* is the portfolio share invested in affected U.S. suppliers (see Appendix A for the full definition). Standard errors are clustered at the fund level. *** p<0.01, ** p<0.05, * p<0.1.

Dependent Variables:	Volatility (1)	Return (2)	Alpha 3F (3)	Alpha 5F (4)
Shock Exposure	0.587*** (0.115)	-9.324*** (2.645)	-4.820*** (1.284)	-3.906*** (1.232)
China Share	0.008 (0.020)	0.015 (0.069)	0.525*** (0.076)	0.620*** (0.082)
Log Fund Size	0.004** (0.002)	-0.063*** (0.007)	-0.099*** (0.009)	-0.076*** (0.008)
Log Family Size	0.002 (0.002)	0.010* (0.006)	0.004 (0.007)	-0.009 (0.008)
Expense Ratio	0.033 (0.414)	-0.036 (1.696)	2.172 (1.970)	3.211* (1.940)
Turnover Ratio	0.007*** (0.003)	-0.016 (0.011)	-0.036** (0.016)	-0.045*** (0.015)
Age	-0.011*** (0.004)	0.038*** (0.012)	-0.006 (0.025)	-0.029 (0.028)
Past Return (1Y)	-0.051*** (0.002)	1.067*** (0.013)	0.434*** (0.011)	0.488*** (0.012)
Lag Fund Volatility	0.116*** (0.004)			
Lag Fund Return		-0.029*** (0.002)		
Lag Alpha 3F			-0.063*** (0.004)	
Lag Alpha 5F				-0.072*** (0.004)
Observations	247,489	247,489	195,659	195,659
Adjusted R ²	0.943	0.891	0.442	0.441
Fund FE	✓	✓	✓	✓
Style×Time FE	✓	✓	✓	✓

Table C.2: Trading in Response to Export Controls with Quarterly Holdings. This table presents the results of estimating Equation (4) for active and passive funds, separately. The dependent variable is *Trade Direction*, which represents the sign of net trading in the same quarter. *Direct* is an indicator variable equal to one in the quarter a stock is affected by export controls for the first time, and zero otherwise. All specifications include *China Share*, fund controls, and firm controls, as in Table 4 (see Appendix A for variable definitions). Standard errors are double clustered at the fund and firm level. *** p<0.01, ** p<0.05, * p<0.1.

Dependent Variables :	Panel A: Active Funds			
	Trade Direction			
	(1)	(2)	(3)	(4)
Direct	-0.046** (0.018)	-0.047*** (0.018)	-0.043** (0.017)	-0.045*** (0.017)
Observations	17,309,806	17,309,806	17,309,806	17,309,806
Adjusted R ²	0.064	0.075	0.078	0.081
Dependent Variables :	Panel B: Passive Funds			
	Trade Direction			
	(1)	(2)	(3)	(4)
Direct	0.012 (0.020)	0.011 (0.019)	0.008 (0.019)	0.008 (0.018)
Observations	13,856,132	13,856,132	13,856,132	13,856,132
Adjusted R ²	0.161	0.195	0.198	0.203
Fund FE	✓	✓	✓	✓
Time FE	✓			
Style×Time FE		✓	✓	
Industry×Time FE			✓	
Style× Industry×Time FE				✓
Fund Controls	✓	✓	✓	✓
Firm Controls	✓	✓	✓	✓

Table C.3: Spillover Effects with Quarterly Holdings. This table presents the results of estimating Equation (5) for active and passive funds, separately. The dependent variable is *Trade Direction*, which represents the sign of net trading in the same quarter. *Spillover* is an indicator variable equal to one if firm j has Chinese customers and is not affected by export controls in quarter t , and fund i holds at least one U.S. supplier whose Chinese customer is newly targeted by export controls in quarter t . All specifications include *China Share*, fund controls, and firm controls, as in Table 6 (see Appendix A for variable definitions). Standard errors are double clustered at the fund and firm level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Dependent Variables :	Panel A: Active Funds			
	Trade Direction			
	(1)	(2)	(3)	(4)
Spillover	−0.026*** (0.007)	−0.027*** (0.007)	−0.021*** (0.006)	−0.021*** (0.006)
Observations	16,570,949	16,570,949	16,570,885	16,560,627
Adjusted R ²	0.063	0.074	0.078	0.081
Dependent Variables :	Panel B: Passive Funds			
	Trade Direction			
	(1)	(2)	(3)	(4)
Spillover	−0.013 (0.009)	0.002 (0.008)	−0.001 (0.008)	−0.001 (0.008)
Observations	13,350,863	13,350,863	13,350,728	13,344,806
Adjusted R ²	0.160	0.194	0.198	0.202
Fund FE	✓	✓	✓	✓
Time FE	✓			
Style×Time FE		✓	✓	
Industry×Time FE			✓	
Style× Industry×Time FE				✓
Fund Controls	✓	✓	✓	✓
Firm Controls	✓	✓	✓	✓

Table C.4: Trading in Response to Export Controls: Excluding Leveraged Funds. This table presents results for actively managed funds whose equity holdings do not exceed their total net assets (equity-to-TNA ratio of at most 100%). Panel A presents the results of estimating Equation (4) as in Table 4. The dependent variable is *Trade Direction*, the sign of net trading in the same month. *Direct* is an indicator variable equal to one in the month a stock is affected by export controls for the first time, and zero otherwise. Panel B presents the results of estimating Equation (5) as in Table 6. The dependent variable is *Trade Direction* in the same month (columns 1 and 2) or the sign of the net change in shares held from month t to month $t + 2$ (columns 3 and 4). *Spillover* is an indicator variable equal to one if firm j has Chinese customers and is not affected by export controls in month t , and fund i holds at least one U.S. supplier whose Chinese customer is newly targeted by export controls in month t . All specifications include *China Share*, fund controls, and firm controls (see Appendix A for variable definitions). Standard errors are double clustered at the fund and firm levels. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Dependent Variables :	Panel A: Direct Response Trade Direction (same month)			
	(1)	(2)	(3)	(4)
Direct	-0.043** (0.017)	-0.044*** (0.016)	-0.042*** (0.016)	-0.045*** (0.016)
Observations	23,441,475	23,441,475	23,441,475	23,441,475
Adjusted R ²	0.066	0.084	0.086	0.091
Fund FE	✓	✓	✓	✓
Time FE	✓			
Style × Time FE		✓	✓	
Industry × Time FE			✓	
Style×Industry× Time FE				✓
Fund Controls	✓	✓	✓	✓
Firm Controls	✓	✓	✓	✓

Dependent Variables:	Panel B: Trading in Other U.S. Firms with Chinese Customers			
	Trade direction (same month)		Trade direction (within 3 months)	
	(1)	(2)	(3)	(4)
Spillover	-0.013* (0.008)	-0.011 (0.008)	-0.037*** (0.008)	-0.038*** (0.008)
Observations	22,420,201	22,420,201	22,419,987	22,419,987
Adjusted R ²	0.084	0.086	0.083	0.086
Fund FE	✓	✓	✓	✓
Style×Time FE	✓	✓	✓	✓
Industry×Time FE		✓		✓
Fund Controls	✓	✓	✓	✓
Firm Controls	✓	✓	✓	✓

Table C.5: Trading in Response to Export Controls by Passive Funds. This table presents the results of estimating Equation (4) for passive funds. *Trade Direction* is defined as the sign of net trading in the same month (Panel A) or over three month horizon (Panel B). *Direct* is an indicator variable equal to one if a stock is affected by export controls in the current period. All specifications include *China Share*, fund controls, and firm controls, as in Table 4 (see Appendix A for variable definitions). Standard errors are double clustered at the fund and firm level. *** p<0.01, ** p<0.05, * p<0.1.

Dependent Variables :	Panel A: Same month Trade Direction			
	(1)	(2)	(3)	(4)
Direct	−0.002 (0.018)	−0.005 (0.017)	−0.013 (0.017)	−0.015 (0.017)
Observations	29,506,404	29,506,404	29,506,404	29,506,404
Adjusted R ²	0.124	0.164	0.167	0.171
Dependent Variables :	Panel B: Within 3 months Trade Direction			
	(1)	(2)	(3)	(4)
Direct	0.015 (0.019)	0.023 (0.017)	0.015 (0.017)	0.010 (0.017)
Observations	29,506,235	29,506,235	29,506,235	29,506,235
Adjusted R ²	0.152	0.184	0.188	0.192
Fund FE	✓	✓	✓	✓
Time FE	✓			
Style×Time FE		✓	✓	
Industry×Time FE			✓	
Style× Industry×Time FE				✓
Fund Controls	✓	✓	✓	✓
Firm Controls	✓	✓	✓	✓

Table C.6: Cumulative Excess Returns Following Export-Control Exposure Relative to Industry Peers. This table repeats the panel regressions of Table 12 with industry-time fixed effects in place of time fixed effects. The dependent variable is the cumulative excess return from the exposure month t through month $t + h$, computed as the sum of monthly excess returns over the window. The window is month t alone (column 1), months t to $t + 1$ (column 2), months t to $t + 3$ (column 3), months t to $t + 6$ (column 4), and months t to $t + 12$ (column 5). Excess returns are monthly stock returns minus the risk-free rate, expressed in percentage points. *Exposed* is an indicator variable equal to one if a firm is exposed to export controls in month t . *Firm China Share* is the share of a firm's disclosed customers that are Chinese in month t . The remaining controls are lagged. *Size* is the logarithm of market capitalization at the end of the previous quarter. *B/M* is the logarithm of book equity divided by market capitalization at the end of month $t - 1$. Book equity is stockholders' equity plus deferred taxes and investment tax credit minus preferred stock, from the most recent fiscal quarter ending at least four months before month t (Hou et al., 2020). *Investment* is the logarithm of one plus the year-over-year growth in total assets of the same fiscal quarter. *Profitability* is operating income before depreciation scaled by lagged total assets in the previous quarter. *Momentum* is the average monthly stock return from month $t - 12$ to month $t - 1$, in percentage points. Standard errors, reported in parentheses, are double clustered at the firm and time levels. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Dependent Variable:	Cumulative Excess Return				
Window (months):	$[t]$ (1)	$[t, t + 1]$ (2)	$[t, t + 3]$ (3)	$[t, t + 6]$ (4)	$[t, t + 12]$ (5)
Exposed	-2.421* (1.287)	-3.021** (1.264)	-1.815 (1.810)	2.488 (3.117)	3.320 (6.582)
Firm China Share	0.317 (0.581)	1.506 (1.067)	3.334* (1.994)	5.243* (2.923)	4.118 (4.390)
Size	0.020 (0.382)	-2.854*** (0.402)	-8.095*** (0.550)	-15.330*** (0.816)	-28.746*** (1.292)
B/M	1.426*** (0.168)	1.498*** (0.222)	1.526*** (0.299)	1.717*** (0.427)	2.506*** (0.686)
Investment	-1.047*** (0.178)	-1.220*** (0.255)	-1.520*** (0.390)	-2.000*** (0.591)	-2.452** (0.967)
Momentum	-0.107*** (0.028)	-0.145*** (0.038)	-0.235*** (0.051)	-0.339*** (0.066)	-0.528*** (0.115)
Profitability	8.128*** (1.497)	19.137*** (2.755)	31.651*** (4.336)	34.279*** (5.423)	34.097*** (7.190)
Firm FE	✓	✓	✓	✓	✓
Industry × Time FE	✓	✓	✓	✓	✓
Observations	591,864	591,864	585,613	568,650	529,268
Adjusted R-squared	0.182	0.205	0.247	0.305	0.403

D Portfolio Sorts

This section complements the panel regressions in Section 6 with a portfolio analysis that tests differences in future returns between firms exposed to export controls and unexposed firms. In June of each year t , we sort stocks into two groups based on whether a firm has been exposed to export controls during the prior year. The portfolios are held from July of year t through June of year $t + 1$, and are rebalanced annually based on updated exposure status.¹⁴ For each portfolio, we compute monthly value- and equal-weighted excess returns. We estimate alphas relative to the CAPM, the Fama–French 3-factor model (FF3), the Fama–French 5-factor model (FF5), and the 5-factor model augmented with momentum (FF6).

Table D.1 reports the average portfolio returns and factor-adjusted alphas. The return spread between the exposed firms’ portfolio (H) and the unexposed portfolio (L) is approximately 1.1% per month in excess returns, which is both statistically significant and economically large. The factor-adjusted alphas remain around 0.9% per month across specifications and are statistically significant in all models. Because the use of export controls has expanded significantly in recent years, we split the sample into two subperiods, 2019–2023 and the years prior, and rerun the analysis separately for each. Table D.2 shows that the long-short portfolio abnormal returns are more significant both statistically and economically in the 2019–2023 subperiod. Given the AI boom in recent years, one concern is that the portfolio result is driven by a small number of large AI-related stocks. To address this concern, we recompute the long-short portfolio excluding Nvidia and AMD. The long-short alphas remain positive and statistically significant (Table D.3).

¹⁴We rebalance at an annual frequency because export-control listings are infrequent. Reforming portfolios monthly or quarterly would leave the exposed portfolio populated by very few newly-exposed stocks, producing an unstable and thinly-diversified long leg.

Table D.1: Portfolio Alphas Sorted on Export-Control Exposure. This table presents value-weighted and equal-weighted average excess returns and risk-adjusted alphas for stock portfolios sorted on firms' exposure to U.S. export controls over the prior year. In June of year t , stocks are assigned to the High portfolio if the firm experienced at least one export-control exposure between July of year $t - 1$ and June of year t . All other firms are assigned to the Low portfolio. Portfolio returns are computed monthly from July of year t to June of year $t + 1$. We construct a long-short portfolio that buys High-exposure stocks and shorts Low-exposure stocks. H and L are the High and Low portfolio returns in excess of the risk-free rate, and H-L is the difference between them. All columns are estimated over the same months, namely the months in which the High portfolio contains at least one firm. Reported alphas are estimated using the CAPM, the Fama-French three-factor model (FF3), the Fama-French five-factor model (FF5), and the six-factor model that augments FF5 with the momentum factor (FF6). Standard errors are reported in parentheses. Standard errors are computed using the Newey-West procedure with six lags. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

	Value-weighted			Equal-weighted		
	H	L	H-L	H	L	H-L
Excess Return	1.932*** (0.552)	0.854** (0.357)	1.078*** (0.339)	1.610*** (0.558)	0.537 (0.504)	1.073*** (0.293)
CAPM	0.769** (0.352)	-0.145*** (0.052)	0.914** (0.375)	0.413 (0.298)	-0.488** (0.238)	0.901*** (0.309)
FF3	0.747** (0.341)	-0.135*** (0.041)	0.883** (0.351)	0.575* (0.298)	-0.324*** (0.113)	0.898*** (0.310)
FF5	0.773** (0.369)	-0.134*** (0.041)	0.906** (0.380)	0.689** (0.297)	-0.265** (0.113)	0.954*** (0.316)
FF6	0.792** (0.369)	-0.114*** (0.042)	0.907** (0.384)	0.709** (0.295)	-0.219** (0.110)	0.928*** (0.326)

Table D.2: Robustness Test: Portfolio Alphas by Subperiod. This table presents value-weighted and equal-weighted average excess returns and risk-adjusted alphas for stock portfolios sorted on firms' exposure to U.S. export controls over the prior year. In June of year t , stocks are assigned to the High portfolio if the firm experienced at least one export-control exposure between July of year $t - 1$ and June of year t . All other firms are assigned to the Low portfolio. Portfolio returns are computed monthly from July of year t to June of year $t + 1$. We construct a long-short portfolio that buys High-exposure stocks and shorts Low-exposure stocks. H and L are the High and Low portfolio returns in excess of the risk-free rate, and H-L is the difference between them. All columns are estimated over the same months, namely the months in which the High portfolio contains at least one firm. Panel A covers January 2019 to December 2023. Panel B covers the earlier months with a non-empty High portfolio, July 2014 to June 2015 and July 2016 to December 2018 (42 months). Reported alphas are estimated using the CAPM, the Fama-French three-factor model (FF3), the Fama-French five-factor model (FF5), and the six-factor model that augments FF5 with the momentum factor (FF6). Standard errors are reported in parentheses. Standard errors are computed using the Newey-West procedure with six lags. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Panel A: 2019-2023						
	Value-weighted			Equal-weighted		
	H	L	H-L	H	L	H-L
Excess Return	2.741*** (0.834)	1.081* (0.601)	1.660*** (0.433)	1.855** (0.880)	0.743 (0.843)	1.112** (0.430)
CAPM	1.412*** (0.434)	-0.120 (0.074)	1.531*** (0.489)	0.457 (0.429)	-0.501 (0.381)	0.957** (0.465)
FF3	1.435*** (0.391)	-0.109** (0.050)	1.544*** (0.413)	0.715 (0.453)	-0.269** (0.133)	0.983** (0.449)
FF5	1.512*** (0.463)	-0.108** (0.047)	1.619*** (0.485)	0.936** (0.432)	-0.205 (0.136)	1.141** (0.443)
FF6	1.516*** (0.462)	-0.098* (0.050)	1.614*** (0.489)	0.909** (0.445)	-0.183 (0.134)	1.093** (0.462)

Panel B: 2014-2018						
	Value-weighted			Equal-weighted		
	H	L	H-L	H	L	H-L
Excess Return	0.776 (0.518)	0.529 (0.411)	0.247 (0.360)	1.260* (0.673)	0.243 (0.524)	1.017*** (0.365)
CAPM	-0.195 (0.422)	-0.162*** (0.053)	-0.033 (0.432)	0.314 (0.393)	-0.435* (0.230)	0.749** (0.361)
FF3	-0.193 (0.426)	-0.164*** (0.055)	-0.029 (0.438)	0.407 (0.383)	-0.353** (0.133)	0.760* (0.406)
FF5	-0.207 (0.438)	-0.160*** (0.058)	-0.047 (0.451)	0.389 (0.391)	-0.347** (0.145)	0.735* (0.419)
FF6	-0.193 (0.449)	-0.148** (0.056)	-0.046 (0.465)	0.431 (0.368)	-0.325** (0.147)	0.756* (0.419)

Table D.3: Robustness Test: Portfolio Alphas Excluding NVIDIA and AMD. This table presents value-weighted and equal-weighted average excess returns and risk-adjusted alphas for stock portfolios sorted on firms' exposure to U.S. export controls over the prior year. In June of year t , stocks are assigned to the High portfolio if the firm experienced at least one export-control exposure between July of year $t - 1$ and June of year t . All other firms are assigned to the Low portfolio. Portfolio returns are computed monthly from July of year t to June of year $t + 1$. We construct a long-short portfolio that buys High-exposure stocks and shorts Low-exposure stocks. NVIDIA and AMD are excluded from both portfolios. H and L are the High and Low portfolio returns in excess of the risk-free rate, and H-L is the difference between them. All columns are estimated over the same months, namely the months in which the High portfolio contains at least one firm. Reported alphas are estimated using the CAPM, the Fama-French three-factor model (FF3), the Fama-French five-factor model (FF5), and the six-factor model that augments FF5 with the momentum factor (FF6). Standard errors are reported in parentheses. Standard errors are computed using the Newey-West procedure with six lags. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

	Value-weighted			Equal-weighted		
	H	L	H-L	H	L	H-L
Excess Return	1.682*** (0.524)	0.839** (0.355)	0.843*** (0.313)	1.586*** (0.557)	0.536 (0.504)	1.050*** (0.289)
CAPM	0.517* (0.304)	-0.154*** (0.055)	0.671** (0.322)	0.386 (0.296)	-0.489** (0.238)	0.875*** (0.302)
FF3	0.538* (0.316)	-0.142*** (0.043)	0.679** (0.324)	0.552* (0.294)	-0.324*** (0.113)	0.877*** (0.305)
FF5	0.593* (0.350)	-0.141*** (0.043)	0.733** (0.361)	0.668** (0.292)	-0.265** (0.113)	0.934*** (0.311)
FF6	0.638* (0.347)	-0.121*** (0.044)	0.759** (0.363)	0.690** (0.289)	-0.220** (0.110)	0.910*** (0.319)