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Abstract

Firm-level geoeconomic risk can affect even broadly diversified mutual fund portfolios. We study U.S. export controls that restrict sales of cutting-edge technology to selected Chinese firms for national security reasons. The stock prices of affected domestic suppliers drop immediately after the policy introduction. Mutual funds holding these stocks experience increased volatility and lower returns. Fund managers respond by selling stocks of exporters to China, buying lottery-like stocks, and increasing portfolio concentration. While stock-picking and market-timing skills do not help, specialist and high-fee funds are better at navigating geoeconomic risk.

JEL classification: G12, F51, F38
Key words: mutual funds, asset allocation, geoeconomic risk, export controls

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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 global investors (BlackRock, 2024; Invesco, 2024). The same multinational corporations that once offered diversification benefits to investors may now expose them to risks that cannot be diversified away. Yet, despite this growing recognition, little is known about how geoeconomic risk affects investor portfolios and how investors perceive and manage it.

We study this question in the context of U.S. domestic equity mutual funds. Although their mandate is to invest in U.S. equities, these funds—managing nearly half of the $34 trillion U.S. mutual fund industry—hold substantial stakes in firms with significant international exposures (Demirci et al., 2022; Bai et al., 2022). We examine how these investors respond to the imposition of U.S. export controls on firms held in their portfolios. A key policy tool in the current U.S.-China technological rivalry, export controls ban the sale of domestic cutting-edge technologies to selected foreign customers, thus imposing financial costs on a subset of "affected" domestic firms (Crosignani et al., 2025). From an empirical standpoint, export controls allow for cleaner *firm-level* identification relative to other geoeconomic shocks, such as tariffs, which are more aggregate in nature.

We find that funds holding stocks of affected firms experience higher volatility and lower returns, indicating that firm-level geoeconomic risk can penetrate even a well-diversified portfolio. In response to these shocks, fund managers reduce holdings of not only directly affected firms but also other firms that export to China, and reallocate toward lottery-like stocks. On net, portfolio concentration increases. Relative to passive funds, actively managed funds better navigate geoeconomic shocks. However, not all management skills are equally effective: market-timing and stock-picking skills offer little protection, whereas specialist and high-fee funds are more effective at navigating geoeconomic shocks.

We begin by examining how export controls affect mutual fund volatility and performance by constructing a fund-level exposure measure. The U.S. Commerce Department restricts domestic companies from exporting certain goods to a list of Chinese firms deemed to be a risk to U.S. national security. We hand-collect names and dates of the Chinese firms added to the list. We then trace the U.S. suppliers that are connected to those targeted firms using supply chain data from FactSet Revere. Finally, through mutual fund holdings data, we construct a fund-level measure of exposure to export controls as the portfolio share of affected U.S. firms held by each fund at a given time. We find that with the imposition of export controls, funds that are more exposed to affected firms display greater volatility and lower returns. The decline in returns is a robust finding, present in raw returns as well as in 3- and 5-factor adjusted returns.

We next explore how actively managed funds respond to export control shocks by examining their trading decisions. Following the imposition of export controls, affected firms experience a 3.6% decline in cumulative abnormal returns. Portfolio managers may choose to hold the affected stocks if they believe that those stocks are temporarily undervalued but have long-term upside potential. Conversely, portfolio managers may sell the affected stocks if they anticipate further declines or face scrutiny by investors.[1] We find that active funds exposed to export controls sell the affected stocks immediately. In addition, exposed mutual funds are also more likely to sell stocks of U.S. firms that export to other Chinese companies not currently targeted by U.S. export controls (a spillover effect). The spillover effect indicates that fund managers who experience export control shocks become more aware of geoeconomic risk and fear future rounds of export controls that may affect their portfolios. Overall, we find that active funds "decouple" their portfolios by selling stocks of U.S. firms connected to China following the imposition of export controls. This portfolio decoupling is broad, including U.S. firms that export goods to Chinese firms targeted by export controls as well as other Chinese firms that are currently not targeted.

After documenting which stocks are more likely to be sold by exposed mutual funds, we explore other dimensions of portfolio rebalancing, namely which stocks they are more likely to buy. We find that active funds more exposed to export controls buy more lottery stocks. Mutual fund managers appear to cater to investor preferences by buying lottery stocks, which tend to attract larger inflows (Agarwal et al., 2022), and can therefore mitigate the effect of their current under-performance on future outflows. We also find evidence that affected funds reduce the overall portfolio allocation to the industry of the affected stock, resulting in greater portfolio concentration in fewer industries and stocks.

Actively managed funds charge higher fees to compensate for their effort in portfolio selection and risk management, while the investment objective of passive funds is to minimize

[1] Fund managers may engage in short-term decision making, especially when under scrutiny by investors, which often happens when they hold stocks that receive negative publicity or that are marred in controversies.

tracking errors relative to a benchmark portfolio. Indeed, we find that passive funds do not trade actively on the affected stocks following the introduction of export controls. We therefore explore the difference in outcomes between active and passive funds. For a given exposure to export controls, passive funds experience a larger decline in performance and Sharpe ratios relative to active ones. Consistent with their worse performance, exposed passive funds experience larger subsequent outflows relative to the active ones. These findings suggest that active funds manage geoeconomic risk in a way that partially shields investors from losses and the portfolio rebalancing efforts of active managers can be seen as a way to mitigate contemporaneous under-performance and avoid sizable future outflows.

We also examine whether fund manager skills play a role in navigating geoeconomic risk. Traditional skills such as stock picking and market timing (Kacperczyk et al., 2014) do not appear to translate into effective geoeconomic risk management. Funds with better market-timing and stock-picking skills experience performance declines similar to their peers, suggesting that conventional skills provide little protection against this new type of risk. By contrast, fund managers who concentrate on a single investment style—specialists (Zambrana and Zapatero, 2021)—are better able to manage geoeconomic shocks. These specialists experience significantly smaller performance declines than generalists who manage multiple investment styles. In addition, funds charging higher fees also exhibit less severe declines in performance, indicating that high-fee funds may offer advantages when dealing with geoeconomic risk.

Finally, the staggered implementation of export controls means that our empirical analysis may suffer from the so-called bad comparison problem (Baker et al., 2022) as a result of using some earlier treated units as controls for later treated ones. To estimate unbiased dynamic effects, we use the local projections method of Dube et al. (2025), which only employs clean controls, namely never treated units as well as yet to be treated ones. Our main results are robust to the implementation of the local projections method and do not appear to be driven by pre-trends.

We contribute to the emerging literature on geoeconomics devoted to studying the effect of geopolitical risk on economic and financial outcomes. The current empirical literature has predominantly focused on tariffs and sanctions (Benguria and Saffie, 2023, 2020; Flaaen et al., 2020; Fajgelbaum et al., 2020; Efing et al., 2023; Ahn and Ludema, 2020; Felbermayr et al., 2020; Crozet et al., 2021; Besedeš et al., 2021), with the exception of Han et al. (2024) and Crosignani et al. (2025) who document the effect of export controls on firms' innovation, supply chains, and profitability. Geopolitical alignment has also been shown to have an effect on global capital allocations (Aiyar et al., 2024; Kempf et al., 2023; Gopinath et al., 2024). Despite the importance of geoeconomic risk in financial markets, there is a lack of evidence on the potential impact on investors. We document for the first time how mutual funds are affected by geoeconomic risk and how they manage it.

This paper also contributes to the mutual funds literature along several dimensions. Regarding portfolio diversification through supply chains, prior literature documents that domestic mutual funds hold multinational firms to benefit from diversification via their offshore markets (Demirci et al., 2022; Bai et al., 2022). Our paper highlights how mutual funds' holdings of multinational firms can also be a vulnerability. Prior literature has examined the impact of large-scale market disruptions, such as the COVID-19 pandemic, on mutual fund portfolios (Pástor and Vorsatz, 2020; Falato et al., 2021). Our paper emphasizes an emerging type of risk, namely geoeconomic risk, that affects domestic portfolios through supply chain linkages. In the literature that debates the performance of active and passive mutual funds (Gruber, 1996; Berk and Van Binsbergen, 2015), we show that active funds display more flexibility in reallocating their portfolios than passive funds and, as a result, perform relatively better after geoeconomic shocks.

Next, we contribute to the literature on the risk-taking behavior of mutual funds. Prior literature documents how risk taking is primarily affected by tournament effects, contractual incentives, and managers' skin in the game.[2] We complement these studies by showing that mutual funds take more risk after experiencing losses caused by exposure to geoeconomic shocks. Our findings are also related to models of financial contagion due to portfolio rebalancing effects (Kyle and Xiong, 2001; Lagunoff and Schreft, 2001; Kodres and Pritsker, 2002) and are especially in line with the predictions of Lagunoff and Schreft (2001) and Kodres and Pritsker (2002) that investors rebalance their portfolios after incurring losses.

Finally, we complement the flow-performance relationship literature (e.g., Ippolito, 1992; Sirri and Tufano, 1998; Del Guercio and Tkac, 2002). While those studies show that worse performance leads to subsequent outflows, we show that within the same month of a negative shock, mutual funds actively increase risk, likely in an attempt to offset the performance decline that might otherwise lead to even larger outflows. Such risk-taking behavior is consistent with managerial incentives. Indeed, fund managers dislike outflows because their

[2] For instance, see Chevalier and Ellison (1997); Brown et al. (1996); Taylor (2003); Massa and Patgiri (2009); Boguth and Simutin (2018); Ma and Tang (2019); Han (2021).

compensation is tied to assets under management and understand that investors tend to withdraw money following periods of poor performance. Consistent with this interpretation, we find that passive funds more exposed to export control shocks perform worse than active ones and subsequently experience significant outflows.

2 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 a selected group of foreign firms. To do so, the BIS includes foreign firms in the Code of Federal Regulations, Part 774, Supplement No. 4, also known as the "Entity List". Originally meant to restrict exports to entities engaging in the production of weapons of mass destruction, the Entity List has been used more recently to curb "activities contrary to the national security or foreign policy interests of the United States". In December 2022, the BIS introduced an additional list, called 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. An entity is removed from the UVL once the BIS validates the legitimacy of the end-user via either a pre-license check or a post-shipment verification.

Since 2014, the BIS has used it authority numerous times and 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 certain Chinese firms, called Chinese targets. As a result of export controls, U.S. firms are negatively impacted once one of their Chinese customers is added to the BIS lists. Indeed, as documented in Crosignani et al. (2025), affected U.S. suppliers experience negative abnormal stock returns and a decline in future profitability following the inclusion of Chinese customers in the BIS lists.

3 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. The other entities are either Russian or Iranian, and have very few supply chain connections with U.S. firms. Multiple subsidiaries and aliases of the same Chinese firm can be included in the BIS lists. From a total of 1,120 Chinese entries, we find 732 unique Chinese entities, of which 470 are corporations and 262 are universities and institutions. Most targeted entities are from the Entity List, which started in 1997 but records a surge in activity only after 2014.

Information on supply chain relations is obtained from FactSet Revere. Each relation includes names and identifiers of both customer and supplier, in addition to the relation's start and end dates. Following Gofman et al. (2020), we combine multiple relations with gaps shorter than 6 months in 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 restrict our analysis to domestic equity funds, namely funds that invest more than 80% of their holdings in domestic equities. We also include leveraged funds with a ratio of equity holdings to total net assets (TNA) of less than 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 level. Fund size is calculated as the sum of total net asset values across share classes, whereas fund returns, fund flows, and expense ratios are calculated as size-weighted averages. We exclude funds with less than $15 million in TNA and with less than 10 stocks in their holdings. We have a total of 5,275 domestic equity funds across 26 investment styles, among which 4,598 are active and 1,111 are passive.[3] The fund investment style is based on the Lipper objective 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, reflecting greater exposure to these markets. In contrast,

[3]The 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.

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. The summary statistics are presented in Table 1. Fund returns are on average positive but aside from compensation for priced factors, their alphas are on average negative. Exposure is defined in Equation (1) as the portfolio share invested in stocks currently affected by export controls. In any given month, the likelihood of holding a newly affected stock, $\mathbb{1}(\text{Exposure}>0)$, is 2.2%. Conditional on new export controls being imposed, the average portfolio exposure to the affected stocks, $\text{Exposure}|_{>0}$, is 2.3% with a standard deviation of 2.5%. On the other hand, the share of assets invested in firms that export to China is 20.3%. Finally, 76.6% of all domestic equity funds are active. Table 2 shows the distribution of funds in each investment style. The science and tech style funds have the highest exposures 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, they hold 8.4% of their portfolios in affected stocks.

4 Empirical Strategy and Results

Using Factset Revere, we identify U.S. firms that supply goods to these Chinese targets and call them affected U.S. suppliers or affected firms, since their profitability is negatively affected by U.S. export controls (Crosignani et al., 2025). Notice that a U.S. firm can be affected by export controls multiple times. First, because its same Chinese customer is included in the BIS lists multiple times, each time including additional subsidiaries previously neglected. Second, the same U.S. firm can 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 in separate occasions. As shown in Figure 2, U.S. suppliers experience a –3.6% cumulative abnormal return when their Chinese customer is added to the BIS lists, with most of the adjustment occurring within the first five days. The immediate stock price reaction serves as motivation for our analysis of how mutual funds deal with this geoeconomic shock.

4.1 Export Controls and Fund Performance

Given the sharp stock price reaction of affected stocks following export controls as shown in Figure 2, we examine whether such firm-level geoeconomic shocks propagate to mutual fund portfolio risk and performance. The average equity mutual fund holds 210 stocks and is exposed to export controls 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, 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:

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

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

The percentage of fund-months observations that incur treatment is 2%. Funds can get treated multiple times over the sample 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 make sure that the current treatment does not capture the dynamics of a previous one.[4]

To study how U.S. export controls impact funds' risk, performance, and future portfolio allocations, we estimate the following two-way fixed effect (TWFE) panel regression:

$$Y_{i,t} = \beta Exposure_{i,t} + \gamma X_{i,t-1} + \mu_i + \mu_t + \varepsilon_{i,t}, \tag{2}$$

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 portfolio alphas are computed as the difference between the monthly return and the required return based on the 3- and 5-factor models of Fama and French (1993, 2015). Defined in Equation (1), the main regressor of interest ($Exposure_{it}$) 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 include a set of lagged fund characteristics as control variables ($X_{i,t-1}$), including the logarithms of fund

[4]As shown later in Section 4.5, the dynamics settle after a few months.

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 include lagged dependent variables in all our specification 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 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*. Otherwise, the main regressor, $Exposure_{it}$, may capture some of the effect of being an exporter to China, which represents one of the largest and most profitable consumer markets. While the baseline specifications include fund and time fixed effects, our preferred specifications include the interaction of investment style and time fixed effects. The latter absorb any time-varying characteristic that is specific to the particular investment style of the fund. As a result, at each point in time treated funds are compared to control funds within the same investment style. For instance, if funds in the aggressive growth style have high levels of both return volatility and exposures to export controls, the inclusion of style-time fixed effects allows us to factor out the time-varying volatility component that is common to the funds in the same investment style. Finally, standard errors are clustered at the fund level.

We first investigate the effects of exposure to export controls on performance for the sample of actively managed funds. The results are displayed in Table 3. Panel A shows the effect on the 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 (column 3) and lower returns (column 6). Conditional on an export control event, a one standard deviation increase in the exposure shock (2.5%) is associated with an increase in the fund volatility by 0.014 to 0.027 percentage points, which corresponds to 2 to 4 percent of its standard deviation.

In addition to increasing fund volatility, exposure to export controls 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 exposure (2.5%) is associated with a 37 to 41 bps decline in monthly returns. Even after including fund controls and investment style-time fixed effects, as in column 6, exposure to export controls retains a sizable negative effect on fund returns. The coefficient of *Exposure* in column 6 indicates that, conditional on an export control event, a one standard deviation increase in exposure is associated with a 22 basis points decline in monthly returns when compared to peer funds within the same investment style.

Panel B considers the effect of exposure to export controls on abnormal fund returns, namely returns adjusted for the fund's exposure to standard equity pricing factors. Across specifications, the magnitude of the effect is smaller once we include the interaction of style and time fixed effects. These fixed effects guarantee that we are comparing exposed funds to control funds with the same investment style. 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 *Exposure* is capturing 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 15 basis points decline in 3 factor-adjusted alphas and a 9 basis points decline in 5 factor-adjusted alphas, respectively.

While for ease of exposition the controls are not shown in Table 3, Appendix Table A.2 displays their 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).

4.2 Trading and Portfolio Decoupling

We next examine how portfolio managers navigate geoeconomic risk by analyzing their portfolio rebalancing decisions. As shown in Figure 2, stocks affected by export controls experience negative returns. How do portfolio managers respond to a decline in the stock price of these stocks? On one hand, they may retain these stocks despite the price drop if they believe that losses are temporary and expect a rebound with long-term gains. On the other hand, they may sell the affected stocks if they are unable to absorb the losses or face pressure from clients to react. Funds may not want to report holding the affected stocks in regulatory filings. Additionally, managers may adopt a pessimistic outlook on these companies if they anticipate that export controls will have a substantial, long-term negative impact on firm performance.

Suppose that fund i holds an equity position in firm j at the beginning of the reporting month and that firm j is affected by export controls during the month. We are interested in estimating whether and how fund i reallocates its portfolio away from stock j after such stock is affected by export controls. Since U.S. firms may be affected by export controls multiple times as different customers are added to the BIS lists at various points in time, we focus on the first instance in which a U.S. stock is affected. This allows us to identify investors' initial trading response to export controls. To do so, we construct a fund-stock-month level panel and estimate the following specification:

$$Y_{i,j,t} = \beta Direct_{i,j,t} + \gamma X_{i,j,t-1} + \mu_i + \mu_t + \varepsilon_{i,j,t}, \tag{3}$$

where Y_{ijt} 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. $Direct_{i,j,t}$ is an indicator variable equal to one if stock j held by fund i is affected by export controls in the current reporting month t. We include fund-level controls, such as 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, such as firm size, firm age, book leverage, and CAPEX. All controls are lagged. The baseline specification includes fund and time fixed effects, while the most saturated ones include fund, investment style-firm industry-time fixed effects. Standard errors are double clustered at the fund and firm levels.[5]

Table 4 displays the results for active funds. In Panel A the dependent variable is the direction of trades that occur over the same month as the export control shock, thus capturing immediate portfolio reallocations. On the other hand, Panel B considers trades that occur within a 3-month window after the export control shock, which allows for a slower portfolio adjustment or a complete reversal of the immediate trade. Given the high dimensionality of the panel (fund-stock-month), we progressively phase in more controls and fixed effects.

Remarkably, 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. The selling occurs rather immediately, as the effect is more pronounced in the same month (Panel A) than within the first three months (Panel B). Nevertheless, the decline in holdings of affected stocks is quite persistent, as we still detect it even 3 months later.[6]

Lastly, to examine the intensity of selling decisions in affected stocks, we 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

[5]Since most funds disclose their holdings at month-end, we use fund-stock observations at the monthly frequency. Funds that only report at quarter-end are included only if export controls occur in the last month of the quarter. Results are qualitatively unchanged if we use funds' holdings at quarterly frequency.

[6]Our results are not driven by leveraged funds, which may display outsized trading responses due to their leverage. Panel A of Appendix Table A.3 indeed shows that our main results are unchanged if we remove leveraged funds from the sample.

complete sell-offs reveals that the documented selling activity is attributable exclusively to partial reductions in holdings (columns 3 and 4), rather than to full liquidations (columns 5 and 6).

4.3 Spillover Effects

So far, we have shown that portfolio managers immediately sell the stocks affected by export controls. The selling is consistent with funds believing that the affected stocks will experience a decline in future performance as a result of export controls. However, it may just be a reaction to the stock price decline rather than a deliberate response to geoeconomic risk.

Under the hypothesis that export control shocks are perceived by fund managers as an increase in geoeconomic risk and not just an idiosyncratic stock price decline, we would expect funds to reassess the overall portfolio exposure to geoeconomic risk coming from supply chain connections to China. In particular, mutual funds that experience the export control shock (treated funds) may 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 that prompts fund managers to learn about supply-chain connections and reassess the exposure of their portfolio to geoeconomic risk. With the potential of further rounds of export controls, treated fund managers may seek to hedge against this risk by selling other holdings that have significant exposure to China. We call this the *spillover* hypothesis.

In contrast, under the alternative hypothesis that the selling of affected stocks was just a response to a decline in their stock prices, we do not expect treated funds to also sell unaffected stocks that are nevertheless exposed to U.S.-China geoeconomic risk. To formally test the spillover hypothesis, we examine whether treated funds reallocate their portfolios away from unaffected U.S. firms selling to Chinese customers that have not yet been subjected to export controls. Specifically, we estimate the following regression at the fund-stock-month level:

$$Y_{i,j,t} = \beta Spillover_{i,j,t} + \gamma X_{i,j,t-1} + \mu_i + \mu_t + \varepsilon_{i,j,t}, \tag{4}$$

where Y_{ijt} 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. $Spillover_{i,j,t}$ 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. 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.[7]

Table 6 displays the results for active funds. Columns 1 and 2 consider the effect on trading in the same month of the export controls, while columns 3 and 4 estimate the effect within a 3-month window. The coefficients of Spillover are not statistically significant in columns 1 and 2, indicating that a fund that holds a newly affected stock is unlikely to immediately decouple its portfolio from other domestic firms that export to China. While there is no immediate spillover effect, columns 3 and 4 estimate a delayed portfolio adjustment.

[7]Results are qualitatively similar if the sample includes stocks that are ever affected.

Indeed, within the first 3 months following a new export control, funds with some direct exposures to export controls are more likely to sell the stocks of *unaffected* domestic firms that export to China. These findings suggest that fund managers require some time to learn about the supply chain connections of their holdings and assess how geoeconomic risk can impact their portfolio.

In sum, export controls generate a broad portfolio decoupling, whereby asset managers quickly sell U.S. stocks directly impacted by export controls as well as the stocks of U.S. firms that export to other Chinese firms, albeit with a short delay. These findings suggest that active fund managers reassess the supply chain relations of their portfolio holdings following an export control shock and tend to decouple their holdings from both actual and potential sources of geoeconomic risk.[8]

4.4 Portfolio Rebalancing

We have shown that active managers sell the affected stocks immediately after the export control shock. It remains to be determined how active managers rebalance the rest of their portfolios within the same time frame. After selling the affected stocks, they could increase their holdings of other stocks proportionally. Alternatively, concerned that posting losses will lead to future outflows, active funds can either increase cash holdings to meet future outflows or increase risk taking to mitigate losses (Brown et al., 1996; Schwarz, 2012). For instance, mutual funds could take additional risk by purchasing lottery stocks (Bali et al., 2011).

[8] The results are robust excluding leveraged funds, as shown in Panel B of Appendix Table A.3.

Finally, funds may want to maintain a stable portfolio and industry concentration, thus substituting the affected stock with a similar firm in the same industry. Alternatively, funds may perceive the industry targeted by export controls as too risky and decide to rebalance their portfolio away from such industry, potentially resulting in a higher concentration of the portfolio or a lower degree of diversification.

To test how affected funds rebalance their portfolios, we apply a similar empirical model as in Equation (4) and estimate the following regression at the fund-stock-month level:

$$Y_{i,j,t} = \beta Lottery_{i,j,t} + \gamma X_{i,j,t-1} + \mu_i + \mu_t + \varepsilon_{i,j,t}, \tag{5}$$

where Y_{ijt} 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 in 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 the lottery feature of a stock, we use the average of the highest five daily returns of the stock 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.

In Table 7 we indeed 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 engage in greater risk-taking even three months after their exposure to export controls. These findings suggest that following the losses incurred as a result of exposures to export controls, affected funds take additional risk to mitigate losses and their effect on future outflows. Indeed, funds' investments in lottery stocks often appear to attract larger inflows (Agarwal et al., 2022).

Lastly, we study whether affected funds change their overall allocations to the industry affected by export controls and how portfolio concentration and diversification change. Specifically, we estimate a variation of Equation 2, where the dependent variables are: (1) the change in portfolio weight assigned to the industry of affected stocks (excluding the directly affected stocks); (2) the change in portfolio industry concentration (Kacperczyk et al., 2005); and (3) 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 industry of the affected stock, excluding the affected stock itself, as the dependent variable. Under the assumption that funds substitute the affected stock with a firm in the same industry, we expect the coefficient of Exposure (holdings of affected stocks) on the affected industry weight to be positive. If instead the fund only sells 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 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 exposures to export controls display an increase in the industry concentration index, suggesting that the portfolio is becoming more concentrated in fewer industries. Similarly, in columns 5 and 6, the positive coefficient of Exposure implies that funds more exposed to export controls experience an increase in the portfolio herfindahl index, suggesting that the portfolio is becoming more concentrated in fewer stocks.

4.5 Impact on Passive Funds

In recent years, the mutual fund industry saw a shift from active to passive management (Anadu et al., 2020). Passive funds often have an investment mandate to track a benchmark index as close as possible. To do so, they hold its constituent stocks or an automatically selected representative sample of constituent stocks. As such, passive funds face constraints on their ability to adjust their holdings to either good or bad news. In contrast, active fund managers charge higher fees and employ discretion in stock selection with the aim of outperforming their benchmarks (Elton et al., 2003). Next, we examine the impact of geoeconomic risk on passive funds, providing a benchmark for the performance and portfolio reallocation of active funds.

Passive Fund Performance. We first consider the effect of export control exposures on the performance of passive funds. Table 9 displays the results. Panel A shows the effects on volatility and raw returns, while Panel B on 3- and 5-factor adjusted returns. Our preferred specifications in columns 3 and 6 include style-time fixed effects and fund controls. Whether we use raw or abnormal returns, passive funds that are more exposed to export controls experience a larger decline in returns than active funds. On the other hand, passive funds exposed to export controls experience a smaller increase in volatility than active funds. This seemingly counterintuitive result suggests that active management aimed at offsetting losses from geoeconomic shocks induces additional volatility.

Passive Fund Trading. Next, we explore how passive funds trade stocks in response to export control shocks. Since the main goal of passive funds is to follow a benchmark with minimum tracking errors, we expect passive funds not to change their holdings in response to export control shocks. This is akin to a placebo test. Table 10 shows the results. We find that the effect of exposure to export controls (Direct) is insignificant among passive funds, regardless of the degree of fixed effects saturation and trading horizon, namely within the first month or the first three months following the shock.

Active vs. Passive Funds. So far we have shown that, relative to passive funds, active ones mitigate the effect of export controls on returns at the expense of higher volatility. The fund Sharpe ratio, defined as monthly returns divided by the monthly standard deviation of daily returns, is a useful measure that captures the trade-off between risk and returns. We next study the effect of export control shock on the Sharpe ratio of active and passive funds. We also estimate the response of fund investors in terms of contemporaneous and future flows.

The results are provided in Table 11. The dependent variables are the Sharpe ratio and current and next-month fund flows. Panel A shows the results for active funds and Panel B for passive ones. Not surprisingly, exposure to export control shocks leads to a significantly lower Sharpe ratio for both active and passive funds. However, it is not ex-ante clear whether active funds should display a less pronounced decline in the Sharpe ratio than passive funds. Indeed, while active funds experience a smaller decline in returns (the numerator of the Sharpe ratio), they also display higher volatility (the denominator of the Sharpe ratio). The net effect of changes in both returns at the numerator and volatility at the denominator therefore depends on their relative magnitude. Comparing the coefficients of column 2 for active and passive funds shows that the Sharpe ratio decline is less pronounced among active funds.

How are mutual fund investors responding to this deterioration in performance? Columns 3 and 4 consider concurrent flows while columns 5 and 6 consider next month's flows (called lead flows). Our estimates indicate that the contemporaneous effect of export control on fund flows is insignificant for both active and passive funds. On the other hand, in the month following the imposition of export controls, passive funds experience significant outflows while active funds experience mild but statistically insignificant outflows. Two comments are in order. First, the fact that active funds better manage geoeconomic shocks is consistent with better relative performance and thus smaller future outflows. Second, the fact that the contemporaneous effect on flows is insignificant while the effect on future outflows is significant is consistent with the flow-performance literature showing that investors respond to prior returns, withdrawing their funds after poor performance (Ippolito, 1992; Sirri and Tufano, 1998; Del Guercio and Tkac, 2002).

Overall, the larger decline in performance among passive funds is consistent with their inability to sell affected stocks in the aftermath of export controls. It appears that active funds' ability to rebalance dampens the negative effect of export controls on performance, while passive funds simply absorb the full price decline.

4.6 Fund Manager Skills

A large body of literature has debated whether fund managers are compensated for their skills and, if so, which skills are more relevant for generating returns. In this section we examine whether standard measures of fund manager skills play a role in navigating geoeconomic risk. On the one hand, fund manager skills could be transferable to new risks. Highly skilled managers may seamlessly adapt to the new geoeconomic risk environment and generate abnormal returns across different market conditions. On the other hand, these skills may not translate effectively to emerging risks. The intense focus on generating abnormal returns could lead to the development of skills tailored to existing risk factors which may become less effective when the investment environment shifts significantly. Thus, it remains an empirical question whether more skilled managers can better adapt to the new risk posed by the forced decoupling of certain U.S. firms from China.

Following Kacperczyk et al. (2014), we measure fund manager skills based on their 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 and investment style.

We also capture other dimensions of manager skill. Zambrana and Zapatero (2021) classify fund managers as specialist if they specialize in one single investment style and as generalists if they run funds with different investment styles. We therefore ask whether specialists have an advantage over generalists in navigating an emerging risk. Lastly, we consider a broader measure of skill. Following the findings in Berk and Van Binsbergen (2015) that total compensation predicts future performance, we also use fees as a proxy for skill and define high-fee funds as those charging fees above the median of funds in the same investment style and time period. For each measure of skill, we estimate the following panel regression:

$$Y_{i,t} = \beta_1 Exposure_{i,t} + \beta_2 Skill_{i,t} + \beta_3 Exposure_{i,t} \times Skill_{i,t} + \gamma X_{i,t-1} + \mu_i + \mu_{s,t} + \varepsilon_{i,t}, \quad (6)$$

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, including high market timing, high stock picking, specialist, and high fee. $X_{i,t-1}$ is a vector of lagged controls as in Equation (2), while μ_i and $\mu_{s,t}$ are fund and style-time fixed effects, respectively. Notice that the style-time fixed effects control for the fact that funds in different investment styles have different propensities to hold stocks more prone to export controls, which predominantly target high-tech stocks. The coefficient of interest is β_3, which indicates whether funds with better skills display a significantly different outcome relative to other funds for a given exposure to export control shocks.

We first examine whether, conditional on similar exposures to export controls, managers with better market timing or stock picking skills exhibit better performance. We focus on actively managed funds. Table 12 presents the results. Columns (1) and (2) in Panel A show the effects on volatility. The baseline coefficients of Exposure are positive and statistically significant, corroborating that exposure to export control shocks increases fund volatility. However, the interactions of Exposure with timing and picking skills are not statistically significant, indicating that neither timing nor picking skills help the fund manager to mitigate the detrimental effect of geoeconomic shocks on fund volatility. Columns (3) to (4) show the effects on fund returns. While the baseline coefficients of Exposure indicate that exposure to export control shocks reduce fund returns, the interaction terms with timing and picking skills are not significant. Panel B considers the effect on 3- and 5-factor adjusted returns, delivering a similar result. Namely, market timing and stock picking skills do not play a significant role in helping managers navigate geoeconomic risk.

Table 13 portrays a different picture when we consider being a specialist and charging high fees as measures of skill. Focusing on returns in columns (3) and (4) of Panel A and factor-adjusted returns in Panel B, the baseline effect of exposure is negative and significant, indicating that exposure to export controls leads to lower returns. Importantly, the interactions of skill and exposure are positive and significant, suggesting that specialist and high fee funds can significantly mitigate the negative consequences of exposure to geoeconomic risk on fund performance. Columns 1 to 2 show that while specialist funds and high-fee funds are able to improve performance, neither fund type exhibits a statistically significant difference in volatility.

In sum, while market timing and stock picking skills do not translate to better geoeconomic risk management, it appears that specialists and high fee funds can more effectively navigate such risk.

4.7 Staggered Treatment and Local Projections

While so far we have estimated the immediate effect of export controls on fund performance, a more rigorous dynamic analysis is warranted. This is what we do next. The BIS enacted a multitude of export controls on Chinese firms since 2014. Given the staggered nature of treatment, a dynamic version of the TWFE model of Equation (2) may lead to biased estimates due to the so-called bad comparison problem (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 ex-ante 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 as well as continuous treatment in a fully dynamic model.

Treated units are funds with equity holdings of U.S. firms that are affected by export controls introduced at time t. For funds treated at time t we have that $\Delta Exposure_{it} > 0$. On the other hand, control units consist of two groups, namely never treated funds and not yet treated ones. Control units need to be similar to treated ones other than for the fact that they hold assets that are currently not exposed to export controls. Since affected firms are a quasi-random subset of U.S. firms that export to Chinese firms, we need to control for the share of a fund portfolio invested in firms that export to China, called China Share. Otherwise, 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. Indeed, similar firms are treated at different times. Thus, using not yet treated firms is useful for identification, as it includes in the control group funds holding firms that are very similar to the treated ones—indeed they will be treated in the near future.

Moreover, it is useful to also include investment style-time fixed effects. That way, control funds have a similar investment strategy to the treated ones. The difference between the two groups is that control funds happen to hold stocks that are not subject to export controls at the moment, but that could be subject to them in the near future. Tech and growth styles see a concentration of stocks that are eventually treated due to the nature of export controls, namely to limit the export of U.S. advanced technology in the fields of microchips, military technology, telecoms, and artificial intelligence to selected Chinese firms.

Finally, a given mutual fund may hold stocks that are 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 consider the effect of export controls to stabilize after 6 months (referred to as 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 continually 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:

$$Y_{i,t+k} - Y_{i,t-1} = \beta_k \Delta Exposure_{i,t} + \gamma X_{it} + \mu_i + \mu_t + \varepsilon_{it}. \tag{7}$$

where the treatment sample is identified by $\text{Exposure}_{it} > 0$ and the controls by $\text{Exposure}_{i,t+h} = 0$ for $h \geq -H$ and $h \leq k$. We include the same lagged controls as in the TWFE models.

The coefficient plots are displayed in Figures 3 and 4. Figure 3 displays the dynamic effects of exposure to export controls on volatility, raw returns, and 3- and 5-factor adjusted returns. Across specifications, there is no significant trend prior to treatment, suggesting that the parallel trends assumption holds in the data. Following the introduction of export controls, more exposed funds experience higher volatility and lower returns. The effect on volatility is persistent but stabilizes after the second month. On the other hand, the persistence of the effect on returns varies, from temporary when considering raw returns to more persistent when looking at 3- and 5-factor adjusted returns.

Finally, Figure 4 displays the dynamic effects of exposure to export controls on the trading direction of affected stocks. In the months prior to treatment, more exposed funds do not trade these stocks any differently, suggesting that they do not anticipate the imposition of export controls. However, once export controls are introduced, exposed funds are more likely to sell affected stocks over the next month. The immediate selling effect may suggest that funds try to sell affected stocks before the news are fully incorporated in prices. The lack of daily holdings data precludes a more precise assessment of the exact timing of the sale.

5 Conclusion

As tensions between the U.S. and China intensify, geoeconomic risk is becoming one of the main concerns for asset managers. About half of the U.S. mutual fund industry by assets is comprised of domestic equity mutual funds, which mostly invest in U.S. stocks. Far from being immune to geoeconomic risk, domestic equity funds invest in large multinational corporations that are in the middle of the geoeconomic tensions between the U.S. and China. In this paper we focus on the main tool used in the U.S.-China technological rivalry, namely export controls. Used by the U.S. government to prevent targeted Chinese firms from acquiring U.S. technology, export controls negatively affect U.S. firms that export these technologies to the targeted Chinese firms. Domestic equity mutual funds that hold more of these affected U.S. stocks experience higher volatility and lower returns.

While passive funds simply replicate a benchmark, active funds charge higher fees in exchange for the promise of managing their portfolios to generate superior returns. In line with this premise, we show that active funds are able to partially shield their performance from the negative geoeconomic shock. To do so, they sell both the affected stocks and the unaffected stocks that are nevertheless exposed to geoeconomic risk. On net, this reallocation results in greater portfolio concentration. We also find evidence that funds more exposed to export control shocks increase risk-taking to avoid posting lower returns.

Finally, we investigate whether traditional fund manager skills, such as market timing and stock picking, help mitigate geoeconomic risk. We find no evidence that these skills are particularly useful in this context. However, fund managers that specialize in one single investment style (specialists) as well as funds that charge higher fees are able to mitigate the negative effects of export control shocks on fund performance.

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Figure 1: Portfolio Allocations to China Exporters by Investment Style. Figure 1 displays the times series 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.

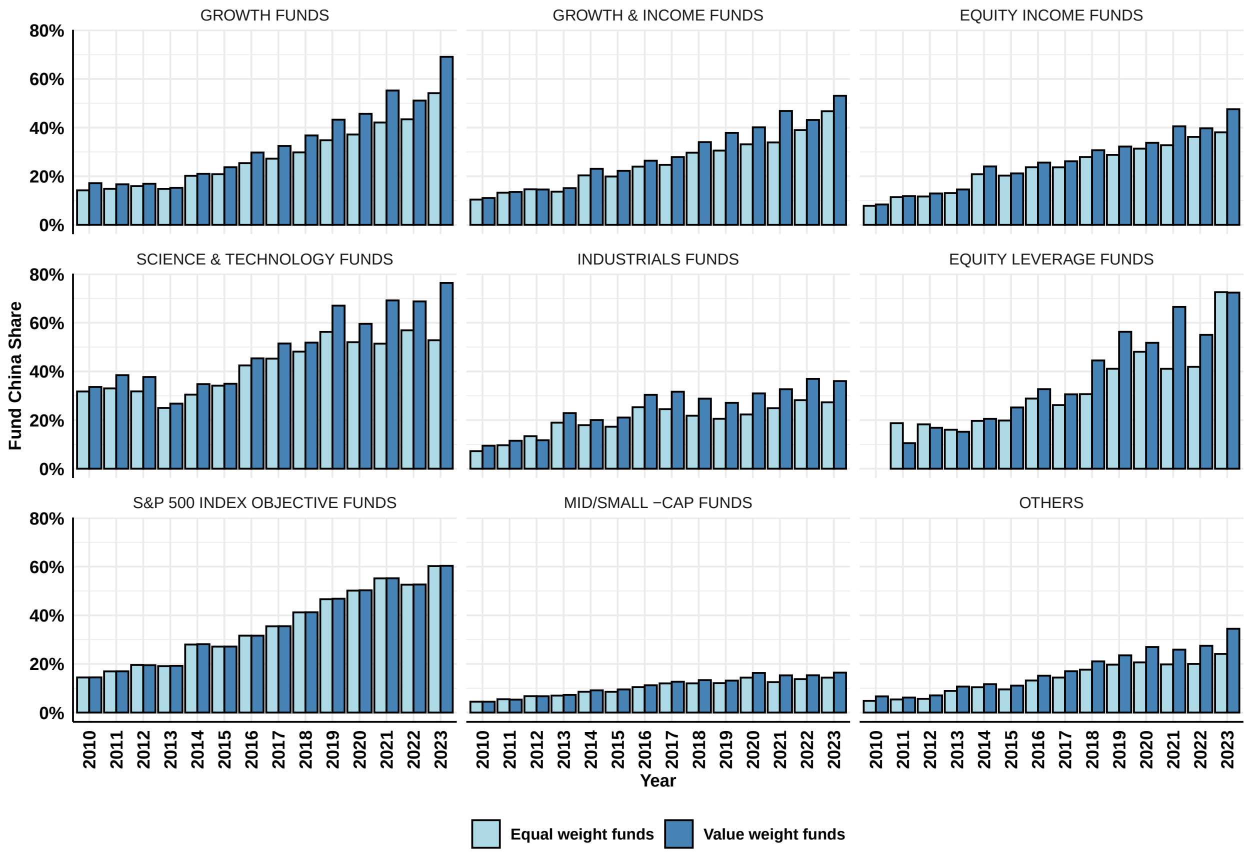

Figure 2: Cumulative Abnormal Returns around Export Control Announcements. Figure 2 displays the cumulative abnormal returns (CAR) of affected U.S. suppliers in a [-10, 20] day window around the announcement date of the inclusion of a Chinese customer in the BIS lists. Panel A shows CARs using the Fama-French 3-factor model (Fama and French, 1993) while Panel B uses the Fama-French 5-factor model (Fama and French, 2015). On the vertical axis are the cumulative abnormal returns in percentages and on the horizontal axis the days relative to the announcement dates. The dashed vertical line represents the day before announcement date. The solid red line represents the average CARs and the dot-dash blue line the 95% confidence intervals. This figure replicates Figure 3 in Crosignani et al. (2025).

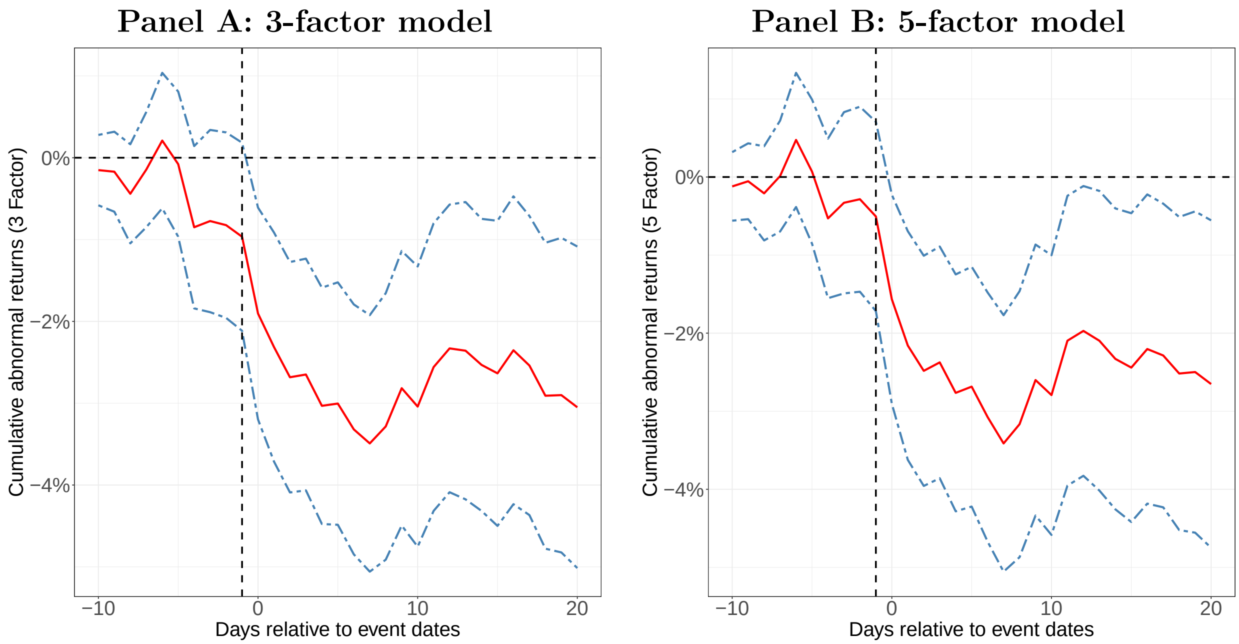

Figure 3: Performance with Local Projections. Figure 3 displays the dynamic coefficient estimates using the local projections approach of Dube et al. (2025), as presented in Equation (7). The dependent variable is the monthly fund volatility in Panel A, fund return in Panel B, the 3-factor adjusted abnormal fund return in Panel C, and the 5-factor adjusted abnormal fund return in Panel D.

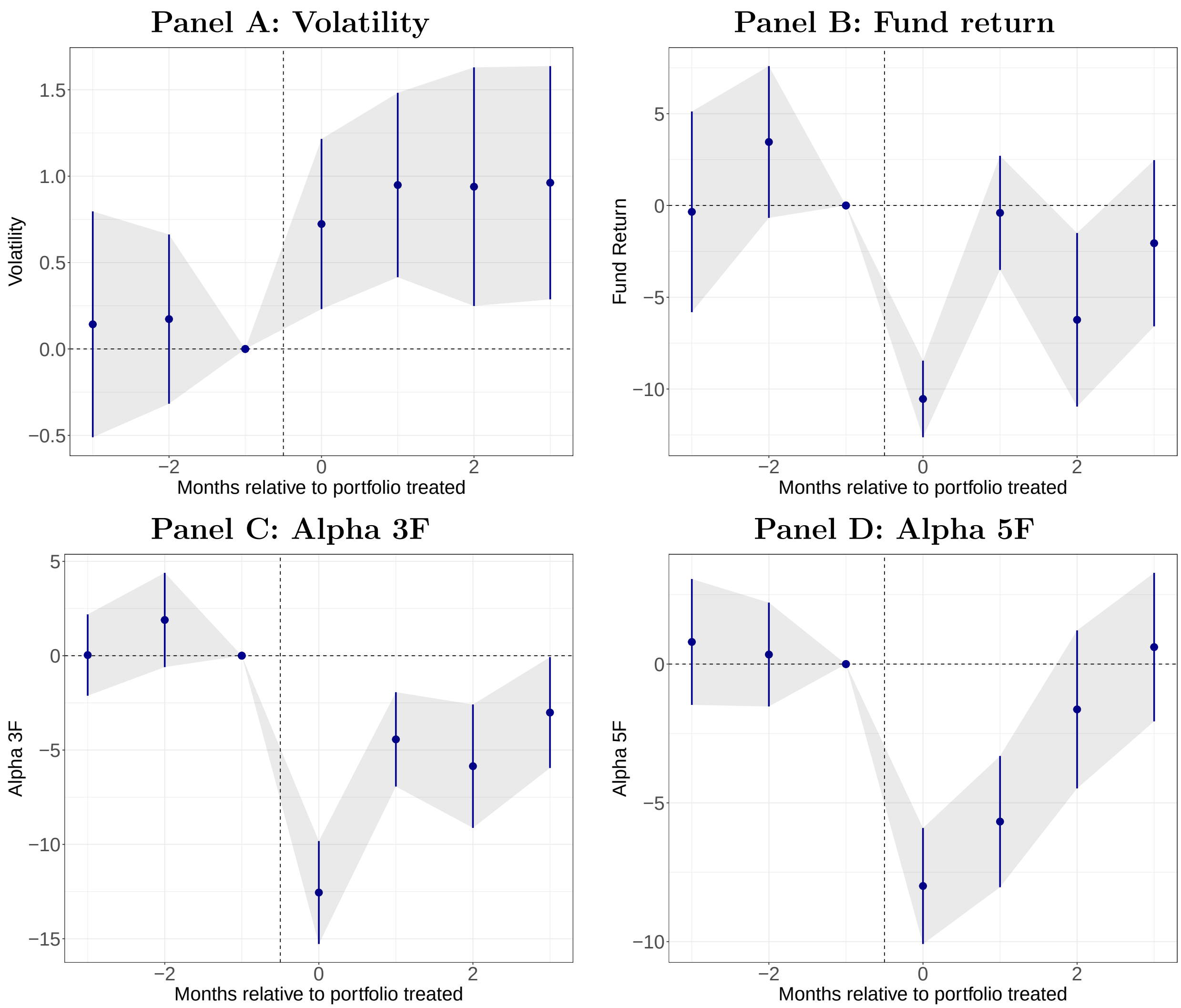

Figure 4: Trading Direction with Local Projections. Figure 4 displays the dynamic coefficient estimates using the local projections approach of Dube et al. (2025). The dependent variable is the trade direction. Panel A is the local projection estimate with fund and time fixed effect. Panel B is the local projection estimation with fund and style-time fixed effects.

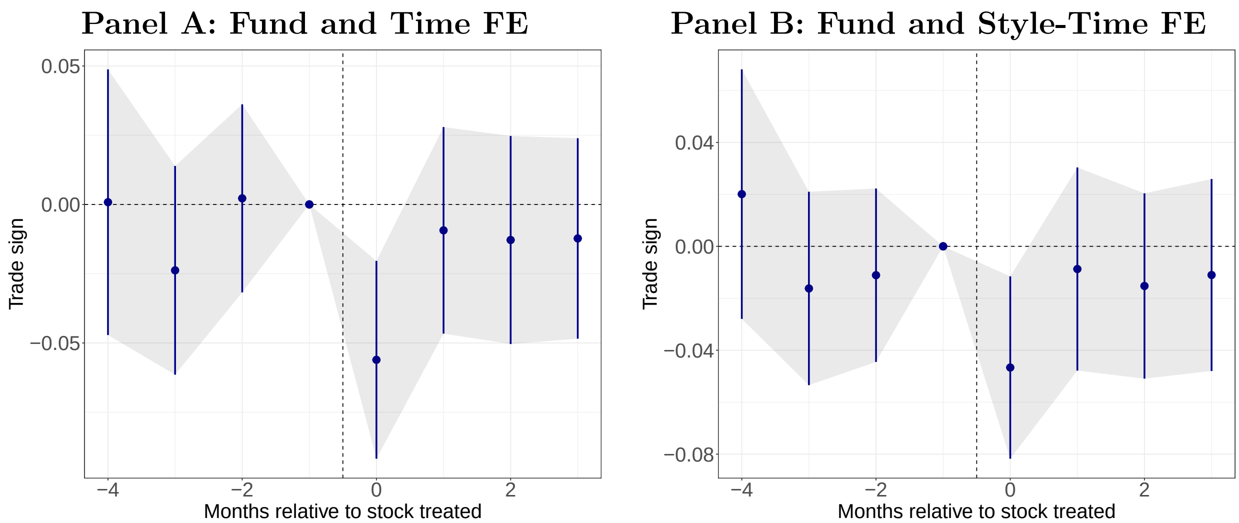

Table 1: Summary Statistics. Table 1 presents summary statistics of fund level characteristics. Volatility is the monthly standard deviation of daily fund returns in percentage points. Fund return is the monthly fund return in percentage points. Alpha 3F and Alpha 5F are the 3-factor and 5-factor adjusted 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. Exposure, defined in Eq. 1, equals the portfolio share invested in affected U.S. suppliers. 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. $\mathbb{1}$(Exposure>0) equals one when Exposure is strictly positive while Exposure$|_{>0}$ equals the portfolio share invested in affected U.S. suppliers conditional on 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), scaled by 100. Family size is the logarithm of the total net assets of the fund's family, scaled by 100. 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 Return (1Y) is the average fund return over the previous year. Finally, as standard in the mutual fund literature, Flow is the percentage change in total net assets minus appreciation, $Flow_{i,t} = [TNA_{i,t} - TNA_{i,t-1}(1 + R_{i,t-1})]/TNA_{i,t-1}$.

Statistic	Mean	St. Dev.	Obs.	p(25)	p(50)	p(75)
Volatility(%)	1.103	0.671	346,171	0.681	0.942	1.324
Fund return (%)	0.796	5.296	346,171	−1.999	1.156	3.765
Alpha 3F(%)	−0.210	2.441	270,028	−1.250	−0.137	0.911
Alpha 5F(%)	−0.155	1.960	270,028	−0.936	−0.120	0.661
$\mathbb{1}$(Exposure>0)	0.022	0.148	346,171	0	0	0
Exposure$|_{>0}$	0.023	0.025	7,741	0.010	0.017	0.028
China Share	0.203	0.160	341,437	0.081	0.159	0.293
Log Fund Size	6.032	1.754	341,437	4.727	5.973	7.197
Log Family Size	11.504	2.821	341,437	9.969	11.747	14.182
Expense Ratio	0.006	0.005	341,437	0.000	0.006	0.010
Turnover Ratio	0.437	0.671	341,437	0.000	0.250	0.600
Log Fund Age	2.439	0.874	341,437	2.027	2.625	3.013
Past 12-month Return (%)	0.982	1.295	328,142	0.205	1.003	1.728
Fund Flow	0.007	0.093	346,171	−0.013	−0.004	0.007
Actively-managed Fund	0.766	0.424	346,171	1	1	1

Table 2: Selected Statistics by Investment Style. Table 2 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. Exposure$|_{>0}$ is the portfolio share invested in affected U.S. suppliers condition on being positive. Exposure is strictly positive only in the month when the Chinese customers of the affected U.S. suppliers are added to the BIS lists; otherwise, there is zero. The table shows sample fund styles with at least five funds in the category.

Fund Style	Obs.	#Funds	#Active	#Passive	#Ever Treat	China Share %	Exposure$\|_{>0}$%
SCIENCE & TECHNOLOGY FUNDS	10,324	135	110	49	93	43.33%	8.36%
S&P 500 INDEX OBJECTIVE FUNDS	7,808	99	1	98	74	35.33%	1.59%
TELECOMMUNICATION FUNDS	1,308	16	11	10	13	34.46%	6.13%
ALTERNATIVE LONG/SHORT EQUITY FUNDS	1,665	70	62	10	36	33.86%	2.18%
GROWTH & INCOME FUNDS	48,410	1,416	1,264	177	982	27.62%	2.12%
EQUITY LEVERAGE FUNDS	2,672	111	93	19	31	26.81%	4.23%
ALTERNATIVE EQUITY MARKET NEUTRAL FUNDS	282	13	12	1	4	26.41%	2.17%
GROWTH FUNDS	100,970	1,925	1,729	336	1,252	26.34%	2.20%
EQUITY INCOME FUNDS	19,685	334	314	67	241	24.46%	2.47%
CONSUMER SERVICES FUNDS	3,265	34	25	18	12	22.61%	0.80%
ABSOLUTE RETURN FUNDS	356	19	19	1	3	22.49%	1.98%
CAPITAL APPRECIATION FUNDS	6,737	113	110	4	77	21.05%	2.09%
INDUSTRIALS FUNDS	3,995	38	26	25	29	20.14%	5.76%
NATURAL RESOURCES FUNDS	6,204	84	63	34	26	16.00%	3.03%
CONSUMER GOODS FUNDS	2,128	19	14	11	3	15.97%	2.00%
BASIC MATERIALS FUNDS	2,026	16	10	12	12	15.08%	2.84%
HEALTH/BIOTECHNOLOGY FUNDS	7,683	89	70	36	31	14.83%	3.26%
MID-CAP FUNDS	41,562	720	639	117	523	12.61%	1.89%
EQUITY MARKET NEUTRAL FUNDS	125	16	15	1	3	12.27%	0.00%
LONG/SHORT EQUITY FUNDS	208	26	23	3	7	11.58%	0.00%
DIVERSIFIED LEVERAGE FUNDS	33	11	11	0	6	9.67%	0.00%
SMALL-CAP FUNDS	54,924	860	769	140	601	8.20%	1.64%
REAL ESTATE FUNDS	11,250	143	120	36	0	6.82%	0.00%
MICRO-CAP FUNDS	2,689	50	46	4	32	6.08%	2.07%
FINANCIAL SERVICES FUNDS	6,218	68	50	35	14	4.12%	2.26%
UTILITY FUNDS	3,140	35	28	13	5	2.25%	1.58%
PRECIOUS METALS EQUITY FUNDS	435	15	11	6	0	2.09%	0.00%
PRECIOUS METALS FUNDS	53	6	5	1	0	0.83%	0.00%

Table 3: Performance and Exposure to Export Controls: Active Funds. Table 3 presents the results of estimating Eq. (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. Fund 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. Exposure is the portfolio share invested in affected U.S. suppliers. 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 the lagged dependent variable and china share, namely the portfolio share invested in U.S. firms that have at least one Chinese customer. Fund Controls include fund size, family size, expense ratio, turnover ratio, age, and past return (1Y), which are all defined in Table 1. Standard errors are clustered at the fund level. *** p<0.01, ** p<0.05, * p<0.1.

	Panel A					
Dependent Variables :	Volatility			Return		
	(1)	(2)	(3)	(4)	(5)	(6)
Exposure	1.079***	1.000***	0.558***	-16.513***	-14.873***	-8.965***
	(0.141)	(0.131)	(0.107)	(2.970)	(3.149)	(2.568)
Fund FE	✓	✓	✓	✓	✓	✓
Time FE	✓	✓		✓	✓	
Fund Controls		✓	✓		✓	✓
Style×Time FE			✓			✓
Observations	260,490	247,673	247,673	260,490	247,673	247,673
R^2	0.912	0.916	0.945	0.791	0.810	0.894
	Panel B					
Dependent Variables :	Alpha 3F			Alpha 5F		
	(1)	(2)	(3)	(4)	(5)	(6)
Exposure	-13.625***	-11.858***	-5.910***	-9.350***	-8.271***	-3.638***
	(1.289)	(1.306)	(1.584)	(1.039)	(1.030)	(1.187)
Observations	204,030	195,787	195,787	204,030	195,787	195,787
R^2	0.132	0.214	0.551	0.092	0.131	0.461
Fund FE	✓	✓	✓	✓	✓	✓
Time FE	✓	✓		✓	✓	
Fund Controls		✓	✓		✓	✓
Style×Time FE			✓			✓

Table 4: Trading in response to Export Controls: Active Funds. Table 4 presents the results of estimating Eq. (3) for active funds. The dependent variables reflect Trade direction, 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 as control, namely the portfolio share invested in U.S. firms that have at least one Chinese customer. 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. Standard errors are 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	-0.047***	-0.047***	-0.045***	-0.044***
	(0.016)	(0.015)	(0.014)	(0.014)
Observations	35,267,952	35,267,952	35,267,952	35,267,952
R^2	0.065	0.080	0.083	0.089
Dependent Variables :	Panel B: Within 3 months Trade Direction			
	(1)	(2)	(3)	(4)
Direct	-0.034*	-0.037**	-0.034**	-0.034**
	(0.018)	(0.017)	(0.016)	(0.016)
Observations	35,267,952	35,267,952	35,267,952	35,267,952
R^2	0.073	0.083	0.086	0.092
Fund FE	✓	✓	✓	✓
Time FE	✓			
Style×Time FE		✓	✓	
Industry×Time FE			✓	
Style×Industry×Time FE				✓
Fund Controls	✓	✓	✓	✓
Firm Controls	✓	✓	✓	✓

Table 5: Trading in response to Export Controls: Partial vs Complete Sell. Table 5 presents the results of estimating Eq. (3) for active funds. 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 that equals one if a stock is affected by export controls in the current period. All specifications include china share as control, namely the portfolio share invested in U.S. firms that have at least one Chinese customer. 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. Standard errors are 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	0.010***	0.010***	0.011***	0.009***	0.000	0.000
	(0.003)	(0.003)	(0.003)	(0.003)	(0.001)	(0.001)
Observations	97,867,404	97,867,404	97,867,404	97,867,404	97,867,404	97,867,404
R^2	0.197	0.198	0.260	0.261	0.018	0.020
Fund Controls	✓	✓	✓	✓	✓	✓
Firm Controls	✓	✓	✓	✓	✓	✓
Fund FE	✓	✓	✓	✓	✓	✓
Style × Time FE	✓	✓	✓	✓	✓	✓
Industry × Time FE		✓		✓		✓

Table 6: Trading Spillovers in Response to Export Controls: Active Funds. Table 6 presents the results of estimating Eq. (4) 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 a firm that exports to China is unaffected by export controls, but is held by a fund which holds stocks currently affected by export controls. All specifications include china share as control, namely the portfolio share invested in U.S. firms that have at least one Chinese customer. 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. Standard errors are 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	-0.009	-0.003	-0.024***	-0.021***
	(0.006)	(0.006)	(0.007)	(0.007)
Observations	33,749,660	33,749,660	33,749,660	33,749,660
R^2	0.080	0.083	0.083	0.085
Fund FE	✓	✓	✓	✓
Style×Time FE	✓	✓	✓	✓
Industry×Time FE		✓		✓
Fund Controls	✓	✓	✓	✓
Firm Controls	✓	✓	✓	✓

Table 7: Portfolio Rebalancing in Response to Export Controls: Active Funds. Table 7 presents the results of estimating Eq. (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). To define lottery feature of a stock, we use the average of the highest five returns of stock in a month following (Agarwal et al., 2022). Then we create Lottery indicator variable that equals to one if lottery feature of the stock is at the top quartile among all the stocks in that month for funds that are affected by export controls. All specifications include china share as control, namely the portfolio share invested in U.S. firms that have at least one Chinese customer. 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. Standard errors are 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	0.044***	0.036***	0.038***	0.027***
	(0.009)	(0.009)	(0.009)	(0.009)
Fund FE	✓	✓	✓	✓
Style×Time FE	✓	✓	✓	✓
Industry×Time FE		✓		✓
Fund Controls	✓	✓	✓	✓
Firm Controls	✓	✓	✓	✓
Observations	33,749,660	33,749,660	33,749,660	33,749,660
R^2	0.080	0.083	0.083	0.085

Table 8: Active Fund Portfolio Concentration. Table 8 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 change in the portfolio's industry concentration index relative to the previous month, where the index is defined following Kacperczyk et al. (2005). Δ Portfolio Herfindahl is the change in the portfolio Herfindahl index, calculated as the sum of squared portfolio weights across all individual stocks for a give fund and time. 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 control, namely the portfolio share invested in U.S. firms that have at least one Chinese customer. 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. Standard errors are clustered at the fund level. *** p<0.01, ** p<0.05, * p<0.1.

Dependent Variables:	Δ Affected Industry Weight		Δ Industry Concentration		Δ Portfolio Herfindahl	
	(1)	(2)	(3)	(4)	(5)	(6)
Exposure	-0.795***	-0.790***	1.548***	1.651***	0.428**	0.410*
	(0.038)	(0.035)	(0.427)	(0.539)	(0.177)	(0.227)
Fund Controls	✓	✓	✓	✓	✓	✓
Fund FE	✓	✓	✓	✓	✓	✓
Time FE	✓		✓		✓	
Style × Time FE		✓		✓		✓
Observations	185,174	185,174	185,174	185,174	187,802	187,802
R^2	0.139	0.193	0.029	0.182	0.075	0.102

Table 9: Passive Funds and Performance. Table 9 presents the results of estimating Eq. (2) for passive funds. The dependent variables are fund volatility and returns in Panel A, and the 3- and 5-factor adjusted abnormal returns in Panel B. Fund 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. Exposure is the portfolio share invested in affected U.S. suppliers. 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 the lagged dependent variable and china share, namely the portfolio share invested in U.S. firms that have 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.

	Panel A					
Dependent Variables :	Volatility			Return		
	(1)	(2)	(3)	(4)	(5)	(6)
Exposure	0.370***	0.397***	-0.043	-15.349***	-15.876***	-12.374***
	(0.137)	(0.136)	(0.113)	(1.809)	(2.039)	(1.869)
Observations	61,279	59,728	59,728	61,279	59,728	59,728
R^2	0.134	0.214	0.675	0.080	0.119	0.591
	Panel B					
Dependent Variables :	Alpha 3F			Alpha 5F		
	(1)	(2)	(3)	(4)	(5)	(6)
Exposure	-14.337***	-13.965***	-8.246***	-11.298***	-11.251***	-7.849***
	(1.811)	(1.837)	(2.009)	(1.668)	(1.705)	(1.708)
Observations	61,279	59,728	59,728	61,279	59,728	59,728
R^2	0.134	0.214	0.675	0.080	0.119	0.591
Fund FE	✓	✓	✓	✓	✓	✓
Time FE	✓	✓		✓	✓	
Fund Controls		✓	✓		✓	✓
Style×Time FE			✓			✓

Table 10: Placebo Test: Trading in Response to Export Controls by Passive Funds. Table 10 presents the results of estimating Eq. (3) for passive funds. The dependent variables reflect Trade direction, 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 as control, namely the portfolio share invested in U.S. firms that have at least one Chinese customer. 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. Standard errors are 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	-0.006	-0.010	-0.016	-0.016
	(0.019)	(0.017)	(0.017)	(0.017)
Observations	34,106,365	34,106,365	34,106,365	34,106,365
R^2	0.129	0.165	0.168	0.175
Dependent Variables :	Panel B: Within 3 months Trade Direction			
	(1)	(2)	(3)	(4)
Direct	0.015	0.019	0.012	0.009
	(0.019)	(0.017)	(0.018)	(0.017)
Observations	34,106,365	34,106,365	34,106,365	34,106,365
R^2	0.157	0.186	0.190	0.197
Fund FE	✓	✓	✓	✓
Time FE	✓			
Style×Time FE		✓	✓	
Industry×Time FE			✓	
Style× Industry×Time FE				✓
Fund Controls	✓	✓	✓	✓
Firm Controls	✓	✓	✓	✓

Table 11: Additional Fund-Level Outcomes: Sharpe Ratio and Flows. Table 11 presents the results of estimating Eq. (2) for active and passive funds, separately. The dependent variables are the fund's Sharpe ratio, concurrent fund flows and lead fund flows. Exposure is the portfolio share invested in affected U.S. suppliers. 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. Fund Controls include the lagged dependent variable, china share, 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.

	Panel A: Active Funds					
Dependent Variables :	Sharpe Ratio		Flows		Lead Flows	
	(1)	(2)	(3)	(4)	(5)	(6)
Exposure	-10.354***	-4.520***	-0.054	-0.071	-0.053	-0.052
	(0.956)	(0.938)	(0.072)	(0.075)	(0.039)	(0.045)
Observations	196,099	196,099	248,035	248,035	247,288	247,288
R^2	0.116	0.439	0.097	0.132	0.089	0.123
	Panel B: Passive Funds					
Dependent Variables :	Sharpe Ratio		Flows		Lead Flows	
	(1)	(2)	(3)	(4)	(5)	(6)
Exposure	-11.327***	-6.505***	0.083	0.008	-0.160**	-0.138**
	(1.591)	(1.644)	(0.132)	(0.127)	(0.065)	(0.065)
Observations	59,764	59,764	77,188	77,188	77,088	77,088
R^2	0.107	0.570	0.113	0.194	0.104	0.184
Fund FE	✓	✓	✓	✓	✓	✓
Time FE	✓		✓		✓	
Style×Time FE		✓		✓		✓
Fund Controls		✓		✓		✓

Table 12: Heterogeneity of Performance and Exposure to Export Controls: Manager Skills. Table 12 presents the results of estimating Eq. (6) 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. Fund 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. Exposure is the portfolio share invested in affected U.S. suppliers. 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. Market timing skills is dummy indicator if the market timing skills is at top quartile of all funds in the year by taking the moving average of funds' past 24 month market timing skills, where the methodology of funds' market timing skills measure follows Kacperczyk et al. (2014). Stock picking skills are a dummy indicator if the stock picking skills are in the top quartile of all funds in the year by taking the moving average of funds' past 24-month stock picking skills, where the methodology of funds' stock picking skills measure follows Kacperczyk et al. (2014). All specifications include the lagged dependent variable and china share, namely the portfolio share invested in U.S. firms that have 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.

	Panel A			
Dependent Variables :	Volatility		Return	
	(1)	(2)	(3)	(4)
Exposure	0.532***	0.593***	-6.895***	-9.545***
	(0.111)	(0.112)	(1.597)	(2.808)
Market timing skills	0.003		0.011	
	(0.002)		(0.011)	
Exposure × Market timing skills	0.096		-7.810	
	(0.266)		(5.708)	
Stock picking skills		0.000		-0.059***
		(0.002)		(0.010)
Exposure × Stock picking skills		-0.166		2.845
		(0.306)		(4.440)
Observations	247,673	247,673	247,673	247,673
R^2	0.945	0.945	0.894	0.894
	Panel B			
Dependent Variables :	Alpha 3F		Alpha 5F	
	(1)	(2)	(3)	(4)
Exposure	-5.064***	-6.879***	-3.023***	-4.412***
	(1.398)	(1.568)	(1.119)	(1.212)
Market timing skills	-0.001		-0.006	
	(0.011)		(0.012)	
Exposure × Market timing skills	-3.053		-2.221	
	(2.992)		(2.293)	
Stock picking skills		-0.038***		-0.010
		(0.011)		(0.010)
Exposure × Stock picking skills		4.473		3.557
		(3.182)		(2.459)
Observations	195,787	195,787	195,787	195,787
R^2	0.551	0.551	0.461	0.461
Fund FE	✓	✓	✓	✓
Style×Time FE	✓	✓	✓	✓
Fund Controls	✓	✓	✓	✓

Table 13: Heterogeneity of Performance and Exposure to Export Controls: Specialist Funds and High Fee Funds. Table 13 presents the results of estimating Eq. (6) 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. Fund 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. Exposure is the portfolio share invested in affected U.S. suppliers. 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. Specialist Fund is a dummy indicator if the fund management team has at least one specialist fund manager, where a fund manager is defined as a specialist if the manager oversees only one investment style fund in a particular quarter following Zambrana and Zapatero (2021). High Fee Fund is a dummy indicator if fund fee is above the median of the fee levels compared to funds in the same investment style and same quarter. All specifications include the lagged dependent variable and china share, namely the portfolio share invested in U.S. firms that have at least one Chinese customer. Fund Controls include fund size, family size, expense ratio, turnover ratio, age, and past return (1Y), which are all defined in Table 1. Standard errors are clustered at the fund level. *** p<0.01, ** p<0.05, * p<0.1.

	Panel A			
Dependent Variables :	Volatility		Return	
	(1)	(2)	(3)	(4)
Exposure	0.515***	0.504***	-10.057***	-12.844***
	(0.108)	(0.141)	(2.747)	(3.771)
Specialist Fund	0.004		-0.010	
	(0.003)		(0.009)	
Exposure × Specialist Fund	0.262		6.604***	
	(0.201)		(2.349)	
High Fee Fund		0.001		0.017
		(0.003)		(0.014)
Exposure × High Fee Fund		0.103		7.313**
		(0.148)		(3.038)
Observations	247,673	247,673	247,673	247,673
R^2	0.945	0.945	0.894	0.894
	Panel B			
Dependent Variables :	Alpha 3F		Alpha 5F	
	(1)	(2)	(3)	(4)
Exposure	-6.701***	-8.425***	-4.494***	-5.444***
	(1.625)	(2.098)	(1.187)	(1.499)
Specialist Fund	-0.017		-0.001	
	(0.012)		(0.014)	
Exposure × Specialist Fund	4.813**		5.213***	
	(2.017)		(1.751)	
High Fee Fund		0.026		0.039**
		(0.017)		(0.017)
Exposure × High Fee Fund		4.767**		3.421**
		(1.914)		(1.506)
Observations	195,787	195,787	195,787	195,787
R^2	0.551	0.551	0.461	0.461
Fund FE	✓	✓	✓	✓
Style×Time FE	✓	✓	✓	✓
Fund Controls	✓	✓	✓	✓

Online Appendix: Not For Publication

A Variable Definitions

Variable Name	Description
Volatility	monthly standard deviation of daily fund returns in percentage points.
Fund return	monthly fund net return 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 month (t-36 through t-1) on each fund over sample period.
Alpha 5F	5-factor adjusted abnormal fund returns. 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.
Exposure	portfolio share invested in affected U.S. suppliers. 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 trad direction is -1.
Direct	Dummy indicator if the firm is first treated by the export control at time t
Lottery stock	Dummy indicator if the MAX5 returns (the average of five highest daily return within a month) of the stock are the the top quartile among all the stocks in the same month.
Passive fund	Dummy indicator if 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.

Continued on next page

Table A.1 – *Continued from previous page*

Variable	**Description**
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 stocks 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.
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 stocks 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 on 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 quarter.
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, $Flow_{i,t} = [TNA_{i,t} - TNA_{i,t-1}(1 + R_{i,t-1})]/TNA_{i,t-1}$.
Assets	firm's total assets in $ million (at).
Firm age	number of years since firm's IPO.
Book leverage	firm's ratio of total debts to total assets (dlttq+dlcq)/atq.
CAPEX	firm's capital expenditures (capx) divided by lagged assets.

Table A.2: Performance and Exposure: Showing Controls. Table A.2 presents the results of estimating Eq. (2) for active funds. The dependent variables are fund volatility, returns, and the 3- and 5-factor adjusted abnormal returns. Fund volatility is the monthly standard deviation of daily fund returns (in basis 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. Exposure is the portfolio share invested in affected U.S. suppliers. 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. Standard errors are clustered at the fund level. *** p<0.01, ** p<0.05, * p<0.1.

Dependent Variables :	Volatility	Return	Alpha 3F	Alpha 5F
	(1)	(2)	(3)	(4)
Exposure	0.558***	-8.965***	-5.910***	-3.638***
	(0.107)	(2.568)	(1.584)	(1.187)
China Share	0.014	0.024	0.286***	0.604***
	(0.020)	(0.068)	(0.080)	(0.081)
Log Fund Size	0.004**	-0.062***	-0.068***	-0.077***
	(0.002)	(0.007)	(0.009)	(0.008)
Log Family Size	0.002	0.011**	0.003	-0.009
	(0.002)	(0.006)	(0.007)	(0.008)
Expense Ratio	0.024	-0.211	2.394	3.130
	(0.414)	(1.735)	(1.988)	(1.944)
Turnover Ratio	0.007**	-0.016	-0.023*	-0.045***
	(0.003)	(0.011)	(0.014)	(0.015)
Age	-0.010***	0.036***	-0.030	-0.030
	(0.004)	(0.012)	(0.026)	(0.028)
Past Return (1Y)	-5.100***	107.533***	97.329***	49.238***
	(0.208)	(1.383)	(1.221)	(1.230)
Lag Volatility	0.116***			
	(0.004)			
Lag Fund Return		-0.029***		
		(0.002)		
Lag Alpha 3F			-0.066***	
			(0.003)	
Lag Alpha 5F				-0.072***
				(0.004)
Obs.	245,551	245,551	194,259	194,259
R^2	0.945	0.894	0.550	0.458
Fund FE	✓	✓	✓	✓
Style×Time FE	✓	✓	✓	✓

Table A.3: Trading in response to Export Controls: Excluding Leveraged Funds. Table A.3 presents the results of estimating Eq. (3) using the sample of actively managed non-leveraged funds. In Panel A, the dependent variable is Trade direction, which represents the sign of net trading in the same month. Direct is an indicator variable equal to one if a stock is affected by export controls in the current period. In Panel B, the dependent variable is Trade direction, which represents the sign of the net trading in the same month or within the three months. Spillover is an indicator variable equal to one if a firm that exports to China is unaffected by export controls, but is held by a fund which holds stocks currently affected by export controls. All specifications include China share as control, namely the portfolio share invested in U.S. firms that have at least one Chinese customer. 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. Standard errors are clustered at the fund and firm level. *** p<0.01, ** p<0.05, * p<0.1.

	Panel A: Direct Response			
Dependent Variables :	Trade Direction (same month)			
	(1)	(2)	(3)	(4)
Direct	-0.044***	-0.043***	-0.040***	-0.039***
	(0.016)	(0.015)	(0.014)	(0.015)
Observations	32,389,575	32,389,575	32,389,575	32,389,575
R^2	0.062	0.077	0.079	0.086
Fund FE	✓	✓	✓	✓
Time FE	✓			
Style × Time FE		✓	✓	
Industry × Time FE			✓	
Style×Industry× Time FE				✓
Fund Controls	✓	✓	✓	✓
Firm Controls	✓	✓	✓	✓

	Panel B: Spillover			
Dependent Variables:	Trade direction (same month)		Trade direction (within 3 months)	
	(1)	(2)	(3)	(4)
Spillover	-0.008	-0.003	-0.029***	-0.027***
	(0.007)	(0.007)	(0.007)	(0.007)
Observations	30,992,669	30,992,669	30,992,669	30,992,669
R^2	0.077	0.079	0.080	0.083
Fund FE	✓	✓	✓	✓
Style×Time FE	✓	✓	✓	✓
Industry×Time FE		✓		✓
Fund Controls	✓	✓	✓	✓
Firm Controls	✓	✓	✓	✓

Table A.4: Trading in response to Export Controls with Quarterly Holdings. Table A.4 presents the results of estimating Eq. (3) 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 if a stock is affected by export controls in the current period. All specifications include china share as control, namely the portfolio share invested in U.S. firms that have at least one Chinese customer. 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. Standard errors are clustered at the fund and firm level. *** p<0.01, ** p<0.05, * p<0.1.

	Panel A: Active Funds			
Dependent Variables :	Trade Direction			
	(1)	(2)	(3)	(4)
Direct	-0.050*	-0.051*	-0.050**	-0.047**
	(0.027)	(0.027)	(0.023)	(0.023)
Observations	17,302,412	17,302,412	17,302,412	17,302,412
R^2	0.064	0.075	0.079	0.086
	Panel B: Passive Funds			
Dependent Variables :	Trade Direction			
	(1)	(2)	(3)	(4)
Direct	-0.042	-0.037	-0.034	-0.033
	(0.027)	(0.026)	(0.024)	(0.025)
Observations	13,846,879	13,846,879	13,846,879	13,846,879
R^2	0.161	0.195	0.199	0.207
Fund	✓	✓	✓	✓
Time	✓			
Style×Time		✓	✓	
Industry×Time			✓	
Style× Industry×Time				✓
Fund Controls	✓	✓	✓	✓
Firm Controls	✓	✓	✓	✓

Table A.5: Spillover Effects with Quarterly Holdings. Table A.5 presents the results of estimating Eq. (3) 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 a firm that exports to China is unaffected by export controls, but is held by a fund which holds stocks currently affected by export controls. All specifications include china share as control, namely the portfolio share invested in U.S. firms that have at least one Chinese customer. 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. Standard errors are clustered at the fund and firm level. *** p<0.01, ** p<0.05, * p<0.1.

	Panel A: Active Funds			
Dependent Variables :	Trade Direction			
	(1)	(2)	(3)	(4)
Spillover	-0.030***	-0.029***	-0.020**	-0.019**
	(0.009)	(0.009)	(0.009)	(0.009)
Observations	16,563,657	16,563,657	16,563,657	16,563,657
R^2	0.064	0.075	0.079	0.087
	Panel B: Passive Funds			
Dependent Variables :	Trade Direction			
	(1)	(2)	(3)	(4)
Spillover	0.010	0.008	0.008	0.008
	(0.010)	(0.010)	(0.010)	(0.010)
Observations	13,341,693	13,341,693	13,341,693	13,341,693
R^2	0.194	0.198	0.198	0.206
Fund	✓	✓	✓	✓
Time	✓			
Style×Time		✓	✓	
Industry×Time			✓	
Style× Industry×Time				✓
Fund Controls	✓	✓	✓	✓
Firm Controls	✓	✓	✓	✓