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

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Abstract

How do investors perceive and navigate the emerging geoeconomic risk? We identify *firm-level* geoeconomic risk using supply-chain links to Chinese firms targeted by U.S. export controls. Affected U.S. suppliers experience negative abnormal returns around policy announcements. These shocks propagate to mutual funds through portfolio holdings, raising volatility and lowering performance. Fund managers respond by reducing exposure to China-linked exporters, increasing portfolio concentration, and buying more lottery-like stocks. A long–short portfolio based on geoeconomic risk exposure earns positive and significant future returns, suggesting investors demand compensation for bearing the high geoeconomic risk.

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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). Multinational corporations, once valued for their diversification benefits, may now expose investors to risks that are difficult to diversify away. Despite growing recognition of its importance, little is known about how geoeconomic risk affects investor portfolios, how investors manage it, and whether such risk is priced.

We study this question in the context of U.S. domestic equity mutual funds, which manage nearly half of the $34 trillion U.S. mutual fund industry. Although these funds are mandated to invest in U.S. equities and may appear insulated from geopolitical tensions, they hold substantial stakes in firms with significant indirect international exposures through global supply chains (Demirci et al., 2022; Bai et al., 2022). We examine how these investors respond when geoeconomic risk materializes for U.S. firms through U.S. export controls. As 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. Through supply chain linkages, these controls impose financial costs on a subset of U.S. firms at different points in time. Crosignani et al. (2025) show that affected U.S. suppliers experience immediate negative abnormal returns around export control announcements. This setting therefore provides clean *firm-level* variation in geoeconomic shocks, allowing us to identify how such shocks propagate to investors through their portfolio holdings.

We find that firm-level geoeconomic risk propagates to the portfolios of well-diversified mutual funds. Funds holding affected firms experience higher volatility and lower performance. In response, fund managers reduce their holdings of directly affected firms as well as other firms that export to China even though not directly affected by export controls, suggesting that investors become more aware of geoeconomic risk. When rebalancing their portfolios, fund managers reduce holdings in the affected industry and buy more lottery-like stocks, resulting in greater portfolio concentration.

Consistent with the mutual fund selling pressure on stocks exposed to geoeconomic risk, we find that investors demand higher risk premia for holding these firms. Specifically, a long–short portfolio based on geoeconomic risk exposure generates over 1% abnormal return per month after adjusting for standard asset pricing factors. Lastly, active fund management may help insulate investors from geoeconomic risk. Relative to actively managed funds, passive funds experience larger performance declines followed by significant outflows. Certain managerial attributes, such as specialization and higher fees, are associated with a greater ability to navigate geoeconomic shocks.

To capture the firm-level geoeconomic risk, we hand-collect names and dates of the Chinese firms targeted by export controls. 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 then trace the U.S. suppliers that are connected to these targeted Chinese firms using supply chain data from FactSet Revere. To measure fund-level exposure to geoeconomic risk, we estimate the share of each mutual fund's portfolio invested in the affected U.S. firms at a given point in time using mutual fund holdings data. Consistent with Crosignani et al. (2025), we find that affected U.S. firms experience a 3.6% decline in cumulative abnormal returns following the imposition of export controls. We further find that this firm-level shock is economically significant as it transmits to the portfolio of presumably well-diversified mutual fund. Funds with greater exposure 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 examine how actively managed mutual funds respond to export control shocks by analyzing their trading decisions. Portfolio managers may choose to hold these stocks if they believe the price decline reflects temporary mispricing with long-term upside potential. Alternatively, managers may reduce their exposure if they perceive the shock as an indication of increasing firms' systematic risk.We find that funds exposed to export controls sell the affected stocks immediately, suggesting investors may consider those stocks too risky.

We then examine how exposed funds adjust other parts of their portfolios. First, we find that exposed mutual funds are more likely to sell stocks of U.S. firms that export to 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 potentially 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. Second, we find that funds more exposed to export controls tilt their portfolio towards lottery-like 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. Lastly, exposed funds reduce their overall allocation to the industry of the affected stocks, leading to greater portfolio concentration and less diversification.

Next, we examine the relation between firms' export control exposure and subsequent stock returns. We conduct both portfolio analyses and cross-sectional Fama–MacBeth regressions (Fama and MacBeth (1973)). A long–short portfolio that buys firms previously exposed to export controls and shorts unexposed firms earns approximately 1% abnormal future return per month after adjusting for standard asset pricing factors. Consistent with this evidence, cross-sectional regressions show that exposed firms earn a positive risk premium in the two months following exposure. Together, these results indicate that export control exposure commands higher expected returns, suggesting that investors demand compensation for bearing geoeconomic risk.

We then explore cross-sectional variation in fund characteristics. As a benchmark comparison, we first examine passive funds and their response to geoeconomic risk. 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 tracking errors relative to a benchmark portfolio. Indeed, we find that passive funds do not actively trade affected stocks. For a given level of exposure to export controls, however, passive funds experience significantly larger declines in returns and Sharpe ratios than active funds, and passive funds also face larger subsequent outflows. These findings suggest that active funds partially shield investors from geoeconomic shocks through portfolio rebalancing, which helps mitigate contemporaneous under-performance and avoid sizable future outflows.

Relatedly, we examine whether managerial skill matters for 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. 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 performance declines, 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 studying the effects of geoeconomic risk on economic and financial outcomes. The current empirical literature has predominantly focused on the effect of geoeconomic shocks, such as tariffs, sanctions, and export controls, on firm outcomes, supply chains, and the labor market (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; Han et al., 2024; Crosignani et al., 2025). Despite the importance of geoeconomic risk in financial markets, there is a lack of evidence on its potential impact on investors. We document for the first time how mutual funds are affected by geoeconomic risk and how they manage it. Geopolitical alignment has also been shown to have an effect on global capital allocations (Kempf et al., 2023; Aiyar et al., 2024; Gopinath et al., 2024). We focus on how domestic investors adjust their portfolio holdings of domestic stocks in response to granular firm-level geoeconomic shocks.

This paper also contributes to the mutual fund literature along several dimensions. 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 source of vulnerability amid rising geopolitical tensions. In addition, 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 provides an ideal empirical setting to identify firm-level shocks. Therefore, we can draw causal inference on mutual funds' trading response to granular shocks. Lastly, 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.

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 its 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.[1] 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, 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.

[1]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.

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. firms. 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. Consistent with Crosignani et al. (2025), Figure 2 shows that U.S. suppliers experience a –3.6% cumulative abnormal return when their Chinese customer is added to the BIS list, with most of the adjustment occurring within the first five days. This immediate stock price reaction serves as a 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's 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.[2]

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 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

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

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.

4.2 Trading Response to Export Controls

We next examine how portfolio managers respond to export controls through their trading decisions. We first study how funds adjust their holdings of firms directly affected by export controls. We then examine spillover effects on other stocks in the portfolio that may become exposed to geoeconomic risk in the future. Finally, we study whether funds tilt their portfolios toward lottery-like stocks and how their overall portfolio composition changes.

4.2.1 Direct Response

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. On the other hand, investors may sell the affected stocks if they anticipate that the firm's exposure to export controls will have a substantial, long-term negative impact.

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:

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

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.[3]

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

[3]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.

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).[4]

4.2.2 Spillover Effects

So far, we have shown that investors immediately sell the stocks affected by export controls. We next examine whether such shock triggers fund manager to reassess the overall portfolio exposure to geoeconomic risk coming from supply chain connections to China. In particular, we examine whether mutual funds that experience the export control shock (treated funds) also sell stocks of domestic firms that export to Chinese customers not currently targeted by export controls. Prior studies suggest that, due to attention constraints, investors often overlook economic linkages between firms despite supply chain information being publicly available (Cohen and Frazzini, 2008). Therefore, the export control shock may serve as a wake-up call 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.

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

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

[4] In unreported results, we show that selling activity is attributable exclusively to partial reductions in holdings rather than to full liquidations. Also, our results are not driven by leveraged funds, as excluding them leaves our estimates qualitatively unchanged.

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.[5]

Table 5 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. 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.[6]

Taken together, 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. 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.

[5]Results are qualitatively similar if the sample includes stocks that are ever affected.
[6]The results are robust excluding leveraged funds.

4.2.3 Portfolio Rebalancing

We have shown that active managers sell the affected stocks and other stocks connected to China after the export control shock. We next examine what stocks investors are likely to buy. Concerned that posting losses will lead to future outflows, active funds may respond by taking on higher risk to help offset losses (Brown et al., 1996). For example, funds' investments in lottery stocks often appear to attract larger inflows (Agarwal et al., 2022).

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 6 we show that funds more exposed to export controls immediately rebalance their portfolios in ways that are suggestive of higher risk-taking, possibly to mitigate the direct losses from export controls. Columns 1 and 2 show that funds exposed to export controls are immediately more likely to buy lottery stocks. Columns 3 and 4 show that affected funds 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.

We then study whether affected funds change their overall allocations to the industry affected by export controls and how portfolio concentration and diversification change. Funds may want to maintain 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. 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 7. 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.

4.3 Exposure to Export Controls and Stock Returns

In this section, we examine how investors perceive firms' geoeconomic risk exposure and whether they demand a risk premium for exposed firms. To test this hypothesis, we analyze the relation between firms' exposure to export controls and subsequent stock returns. We conduct both portfolio-level analysis and cross-sectional tests using Fama–MacBeth regressions (Fama and MacBeth, 1973).

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

Table 8 reports the average portfolio returns and factor-adjusted alphas. The return spread between the exposed firms' portfolio (H) and the unexposed portfolio (L) is approximately 1.3% per month in excess returns, which is both statistically significant and economically large. The factor-adjusted alphas remain around 1.1% per month across specifications and are statistically significant in all models. These findings suggest that firms with high exposure to export controls earn higher subsequent average returns, and that these returns are not fully explained by traditional asset pricing factors.

We further examine whether exposure to export controls is associated with higher expected returns using Fama–MacBeth cross-sectional regressions. At the end of each month, we regress firms' excess returns on an indicator for export control exposure and a set of firm-level control variables. We consider different return horizons, including contemporaneous returns, one-month-ahead returns, and two-month-ahead returns relative to the exposure month. We then test whether the time-series averages of the estimated coefficients are statistically different from zero. Standard errors are computed using the Newey–West (Newey and West, 1987) adjustment with six lags.

Table 9 presents the results. In column 1, we examine the relation between contemporaneous stock returns and export control exposure. Consistent with Figure 2, firms subject to export controls experience significant price declines in the same month as the exposure. In columns 2 and 3, we analyze one-month-ahead and two-month-ahead returns. We find a positive relation between export control exposure and future returns, with the effect becoming statistically significant beginning two months after exposure.

Taken together, these findings indicate that although export controls trigger immediate negative price reactions, exposed firms subsequently earn higher average returns. This pattern suggests that investors view export control exposure as a source of non-diversifiable risk and demand a higher risk premium for holding such stocks.

4.4 Impact on Passive Funds

Next, we examine the impact of geoeconomic risk on passive funds, providing a benchmark for the performance and portfolio reallocation of active 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).

We first consider the effect of export control exposures on the performance of passive funds. Table 10 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.

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 11 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.

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 12. The dependent variables are the Sharpe ratio, current-month fund flows, and next-month fund flows. Panel A shows the results for active funds and Panel B for passive ones. Columns 1 and 2 show that exposure to export control shocks significantly lowers the Sharpe ratio for both groups, although the decline is smaller for active funds. Columns 3 and 4 show no significant contemporaneous effect on fund flows for either group. Columns 5 and 6 show that, in the following month, passive funds experience significant outflows, whereas active funds experience only mild and statistically insignificant outflows. These findings suggest that active funds manage geoeconomic shocks more effectively, resulting in better relative performance and smaller subsequent outflows.

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.

4.5 Fund Manager Skills

In this section we examine whether active fund manager skills play a role in navigating geoeconomic risk. 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. 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 emerging geoeconomic risk.

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 examine whether specialist funds and high-fee funds respond differently. Following Zambrana and Zapatero (2021) we classify a fund as specialist if its manager focuses on a single investment style, and as generalist otherwise. This allows us to test whether specialists have an advantage in navigating emerging risks. In addition, we 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 13 presents the results. In Panel A, columns 1 and 2 show that Exposure significantly increases fund volatility, but its interactions with timing and picking skill are insignificant. Columns 3 and 4 show that Exposure reduces fund returns, yet neither interaction term is significant. Panel B shows similar results for 3- and 5-factor adjusted returns. Overall, market-timing and stock-picking skills do not appear to help managers mitigate geoeconomic risk.

Table 14 portrays a different picture when we consider being a specialist and charging high fees as measures of skill. In Panel A, columns 3 and 4, and in Panel B, the coefficient on Exposure is negative and significant, indicating that export control exposure lowers fund performance. However, the interactions between Exposure and specialist or high-fee status are positive and significant, suggesting that these funds are better able to mitigate the adverse performance effects of geoeconomic risk. By contrast, columns 1 and 2 show no significant differences in volatility across fund types. 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.

4.6 Staggered Treatment and Local Projections

So far, we have focused on the immediate effects of export controls on fund performance. We now turn to a dynamic analysis. 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 Exposure$_{it} > 0$ and the controls by 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 has become a central concern for asset managers. Despite their focus on U.S. stocks, domestic equity mutual funds are not fully insulated from geopolitical frictions. Many of their largest holdings are high-technology firms, such as semiconductor and advanced computing companies, that have been central drivers of recent U.S. stock market upturns. These firms also sit at the heart of global technology supply chains and are directly exposed to U.S.–China tensions. We focus on export controls, the primary policy instrument in the technological rivalry between the two countries. Designed to restrict targeted Chinese firms' access to U.S. technology, export controls generate negative spillovers for U.S. suppliers exporting to these firms. Domestic equity mutual funds with greater exposure to such affected stocks experience higher volatility and lower returns following these policy shocks.

To examine how investors respond to the geoeconomic risk, we find that active funds rebalance away not only from directly affected firms but also from firms indirectly exposed to geoeconomic risk. At the same time, funds with greater exposure to export control shocks exhibit higher risk-taking, suggesting that managers have incentives to offset performance shortfalls. This reallocation leads to increased portfolio concentration. We also find that firms with greater exposure to geoeconomic risk earn higher future returns relative to less exposed firms, indicating that investors demand a positive risk premium for bearing this non-diversifiable policy risk.

In contrast to active funds, passive funds designed to mechanically replicate benchmarks experience larger performance declines and subsequent investor outflows following export control shocks. When we examine cross-sectional differences in managers' ability to navigate geoeconomic risk, we find no evidence that standard skills, such as market timing and stock picking, are helpful in this setting. However, fund managers that specialize in one single investment style (specialists) and 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.

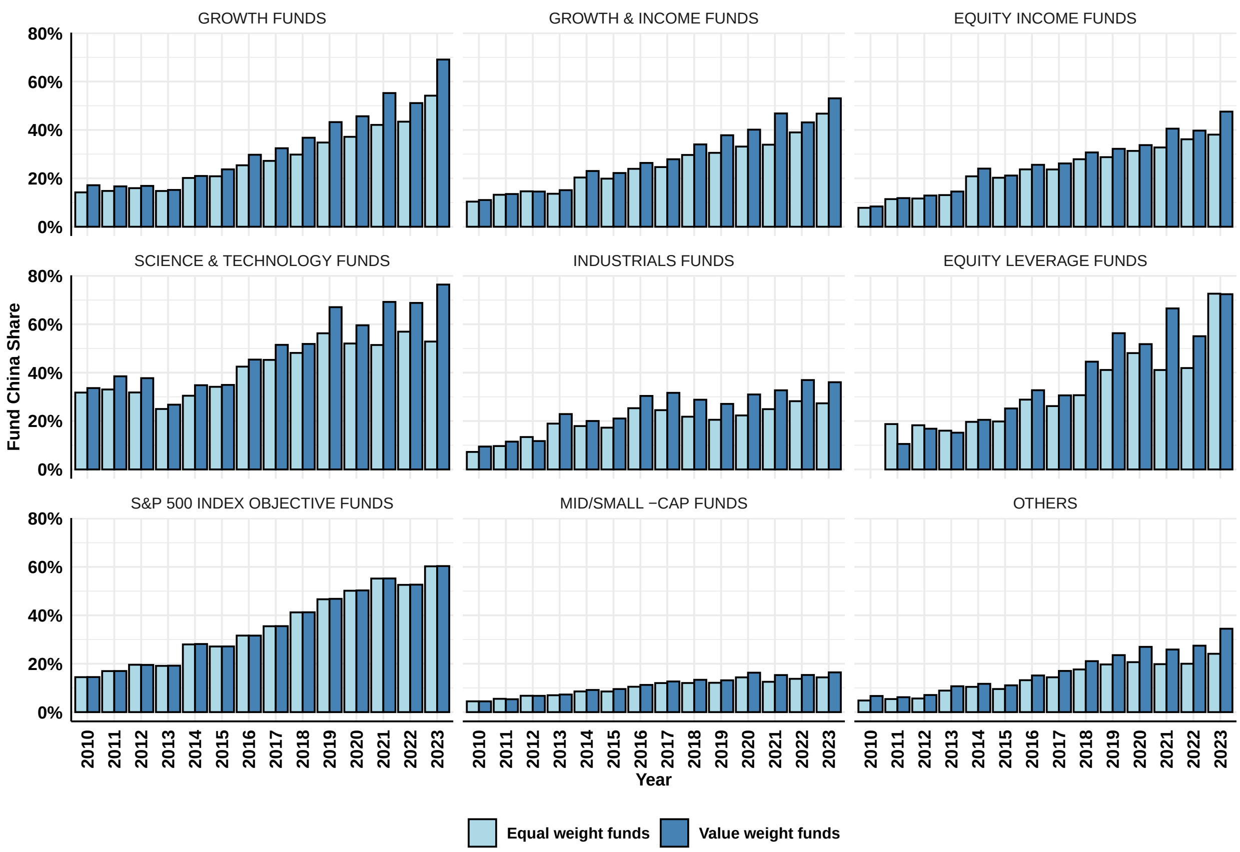

Figure 2: Cumulative Abnormal Returns around Export Control Announcements. Figure 2 displays the cumulative abnormal returns (CAR) of affected U.S. suppliers in a [-10, 20] day window around the announcement date of the inclusion of a Chinese customer in the BIS lists. Panel A shows CARs using the Fama-French 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).

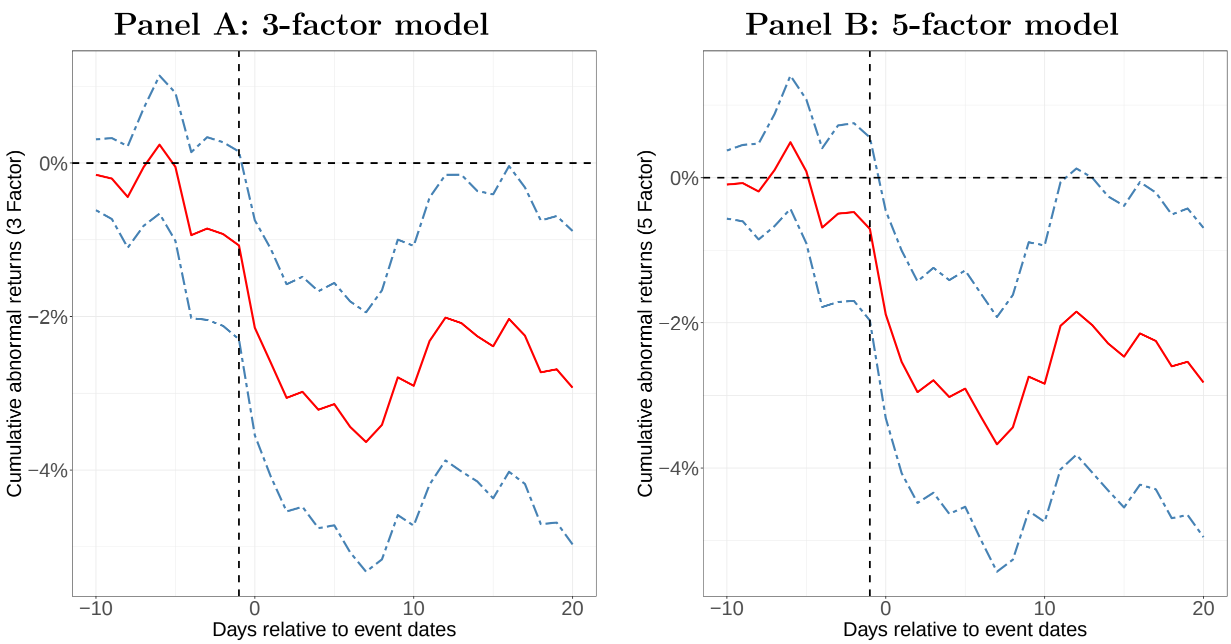

Figure 3: Performance with Local Projections. Figure 3 displays the dynamic coefficient estimates using the local projections approach of Dube et al. (2025), as presented in Equation (7). The dependent variable is the monthly fund volatility in Panel A, fund return in Panel B, the 3-factor adjusted abnormal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

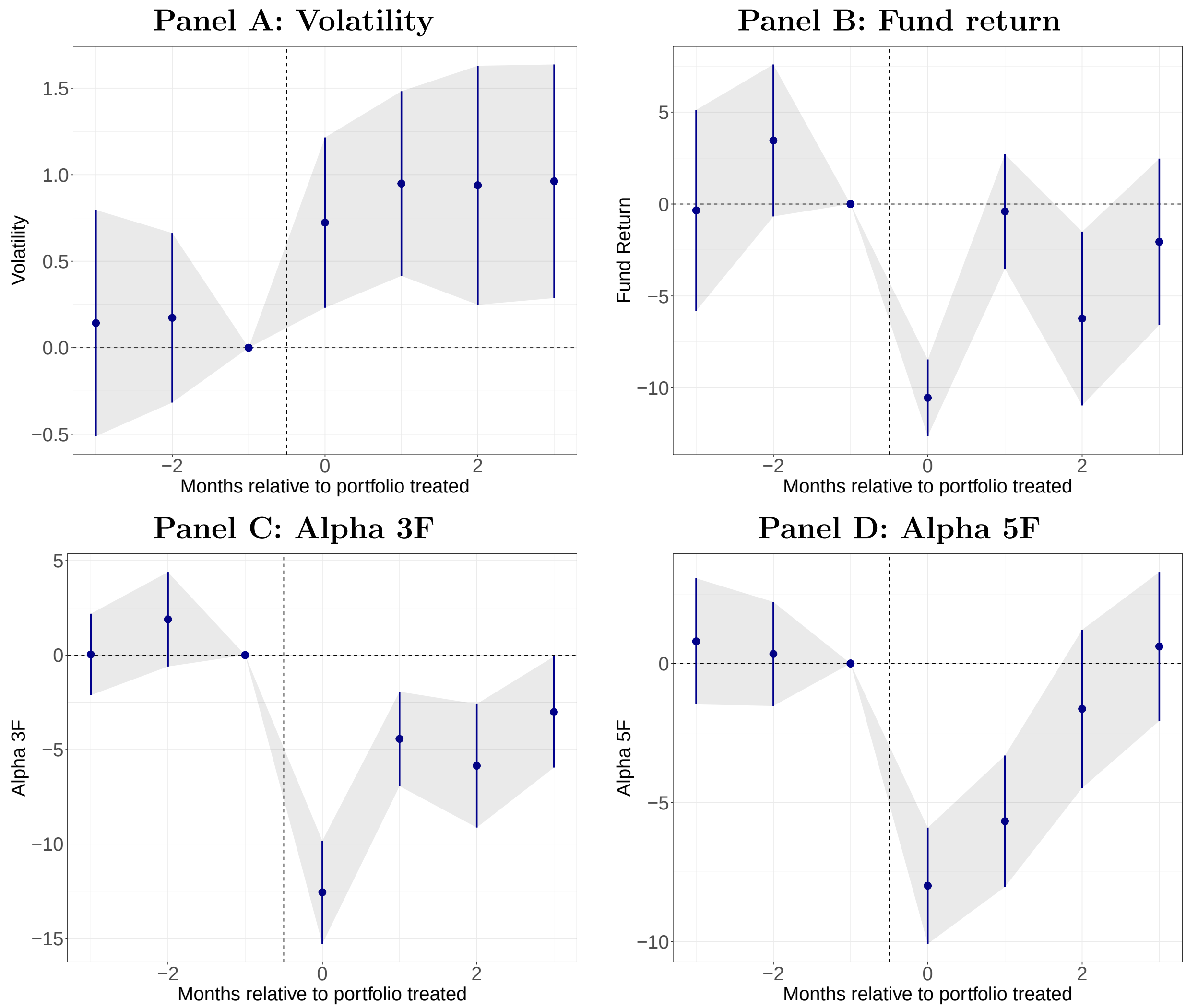

Figure 4: Trading Direction with Local Projections. Figure 4 displays the dynamic coefficient estimates using the local projections approach of Dube et al. (2025). The dependent variable is the trade direction. Panel A is the local projection estimate with fund and time fixed effect. Panel B is the local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

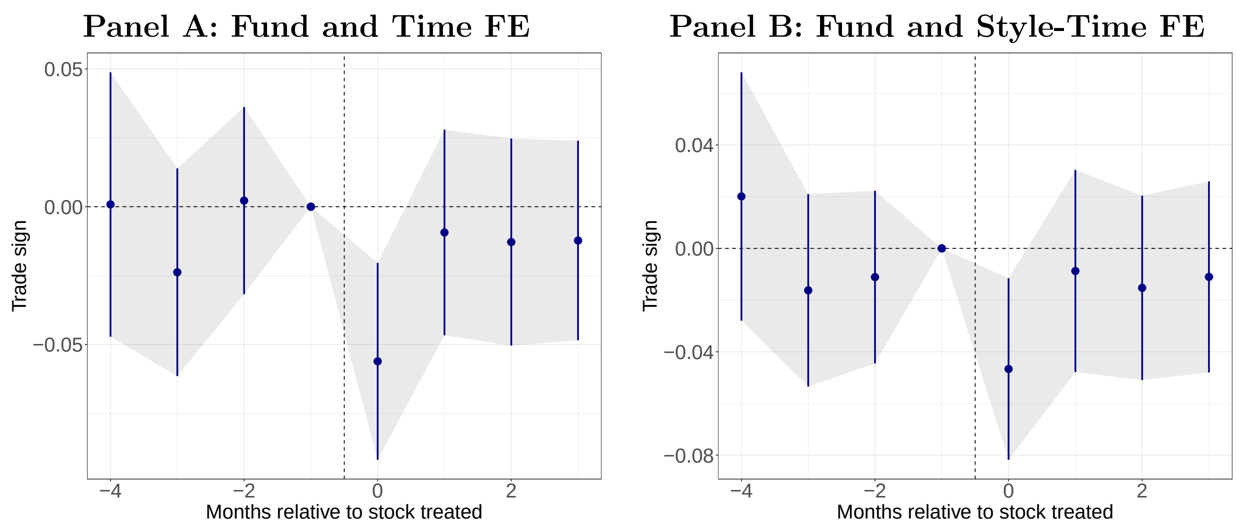

Table 1: Summary Statistics. Table 1 presents summary statistics of fund level characteristics. Volatility is the monthly standard deviation of daily fund returns in percentage points. Fund return is the monthly fund return in percentage points. Alpha 3F and Alpha 5F are the 3-factor and 5-factor adjusted 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)	(2.567)
Fund FE	✓	✓	✓	✓	✓	✓
Time FE	✓	✓		✓	✓	
Fund Controls		✓	✓		✓	✓
Style×Time FE			✓			✓
Observations	260,389	247,521	247,353	260,389	247,521	247,353
Adjusted R^2	0.910	0.914	0.943	0.787	0.806	0.891
	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)	(1.186)
Observations	203,961	195,692	195,465	203,961	195,692	195,465
Adjusted R^2	0.115	0.198	0.534	0.074	0.113	0.439
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	35,267,932	35,254,104
Adjusted R^2	0.065	0.080	0.082	0.086
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	35,267,932	35,254,104
Adjusted R^2	0.073	0.083	0.085	0.088
Fund FE	✓	✓	✓	✓
Time FE	✓			
Style×Time FE		✓	✓	
Industry×Time FE			✓	
Style×Industry×Time FE				✓
Fund Controls	✓	✓	✓	✓
Firm Controls	✓	✓	✓	✓

Table 5: Trading Spillovers in Response to Export Controls: Active Funds. Table 5 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 China	-0.009	-0.003	-0.024***	-0.021***
	(0.006)	(0.006)	(0.007)	(0.007)
Observations	33,749,660	33,749,638	33,749,660	33,749,638
Adjusted R^2	0.080	0.082	0.082	0.085
Fund FE	✓	✓	✓	✓
Style×Time FE	✓	✓	✓	✓
Industry×Time FE		✓		✓
Fund Controls	✓	✓	✓	✓
Firm Controls	✓	✓	✓	✓

Table 6: Portfolio Rebalancing in Response to Export Controls: Active Funds. Table 6 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	33,749,638	33,749,660	33,749,638
Adjusted R^2	0.080	0.082	0.082	0.085

Table 7: Active Fund Portfolio Concentration. Table 7 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***	-0.791***	1.452***	1.538***	0.489***	0.494***
	(0.038)	(0.035)	(0.426)	(0.530)	(0.147)	(0.176)
Fund Controls	✓	✓	✓	✓	✓	✓
Fund FE	✓	✓	✓	✓	✓	✓
Time FE	✓		✓		✓	
Style × Time FE		✓		✓		✓
Observations	185,129	184,917	185,129	184,917	187,639	187,427
Adjusted R^2	0.122	0.162	0.068	0.305	0.034	0.062

Table 8: Portfolio Alphas Sorted on Export Control Exposure Table 8 presents value-weighted and equal-weighted average excess returns and risk-adjusted alphas for stock portfolios sorted on firms' exposure to U.S. export control over the prior year. In June of year t, stocks are assigned to the High portfolio if the firm experienced at least one export control exposure between July of year t-1 and June of year t; all other firms are assigned to the Low portfolio. Portfolio returns are computed monthly from July of year t to June of year t+1. We construct a long–short portfolio that buys High-exposure stocks and shorts Low-exposure stocks. Reported alphas are estimated using the CAPM, the Fama–French three-factor model (FF3), the Fama–French five-factor model (FF5), and the six-factor model that augments FF5 with the momentum factor (FF6). Standard errors reported in parentheses. Standard errors are computed using the Newey–West procedure with six lags. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

	Value-weighted			Equal-weighted		
	H	L	H–L	H	L	H–L
Raw	1.909***	0.653**	1.275***	1.610***	-1.209**	2.369***
	(0.560)	(0.300)	(0.341)	(0.570)	(0.593)	(0.550)
CAPM	0.745**	-0.406***	1.105***	0.415	-2.360***	2.286***
	(0.364)	(0.075)	(0.370)	(0.299)	(0.412)	(0.549)
FF3	0.723**	-0.407***	1.072***	0.579*	-2.149***	2.264***
	(0.351)	(0.077)	(0.346)	(0.308)	(0.412)	(0.561)
FF5	0.749*	-0.405***	1.077***	0.692**	-2.141***	2.323***
	(0.384)	(0.080)	(0.368)	(0.309)	(0.422)	(0.557)
FF6	0.772**	-0.381***	1.079***	0.716**	-2.065***	2.274***
	(0.383)	(0.078)	(0.369)	(0.305)	(0.413)	(0.573)

Table 9: Fama-MacBeth Regressions Table 9 reports the results of Fama–MacBeth cross-sectional regressions of monthly excess stock returns on firms' export control exposure. The dependent variable, Excess Return, is the monthly stock return in excess of the risk-free rate in month t. Lead 1 Return and Lead 2 Return are the one-month-ahead (t+1) and two-month-ahead (t+2) excess returns, respectively. Exposure is an indicator variable equal to one if a firm is exposed to export controls in month t. Size is the logarithm of market capitalization. B/M is the logarithm of the book-to-market ratio. Investment is capital expenditures scaled by total assets. Momentum is the average stock return over the prior 12 months. Profitability is operating income scaled by total assets. All control variables are measured at time t. Standard errors are reported in parentheses and are computed using the Newey–West procedure with six lags. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Dependent Variables:	Excess Return (1)	Lead 1 Return (2)	Lead 2 Return (3)
Exposure	-0.057*	0.016	0.053***
	(0.028)	(0.013)	(0.012)
Size	-0.006**	-0.001	-0.007**
	(0.002)	(0.003)	(0.003)
B/M	-0.029	0.067	0.202
	(0.066)	(0.054)	(0.191)
Investment	-0.084***	-0.026	-0.011
	(0.031)	(0.032)	(0.032)
Momentum	0.910***	0.129***	0.114***
	(0.136)	(0.031)	(0.027)
Profitability	-0.015	-0.175***	-0.130***
	(0.030)	(0.039)	(0.042)
Constant	0.090***	0.031	0.105**
	(0.035)	(0.041)	(0.045)
Average obs./month	3661	3661	3661
Average R-squared	0.11	0.02	0.02

Table 10: Passive Funds and Performance. Table 10 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)	(1.865)
Observations	79,952	77,090	76,779	79,952	77,090	76,779
Adjusted R^2	0.911	0.912	0.955	0.754	0.775	0.900
	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)	(2.005)	(1.668)	(1.704)	(1.704)
Observations	61,250	59,698	59,433	61,250	59,698	59,433
Adjusted R^2	0.119	0.200	0.651	0.064	0.103	0.558
Fund FE	✓	✓	✓	✓	✓	✓
Time FE	✓	✓		✓	✓	
Fund Controls		✓	✓		✓	✓
Style×Time FE			✓			✓

Table 11: Trading in Response to Export Controls by Passive Funds. Table 11 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	34,106,346	34,097,285
Adjusted R^2	0.129	0.165	0.168	0.172
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	34,106,346	34,097,285
Adjusted R^2	0.157	0.186	0.189	0.194
Fund FE	✓	✓	✓	✓
Time FE	✓			
Style×Time FE		✓	✓	
Industry×Time FE			✓	
Style× Industry×Time FE				✓
Fund Controls	✓	✓	✓	✓
Firm Controls	✓	✓	✓	✓

Table 12: Additional Fund-Level Outcomes: Sharpe Ratio and Flows. Table 12 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	196,003	195,775	247,885	247,716	247,148	246,973
Adjusted R^2	0.097	0.417	0.079	0.101	0.072	0.093
	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)	(1.641)	(0.132)	(0.127)	(0.065)	(0.065)
Observations	59,735	59,471	77,158	76,847	77,062	76,751
Adjusted R^2	0.091	0.539	0.099	0.146	0.089	0.136
Fund FE	✓	✓	✓	✓	✓	✓
Time FE	✓		✓		✓	
Style×Time FE		✓		✓		✓
Fund Controls		✓		✓		✓

Table 13: Heterogeneity of Performance and Exposure to Export Controls: Manager Skills. 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. 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)	(1.596)	(2.807)
Market timing skills	0.003		0.011	
	(0.002)		(0.011)	
Exposure × Market timing skills	0.096		-7.810	
	(0.266)		(5.707)	
Stock picking skills		0.000		-0.059***
		(0.002)		(0.010)
Exposure × Stock picking skills		-0.166		2.845
		(0.306)		(4.439)
Observations	247,353	247,353	247,353	247,353
Adjusted R^2	0.943	0.943	0.891	0.891
	Panel B			
Dependent Variables :	Alpha 3F		Alpha 5F	
	(1)	(2)	(3)	(4)
Exposure	-5.064***	-6.879***	-3.023***	-4.412***
	(1.398)	(1.567)	(1.118)	(1.211)
Market timing skills	-0.001		-0.006	
	(0.011)		(0.012)	
Exposure × Market timing skills	-3.053		-2.221	
	(2.991)		(2.292)	
Stock picking skills		-0.038***		-0.010
		(0.011)		(0.010)
Exposure × Stock picking skills		4.473		3.557
		(3.180)		(2.457)
Observations	195,465	195,465	195,465	195,465
Adjusted R^2	0.534	0.534	0.439	0.439
Fund FE	✓	✓	✓	✓
Style×Time FE	✓	✓	✓	✓
Fund Controls	✓	✓	✓	✓

Table 14: Heterogeneity of Performance and Exposure to Export Controls: Specialist Funds and High Fee Funds. Table 14 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)	(2.746)	(3.769)
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)		(3.037)
Observations	247,353	247,353	247,353	247,353
Adjusted R^2	0.943	0.943	0.891	0.891
	Panel B			
Dependent Variables :	Alpha 3F		Alpha 5F	
	(1)	(2)	(3)	(4)
Exposure	-6.700***	-8.425***	-4.494***	-5.444***
	(1.624)	(2.097)	(1.187)	(1.498)
Specialist Fund	-0.017		-0.001	
	(0.012)		(0.014)	
Exposure × Specialist Fund	4.812**		5.213***	
	(2.015)		(1.750)	
High Fee Fund		0.026		0.039**
		(0.017)		(0.017)
Exposure × High Fee Fund		4.767**		3.421**
		(1.913)		(1.505)
Observations	195,465	195,465	195,465	195,465
Adjusted R^2	0.534	0.534	0.439	0.439
Fund FE	✓	✓	✓	✓
Style×Time FE	✓	✓	✓	✓
Fund Controls	✓	✓	✓	✓