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

Matteo Crosignani
New York Fed, CEPR

Lina Han
UMass Amherst

Marco Macchiavelli
UMass Amherst

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Abstract

We study the effect of geopolitical risk on U.S. mutual funds. U.S. export controls offer a quasi-natural experiment to identify domestic stocks exposed to geopolitical risk. Mutual funds with greater exposures to affected stocks experience increased volatility and lower returns. Active funds respond by selling these stocks and others that are currently unaffected but nevertheless prone to geopolitical risk. They also reallocate portfolios toward lottery and high-risk factor stocks to offset potential performance declines. Passive funds do not adjust holdings and suffer larger performance drops. Timing and stock-picking skills prove ineffective in navigating geopolitical risk, while being a specialist helps.

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1 Introduction

Geopolitical risk has become a primary concern for asset managers, with BlackRock (2024) and Invesco (2024) listing geopolitical tensions and fragmentation as top risks to economic growth going forward. Domestic mutual funds investing in U.S. equities manage nearly half of the $34 trillion U.S. mutual fund industry (Investment Company Institute, 2024). Despite their domestic focus, these funds hold considerable stakes in U.S. firms with significant international exposures (Demirci et al., 2022; Bai et al., 2022). Prior studies suggest that such indirect international exposure have been beneficial for domestic funds through diversification. However, with increasing geopolitical uncertainty, the question arises as to whether such diversification becomes costly. In this paper, we study the effect of geopolitical risk on domestic mutual fund portfolios and how portfolio managers navigate such risk.

Export controls provide an ideal laboratory to study the effect of geopolitical shocks on asset managers. As a key policy tool in the current U.S.-China technological rivalry, export controls are imposed by the U.S. government on domestic firms to limit their ability to sell advanced technologies to selected Chinese firms. While the prior literature measures geopolitical risk and economic uncertainty at the aggregate level (Caldara and Iacoviello, 2022; Baker et al., 2016), export controls impose financial costs on a subset of domestic firms, namely those that sell controlled technologies to selected Chinese firms (Crosignani et al., 2023). As a result, they allow for a cleaner identification of geopolitical shocks.

We first examine 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. suppliers held by each fund at a given time. We find that with the imposition of export controls, actively managed 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 2.5% decline in cumulative abnormal returns. Portfolio managers may choose to hold the affected firms 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 constraints that limit their ability to hold them.[1] We find that active funds exposed to export controls sell the affected stocks immediately. In addition to selling affected stocks, exposed mutual funds are also more likely to sell stocks of U.S. firms that export to other Chinese companies that are 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 geopolitical risk and fear future

[1]For example, fund managers are frequently evaluated by investment companies and fund investors. As a result, fund managers may engage in short-term decision making when their funds experience distress.

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 and which risk factors they are more likely to gain exposure to. We find that active funds more exposed to export controls buy more lottery stocks and stocks with higher exposure to size and value risk factors. 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 flows.

Similarly, gaining additional exposure to priced risk factors, such as size and value, is consistent with active fund managers trying to limit the decline in returns following the export control shock. Indeed, posting a larger decline in performance could lead to more pronounced outflows in the following month, as widely documented in the flow-performance relationship literature (e.g., Ippolito, 1992; Sirri and Tufano, 1998; Del Guercio and Tkac, 2002). Overall, active mutual funds exposed to export control shocks display higher idiosyncratic as well as systematic return volatility. While the increase in idiosyncratic volatility is likely due to both the direct exposure to export control shocks and the portfolio rebalancing towards lottery stocks, the increase in systematic volatility can be attributed to the portfolio rebalancing toward size and value risk factors.

Actively managed funds charge higher fees to compensate for their effort in the portfolio selection and risk management, while the investment objective of passive funds is to minimize tracking errors relative to a benchmark portfolio. We therefore test whether active and passive funds manage geopolitical shocks differently. We find that for a given exposure to export controls, active funds experience a smaller decline in performance relative to passive ones. In addition, passive funds do not trade actively on the affected stocks, consistent with the fact that passive funds just aim to replicate a benchmark. As a comparison, we find that exposed passive funds, which experience larger drops in performance, also see larger subsequent outflows relative to exposed active funds. These findings suggest that active funds manage geopolitical 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. Specifically, active managers reduce the sensitivity of returns to export control shocks by 43 percent, a sizable loss mitigation. This shift away from affected stocks by active funds has aggregate consequences. Following the introduction of export controls, affected U.S. firms see a decline in their ownership by active mutual funds, which may have negative consequences for the pricing efficiency of these stocks (Stambaugh, 2014).

We also examine whether traditional fund manager skills, namely stock picking and market timing skills (Kacperczyk et al., 2014), translate to effective geopolitical risk management. Our findings suggest that neither stock picking nor market timing skills enhance a fund manager's ability to navigate geopolitical risk. Funds with better stock picking or market timing skills exhibit similar declines in performance, indicating that these traditional skills do

not provide a significant advantage in managing a new type of 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. (2022), 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. (2023) 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 geopolitical risk in financial markets, there is a lack of evidence on the potential impact on U.S. mutual funds. We document for the first time how mutual funds are affected by geopolitical 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 geopolitical 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 geopolitical 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 geopolitical 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

[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).

shock, mutual funds take additional risk, likely to mitigate the decline in performance which could lead to more severe outflows. Trying to avoid sizable declines in performance by taking additional risk is consistent with managerial incentives. Indeed, fund managers dislike outflows as they get paid a percentage of the assets they manage but know that investors will withdraw their funds if they observe a negative performance. Consistently, we show that passive funds more exposed to export control shocks perform worse than active ones and subsequently experience larger 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 to be 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. (2023), 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.

For illustrative purposes, we next discuss some inclusions of Chinese firms in the BIS lists. In 2019, the BIS added Huawei to the Entity List citing violations of U.S. sanctions on Iran without obtaining a license. SMIC, the largest semiconductor manufacturer in China, was included as a result of its activities in support of the Chinese military. Other firms, such as Jinhua, are included in response to their theft of intellectual property (IP) from U.S. companies. In particular, Jinhua was targeted by export controls as a result of the theft of IP from Micron, a U.S. company specialized in computer memory and data storage. To avoid the wrongful attribution of IP theft effects (see e.g. Curti et al., 2023) to export controls, we remove from the sample of affected U.S. suppliers the very few companies that were subject to IP theft as the motivation for the inclusion of the related Chinese entity 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 497 are corporations and 245 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 92 Chinese firms targeted by U.S. export controls and 357 affected U.S. suppliers, of which 175 have supply chain relations overlapping with the date of inclusion of the pertaining Chinese customer in the BIS lists.

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. Passive funds are included only when we compare the effect on passive and active funds. We have a total of 5,167 domestic equity funds across 27 investment styles, among which 4,504 are active and 1,097 are passive.[3] The fund investment style is based on 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% and conditional on new export controls being imposed the average portfolio exposure to the affected stocks, $\text{Exposure}|_{>0}$, is 2% with a standard deviation of 2.4%. On the other hand, the share of assets invested in firms that export to China is 27.5%. Finally, 76.5% of all domestic equity funds are active. Table 2 shows the distribution of funds in each investment styles. The science and

[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 fund during our sample period, or vice versa.

tech style funds have the highest exposures to export controls. On average, they invest 55.3% of their portfolios in domestic firms that export to China and, conditional on a new round of export controls, they hold 6.9% of their portfolios in affected stocks.

4 Empirical Strategy and Results

Since inception, a total of 497 unique Chinese firms have been added to the BIS lists. In a few occasions, the same firm is added more than once, with subsequent entries including subsidiaries that were previously excluded. 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., 2023). Using International Securities Identification Numbers (ISINs) and name matching, we identify 92 Chinese entities subject to export controls (target firms) with supply chain relations with 358 affected suppliers. Of these, 131 have supply chain relations overlapping with the export control event dates and appear in the mutual fund holdings.

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, as soon as a Chinese customer is added to the BIS lists, its U.S. suppliers experience a negative cumulative abnormal return of 3% within the

first 20 days, with most of the repricing occurring within the first 5 days. The immediate stock price reaction serves as motivation for our analysis of how mutual funds deal with this geopolitical 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 expect mutual funds with a larger share of assets invested in affected stocks to experience worse performance, in terms of both higher volatility and lower returns. 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 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 2.04%. 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). Results are qualitatively unchanged if we use the 4-factor model of Carhart (1997). 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 funds' 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

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

as the average return over the past year. We include lagged dependent variables in all our specification to control for potential autocorrelation in funds' 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 (2.4%) is associated with an increase in the fund volatility by 0.017 to 0.030 percentage points, which corresponds to 2.5 to 4.5 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 (2.4%) is associated with a 35 to 37 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.

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 14 basis points decline in fund 3 factor-adjusted alphas and 8 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 higher returns (see the coefficients of China Share in columns 2 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 2 to 4, respectively).

4.2 Trading and Portfolio Decoupling

We next examine how portfolio managers navigate geopolitical 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 the 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 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 and minus one if it reduces them over month t. 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 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-time and firm industry-time fixed effects. Standard errors are double clustered at the fund and firm level.[5]

[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

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. The negative coefficient of Direct indicates that following the introduction of export controls affecting stock j, the average active fund that holds stock j is more likely to sell it. This is true regardless of the level of fixed effects saturation. 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.

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 geopolitical risk.

of the quarter. Results are qualitatively unchanged if we use funds' holdings at quarterly frequency.

Under the hypothesis that export control shocks are perceived by fund managers as an increase in geopolitical risk and not just an idiosyncratic stock price decline, we would expect funds to reassess the overall portfolio exposure to geopolitical 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 geopolitical 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 *information 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 geopolitical risk. To formally test the information 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 and minus one if it decreases it over month t. $Spillover_{i,j,t}$ 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. Results are qualitatively similar if the sample includes stocks that are ever affected.

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 geopolitical 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 geopolitical risk.

4.4 Portfolio Rebalancing and Risk-Taking

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 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). Mutual funds can take additional risk by increasing their loadings on risk factors which are known to earn significant risk premia (Massa and Patgiri, 2009) or buying lottery stocks (Bali et al., 2011).

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 and minus one if it decreases them over the month. $Lottery_{i,j,t}$ 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 is in the top quartile in that month. We consider other independent variables that capture stock characteristics that may also be relevant for portfolio rebalancing. We define $High\ Market_{i,j,t}$, $High\ SMB_{i,j,t}$, and $High\ HML_{i,j,t}$ as indicator variables equal to one if stock j is in the top quartile of market beta, size (SMB) beta, or value (HML) beta, respectively, and if fund i holds stocks currently affected by export controls.

In Table 6 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 more likely to buy lottery stocks. Funds can also take additional risk by increasing their loadings on known risk factors. Columns 3 and 4 show that affected funds do not increase their allocations to stocks with high market beta. However, they increase allocations to stocks with greater exposure to the size and value factors, as shown in columns 5 to 8. Even-numbered columns are our preferred specifications as they include style-time fixed effects, which control for the differential propensity of funds in different investment styles to load on various risk factors. These are also the columns that display the most statistical significance in the reallocation towards lottery stocks and stocks with higher loadings on the size and value risk factors. In unreported results we find no significant effect of exposure to export controls on cash holdings.

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

flows. Indeed, funds' investments in lottery stocks often appear to attract larger inflows Agarwal et al. (2022). Similarly, our finding that funds mitigate losses and prevent future outflows by loading up on size and value factors is reminiscent of Barber et al. (2016), which finds that investors treat returns attributable to size and value factors as alpha and reward these factor exposures with inflows.

However, risk-taking usually comes at the expense of additional volatility. Next, we assess the overall effect of exposure to export controls on different components of fund volatility. As export controls affect a few domestic firms at a time, they are likely to contribute to idiosyncratic volatility but not to the systematic one, namely the volatility of returns attributable to the risk factors themselves. Table A.3 shows that active funds that are more exposed to export control shocks experience an increase in both idiosyncratic and systematic volatility. The increase in idiosyncratic volatility is likely the result of the volatility of affected stocks following export controls as well as the volatility induced by rebalancing towards lottery stocks. On the other hand, the increase in systematic volatility is likely to be the result of rebalancing toward size and value stocks to make up for the losses on the affected 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. On the other hand, active fund managers charge higher fees and employ discretion in stock selection with the promise to outperform a benchmark (Elton et al., 2003). Next, we examine the effect of geopolitical risk on passive funds as a benchmark for the performance of active funds.

Passive Fund Performance. We first consider the effect of export control exposures on the performance of passive funds. Table 7 shows 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. Importantly, the magnitude of the effect on returns for passive funds is often times almost twice as large as the magnitude for active funds shown earlier in Table 3. 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 to offset losses from geopolitical 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 8 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 therefore one consider 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 10. 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 more muted decline in returns (the numerator of the Sharpe ratio), active funds 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. Since the relative decline in active fund returns is smaller than the relative increase in volatility, the Sharpe ratio of active funds is expected to decline by less than for passive funds. Indeed, 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 geopolitical 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 mutual fund 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 in passive funds is consistent with their inability to sell affected stocks in the aftermath of export controls. It appears that active funds' active rebalancing dampens the negative effects of export controls on their performance, while passive funds simply absorb the full price decline.

Ownership Gap. The previous findings indicate that active funds sell affected U.S. suppliers after their Chinese customers are subject to export controls, whereas passive funds do not. It is therefore likely that, after the imposition of export controls, the ownership structure of affected suppliers may shift away from active funds. Table 9 tests this conjecture. The dependent variables are Active Ownership, the ratio of shares held by active funds over total shares outstanding, Passive Ownership, the ratio of shares held by passive funds over total shares outstanding, and Ownership Gap, the difference between active and passive ownership.

The negative and significant coefficients of *Direct* in columns (1) and (2) indicate that, after the imposition of export controls, active fund ownership of affected firms declines. On the other hand, the ownership by passive funds is unchanged (columns 3–4). Active funds often take advantage of opportunities to profit from the mispricing induced by noise traders (Stambaugh, 2014). The decline in the active ownership of affected stocks could have further implications for the pricing efficiency of these stocks in the future, a topic that is beyond the scope of this study.

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 geopolitical risk. On the one hand, fund manager skills could be transferable to new risks. Highly skilled managers may seamlessly adapt to the new geopolitical risk environment and generate abnormal returns across different market conditions. On the other hand, these skills may not translate effectively to new 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 ability. 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 above the median of the 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 is a vector of 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 11 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 geopolitical 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 geopolitical risk.

Table 12 portrays a different picture when using 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 on skill and exposure are positive and significant, suggesting that specialist and high fee funds can significantly mitigate the negative consequences of exposure to geopolitical risk on fund performance. The only difference between the two measures can be found in columns (1) and

(2) of Panel A. While specialist funds are able to improve performance at the expense of higher volatility, high fee funds can achieve better performance without significantly increasing fund volatility.

In sum, while market timing and stock picking skills do not translate to better geopolitical 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. (2022), 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.

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 $\text{Exposure}_{it-1} = 0$, 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, more 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, geopolitical 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 can only invest in U.S. stocks. Far from being immune to geopolitical risk, domestic equity funds invest in large multinational corporations that are in the middle of the geopolitical 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 collect larger fees with the promise to actively manage their portfolio in an attempt to produce higher returns. In line with this premise, we show that active funds are able to partially shield their performance from the negative geopolitical shock. Following export controls, active funds are more likely to sell not only the affected U.S. firms, but also U.S. firms that export to other Chinese firms besides the targeted ones. The selling of unaffected stocks that are nevertheless exposed to China suggests that treated funds have become concerned that other Chinese firms may be soon included in the export control lists. We also show evidence that funds more exposed to export control shocks increase risk-taking to avoid posting lower returns. To do so, they purchase lottery stocks as well as stocks with higher loadings on the size and value risk factors, which in expectation earn the fund a risk premium but also increase systematic volatility.

Finally, we investigate whether traditional fund manager skills, such as market timing and stock picking, help mitigate geopolitical 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.

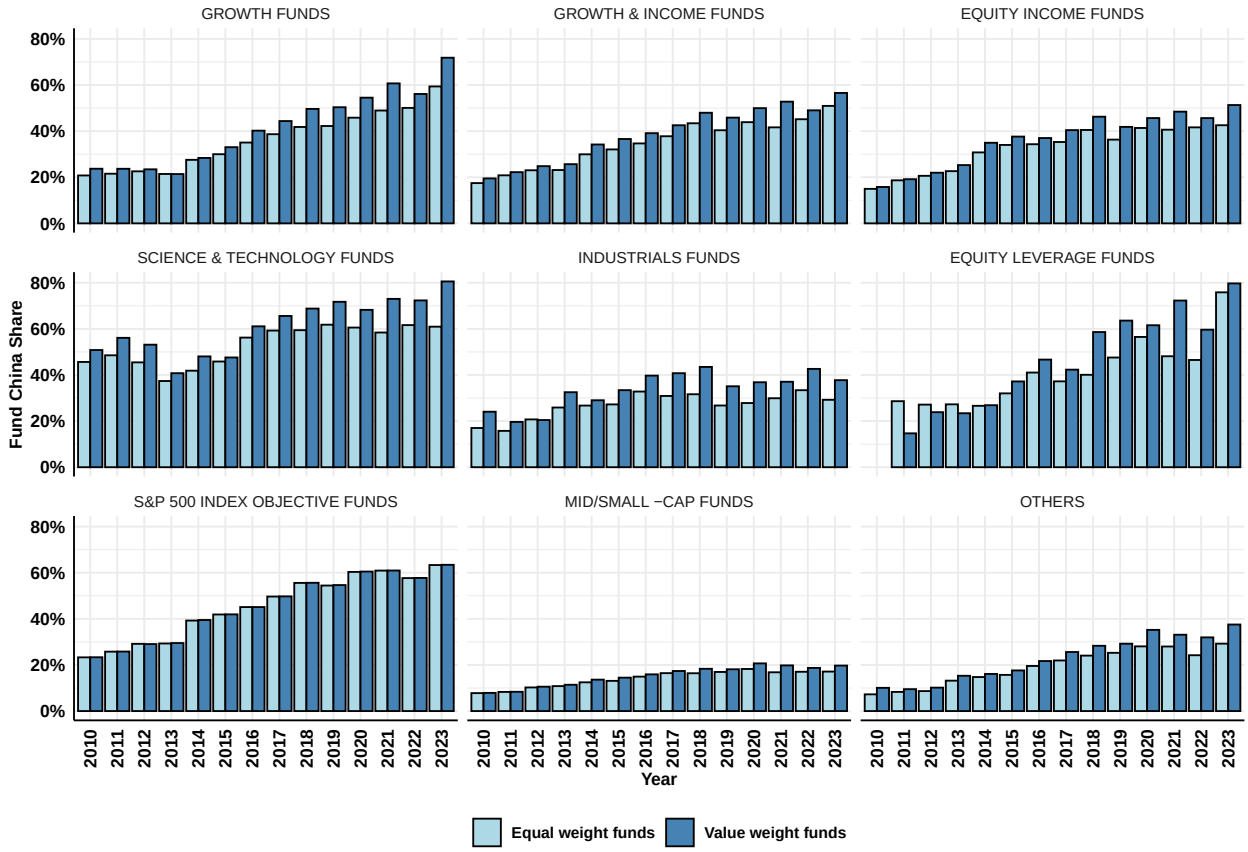


Figure 2: Cumulative Abnormal Returns around Export Control Announcements. Figure 2 displays the cumulative abnormal returns (CAR) of affected U.S. suppliers in a [-10, 20] day window around the announcement date of the inclusion of a Chinese customer in the BIS lists. Panel A shows CARs using the Fama-French 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. (2023).

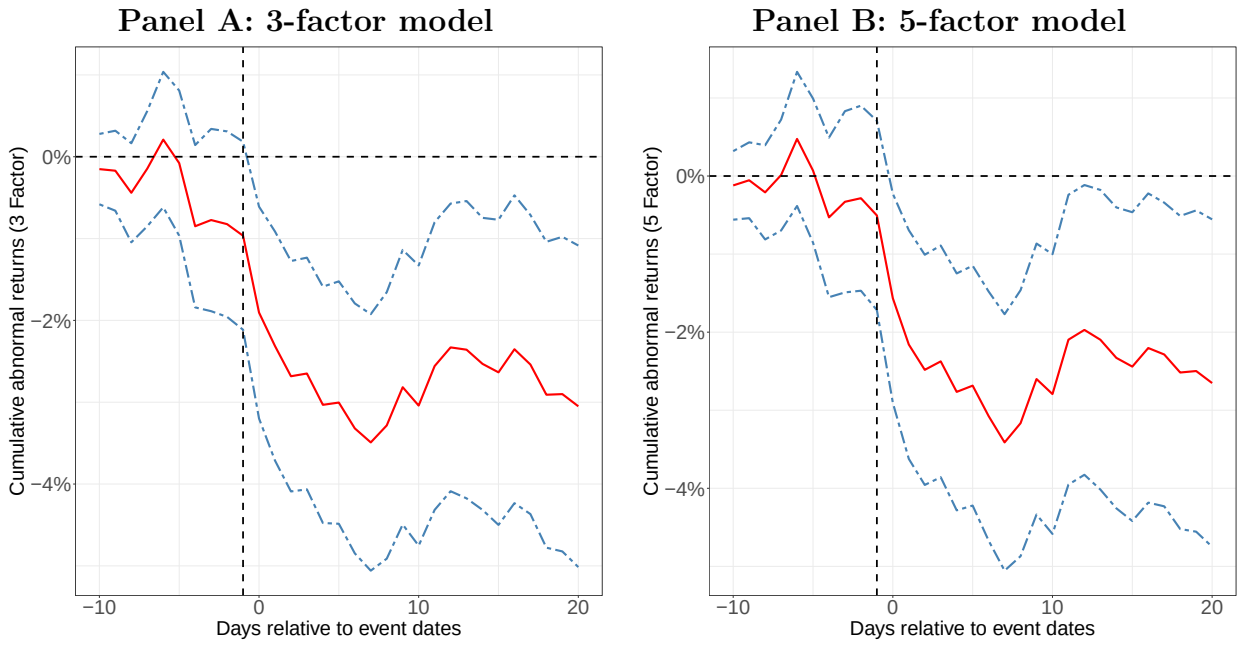


Figure 3: Performance with Local Projections. Figure 3 displays the dynamic coefficient estimates using the local projections approach of Dube et al. (2022), as presented in Equation (7). The dependent variable is the monthly fund volatility in Panel A and the 5-factor adjusted abnormal fund returns in Panel B.

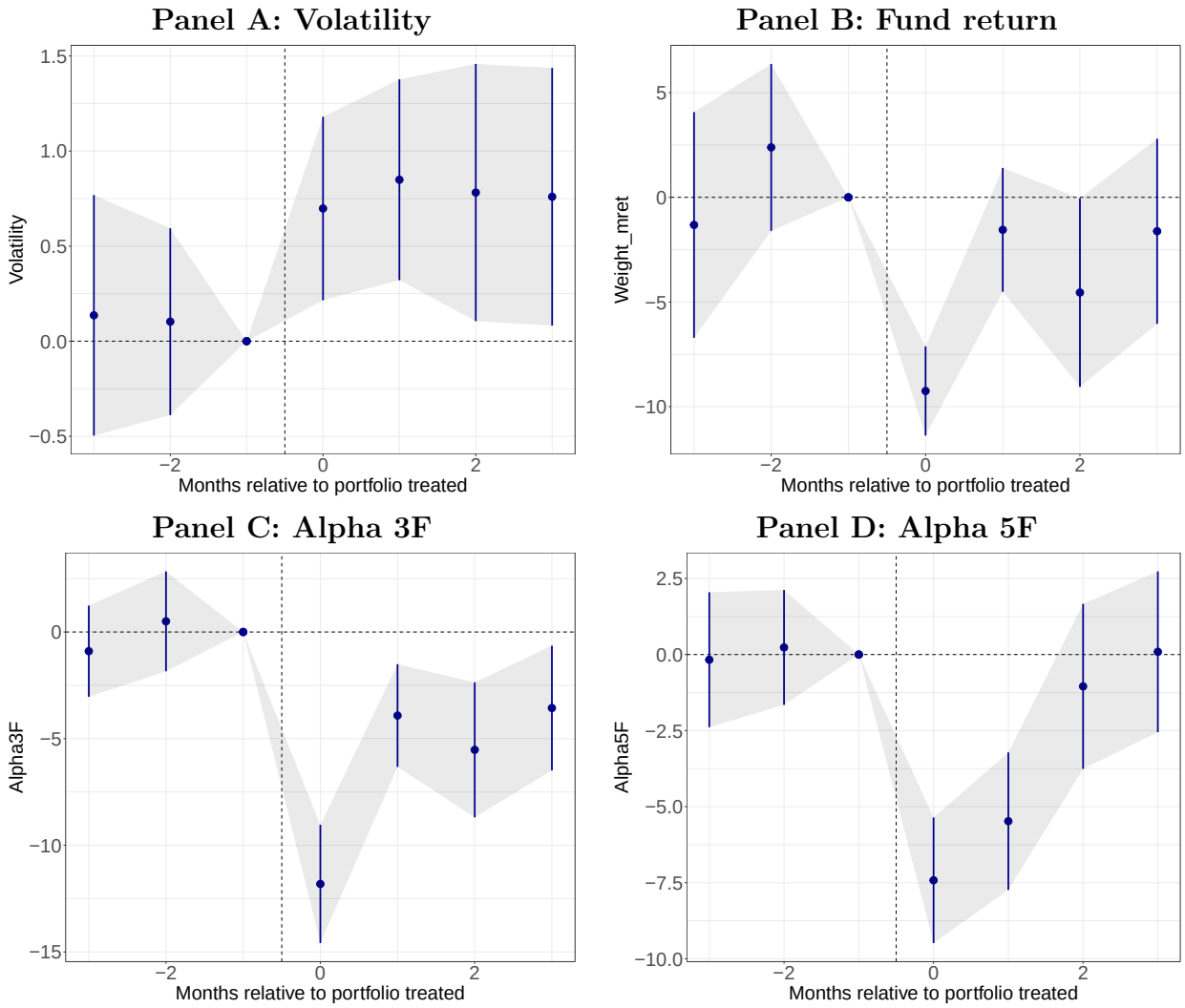


Figure 4: Trading Direction with Local Projections. Figure 4 displays the dynamic coefficient estimates using the local projections approach of Dube et al. (2022). The dependent variable is the trade direction. Panel A is the local projection estimate with fund and time fixed effect. Panel B is the local projection estimation with fund and style*time fixed effects.

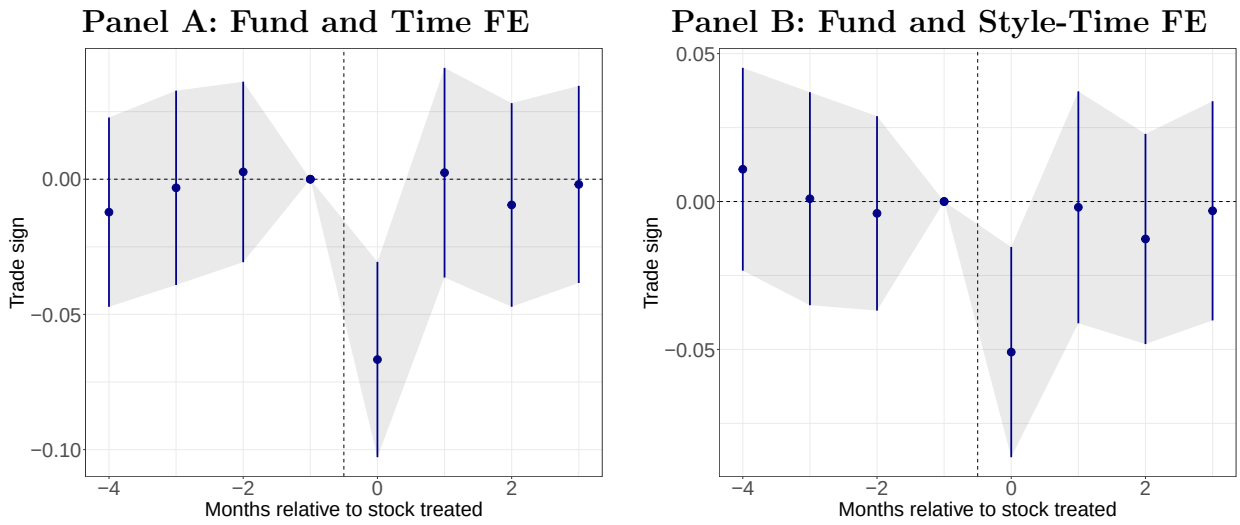


Table 1: Summary Statistics. Table 1 presents summary statistics of fund level characteristics. Volatility is the monthly standard deviation of daily fund returns in percentage points. Fund return is the monthly fund return in percentage points. Alpha 3F and Alpha 5F are the 3-factor and 5-factor adjusted 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 $\text{Exposure}|_{>0}$ 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	343,255	0.681	0.942	1.324
Fund return (%)	0.797	5.293	343,255	−1.996	1.158	3.766
Alpha 3F(%)	−0.209	2.442	267,972	−1.250	−0.136	0.912
Alpha 5F(%)	−0.154	1.960	267,972	−0.937	−0.120	0.662
$\mathbb{1}$(Exposure>0)	0.020	0.142	343,255			
$\text{Exposure}\|_{>0}$	0.020	0.024	7,024	0.008	0.014	0.026
China Share	0.275	0.183	338,585	0.128	0.239	0.407
Log Fund Size	6.029	1.755	338,585	4.722	5.968	7.196
Log Family Size	11.495	2.821	338,585	9.967	11.733	14.173
Expense Ratio	0.006	0.005	338,585	0.000	0.006	0.010
Turnover Ratio	0.438	0.669	338,585	0.000	0.250	0.600
Log Fund Age	2.438	0.875	338,585	2.025	2.622	3.012
Past Return (1Y) (%)	0.982	1.294	325,425	0.206	1.003	1.728
Flows	0.007	0.093	343,255	−0.014	−0.004	0.007
Actively-managed Fund	0.765	0.424	343,255			

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	10,324	135	110	49	94	55.3%	6.9%
S&P 500 INDEX OBJECTIVE	7,589	94	1	93	72	46.4%	1.5%
TELECOMMUNICATION	1,307	15	10	10	13	43.8%	6.0%
ALT. LONG/SHORT EQUITY	1,665	70	62	10	35	42.0%	1.9%
EQUITY LEVERAGE	2,651	106	88	19	36	36.4%	3.9%
GROWTH & INCOME	48,063	1,395	1,243	177	940	35.7%	2.0%
ALT. EQUITY MARKET NEUTRAL	282	13	12	1	4	35.4%	1.9%
GROWTH	100,282	1,897	1,704	333	1,178	35.1%	1.9%
EQUITY INCOME	19,620	331	311	67	233	34.3%	2.4%
CONSUMER SERVICES	3,265	34	25	18	11	31.1%	0.7%
BASIC MATERIALS	2,026	16	10	12	11	29.3%	2.8%
CAPITAL APPRECIATION	6,637	109	106	4	72	28.9%	1.8%
INDUSTRIALS	3,995	38	26	25	27	27.8%	5.7%
ABSOLUTE RETURN	356	19	19	1	3	27.8%	1.9%
CONSUMER GOODS	2,128	19	14	11	2	25.7%	2.0%
NATURAL RESOURCES	6,166	83	62	34	22	23.2%	3.3%
HEALTH/BIOTECHNOLOGY	7,683	89	70	36	40	20.4%	3.5%
EQUITY MARKET NEUTRAL	125	16	15	1	3	20.0%	0.0%
MID-CAP	41,021	704	626	114	507	18.0%	1.6%
SMALL-CAP	54,585	848	760	137	582	11.9%	1.4%
REAL ESTATE	10,987	140	117	36	-	9.9%	0.0%
MICRO-CAP	2,689	50	46	4	31	9.0%	1.8%
FINANCIAL SERVICES	6,218	68	50	35	12	5.5%	1.1%
UTILITY	3,140	35	28	13	5	3.6%	1.6%
PRECIOUS METALS EQUITY	435	15	11	6	-	2.4%	0.0%

Table 3: Performance and Exposure to Export Controls: Active Funds. Table 3 presents the results of estimating Eq. (2). 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					
Dep. var.:	Volatility			Return		
	(1)	(2)	(3)	(4)	(5)	(6)
Exposure	1.258***	1.212***	0.711***	-15.592***	-14.743***	-8.904***
	(0.149)	(0.135)	(0.107)	(3.386)	(3.509)	(2.809)
Observations	259,004	246,250	246,250	259,004	246,250	246,250
R^2	0.911	0.915	0.945	0.790	0.808	0.893
	Panel B					
Dep. var.:	Alpha 3F			Alpha 5F		
	(1)	(2)	(3)	(4)	(5)	(6)
Exposure	-12.795***	-11.790***	-6.075***	-9.192***	-8.500***	-3.441***
	(1.380)	(1.416)	(1.734)	(1.093)	(1.091)	(1.271)
Observations	202,981	194,803	194,803	202,981	194,803	194,803
R^2	0.131	0.213	0.550	0.090	0.129	0.458
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 and passive funds, separately. The dependent variable is Trade direction, which represents the sign of net trading. 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.

Dep. var.:	Panel A: Same month Trade Direction			
	(1)	(2)	(3)	(4)
Direct	-0.046***	-0.047***	-0.043***	-0.042***
	(0.015)	(0.014)	(0.014)	(0.014)
Observations	30,702,812	30,702,812	30,702,812	30,702,812
R^2	0.073	0.090	0.092	0.099
Dep. var.:	Panel B: Within 3 months Trade Direction			
	(1)	(2)	(3)	(4)
Direct	-0.033*	-0.035**	-0.030*	-0.030*
	(0.017)	(0.016)	(0.016)	(0.016)
Observations	30,702,812	30,702,812	30,702,812	30,702,812
R^2	0.081	0.092	0.094	0.101
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, separately. 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.

Dep. var.:	Trade direction (same month)		Trade direction (within 3 month)	
	(1)	(2)	(3)	(4)
Spillover	-0.002	0.002	-0.017***	-0.017***
	(0.006)	(0.006)	(0.006)	(0.007)
Observations	30,279,464	30,279,464	30,279,464	30,279,464
R^2	0.091	0.093	0.092	0.095
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 and passive funds, separately. The dependent variable is Trade direction, which represents the sign of net trading in the same month. 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 hold stocks currently affected by export controls. High Market, High SMB, and High HML are indicator variables equal to one if the stock is in the top quartile of market beta, size (SMB) beta, or value (HML) beta, respectively, and for funds that hold 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.

Dep. var.:	Trade direction (same month)							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Lottery	0.031***	0.025***						
	(0.008)	(0.008)						
High Market			0.008	0.011				
			(0.006)	(0.006)				
High SMB					0.021**	0.019**		
					(0.009)	(0.009)		
High HML							0.017**	0.018**
							(0.007)	(0.008)
Observations	30,279,464	30,279,464	30,279,464	30,279,464	30,279,464	30,279,464	30,279,464	30,279,464
R^2	0.091	0.093	0.091	0.093	0.091	0.093	0.091	0.093
Fund FE	✓	✓	✓	✓	✓	✓	✓	✓
Style×Time FE	✓	✓	✓	✓	✓	✓	✓	✓
Industry×Time FE		✓		✓		✓		✓
Fund Controls	✓	✓	✓	✓	✓	✓	✓	✓
Firm Controls		✓		✓		✓		✓

Table 7: Passive Funds and Performance. Table 7 presents the results of estimating a variation of Eq. (2). 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. Active is an indicator variable that identifies actively managed funds. All specifications include the lagged dependent variable, the Active indicator 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					
Dep. var.:	Volatility			Return		
	(1)	(2)	(3)	(4)	(5)	(6)
Exposure	0.406***	0.454***	-0.001	-17.777***	-19.124***	-15.724***
	(0.134)	(0.131)	(0.122)	(2.048)	(2.270)	(1.960)
Observations	79,504	76,674	76,674	79,504	76,674	76,674
R^2	0.912	0.914	0.957	0.756	0.778	0.905
	Panel B					
Dep. var.:	Alpha 3F			Alpha 5F		
	(1)	(2)	(3)	(4)	(5)	(6)
Exposure	-19.026***	-19.105***	-12.421***	-15.589***	-15.846***	-10.957***
	(2.146)	(1.960)	(2.168)	(1.917)	(1.872)	(1.901)
Observations	60,961	59,426	59,426	60,961	59,426	59,426
R^2	0.133	0.213	0.674	0.079	0.118	0.591
Fund FE	✓	✓	✓	✓	✓	✓
Time FE	✓	✓		✓	✓	
Fund Controls		✓	✓		✓	✓
Style×Time FE			✓			✓

Table 8: Placebo Test: Trading in Response to Export Controls by Passive Funds. Table 8 presents the results of estimating Eq. (3) for active and passive funds, separately. The dependent variable is Trade direction, which represents the sign of the net trading. 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.

Dep. var.:	Panel A: Same month Trade Direction			
	(1)	(2)	(3)	(4)
Direct	-0.014	-0.015	-0.023	-0.023
	(0.016)	(0.015)	(0.015)	(0.015)
Observations	29,701,870	29,701,870	29,701,870	29,701,870
R^2	0.134	0.171	0.174	0.182
Dep. var.:	Panel B: Within 3 months Trade Direction			
	(1)	(2)	(3)	(4)
Direct	-0.013	-0.003	-0.011	-0.016
	(0.017)	(0.015)	(0.016)	(0.016)
Observations	29,701,870	29,701,870	29,701,870	29,701,870
R^2	0.163	0.193	0.196	0.204
Fund FE	✓	✓	✓	✓
Time FE	✓			
Style×Time FE		✓	✓	
Industry×Time FE			✓	
Style× Industry×Time FE				✓
Fund Controls	✓	✓	✓	✓
Firm Controls	✓	✓	✓	✓

Table 9: Firm Level Analysis: Active vs Passive Fund Ownership. Table 9 presents the results of ownership by active and passive funds on stocks. Active ownership is the total shares of stocks held by all active funds relative to the total shares outstanding, adjusted with a factor of 1000. Passive ownership is the total shares of stocks held by all passive funds relative to the total shares outstanding, adjusted with a factor of 1000. The ownership gap is the difference of ownership between active and passive mutual funds. Direct is an indicator variable equal to one the first time that a U.S. supplier is affected. All specifications include as firm controls total assets, firm age, CAPEX, book leverage, the weight in the market portfolio, and an indicator for whether the firm exports to China. Standard errors are clustered at the stock and quarter level. *** p<0.01, ** p<0.05, * p<0.1.

Dep. var.:	Active Ownership		Passive Ownership		Ownership Gap	
	(1)	(2)	(3)	(4)	(5)	(6)
Direct	-4.807**	-5.601**	0.200	1.063	-5.007**	-6.664**
	(2.392)	(2.595)	(1.005)	(1.286)	(2.497)	(2.641)
Obs.	191,423	191,423	191,423	191,423	191,423	191,423
R^2	0.812	0.821	0.887	0.892	0.697	0.714
Firm FE	✓	✓	✓	✓	✓	✓
Time FE	✓		✓		✓	
Industry× Time FE		✓		✓		✓
Firm Controls	✓	✓	✓	✓	✓	✓

Table 10: Additional Fund-Level Outcomes: Sharpe Ratio and Flows. Table 10 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. All specifications 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					
Dep. var.:	Sharpe Ratio		Flows		Lead Flows	
	(1)	(2)	(3)	(4)	(5)	(6)
Exposure	-8.449***	-3.023***	-0.055	-0.072	-0.066*	-0.070
	(1.025)	(1.055)	(0.082)	(0.080)	(0.039)	(0.045)
Observation	194,803	194,803	246,250	246,250	245,717	245,717
R^2	0.114	0.436	0.097	0.131	0.089	0.122
	Panel B: Passive Funds					
Dep. var.:	Sharpe Ratio		Flows		Lead Flows	
	(1)	(2)	(3)	(4)	(5)	(6)
Exposure	-14.155***	-8.696***	0.136	0.075	-0.194***	-0.207***
	(1.790)	(1.733)	(0.156)	(0.151)	(0.074)	(0.079)
Observations	59,426	59,426	76,674	76,674	76,585	76,585
R^2	0.107	0.570	0.114	0.195	0.105	0.187
Fund FE	✓	✓	✓	✓	✓	✓
Time FE	✓		✓		✓	
Style×Time FE		✓		✓		✓
Fund Controls		✓		✓		✓

Table 11: Heterogeneity of Performance and Exposure to Export Controls: Manager Skills. Table 11 presents the results of estimating Eq. (6). 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), 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			
Dep. var.:	Volatility		Return	
	(1)	(2)	(3)	(4)
Exposure	0.696***	0.796***	-6.214***	-6.766***
	(0.119)	(0.116)	(1.812)	(1.707)
Market timing skill	0.003		0.010	
	(0.002)		(0.011)	
Exposure × Market timing skill	0.074		-10.096	
	(0.309)		(6.707)	
Stock picking skill		0.000		-0.054***
		(0.002)		(0.010)
Exposure × Stock picking skill		-0.330		-9.167
		(0.354)		(7.534)
Observations	245,551	245,551	245,551	245,551
R^2	0.945	0.945	0.894	0.894
	Panel B			
Dep. var.:	Alpha 3F		Alpha 5F	
	(1)	(2)	(3)	(4)
Exposure	-5.000***	-5.770***	-2.563**	-3.388***
	(1.547)	(1.444)	(1.284)	(1.162)
Market timing skill	0.000		-0.006	
	(0.011)		(0.012)	
Exposure × Market timing skill	-3.888		-2.989	
	(3.484)		(2.669)	
Stock picking skill		-0.035***		-0.008
		(0.010)		(0.010)
Exposure × Stock picking skill		-1.295		-0.080
		(3.867)		(3.006)
Observations	194,259	194,259	194,259	194,259
R^2	0.550	0.550	0.458	0.458
Fund FE	✓	✓	✓	✓
Style×Time FE	✓	✓	✓	✓
Fund Controls	✓	✓	✓	✓

Table 12: Heterogeneity of Performance and Exposure to Export Controls: Specialist Funds and High Fee Funds. Table 12 presents the results of estimating Eq. (6). 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			
Dep. var.:	Volatility		Return	
	(1)	(2)	(3)	(4)
Exposure	0.642***	0.582***	-10.238***	-13.549***
	(0.111)	(0.153)	(3.094)	(4.339)
Specialist Fund	0.003		-0.013	
	(0.003)		(0.009)	
Exposure × Specialist Fund	0.473**		7.981***	
	(0.238)		(2.802)	
High Fee Fund		0.001		0.013
		(0.003)		(0.014)
Exposure × High Fee Fund		0.260		8.863**
		(0.176)		(3.801)
Observations	245,551	245,551	245,551	245,551
R^2	0.945	0.945	0.894	0.894
	Panel B			
Dep. var.:	Alpha 3F		Alpha 5F	
	(1)	(2)	(3)	(4)
Exposure	-6.954***	-8.907***	-4.306***	-5.341***
	(1.780)	(2.347)	(1.326)	(1.718)
Specialist Fund	-0.021*		-0.005	
	(0.012)		(0.014)	
Exposure × Specialist Fund	5.411**		5.695***	
	(2.314)		(1.975)	
High Fee Fund		0.020		0.036**
		(0.017)		(0.017)
Exposure × High Fee Fund		5.439**		3.745**
		(2.309)		(1.829)
Observations	194,259	194,259	194,259	194,259
R^2	0.550	0.550	0.458	0.458
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.
High market beta stock	Dummy indicator if the market beta exposure of the stock daily returns is at the top quartile of all the stocks at the same month. The market beta is estimated based on Fama-French 3-factor model with daily stock return over the past 6 months.

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Table A.1 – *Continued from previous page*

Variable	**Description**
High SMB beta stock	Dummy indicator if the size beta exposure of the stock returns is at the top quartile of all the stocks at the same month. The market beta is estimated based on Fama-French 3-factor model with daily stock return over the past 6 months.
High HML beta stock	Dummy indicator if the book-to-market beta exposure of the stock returns is at the top quartile of all the stocks at the same month. The market beta is estimated based on Fama-French 3-factor model with daily stock return over the past 6 months.
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.
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.

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Table A.1 – *Continued from previous page*

Variable	**Description**
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). 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. All specifications include the lagged dependent variable. 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.

Dep. var.:	Volatility	Return	Alpha 3F	Alpha 5F
	(1)	(2)	(3)	(4)
Exposure	0.717***	-8.956***	-6.096***	-3.406***
	(0.111)	(2.868)	(1.716)	(1.304)
China Share	-0.008	0.135**	0.233***	0.447***
	(0.017)	(0.057)	(0.067)	(0.074)
Log Fund Size	0.004**	-0.064***	-0.071***	-0.077***
	(0.002)	(0.007)	(0.008)	(0.008)
Log Family Size	0.002	0.011**	0.003	-0.009
	(0.002)	(0.006)	(0.007)	(0.008)
Expense Ratio	0.013	-0.352	2.306	3.126
	(0.416)	(1.734)	(1.996)	(1.948)
Turnover Ratio	0.007**	-0.014	-0.024*	-0.045***
	(0.003)	(0.011)	(0.014)	(0.015)
Age	-0.011***	0.036***	-0.031	-0.036
	(0.004)	(0.012)	(0.025)	(0.027)
Past Return (1Y)	-5.111***	107.722***	97.725***	49.798***
	(0.210)	(1.336)	(1.149)	(1.221)
Lag Volatility	0.116***			
	(0.004)			
Lag Fund return		-0.029***		
		(0.002)		
Lag Alpha 3F			-0.067***	
			(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	✓	✓	✓	✓
Fund Controls	✓	✓	✓	✓
Style×Time FE	✓	✓	✓	✓

Table A.3: Volatility Decomposition for Active Funds. Table A.3 presents the results of estimating a variation of Eq. (2) for active funds. The dependent variables are the fractions of fund volatility that is systematic (Sys Vol) and idiosyncratic (Id Vol), using the 3-factor model of (Fama and French, 1993). 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, China Share, 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.

Dep. var.:	Sys Vol		Id Vol	
	(1)	(2)	(3)	(4)
Exposure	0.734***	0.443***	1.365***	0.964***
	(0.132)	(0.094)	(0.177)	(0.165)
Obs.	197,727	197,727	197,727	197,727
R^2	0.924	0.957	0.905	0.934
Fund FE	✓	✓	✓	✓
Time FE	✓		✓	
Style×Time FE		✓		✓
Fund 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 that 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 level. *** p<0.01, ** p<0.05, * p<0.1.

Dep. var.:	Panel A: Active Funds Trade Direction			
	(1)	(2)	(3)	(4)
Direct	-0.037**	-0.037**	-0.032**	-0.033**
	(0.015)	(0.015)	(0.014)	(0.014)
Observations	16,459,341	16,459,341	16,459,341	16,459,341
R^2	0.072	0.084	0.086	0.091
Dep. var.:	Panel B: Passive Funds Trade Direction			
	(1)	(2)	(3)	(4)
Direct	0.002	0.005	-0.001	-0.001
	(0.018)	(0.017)	(0.017)	(0.017)
Observations	13,596,055	13,596,055	13,596,055	13,596,055
R^2	0.164	0.194	0.198	0.204
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 that 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 level. *** p<0.01, ** p<0.05, * p<0.1.

Dep. var.:	Panel A: Active Funds Trade Direction			
	(1)	(2)	(3)	(4)
Spillover	-0.014**	-0.014**	-0.011**	-0.011**
	(0.006)	(0.005)	(0.005)	(0.005)
Observations	15,717,431	15,717,431	15,717,431	15,717,431
R^2	0.072	0.084	0.086	0.091
Dep. var.:	Panel B: Passive Funds Trade Direction			
	(1)	(2)	(3)	(4)
Spillover	-0.003	0.011	0.008	0.008
	(0.009)	(0.007)	(0.007)	(0.007)
Observations	13,070,721	13,070,721	13,070,721	13,070,721
R^2	0.163	0.193	0.197	0.203
Fund	✓	✓	✓	✓
Time	✓			
Style×Time		✓	✓	
Industry×Time			✓	
Style× Industry×Time				✓
Fund Controls	✓	✓	✓	✓
Firm Controls	✓	✓	✓	✓