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ABSTRACT

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1. Introduction

Half a century ago, Malkiel (1973) wrote "I have become increasingly convinced that the past records of mutual fund managers are essentially worthless in predicting future success." Concluding the stock market is sufficiently informationally efficient to render picking stocks pointless, he proposed a radical new investment strategy: passive investment in the form of index funds.[1] Since Vanguard launched the first index fund in 1973, the total value of assets under passive management worldwide has grown to US$14.5 trillion in 2022 (Kerzérho 2023).[2] Indeed, by 2022, passive managers reportedly ran more US equity than did active managers.[3] This is perhaps the most consequential contribution of academic research to the investment management sector.

However, no innovator escapes rebuke. Malkiel's critics charge index investing with undermining the very informational efficiency that he argues justifies its existence. As Shiller explains, "indexing … is really free-riding on other people's work … So people say, 'I'm not going to try to beat the market. The market is all-knowing.' But how in the world can the market be all-knowing, if nobody is trying — well, not as many people — are trying to beat it?"[4]

That is, the informational efficiency that renders passive investment viable depends on trading by active investors with private information (Grossman and Stiglitz 1980; Roll, 1988). Indeed, active investment underlies all the positive externalities of informationally efficient stock prices: Active informed trading pushes stocks to prices near their fundamental values, and so provide uninformed diversified savers (including index fund investors) acceptable risk-adjusted returns (Black 1986). Second, stocks priced near their fundamental values validate the costs of capital corporate managers use in capital budgeting decisions. Third, changes in stock prices that track changes in fundamental values give corporate managers informed market feedback about their decisions (Bond, Edmans and Goldstein, 2012).[5]

Thus, a major shift of funds away from active managers and into indexing can untether stock prices from fundamentals with adverse consequences for investors and the economy

1 Renshaw and Feldstein (1960) had also suggested a diversified buy-and-hold strategy.
2 Bogle (2014) stresses Paul Samuelson's (1976) encouragement of Vanguard's indexing initiative.
3 Johnson, S. 2022. Passive fund ownership of US stocks overtakes active for first time. *Financial Times* June 5.
4 Quoted in Landsman (2017).
5 On stock prices feeding back to alter corporate decisions, see also Dow and Gorton (1997); Chen, Goldstein and Jiang (2007); Bakke and Whited (2010); Foucault and Frésard (2012, 2014); and Edmans, Jayaraman and Schneemier (2017).

(Wurgler 2011). Indeed, *in reductio ad absurdum*, if all investors bought only index funds, the market capitalizations of stocks included in index funds would sum to, and rise and fall in synch with, aggregate demand for equities. However, Malkiel counters "We don't have too much indexing; we have too much active management. I think the market could function fine with just 2% or 3% of investors being active and making sure that information was reflected properly in prices" (Akst, 2022).

Whether or not the escalating scale of index investing in recent decades has reduced the information content of stock prices is thus an empirical question of considerable importance (Landsman 2017). An empirical test to measure differences in ongoing information incorporation into stock prices due to differences in the level of index investing requires overcoming several challenges.

First, such tests require exogenous ongoing information inflows of comparable importance when the stock is in the index and when it is not. Section 2 argues that foreign currency rate (forex) fluctuations in the currencies of major U.S. trading partners serve this purpose. First, forex markets are global, and thus unlikely to be affected by any US firm being in or not in the S&P500 index. Second, forex markets are highly visible to all market participants. Third, forex fluctuations affect firms idiosyncratically, benefiting some, harming others, and leaving yet others undisturbed. Our tests therefore focus on the information in forex fluctuations that move U.S. stocks.

Second, such tests must distinguish information-driven stock-price movements from other stock price movements. Event studies demonstrate that information moves stock prices, but financial history demonstrates that manias, panics, and crashes do so as well. Samuelson (Shiller 2001, p. 243) famously notes this juxtaposition of micro-efficiency with macro inefficiency. Section 2 draws on the accumulating empirical and theoretical work that affirms and explains this Samuelson's Dictum effect to argue that tests for differences in ongoing information incorporation most efficaciously exclude macro (systematic or market-related) and focus on micro (idiosyncratic or firm-specific) stock price movements. Our tests, therefore, assess ongoing information incorporation by measuring idiosyncratic stock price reactions to idiosyncratic fluctuations in foreign currencies.

Third, such a test must compare ongoing information incorporation for the same stock at discretely different levels of index fund ownership. More money is indexed to the S&P500 than to any other index, so we focus on firms being included in or dropped from the S&P500, mechanically precipitating increases or decreases, respectively, in the ongoing level of index fund ownership of their stocks. Many researchers follow Shleifer (1986) in interpreting abnormal returns on stocks' inclusion and deletion dates as reflecting increased or decreased passive demand, a non-information-driven firm-specific stock price change, and thus an exception to Samuelson's Dictum. Others argue that index composition changes are, at least partly, predictable or that abnormal returns on those changes, at least partly, reflect new information or changes in transparency or liquidity associated with index membership. Section 2 explains how this literature leads us to exclude a blackout window of data immediately surrounding a firm's addition to or deletion from the S&P500 index and to assess differences in its idiosyncratic sensitivity to idiosyncratic foreign currency shocks at different levels of index ownership when it is in versus not in the index.

Given these three considerations, our tests focus on firms that are added to or dropped from the S&P500 index and are idiosyncratically (positively or negatively) sensitive to a major U.S. trading partner's currency. We call these *treated* firms. Our tests use twelve months of firm-specific returns data surrounding each treated firm's addition to or deletion from the index, omitting twenty trading days on either side of the date of the change itself. These data allow us to estimate differences in sensitivity to idiosyncratic information (foreign currency fluctuations) given differences in the level of index investment (when the stock is in the index versus not in it). Each added or dropped stock's foreign currency sensitivity is assessed in a six month out-of-index window adjacent to the twelve-month window described above, and only stocks whose idiosyncratic returns significantly track a major foreign currency are included as treated firms.

Our baseline tests reveal a 50% drop ($t = -4.31, p \cong 0.00$) in stocks' idiosyncratic currency sensitivity when in versus not in the S&P500, whereas the magnitude of idiosyncratic currency shocks does not change. Moreover, the drop grows larger over time, in lockstep with plausible proxies for the rising importance of index investing. These results are consistent with the idea that index investing impairs the incorporation of firm-specific information into stock prices, validating Shiller's concern.

Further tests show our baseline results to be highly robust. First, alternative winsorization bounds, data frequencies, idiosyncratic returns estimation procedures, and other changes yield qualitatively similar results, meaning identical patterns of signs and significance and comparable point estimates. Second, no lagged idiosyncratic stock return responses to idiosyncratic currency fluctuations are evident, so responses to information are damped, not just delayed a few days. Third, other business environment changes coincident to the treated firms' index status changes do not drive the results because placebo firms, each matched to a treated firm by size, past returns, and idiosyncratic sensitivity to the same foreign currency, exhibit no significant difference in idiosyncratic currency sensitivities around their matched treated firms being added to or dropped from the S&P500. Moreover, a balanced difference-in-differences event study test, contrasting the treated and placebo firms, reproduces the baseline result precisely. When the treated firms are in the S&P500 index, their idiosyncratic currency sensitivity is significantly lower than that of their matched placebo firms; when the treated firms are not in the S&P500 index, their idiosyncratic currency sensitivity is statistically indistinguishable from that of their matched placebo firms.

Yet further tests consider and reject alternative explanations of the baseline finding. One alternative explanation is that inclusion in the S&P500 index recognizes a firm as an established leader in its industry, and more established firms tend to be more risk-averse (Bertrand and Mullainathan, 2003; Chun et al., 2008; John et al., 2008). Thus, firms might hedge risk more intensely when in the S&P500 than when not in it. Our baseline results are unaffected by controlling for in- versus out-of-index differences in accounting ratios that measure hedging intensity, currency hedging intensity measures constructed from text scans of disclosure documents, and artificial intelligence assessments of firms' currency hedging intensity. Moreover, firms do not appear to hedge more intensely when in the index than not in it. Controlling for differences in hedging intensity might be insufficient if firms adopt markedly more conservative strategies immediately after accession to the S&P500, as this would reduce their fundamentals sensitivity to currency fluctuations with hedging unchanged. We can also reject this because our results are robust to controlling for changes in the sensitivity of fundamental returns to currencies.

Three conclusions follow. First, concerns about escalating index investing blunting the incorporation of information into stock prices cannot be dismissed. Second, neither can attendant concerns about index investing thereby decreasing the large positive externalities of informationally efficient stock markets, including greater allocative efficiency (Wurgler 2000) and more useful feedback from stock prices to corporate decision-makers (Bond et al. 2012). Third, our empirical techniques might find more general application. Differences in idiosyncratic stock return responses to other ongoing streams of idiosyncratic information around other differences in firms' information environments might enhance our understanding of the strengths and weaknesses of stock markets in processing information and coordinating economic activity. We welcome further research into these topics.

2. Considerations in Formulation of Empirical Tests

Testing for differences in the incorporation of information into stock prices due to differences in the level of index investing encounters several challenges. First, such tests require ongoing series of information events relevant to a stock, but unaffected by the level of index investment in that stock. Second, such tests must distinguish between information-driven and demand- or sentiment-driven stock price changes. Third, such tests require exogenous differences in the level index investing. This section explains how prior work relevant to these issues motivates our empirical methodology: identifying stocks sensitive to foreign currency fluctuations, focusing on idiosyncratic returns, and testing for differences in idiosyncratic stock returns sensitivities when a stock has different levels of index fund ownership as a result of having been recently included in or dropped from the S&P500.

2.1 Directly Comparable Information Events

Our tests leverage the ongoing information flow of information from foreign currency markets to stock markets, as this information flow is exogenous to any individual stock being in or out of the S&P500. We identify stocks that are sensitive to major US trading partner currencies when not in the index. Because foreign currency fluctuations affect some firms positively, others negatively, and yet others not at all, their impact on individual stocks can be idiosyncratic. We then contrast the magnitudes of the stock's idiosyncratic fluctuations as the foreign currency moves when the stock is in the S&P500 versus not in it, ascertaining that the magnitude of idiosyncratic currency fluctuation is unchanged.

Our approach is fundamentally different from those used in the prior literature, which relies on various indirect proxies for the information content of stock prices and arrives at divergent conclusions. Many credible empirical studies link indexing to reduced informational efficiency and impressive theoretical work explains this. See e.g. Goetzmann and Massa (2002); Israeli et al. 2017; Qin and Singal (2015); Israel et al. (2017); Ben-David et al. (2018); Broman (2016); Da and Shive (2018); Bennett et al. (2020); Billett, Diep-Nguyen and Garfinkel (2020) and Brown et al. (2021)). Other equally credible empirical studies, likewise buttressed by impressive theoretical models, reach diametrically opposite conclusion. See e.g. Boehmer and Kelley, 2009; Chan et al. 2013; Cremers et al. 2016; Marshall et al., 2013; Stambaugh, 2014; Boone et al., 2015; Madhavan, 2016; Madhavan and Sobczyk, 2016; Bai et al., 2016; Schmidt and Fahlenbrach, 2017; Breugem and Buss, 2019; Weissensteiner, 2019; Glosten et al., 2021; Huang et al., 2021; Li et al., 2022. Yet others, see e.g. Coles et al. (2022), report that indexing does not alter informational efficiency. Moreover, more nuanced approaches that allow for both possibilities also disagree. For example, Baruch and Zhang (2022) link increased indexing to lower firm-specific informational efficiency and higher market-wide informational efficiency; whereas, Bond and Garcia (2022) reverse this conclusion. In summary, how indexing affects stock market informational efficiency remains debatable.

One reason this debate continues is that the empirical work relies on indirect proxies for either the scale of passive investment or the incorporation of information into stock prices, or both. Many of the above studies use ETF ownership to proxy for passive investment; however, many ETFs follow explicit index-beating active strategies (Easley et al. 2021). Many also use information proxies with context-dependent interpretations. One such proxy is idiosyncratic volatility in stock returns (Morck et al. 2000). All else equal, less idiosyncratic stock return volatility is theoretically linked to less idiosyncratic information entering stock prices (Veldkamp 2006; Wei and Zhang 2006). However, Roll (1988) allows that idiosyncratic stock price movements might also reflect "investor frenzy" and some studies thus deem idiosyncratic variation to be noise.[6] Bennet et al. (2020) and many others measure idiosyncratic volatility as a ratio: idiosyncratic over either systematic or total volatility. However, Li et al. (2014) note that many phenomena can affect both idiosyncratic and systematic volatility, and thus recommend the numerator alone to best reflect idiosyncratic information. In our context, stocks added to major indexes start co-moving more with those indexes (Barberis et al. 2005; Vijh 1994), increasing their systematic volatility and lowering the ratio. Other popular proxies, such as GPIN, derive from bid-ask spreads. These proxies gauge information asymmetry between market makers and other investors (Aktas et al., 2007), rather than the information content in stock returns, which is not the primary concern raised by critics of indexing. Thus, Bennet et al. (2020) report their GPIN result attenuating over time as indexing expanded. Yet another proxy for market efficiency, the proximity of stock returns to a random walk, is challenged by Griffin et al. (2010). Baltussen et al. (2019) argue that indexing might alter such measures without changing informational efficiency.

[6] See e.g. Bhagat et al. (1985), Krishnaswami et al. (1999) and Aabo et al. (2017).

Our tests have several key advantages. First, by entirely avoiding proxies for information efficiency and instead directly testing the incorporation of an ongoing flow of information about exchange rate changes into stock prices, our tests circumvent the criticisms of indirect proxies mentioned above. Second, exchange rate fluctuations are exogenous to any firm's index membership status because they are set in global markets. Third, the exchange rates we use are those of major US trading partners and are all highly liquid and are visible to all market participants.

2.2 Idiosyncratic Returns as Information

Prior research on stocks being added to and dropped from widely followed indexes has been pivotal in revealing that sentiment-driven investor demand, as well as information, can move stock prices (Vijh, 1994; Barberis and Shleifer, 2003; Barberis et al., 2005; Greenwood, 2008; Boyer, 2011, Wahal and Yavuz, 2013). To explore differences in how information moves a stock when it is in versus not in the S&P500 index, we must distinguish stock price fluctuations that are most likely information-driven from those that are most likely sentiment-driven.

To do this, we evoke Samuelson's Dictum (Shiller 2001, p. 243) that "markets show considerable micro efficiency. ... [but] considerable macro inefficiency, in the sense of long waves in the time series of aggregate indexes of security prices below and above various definitions of fundamental values." Samuelson's Dictum follows from the juxtaposition of two streams of research. Financial history links intermittent stock market manias, panics and crashes (Kindleberger 1978; Lee, Shleifer and Thaler 1991; Shiller 1981, 1990; De Long et al. 1990; Aliber et al. 2015) to peaks and troughs in sentiment-driven demand for stocks. Event studies (Fama et al. 1969) consistently relate changes in individual firms' stock prices relative to market indexes to new information relevant to those firms not just in economics and finance (Doron and Gurevic, 2014), but also in accounting (Corrado, 2011), international business (El Ghoul et al., 2022), law (Bhagat and Romano, 2002); marketing (Johnston, 2007), operations and supply chain management (Ding et al., 2018), and elsewhere.

Samuelson's dictum has accumulated compelling evidence. Excess volatility is evident in stock market index returns, but not in firm-specific stock returns (Jung and Shiller, 2005; Choi et al., 2020). Market-wide fluctuations tend to be transitory (Campbell, 1991), while firm-specific stock price changes tend to be permanent (Vuolteenaho, 2002). New share issues, associated with overvaluations (Myers and Majluf 1984), rise with market-wide, but not firm-specific, upswings

(Lamont and Stein 2006). Idiosyncratic stock return volatility is information-driven (Durnev et al., 2003; Jeon et al., 2022) and enhances allocative efficiency (Wurgler, 2000; Durnev et al., 2004). Market-wide returns reflect sentiment-driven aggregate demand for savings (Gabaix and Koijen, 2021). Combining these findings, Gârleanu and Pedersen (2022) and Glasserman and Mamaysky (2023) derive Samuelson's Dictum in information economics models.

Therefore, to examine whether escalating indexing has reduced the information content of stock prices, we focus on variation in firm-specific returns. This has the added advantage of removing elevated market-related volatility associated with index membership (Vijh, 1994; Barberis and Shleifer, 2003; Barberis et al., 2005; Greenwood, 2008; Boyer, 2011).

2.3 Exogenous Differences in the Level of Index Investing

The stockholdings of S&P500 index funds are mechanically determined by the composition of the S&P500 index (Bennett et al. 2020). S&P intermittently adds and drops firms to reflect the changing importance of different industries and also adds firms to replace S&P index firms delisted after being taken over. Because index fund managers are incentivized to minimize tracking error, not to outperform the index, they sell all their shares of firms dropped from the S&P500 on the dates the firms are dropped and buy shares of firms added to the index on the dates their inclusions become effective. Consequently, being in versus not in the S&P500 index indicates, respectively, an exogenously higher or lower level of index fund investment.

Prior research links abnormal returns on these event dates to exogenous changes in index fund demand (Shleifer 1986). However, because Standard and Poor's, which oversees the S&P500, is a bond rating agency with proprietary information, its choices of which firms to include or drop may convey information (Dhillon and Johnson, 1991). Front running and illiquidity-linked reversals are also reported in ten to twenty trading day windows around these event dates (Lynch and Mendenhall, 1997; Hedge and McDermott, 2003). Because we are interested in stocks in versus not in the index, rather than abnormalities on their entry or exit dates, we can mitigate these problems by excluding a blackout window of 20 trading days before after the event dates. Thus, even if S&P500 composition changes are not random, and this affects abnormal returns on and immediately around those changes, future changes in the sensitivity of firms' idiosyncratic returns to idiosyncratic currency fluctuations are unlikely to drive S&P500 composition changes. Therefore, we believe that the difference in index ownership in the longer 12-month test window surrounding the event date, excluding the blackout window, is exogenous for our purposes.

3. Data and Methodology

3.1 Data Sources

We obtain inclusion and deletion events from the CRSP S&P500 list, which provides the beginning and end dates of firms that are included in the S&P500 Index[7]. Our sample period covers the time period between 1970 and the end of 2019. Stock returns are from CRSP and accounting information is from the CRSP-Compustat merged dataset.

Daily exchange rate returns relative to the US dollar for the largest 15 trade partners of the US, listed in Table 1, are from the Federal Reserve. Eurozone countries' national currencies are used prior to their accessions to the Eurozone. We exclude the Chinese Yuan from January 1999 to June 2005 when it was hard-pegged to the US Dollar.

To infer hedging-related activities from treated firms' EDGAR SEC 10-Ks, 10-K405s, 20-Fs, and 40-Fs files, which are available from 1994 on, we map CRSP permnos to SEC CIKs.[8] Because deletions often follow mergers and acquisitions, using one CIK per firm-event may result in missing filings before (or after) the event date. In such cases, we manually search for information in the firm's filing closest to the event date to identify the firms involved in those transactions and use their filings. Once we have identified all relevant CIKs, we search all SEC filings for up to two years before and two years after the event date.

3.2 Estimating Idiosyncratic Stock and Currency Returns

We refer to firm i being added to or dropped from the S&P500 index on day t as the *index change event* (i, t). Our goal is to see if the incorporation of firm specific information into stock i's returns differs when i is in versus not in the S&P500 index.

To calculate the idiosyncratic component of returns we use the Market Model, with the CRSP value-weighed total market return serving as the market return as follows

$$R_{i,\tau} = \alpha_i + \beta_i R_{m,\tau} + \varepsilon_{i,\tau}, \tag{1}$$

where $R_{i,\tau}$ is the day τ total (cum dividend) return of stock i, $R_{m,\tau}$ is the value weighted market total return and $\varepsilon_{i,\tau}$ is the firm specific component of stock i return at time τ. Consistent with the

7 We drop a few firms that are added to and dropped from the S&P500 the same day. These are new spinoffs of S&P500 firms. Some firms are added to and/or dropped from the S&P500 more than once. We require these events to be at least 2 years apart to avoid estimation windows overlap.

8 We rely on three different sources: i) Capital IQ, ii) WRDS SEC linking tables, and iii) CRSP/Compustat Merged linking tables. In all three, we match permnos with CIKs through Compustat's gvkey identifiers. We prioritize matches from sources i) and ii) since the CRSP/Compustat Merged linking table only provides header CIKs.

literature (e.g. Morck et al. 2000; Campbell et al. 2001), the median R^2 of regressions [1] across all event stocks is 0.18 – that is, 18% of variation is systematic and 82% is idiosyncratic.

An analogous specification calculates idiosyncratic currency returns:

$$R_{c,\tau} = \alpha_i + \beta_c R_{m,\tau} + \varepsilon_{c,\tau}, \qquad [2]$$

where $R_{c,\tau}$ is the day τ return in US dollars of holding currency c in US dollars, $R_{m\tau}$ is the value weighted market return and $\varepsilon_{c\tau,}$ is the idiosyncratic component of currency c return for day τ. Unsurprisingly, the R^2 of [2] is higher for countries more integrated with the US and in later time periods when globalization is more complete.

3.3 Identifying Idiosyncratically Currency-sensitive Firms

For each index change event (i, t), we regress stock i's idiosyncratic returns, the $\varepsilon_{i,\tau}$ from [1], on the idiosyncratic returns of every currency $\varepsilon_{i,\tau}$from [2] for all possible matchings of events (i, t) to currencies c. That is,

$$\varepsilon_{i,\tau} = a_{c,i,t} + b_{c,i,t}\,\varepsilon_{c,\tau}, \qquad \tau \in W_{i,t}^{e} \qquad [3]$$

The $\varepsilon_{i,\tau}$ and $\varepsilon_{c,\tau}$, are estimated in a window $W_{i,t}^{e}$ when the firm is outside S&P500: the 6-month time period spanning 7 to 13 months before (after) the event date t for stocks added to (dropped from) the index. This precludes any change in idiosyncratic currency-sensitivity due to index membership from affecting $b_{c,i,t}$. It also leaves a 12-month span around the event date t in which estimate the difference in stock i's idiosyncratic currency sensitivity when in versus not in the index.

We classify stock i as *idiosyncratically currency sensitive* to currency c around event date t if the absolute value of the t-statistic for $b_{c,i,t}$, designated $|t(b_{c,i,t})|$, is larger than or equal to 2. If firm i matches to multiple currencies, we pick the currency whose $|t(b_{c,i,t})|$ is largest. Matching by $|t(b_{c,i,t})|$ treats positive and negative stock price sensitivity to a currency shock equally. If this procedure matches firm i to currency c, we have a usable event (c, i, t) with $b_{c,i,t}$ gauging firm i's idiosyncratic currency sensitivity to currency c for that event.

Vetting all S&P500 changes from 1970 through 2019 in this way yields 583 usable events (c, i, t), in which firm i's index status changes on day t, firm i is sensitive to currency c, and firm i stock returns data are available in sufficiently long windows, both before and after t, to allow the tests below. Of these events, 398 are firms being added to the S&P500 and 185 are firms being dropped from it. We have fewer dropped firms because many are acquired and delisted, and so lack stock returns data after being dropped from the index. The replacements S&P selects for these dropped firms are all previously listed, so in-index and out-of-index returns are available for firms added to the index.

Table 1 summarizes the distribution of these events across currencies The most, 94, are sensitive to the Canadian dollar, 85 to the Chinese Yuan, and lesser numbers are sensitive to the currencies of other major US trading partners. Figure 1 shows that the distribution of events over time has no apparent trend.

3.4 Estimating Differences in Idiosyncratic Information Incorporation Associated with Differences in Passive Investment

For each usable event (c, i, t), we estimate the difference in firm i's idiosyncratic currency sensitivity, $b_{c,i,t}$, between proximate windows around then index status change date t when i is in and when not in the S&P500. To do this, we run the regressions

$$\varepsilon_{i,\tau} = a_{c,i,t}^{out} + b_{c,i,t}^{out} sign(b_{c,i,t})\varepsilon_{c,\tau} + e_{i,\tau}, \ \ \tau \in W_{c,i,t}^{out} \qquad [4]$$

$$\varepsilon_{i,\tau} = a_{c,i,t}^{in} + b_{c,i,t}^{in} sign(b_{c,i,t})\varepsilon_{c,\tau} + e_{i,\tau}, \ \tau \in W_{c,i,t}^{in} \qquad [5]$$

where $\varepsilon_{i,\tau}$ is the daily idiosyncratic return of stock i at time τ from [1], and $\varepsilon_{c,\tau}$ is the daily idiosyncratic return of currency c at time τ from [2]. If the event involves firm i being added to the index at time t, the estimation window $W_{c,i,t}^{out}$ is seven to one month prior to the event, and $W_{c,i,t}^{in}$ is one to seven months after the event. If i is being dropped from the index at t, $W_{c,i,t}^{out}$ is seven to one month after the event, and $W_{c,i,t}^{in}$ is from one to seven months before the event. Omitting a blackout window $[t_L, t_U]$ of one month (20 trading days) on either side the event day t excludes abnormal returns due to the index status change itself. We multiply idiosyncratic currency returns by $sign(b_{c,i,t})$, the sign of firm i's idiosyncratic sensitivity to c, so the expected $b_{c,i,t}^{out}$ and $b_{c,i,t}^{in}$ are always positive. Figure 2 shows the estimation timeline for currency matching and estimation windows before and after the event.

After running the regressions for each firm and event we calculate

$$\Delta b_{c,i,t} = b_{c,i,t}^{in} - b_{c,i,t}^{out}. \qquad [6]$$

the difference in the currency-sensitive firm $\boldsymbol{i}$'s stock when it is in the S&P500 minus when it is not in the S&P500. The tests below all focus on [6] or variants thereof.

4. Findings

4.1 Baseline Result

Table 2 summarizes the difference in idiosyncratic currency sensitivity, $\Delta b_{c,i,t}$, for firms added to or dropped from the S&P500. The $\Delta b_{c,i,t}$ are winsorized at 10% to mitigate the influence of outliers (robustness tests provide results without winsorization). Column 2.1 show an average idiosyncratic currency sensitivity is -0.19 (t = -3.79) lower when firms are in the index than when the same firms are not in the index. Meanwhile, the magnitudes of the idiosyncratic currency shocks affecting these firms when in versus not in the index are statistically indistinguishable (difference in means = -0.00001, p = 0.70).

Because indexing became more prominent after the early 1990s, we re-estimate 2.1 in two subperiods: 1970 to 1990 and 1990 to 2019. Column 2.2 shows no significant difference in idiosyncratic currency sensitivity around events prior to 1990 and column 2.3 shows a significant -0.23 (t = -4.31) change in idiosyncratic currency sensitivity associated with index membership after 1990. We therefore focus on the latter period of 1990 through 2019 and take column 2.3 of Table 2 as our baseline result.

4.1 Idiosyncratic Information and the Scale of Index Investing

The difference in incorporation of idiosyncratic information around entry and exit events, especially in the latter period 1990 to 2019, is consistent with index investing damping the incorporation of idiosyncratic information into stocks prices. This section explores the correlation of this effect with various proxies for the extent of index investing.

The first is the fraction of quarterly holdings by mutual funds included in the CRSP mutual funds index held by S&P500 index funds. To identify index funds, we regress each mutual funds' monthly returns on the S&P500 index return and deem any fund whose market beta falls between 0.99 and 1.01 and whose regression R^2 exceeds 0.98 an S&P index fund. This captures so-called closet or shadow indexers, which claim manage actively but are actually de facto index funds and which Cremers and Petajisto (2009) show to be important. The second quarterly proxy augments the first by including ETFs. Because many ETFs have active portfolio strategies (Easley et al. 2021), we use the same methodology as above to identify index ETFs. The third index investing proxy includes all passive funds regardless of which index they track over all institutional investors' holdings in S&P500 stocks. This measure is from Billett, Diep- Nguyen and Garfinkel (2020), who flag funds that track any index as passive (for background, see Schmidt and Fahlenbrach 2017; Cremers and Petajisto 2009). The data span 1996 through 2017.

The final index investing proxy is monthly mentions of the term "index fund" in the Wall Street Journal (WSJ). Figure 3 shows this near zero prior to 1990 and escalating thereafter. This proxy has two advantages: it does not rely on institutional investor portfolio holdings reports and is available monthly throughout the sample period. We use monthly values for this variable, but repeat the test using a quarterly variable (the average across months in each quarter) for comparability.

Table 3 summarizes regressions of event firms' idiosyncratic currency decline on the index membership on the proxies. All regression are quarterly with the exception of Column 3.4, which is monthly. All significantly associate more negative differences in idiosyncratic currency sensitivities when stocks are in versus not in the S&P500 with a larger-scale indexing. This is consistent with the increased scale of indexing driving the damped idiosyncratic information sensitivity in Table 2.

4.2 Robustness of Baseline Results

We have made several empirical choices in estimating the difference in the sensitivity of idiosyncratic stock returns to idiosyncratic currency returns around index inclusion and deletion events. Table 4 presents the baseline results in row 4.0 and then reconsiders these choices as robustness checks 4.2 through 4.11.

Robustness checks 4.1 and 4.2 repeat the entire sequence of steps leading to the baseline result, but with no winsorization and with winsorization at 5%, respectively. In both, the magnitudes of coefficients are higher and statistically significant, but slightly less so than in the baseline result. Overall, our results are robust to different levels of winsorization, however the greater significance with winsorization at 10% suggests presence of outliers, which justifies winsorization and Wilcoxon signed-rank test below.

Robustness check 4.3 reruns the baseline using the methodology Faccio, Morck and Yavuz (2021) employ to estimate idiosyncratic stock return sensitivities and idiosyncratic commodity returns in their study of business groups, which differs from ours in two ways: First, our baseline result is inferred from daily returns. Because they pool data from many stock exchanges around the world, they use weekly returns to mitigate thin trading and time-zone mismatch problems. Our stock and currency returns are all in the New York City time zone, all stocks in or on the threshold of being in the S&P500 are highly liquid, and the major US trading partner currencies we use are also all highly liquid. Second, we let each stock's market beta differ when the stock is in versus out of the index, whereas Faccio et al. (2021) take each firm's market beta as constant. Robustness check 4.3, using this approach, generates a difference in idiosyncratic currency sensitivity of -0.45 (t = -4.26) with index inclusion, which is larger in magnitude and more statistically significant compared to our main results An intermediate approach, robustness check 4.4 lets market betas time-vary via 10-year rolling regressions. This yields a -0.39 (t = -5.44) difference in idiosyncratic currency sensitivity when stocks are in the S&P500 versus not in it.

Dimson betas, obtained by regressing idiosyncratic stock returns on contemporaneous and lagged idiosyncratic currency returns and testing for a difference in the sum of the coefficients, are used to mitigate lagged stock return responses that thin trading can cause. Using Dimson betas for contemporaneous, one-day, and two-day lagged currency returns, robustness check 4.5 shows a difference in three-day cumulative idiosyncratic currency sensitivity of -1.11 (t = -7.02) when stocks are in the index versus not in it. This is substantially more statistically significant than the baseline result.

Robustness check 4.6 revisits the baseline result, but calculates the idiosyncratic components of stock returns and currency returns using Fama and French's 5-factor model. Idiosyncratic stock returns are the residuals $\varepsilon_{i,\tau}$ from the regression:

$$R_{i,\tau} = \alpha_i + \beta_{i1}(R_{m,\tau} - r_\tau) + \beta_{i2} smb_\tau + \beta_{i3} hml_\tau + \beta_{i4} rmw_\tau + \beta_{i5} cma_\tau + \varepsilon_{i,t}, \qquad [7]$$

where $R_{i,\tau}$ is the day τ total return of stock i and $R_{m,\tau}$, r_τ, smb_τ, hml_τ, rmw_τ and cma_τ are the contemporaneous value weighted market return, risk-free rate, and standard Fama-French risk factors (Fama and French 2015). Robustness check 4.6 replaces [1] with [7] and [2] with an analog to [7] explaining currency returns. This yields a 0.16 lower idiosyncratic sensitivity to currency shocks (t = -3.52) in the index than when not in it.

Our main tests and the above robustness checks decompose raw returns into idiosyncratic and systematic components using alternative asset pricing models. Robustness check 4.7 reruns the test using raw (systematic plus idiosyncratic) stock and currency returns. This avoids choosing an asset pricing model; but weighs against replicating the baseline result because prior research shows index membership increases behaviorally driven systematic noise in stock returns (Vijh 1994; Barberis et al. 2005; Greenwood 2008; Boyer 2011). Nonetheless, 4.7 shows a -0.07 (t = -

1.84) change in raw stock return sensitivity to raw currency returns when stocks are in the S&P500 index versus when they are not.

Eleven of the 398 S&P500 firms in the baseline result are legally based outside the US, though all do the bulk of their business in the US. Nonetheless, they could be subject to foreign market shocks. Robustness check 4.8 shows dropping these stocks does not alter the baseline result.

The baseline result pools firms added to the S&P500 index with firms dropped from that index. Robustness checks 4.9 and 4.10 retain the methodology of the baseline result, but estimate average difference in idiosyncratic currency sensitivity for firms added to and dropped from the S&P500 index separately. Firms added to and dropped from the index show declines in sensitivity to idiosyncratic currency shocks of -0.21 (t = -3.61) and -0.30 (t = -2.27) respectively. The two point estimates are statistically indistinguishable (t = 0.75).

The baseline result contrasts means. Robustness check 4.11 shows a difference in median idiosyncratic currency sensitivity of -0.07 (p = 0.02) for firms in the index versus not in it.

Overall, while reasonable differences in methodology change the number of currency-sensitive firms and the magnitude of differences, idiosyncratic stock returns are always significantly less sensitive to idiosyncratic currency returns when stocks are in than not in the S&P500.

5. Alternative Explanations Excluded

Idiosyncratic currency shocks are global events, so the idiosyncratic components of currency returns relative to the US market return are unlikely to be caused by any firm being added to or dropped from the S&P500 Index. This helps with identification by excluding an entire class of reverse causality scenarios. Thus, we focus on the remaining class of identification issues. One remaining issue is the possibility that firms are added to (dropped from) the S&P500 index when their idiosyncratic currency sensitivities are abnormally high (low) and then subject to mean reversion. Another remaining issue is that being added to or dropped from the S&P500 index might affect a firm's policies or fundamentals in ways that alter its stock's idiosyncratic sensitivity to idiosyncratic currency shocks. This section considers and rejects these classes of alternative explanations for our baseline findings.

5.1. Differences in Differences Using Matched Firms

We first use a difference in differences test using a control sample of matched firms similar to the event firms, but not then included in the S&P500. We assemble this control sample of placebo firms as follows:

For each event, we consider potential matched control firms that are not in the S&P500 but among the largest 1000 firms by market capitalization as of the year-end prior to the event. We estimate their propensities for being added to or dropped from the index separately using the prior 12 months' stock returns and firm sizes as covariates. For each event firm, we select a matched control firm that: (1) is sensitive to the same currency in the same time period as the event firm, (2) whose propensity score differs in absolute value from that of the event firm by less than 0.1, (3) whose idiosyncratic currency sensitivity is closest to the idiosyncratic currency sensitivity of the event firm.

Table 5 summarizes the difference in idiosyncratic currency sensitivity (when not in the index minus when in the index) for treated firms, for matched control firms in the same time period, and the difference between the two differences. The control firms exhibit no significant difference in idiosyncratic currency sensitivity when the treated firms are added to or dropped from the index: The idiosyncratic currency sensitivity of control firms changes by a mere -0.01 (t = -0.50). As a result, event firms' currency sensitivity relative to that of control firms falls -0.23 (t = -4.07), similar to the baseline results.

Robustness tests (unreported) selecting placebo firms whose propensity score (rather than currency sensitivity) is closest to that of the event firm generates similar results: event firms' currency sensitivity falls -0.21 (t = -3.43).

Further examining the placebo firms also rules out our results being an artifact of currency matches in periods when firms have abnormally high idiosyncratic currency sensitivity, which then attenuates with distance in time from the currency-matching window. No such attenuation is evident in the control firms. Table 6 also precludes S&P systematically adding (dropping) S&P500 member firms shortly after (before) differences in political, macroeconomic, or other conditions that reduce (increase) idiosyncratically currency sensitive firms' sensitivity to idiosyncratic currency shocks.

5.2. Controlling for Differences in Currency Risk Hedging

A second class of alternative causality scenarios remains possible: firms added to (dropped from the S&P500 index might revise their decision-making to make their stocks less (more) sensitive to idiosyncratic currency shocks. The control firms in section 4.1, because they are not added to or dropped from the index, would not do likewise.

Firms can quickly change their sensitivity to currency shocks by changing their hedging of currency risk using futures and other derivatives. If firms intensified (reduced) such hedging after being added to (dropped from) the index, our baseline results might ensue.

We control for hedging changes in three ways. First, we control for differences in ratios of accounting statement items associated with hedging around the index status change event. Second, we measure differences in how often firms mention foreign currency hedging in their SEC disclosures, as explained in the next section. Third, we have ChatGPT read firm documents and flag changes in their currency hedging.

5.2.1 Controlling for Differences in Hedging Activity in Accounting Statements

The accounting ratios for firm i whose index status changes at t, denoted $\eta_{h,i,t}$, are; "Absolute Value of Derivatives Unrealized Gain and Loss / Total Assets", "Absolute Value of Derivatives Unrealized Gain and Loss / Sales", "Absolute Value of Derivative Gain Loses / Sales", "Absolute Value of Derivative Gain Loses / EBITDA", "Derivative Assets Current / Total Assets", "Derivative Assets Long-Term / Total Assets", "Derivative Liabilities Current/ Total Assets", "Derivative Liabilities Long-Term/ Total Assets", " Absolute Value of Net Derivative Assets/ Total Assets."

If the denominator is missing or negative, we drop that observation. For example, if the firm has a negative EBITDA then these observations are dropped in the ratio using EBITDA as the denominator. If accounting items entering the numerator of a ratio are unreported, we set them to zero because firms with negligible derivatives use can omit these line items from their financial reports.

We calculate the difference in balance sheet and income statement-based ratios summarizing hedging activity between the fiscal year -1 and fiscal year +1, with year zero is the year containing the event (c, i, t). To match the convention in calculating differences in currency sensitivity, we index the fiscal year when the firm is in the index $S = in$ and that when the firm is out of the index $S = out$. The difference in each hedging ratio associated with being in the index is then $\Delta\eta_{h,i,t} = \eta_{h,i,t}^{in} - \eta_{h,i,t}^{out}$.

Each financial ratio above is a measure of general hedging activity and therefore an imperfect measure of currency hedging activity. However, a large difference in firms' currency risk hedging policies would presumably cause a difference in some or all of these ratios. We control for differences in the ratios around the event (c, i, t) by estimating the regression:

$$\Delta b_{c,i,t} = \mu + \sum_h b_h \Delta\eta_{h,i,t} + u_{i,t}, \qquad [8]$$

where $\Delta b_{c,i,t}$ is the difference in firm i's idiosyncratic currency c sensitivity around its time t index status change, from [6], and $\Delta\eta_{h,i,t}$ is the difference in the firm's h^{th} hedging proxy or proxies around the event year. The intercept μ is then the average of $\Delta b_{c,i,t}$ across all inclusion and deletion events unexplained by differences in the firms' hedging ratios.

Table 6 reports μ and its statistical significance in regression specifications when differences in the hedging ratios are included individually in regressions 6.1 through 6.9 and then all together in 6.10. Panel A uses OLS regressions and Panel B uses weighted least square (WLS) regressions, assigning higher weights to more precise $\Delta b_{c,i,t}$ estimates. We find that differences in Absolute Value of Derivative Gain Losses/ EBITDA ratio negatively and statistically significantly predicts $\Delta b_{c,i,t}$ in WLS regressions. This result makes sense given that when firms use derivatives more, as measured by the Absolute Value of Derivative Gain Losses/ EBITDA ratio, they have lower sensitivity to idiosyncratic currency shocks. Regardless, in all specifications, the average difference in idiosyncratic currency sensitivity is negative and statistically significant. Our results are therefore unlikely to be artifacts of changes in hedging happening contemporaneously with differences in index membership status.

5.3.2 Controlling for Differences in Mentions Currency Hedging

Because accounting data aggregate derivative positions in foreign currencies, commodities, and interest rates, the above ratios do not specifically track differences in foreign currency hedging. Firms whose foreign currency hedging activities are more material may highlight this in their communications to investors, and firms that avoid foreign currency hedging may likewise communicate this.

Scraping each event firm's EDGAR files (10-Ks, 10-K405s, 20-Fs, and 40-Fs) for the fiscal years before and after their inclusion / deletion events for phrases associated with currency hedging provides a second approach to assessing differences in hedging. Following Manconi, Massa, and Zhang (2018) we count phrases associated with firm i indicating it is hedging currency risk[9] and another set of phrases indicating it is not hedging currency risk.[10] For each firm i whose membership changes at time t, we count phrases indicating currency hedging activity when the firm is in the S&P500, $n_{H,i}^{in}$, and when it is not in the S&P500, $n_{H,i}^{out}$, and count phrases indicating no hedging activity in the same periods, denoted $n_{N,i}^{in}$, and $n_{N,i}^{out}$ respectively;

We combine these counts to generate two hedging attention variables. The first is a currency "hedger" dummy variable set to one if the firm has at least three instances of the keywords indicating currency hedging and no instances of keywords indicating no currency hedging, as in Manconi, Massa and Zhang (2018). We calculate these differences between the fiscal year -1 and fiscal year +1 where year zero is the event year. For consistency across additions to and deletions from the S&P500, we index these fiscal years $S = in$ and $S = out$ indicating the years when the firm is in and out of the S&P500, respectively.

$$H_{1,i,t}^{S} = \begin{cases} 1 & n_{H,i,t}^{S} \geq 3 \ \& \ n_{N,i,t}^{S} = 0 \text{ in time period } S = in \text{ or } out \\ 0 & \text{otherwise} \end{cases} \qquad [9]$$

Our first hedging attention difference variable is then

$$\Delta H_{1,i,t} \equiv H_{1,i}^{in} - H_{1,i}^{out} \qquad [10]$$

Thus, $\Delta H_{1,i,t}$ is plus one for firms that do currency hedging when in the index but not when not in the index, zero for firms whose currency hedging does not change, and minus one for firms that do not hedge currency risk when in the index but do when not in it.

Panel A of Table 8 presents summary statistics showing no marked currency hedging difference in 90% of events, markedly more currency hedging when in the index in 5% of events and markedly less in the remaining 5%. The differences in idiosyncratic currency sensitivity for each of these groups of events are 0.11, -0.21 and -0.98 with t-statistics 0.67, -3.51 and -2.79,

9 The set of phrases we count as indicative of foreign currency hedging are: 'foreign exchange forward', 'forward foreign exchange', 'foreign exchange rate forward', 'currency forward', 'currency rate forward', 'foreign exchange option', 'currency option', 'foreign exchange rate option', 'currency rate option', 'foreign exchange future', 'currency future', 'foreign exchange rate future', 'currency rate future', 'foreign exchange swap', 'currency swap', 'foreign exchange rate swap', 'currency rate swap', 'foreign exchange cap', 'currency cap', 'foreign exchange rate cap', 'currency rate cap', 'foreign exchange collar', 'currency collar', 'foreign exchange rate collar', 'currency rate collar', 'foreign exchange floor', 'currency floor', 'foreign exchange rate floor', 'currency rate floor'.

10 The set of phrases count as indicating an absence of foreign currency hedging are: 'we do not have any foreign exchange derivatives', 'we do not utilize any foreign exchange derivatives', 'we do not enter any foreign exchange derivatives', 'the company does not have any foreign exchange derivatives', 'the company does not utilize any foreign exchange derivatives', 'the company does not enter any foreign exchange derivatives'

respectively. This shows firms that hedge currency risk only when in the index have statistically significantly more depressed idiosyncratic currency sensitivity when in the index, and vice versa. Therefore, higher values of currency hedging [10] correspond to greater declines in idiosyncratic currency sensitivity. However, the number of firms hedging only when in the index is only 17 and the number doing the opposite is 18, rendering changed currency hedging unlikely to seriously bias our results. Nonetheless, we revisit our baseline regression controlling for $\Delta H_{1,i,t}$.

Our second hedging attention difference variable is the count of phrases indicating foreign currency hedging after the event minus the analogous count before the event:

$$\Delta H_{2,i,t} = n_{H,i,t}^{in} - n_{H,i,t}^{out} \qquad [11]$$

The mean of $\Delta H_{2,i,t}$ is 0.26, its standard deviation is 3.87, and its 10th and 90th percentiles are -2 and 3, respectively. For observations within the 25th and 75th percentile there is no difference in currency hedging. Next, we control for differences in currency hedging around each event alongside the accounting ratio hedging measures in 5.2.1 in regressions of the form

$$\Delta b_{c,i,t} = \mu + \textstyle\sum_h c_h \Delta H_{h,i,t} + \sum_h b_h \Delta \eta_{h,i,t} + u_{i,t}, \qquad [12]$$

where $\Delta b_{c,i,t}$ is the difference in firm i's idiosyncratic currency sensitivity firm associated with index membership estimated around its event t index status change. As above, μ is the mean difference in idiosyncratic currency sensitivity unexplained by differences in hedging emphasis in the firm's communications to investors.

Panels B and C of Table 7 summarize OLS and $\Delta b_{c,i,t}$ precision-weighted WLS regression of [12]. Both show the difference in attention dummy $\Delta H_{1,i,t}$ and difference in the counts of phrases $\Delta H_{2,i,t}$ to be individually and jointly statistically significant in explaining differences in sensitivity to currency shocks. These findings confirm that the two proxies of currency hedging are relevant to currency hedging activity. The F-statistics in the column 4 regression affirm that accounting-based hedging proxies and hedging proxies based on keywords are jointly statistically significant. Regardless, of which hedging proxy or proxies are included, the mean difference in idiosyncratic currency sensitivity remains significantly negative, and its magnitude is little affected.

5.2.3 ChatGPT Interpretation of Foreign Currency Hedging Activity

After identifying phrases that are indicative of or absence of foreign currency hedging firm's EDGAR files (10-Ks, 10-K405s, 20-Fs, and 40-Fs), we ask ChatGPT to read scripts of text that is

50 words before and after the key phrases for each firm and year and answer the following two questions[11].

Question1: Does the firm hedge its currency risk? [Yes, No].

Question 2: Rate the intensity of currency hedging activity by the firm. Use five levels. [Very High, High, Medium, Low, Very Low].

We assign a score of $G_{1,i,t}^{T} = 1$ for yes answers to the first question and otherwise zero. For the second question, we assign scores starting from $G_{1,i,t}^{T} = 1$ for answers of "Very Low" and up to 5 for answers of "Very High". Next, we calculate the differences in these scores between the fiscal year end of year -1 and year 1, relative to the event year. The difference in hedging activity variables are then

$$\Delta G_{h,i,t} \equiv G_{h,i}^{in} - G_{h,i}^{out}. \qquad [13]$$

Where $h \in \{1,2\}$ represents the two measures. $\Delta G_{1,i,t}$ is plus one for firms that hedges their currency when in the index but not when outside, zero for firms that their hedging behavior does not change, and minus one for firms that do not hedge when in the index but hedge outside. $\Delta G_{2,i,t}$ may take values between -4 to +4, which approximates differences in intensity of hedging when the firm is in the index versus not in it.

Panel A of Table 8 presents summary statistics of $\Delta G_{1,i,t}$. About 8% of the sample firms show evidence of currency risk hedging when out of index, but not when in it and another roughly 7% show the reverse pattern. The remaining 85%, show similar attention (or lack of attention) to currency hedging throughout, and are substantially less currency sensitive when in the index (difference –in-differences = -0.27, *t* =- 4.29). Because few firms change their hedging behavior and because our baseline result is evident in firms that do not change their hedging behavior, it is unlikely that differences in hedging associated with index membership explain our results. Regardless, we revisit our baseline regression controlling for $\Delta G_{1,i,t}$ and also all previous controls using the following regression specification

$$\Delta b_{c,i,t} = \mu + \sum_h d_h \Delta G_{h,i,t} + \sum_h c_h \Delta H_{h,i,t} + \sum_h b_h \Delta \eta_{h,i,t} + u_{i,t}, \qquad [14]$$

where $\Delta b_{c,i,t}$ is the difference in firm i's idiosyncratic currency sensitivity firm associated with index membership estimated around its event t index status change. As above, μ is the mean difference in idiosyncratic currency sensitivity unexplained by differences in control variables.

[11] We set ChatGPT "temperature" to zero to remove randomization from its responses.

Panels B and C of Table 8 summarize OLS and $\Delta b_{c,i,t}$ precision-weighted WLS regression of [14]. Regardless of which proxy or proxies for differences in hedging, attention to currency hedging, or financial ratios related to hedging are included; the average difference in idiosyncratic currency sensitivity is negative and highly statistically significant.

Tables 6, 7 and 8 together suggest that differences in currency hedging are unlikely to underlie the decreased in idiosyncratic currency sensitivity when firms are in the index.

5.3 Controlling for Changes in Fundamentals' Sensitivity to Currency Shocks

Another possibility is that firm's fundamentals change when they are added to (dropped from) the S&P500 in ways that render their fundamentals, and hence their stock returns, less (more) sensitive to idiosyncratic currency shocks. For example, a firm added to the S&P500 has likely been large and successful. Large successful firms can have market power, which can reduce their firm-specific returns volatility (Irvine and Pontiff 2009). Such firms might also have pioneered major new technologies which, once firmly in place, can also reduce firm-specific returns volatility (Pastor and Veronesi 2003; Chun et al. 2008, 2011). Such firms might also become dominant in their supply chains, and thus able to offload risk to intermediate goods suppliers or buyers (Mihov and Naranjo 2017). Indeed, firms in the S&P500 might vary their strategies, target markets, or supply chain locations in any number of ways to decrease the idiosyncratic volatility in their fundamentals, and consequently, in their stock returns.

However, such changes gather force over years or decades, whereas our tests focus on months surrounding firms' inclusions in or exclusions from the S&P500. Market power, technological supremacy, supply chain dominance and other such things are unlikely to change greatly in the relatively short windows we study. In addition, while these changes may lower idiosyncratic volatility of stock prices, it is not clear whether they will affect firms' sensitivity to idiosyncratic currency shocks. Nonetheless, to mitigate such effects we control for differences in idiosyncratic fundamental returns sensitivity to idiosyncratic currency shocks. These tests use the same sample of foreign currency-sensitive firms as above, but longer in-index and out-of-index periods to accommodate quarterly fundaments data.

Our proxy for fundamental returns is Return on Equity (ROE) – that is, net income over lagged book equity.[12] We first calculate idiosyncratic components of ROE as the residuals from

[12] Book equity is calculated as in Fama and French (1993).

regressions of ROE (from quarterly financial statements) on the CRSP quarterly value-weighted total market return. Then we compare the sensitivity of the idiosyncratic components of firms' ROEs to the idiosyncratic components of currency returns in 5 years when the firm is in the index versus 5 years when it is not, surrounding but excluding the quarter in which the firms was added to or dropped from the index. We drop event firms that have non-positive lagged book equity or fewer than 12 quarters of data before and after the event.[13].

Table 9 Panel A shows that the average sensitivity of the idiosyncratic component of ROE to idiosyncratic currency shocks declines when the stock is included in the index. However, this decline is very small and statistically insignificant. In fact, the median difference is positive (not reported in the Table). Therefore, on average, there is no evidence of fundamentals becoming less sensitive to idiosyncratic currency shocks during times when a stock is in versus not in the S&P500.

Next, controlling for the sensitivity of the idiosyncratic component of firm i's ROE to the idiosyncratic sensitivity to its matched currency c as $\Delta b_{ROE,i,c,t}$, we revisit idiosyncratic stocks returns' sensitivity to idiosyncratic components of their matched currencies' fluctuations using regression of the form

$$\Delta b_{c,i,t} = \mu + e_{ROE}\, \Delta b_{ROE,c,i,t} + \textstyle\sum_h d_h \Delta G_{h,i,t} + \sum_h c_h \Delta H_{h,i,t} + \sum_h b_h \Delta \eta_{h,i,t} + \ a, \qquad [15]$$

The coefficient of interest, the intercept μ, is the average difference in the idiosyncratic currency sensitivity of the firm's stock, $\Delta b_{c,i,t}$, unexplained by differences in the stock's idiosyncratic currency sensitivity of its ROE and other controls.

Panels B and C of Table 9 summarize OLS and $\Delta b_{c,i,t}$ precision-weighted WLS regression of [14]. Second and third columns includes additional control variables considered in Tables 6, 7 and 8. The difference in idiosyncratic currency sensitivity is explained neither individually nor jointly by these variables. The average $\Delta b_{c,i,t}$ after controlling for differences in the idiosyncratic currency sensitivity of their ROE and all other control variables varies between -0.27 to -0.31 and is always highly statistically significant.

[13] If a firm has more than one event and the event periods overlap, the overlapping period is used only for the later event. For example, if a firm is recently included in S&P500 index and subsequently dropped out of index after 2 years then only the latter event is included in the study. Dropping this restriction does not affect our results.

5.6 Slow Incorporation of Information

Idiosyncratic information might be incorporated into prices of stocks listed on the S&P500 index with a certain lag. In other words, although stock prices do eventually adjust to reflect relevant information accurately, they do so after a short delay. While such an observation suggests a deviation from semi-strong market efficiency—where stock prices are expected to instantaneously incorporate all available public information—it also indicates that the repercussions of this sluggish information integration on long-term capital allocation decisions could be negligible because mispricing does not persist or compound over time.

The robustness tests we've conducted, employing Dimson betas that account for up to two days of lag and examining weekly returns, alleviate this concern partially. To further investigate if idiosyncratic currency shocks are incorporated into prices with a delay, we replicate our main analysis utilizing lagged currency returns spanning up to 20 trading days. Should there be a delay in the integration of information, the initial reduction in contemporaneous currency sensitivity we find might be offset by an increase in lagged sensitivity. A delay in information incorporation when stocks are in the index than when not in it would still be evidence of muted information sensitivity. A longer delay would presumably more seriously affect investors' returns, firms' costs of capital calculations, and managers' feedback from markets.

To explore this, we regress current and 20 lags (roughly one calendar month) of idiosyncratic stock returns on idiosyncratic currency returns. Specifically, replace [4] with

$$\varepsilon_{i,\tau+k} = a^{out}_{c,i,t} + b^{out}_{c,i,t}(k)\, sign\big(b_{c,i,t}\big)\, \varepsilon_{c,\tau} + e_{i,\tau},\ \ \tau \in W^{out}_{c,i,t} \qquad [16]$$

$$\varepsilon_{i,\tau+k} = a^{in}_{c,i,t} + b^{in}_{c,i,t}(k)\, sign\big(b_{c,i,t}\big)\, \varepsilon_{c,\tau} + e_{i,\tau},\ \tau \in W^{in}_{c,i,t} \qquad [17]$$

to obtain 21 values of each of $b^{out}_{c,i,t}(k)$ and $b^{out}_{c,i,t}(k)$, one for each lag k from zero to twently trading days. All other variables are as in [4] and [5]; and $b^{out}_{c,i,t}(0)$ and $b^{out}_{c,i,t}(0)$ reproduce $b^{out}_{c,i,t}$ and $b^{out}_{c,i,t}$, from [4] and [5]. Then, paralleling [6], we calculate 21 corresponding differences in lagged idiosyncratic currency sensitivity when the stock is in the index minus not in it:

$$\Delta b_{c,i,t}(k) = b^{in}_{c,i,t}(k) - b^{out}_{c,i,t}(k),\ k \in \{0, 1, 2, \dots 20\}. \qquad [18]$$

The $k = 0$ regression reproduces $\Delta b_{c,i,t}$ from [6] and the baseline result. Figure 3 plots the means across all events of the $\Delta b_{c,i,t}(k)$. The baseline result is evident at $k = 0$ and the differences at all longer lags are comparatively small and mostly statistically insignificant.[14] The figure also sums the differences from lags zero to k for each k to calculate cumulative sensitivity. The average of all lagged differences is -0.18, which is not statistically significant (t=-1.03). This shows no reversal, but instead a drift further into negative territory.

6. Generalizations

The econometric tests we utilize are designed to address endogeneity concerns related to a firm's changing information environment around index inclusion and exclusion. We use currency shocks that are determined exogenously in global markets and are readily observable by all market participants, which sidelines endogeneity issues discussed above.

Our results imply that all types of idiosyncratic shocks are likely to be incorporated less into stock prices when firms are in the index than when they are not. Our methodology also possesses broader applicability in various contexts where assessing the integration of exogenous information shocks into stock prices is crucial. We examine how stocks react to the ongoing flow of information about currency changes when in the S&P500 versus not in it. Alternative shifts in information environments might include regulatory changes, cross-listings, changes in ownership structure, or adjustments in capital structure. Furthermore, other ongoing flows of idiosyncratic information might include changes in commodity prices, weather-related incidents, and other streams of exogenous shocks unaffected by the changes in the firms' information environment. Next, we provide evidence that our results can generalized to other types of idiosyncratic shocks.

6.1 Idiosyncratic Commodity Price Shocks

Commodity prices are determined exogenously and are readily observable by all market participants and therefore provide an alternative to currency shocks. We replicate our analysis using a set of weekly commodity and commodity indexes prices[15]. We use weekly returns to mitigate concerns related to differences between the trading times of commodities and stocks in different locations. Paralleling the baseline tests, we first identify stocks that are added to or

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[14] The few exceptions include differences in coefficients at lags of 9, 16, and 20 days, which are negative and significant at 5%, and the differences for coefficients at a lag of 2 days, which is positive and significant at 10%.

[15] The list includes Aluminum Spot Price, Heavy Melting Steel Scrap in Chicago Price, Bloomberg Commodity Index, Live Cattle Spot Price, S&P GSCI Agricultural Index, S&P GSCI Industrial Metals Index, S&P GSCI Livestock Index, CSCE Cocoa Futures Prices, Brazil Santos Arabicas Spot Price, NYCE Cotton Futures Prices, Chicago Yellow Corn No. 2 Spot Price, CME Live Hog Futures, Zinc Special High Grade, CBOT Oat Futures Price, NYMEX Platinum Futures Contract, CSCE Sugar No. 11 Futures Prices, Soybeans Cash Price, West Texas Intermediate Oil Price, Wheat #2 Cash Price, Silver Cash Price, Gold Spot Price-London PM Fixing.

dropped from the S&P500 index and whose idiosyncratic returns are sensitive to idiosyncratic commodity price changes. We then test whether their idiosyncratic sensitivities to those commodities differ when the stock is in the S&P500 index versus not in it. Table 10 Panel A shows this difference in idiosyncratic commodity sensitivity to be -0.06 (t = -3.27). That is, commodity-sensitive firms' sensitivity to commodity fluctuations drops when they are in the index relative to when they are not. This test not only serves as a robustness check of our main results but also indicates that S&P500 membership blunts other forms of idiosyncratic information sensitivity.

6.2 Idiosyncratic Volatility in General

Next, we test whether overall idiosyncratic volatility drops when stocks are in the index. Table 10 Panel B reports differences in the standard deviation of daily idiosyncratic stock returns when the stock is in the index versus when it is not. These tests use all stocks with index inclusion and deletion events in 1990 through 2019, not just firms idiosyncratically sensitive to currency fluctuations. The standard deviation of daily idiosyncratic returns is statistically significantly lower (-0.13, t = -4.49) when the firms are in the index than when they are not. In contrast, Panel C shows the standard deviation of raw (systematic plus idiosyncratic) returns to be insignificantly slightly higher (0.03) when the firms are in the S&P500 index than when it is not. This is consistent with prior work showing elevated market-related volatility in S&P500 firms (Vijh, 1994; Barberis and Shleifer, 2003; Barberis et al., 2005; Greenwood, 2008; Boyer, 2011). Also, although it is obviously a first pass only, it suggests that our approach might be practicable for assessing changes in the incorporation other idiosyncratic information flows.

6.3 A General Approach for Stock Return Information Content Analysis

We posit that the estimation process described in Section 3 might have application in other contexts where changes in a firm, its business conditions, or institutions are suspected of affecting the information content of stock returns. The process might be improved and streamlined in various ways. For example, alternative windows or asset pricing models might provide results better suited to alternative environments.

We suggest that the following basic themes be retained. First, the estimation process requires identifying a common event or a set of firm-specific events that could change the information content of stock prices. Second, the process requires identifying a set of well-defined comparable exogenous information events. We argue that firm-specific information events are preferable because of Samuelson's Dictum, which suggests that firm-specific stock price variation is more likely to be information-driven than market-wide stock price variation. This calls for removing components of both stock returns and information events that correlate with the stock market.

All the above done, the final step is a difference-in-differences test: Are differences in a firm, its business environment, or its institutional setting associated with differences in the idiosyncratic response of stock prices to comparable firm-specific information events? We welcome criticisms, suggestions for improvement, or alternative approaches.

7. Conclusion and Implications

We conclude that indexing roughly halves the reactions of stock prices to relevant idiosyncratic information about foreign currency fluctuations. More precisely, our baseline finding is that a stock sensitive to idiosyncratic foreign currency fluctuations is economically and statistically twice as sensitive when not in the S&P500 than when in it. This finding is highly robust, evident in simple difference-in-difference tests, and in difference-in-difference tests contrasting treated firms with placebo firms matched by idiosyncratic currency sensitivity and propensity score to the event firms. Our findings are not explained by changes in economic conditions, firm hedging, or idiosyncratic fundamental return sensitivity to currency fluctuations.

Our tests advance the literature in several ways. First, our tests directly measure information flow into stock prices – specifically, the incorporation of information about idiosyncratic foreign currency fluctuations into idiosyncratic stock returns. Second, our tests are sufficiently well identified to constitute evidence of causality: that it, being in the S&P500 damps information flow into stock prices. Third, this damping grows more pronounced in lockstep with increases in aggregate indexed investment.

Bodie et al. (2021), one of the most widely used *Investments* textbooks, provides students with the conclusion (p. 665) "There are three key benefits to investing in index funds: broad diversification, low costs, and solid returns," and the advice (p. 667) "Whether you're new to investing or not, an index fund is a great asset to add to your portfolio. It takes a little time to find the right index fund for you, but once you do, you can sit back and let your money grow." Other major textbooks echo this advice. However, our tests show that if enough investors follow this advice, their collective actions can combine to undermine the economics justifying that advice. Escalating indexing renders share price changes less informative, less useful in providing feedback about corporate decisions (Bond et al. 2012), and thereby renders corporate resource allocation less efficient (Wurgler 2000, 2011; Durnev et al. 2004; Chen et al. 2007; Morck et al. 2013).

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Figure 1: Inclusion and Deletion Events of S&P500 Firms Matched to a Currency

The figure shows the time series of number of firms added to or dropped from S&P500 index that can also be matched to a currency.

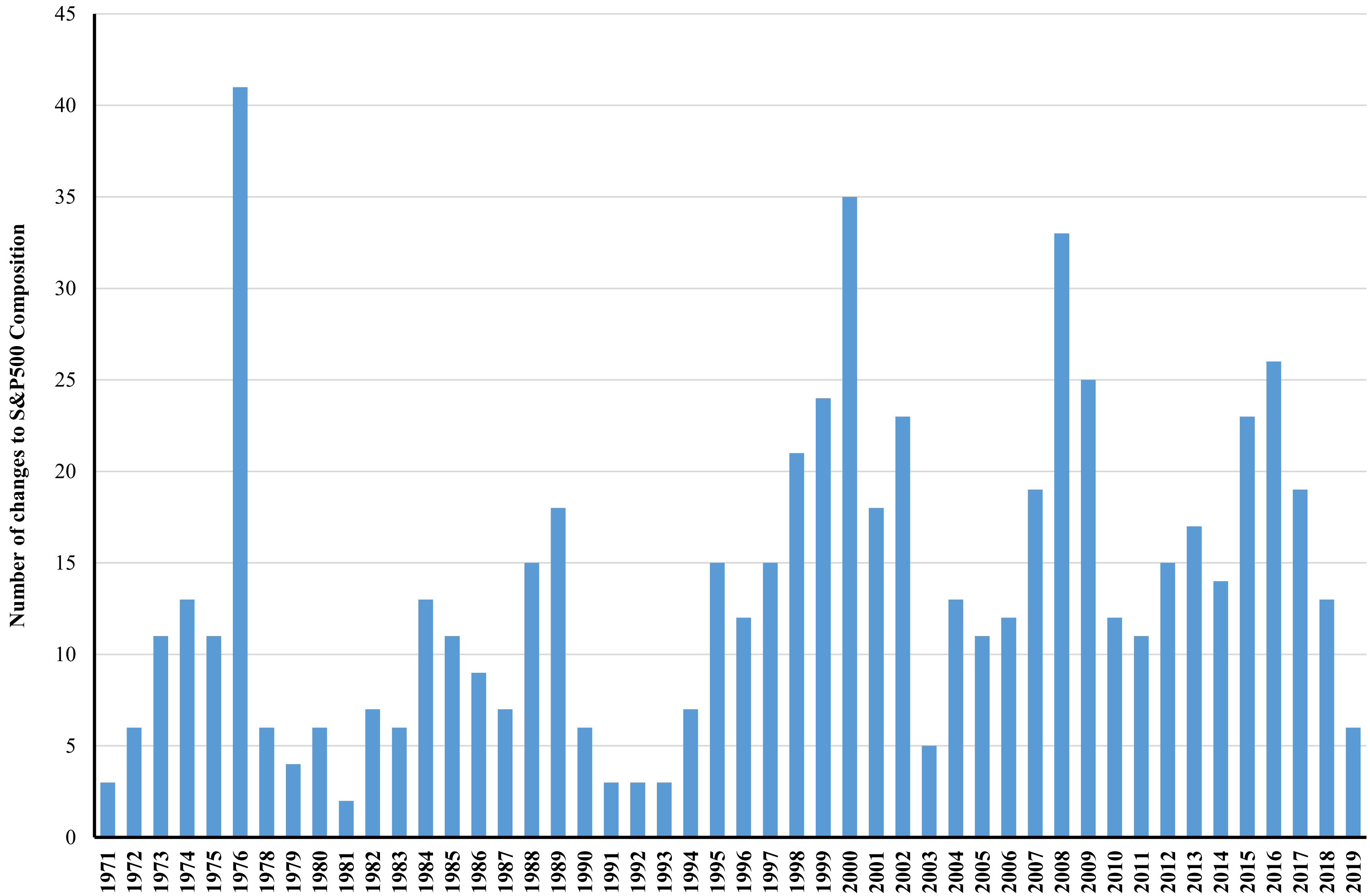

Figure 2. Currency Matching and Idiosyncratic Currency Sensitivity Estimation Windows

This figure provides details about the timeline of currency matching and idiosyncratic currency sensitivity measurement windows for a firm newly included in the S&P500 index as of the event date t. Matching of the firm's idiosyncratic stock returns to an idiosyncratic currency return uses the six-month window from thirteenth to the seventh month prior to the inclusion event date. The idiosyncratic stock return's sensitivity to the idiosyncratic return of the matched currency is then estimated in a window from one to seven months before the inclusion event date and in another from one to seven months after the inclusion event date t, respectively. One month of data before and after the event date (41 trading days = the event date, twenty trading days before it & twenty trading days after) are dropped. Twenty trading days roughly equal one month. The timeline for deletions from the S&P500 index is analogous, but the pre-event window measures idiosyncratic currency sensitivity when the firm is in the index, the post-event window estimates it when the firm is out of the index & matching with the currency is estimated in the seventh to thirteenth month after the stock is dropped from the S&P500 index. This means that in both cases, the currency matching is done while the stock is not in the index.

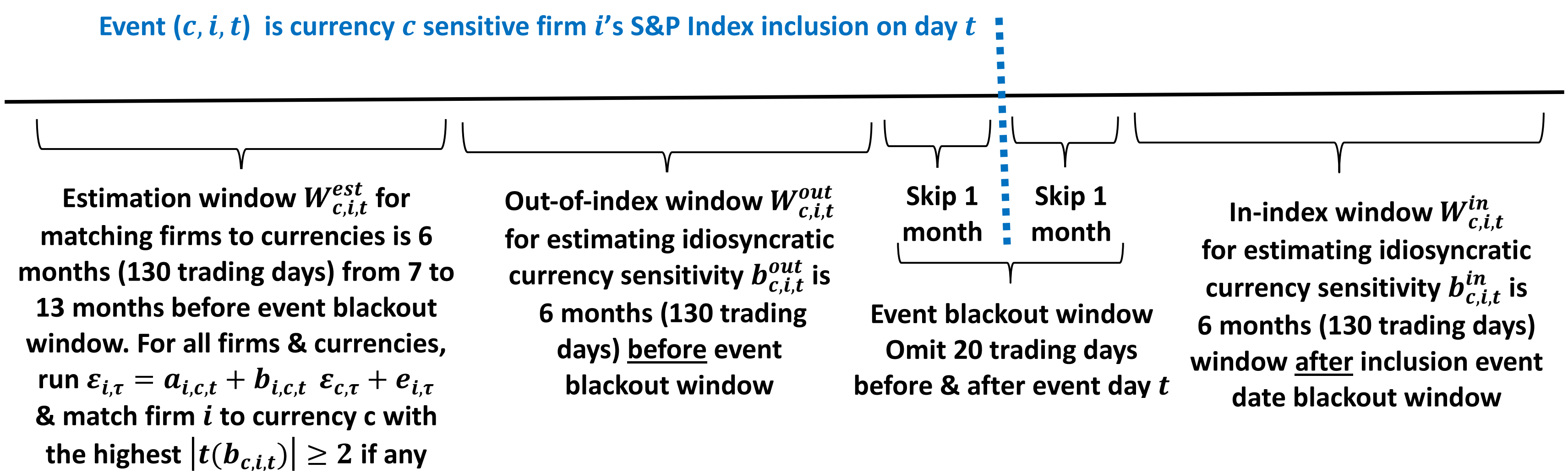

Figure 3. Importance of Index Investing Over Time

The figure plots annual number of mention of "index fund" in the Wall Street Journal (WSJ), monthly values averaged annually and S&P500 Index mutual funds holdings as fraction of all holdings of all mutual funds measured quarterly and then averaged annually.

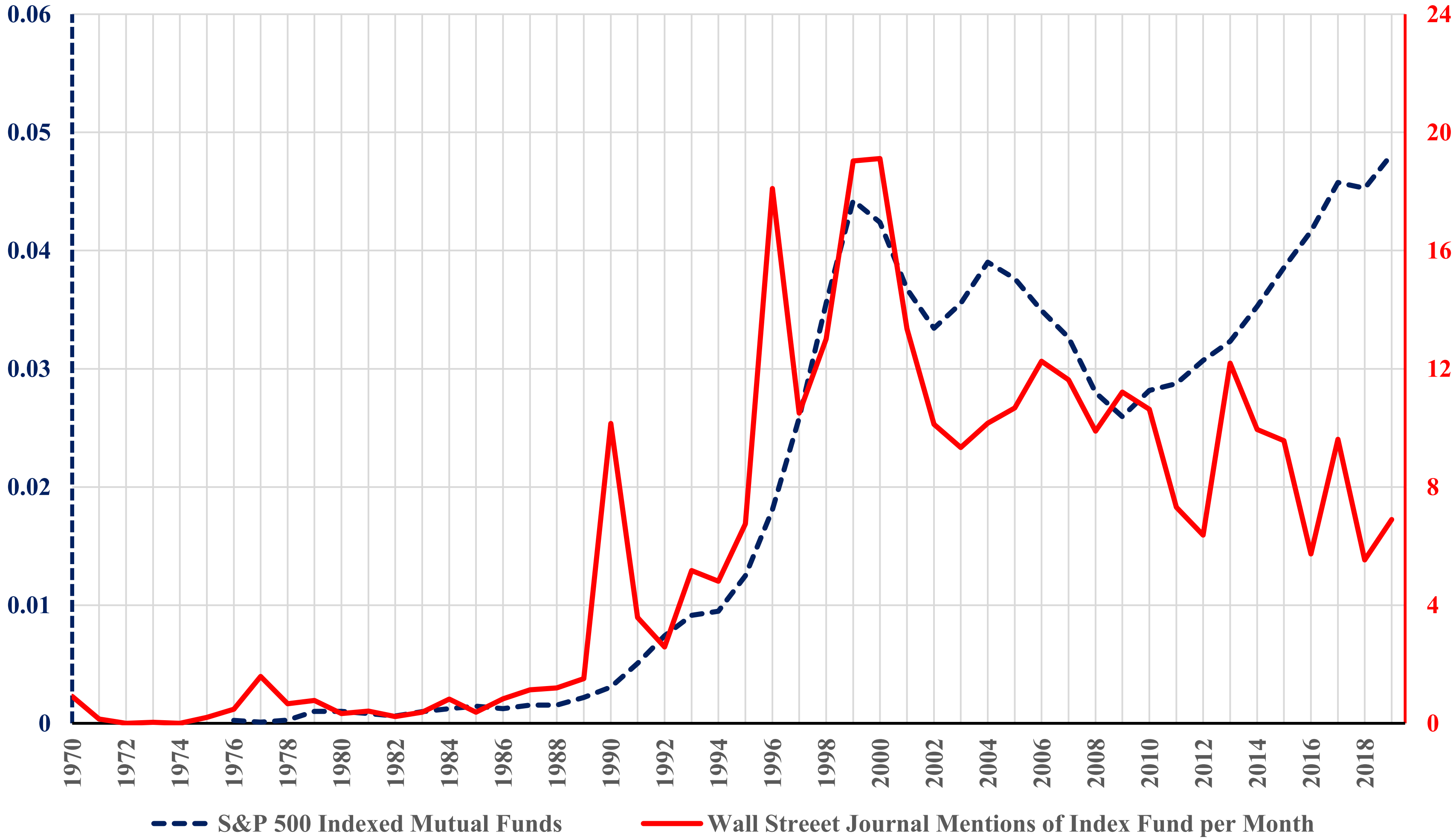

Figure 4. Difference in Lagged Sensitivity to Foreign Currency Shocks Given Difference in Index Status

The figure plots differences in stocks' idiosyncratic currency sensitivity around their inclusions in or deletions from the S&P500 index from 1990 through 2019 using 0 to 20 day lagged currency returns.

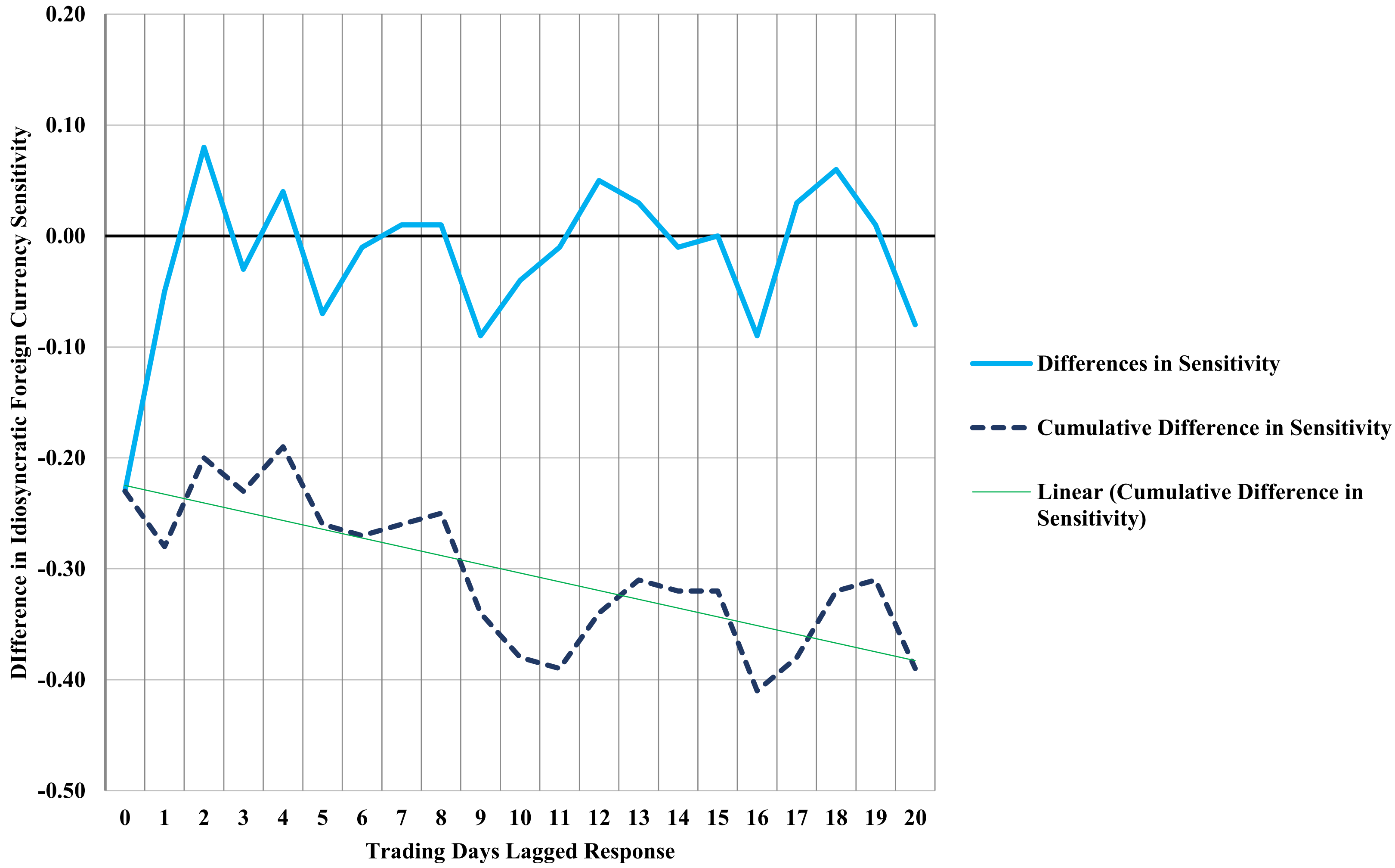

Table 1: Inclusion/deletion Firm matches to Currencies

The Table shows the distribution of firms added to or dropped from S&P500 Index and matched to currency of one of the main trading partners of US. The sample period is from 1970 to 2019. For countries who became Eurozone members on or after January 1999 we use Euro after they join Eurozone and their national currency prior to joining to Eurozone.

Trading Partner	Number of index addition or drop events matched to the currency of the trading partner	Percentage
Brazil	41	7
Canada	94	16
China	85	15
Eurozone	27	5
France	15	3
Germany	12	2
India	48	8
Ireland	12	2
Italy	24	4
Japan	63	11
Mexico	40	7
Netherlands	16	3
South Korea	26	4
Taiwan	30	5
United Kingdom	50	9
Total	583	100

Table 2: Differences in Incorporation of Idiosyncratic Information on Difference in Index Status

The table shows differences in stocks' idiosyncratic currency sensitivity around their inclusions in or deletions from the S&P500 index from 1970 through 2019. We drop data in a 2-month exclusion windows around event dates (the event date, 20 trading days before the event date & 20 trading days after it) and estimate the stock's pre-event idiosyncratic sensitivity to its matched currency in the six months (130 trading days) before the exclusion window and its post-event idiosyncratic sensitivity to its matched currency in the six months (130 trading days) after the event. Stocks are matched to currencies in the 130 trading days of data prior to the earliest of the above windows for inclusion stocks and in the 130 trading days after the latest of the above windows for excluded stocks. Idiosyncratic stock and currency returns are orthogonal to the value-weighted market index of all stocks and are estimated separately when the stock is in and not in the Index. Differences in idiosyncratic currency sensitivity are winsorized at 10% within 1970-2019.

		2.1	2.2	2.3
Index status difference events		**All 1970 - 2019**	**Sub-Period 1970 - 1990**	**Sub-Period 1990 - 2019**
t-test rejecting zero mean difference $\Delta b_{c,i,t}$ in idiosyncratic stock return currency sensitivity (in-index minus out-of-index)	mean difference	-0.19	-0.13	-0.23
	t-ratio	-3.79	-1.55	-4.31
	p-level	0.00	0.12	0.00
Observations		583	185	398

Table 3: Index Investing and Differences in Difference in Idiosyncratic Information on Difference in Index Status

The table shows regressions of difference in idiosyncratic stock return currency sensitivity to index investing proxies (defined in Table 2 and explained in Section 3.1). The difference in idiosyncratic stock return currency sensitivity is smoothed over 2 years. We have one observation per quarter and variables are either measured quarterly or averaged (collapsed) quarterly with the exception of column 3.4, which is monthly. Coefficients are multiplied by 100 in 3.4 and 3.5. Each triad of rows reports coefficients, t-statistics and p-levels.

		S&P500 Index Mutual Funds Holdings as Fraction of All Holdings of All Mutual Funds	**S&P500 Index Mutual Funds and ETF Holdings as Fraction of All Holdings of All Mutual Funds and ETFs**	**Passive Investor Share among S&P500 Stocks**	**WSJ mentions of index funds (monthly)**	**WSJ mentions of index funds (quarterly)**
		3.1	3.2	3.3	3.4	3.5
Time Period		1976 to 2019	1976 to 2019	1996 to 2017	1996 to 2019	1970 to 2019
Correlation with difference in idiosyncratic stock return currency sensitivity (in-index minus out-of-index)	*coefficient*	-3.25	-1.88	-8.10	-1.28	-1.31
	t-ratio	-2.64	-1.88	-2.30	-5.86	-4.36
	p-level	0.01	0.06	0.02	0.00	0.00
	Number of Observations	144	144	79	281	160

Table 4 Robustness Checks

The table summarizes robustness checks of the baseline result in Table 2. The baseline regression, 2.3 in Table 2, reproduced for comparison in 4.0, winsorizes differences in daily idiosyncratic stock return currency sensitivity around events at 10% and uses all inclusion and deletion events from 1990 through 2019. Rows 4.1 to 4.11 summarize results using successive alternate methodologies. Idiosyncratic currency sensitivities are described in Table 2. Index inclusion and deletion events lie in the period from 1990 to 2019.

	Difference in idiosyncratic stock return sensitivity to idiosyncratic currency shocks (in-index minus out-of-index)			
Difference in estimation procedure	**mean**	**t-ratio**	**p-level**	**observations**
4.0 Baseline result	-0.23	-4.31	0.00	398
4.1 Re-estimated with no winsorization, otherwise as in baseline result.	-0.31	-1.92	0.05	398
4.2 Re-estimated winsorizing at 5%, otherwise as in baseline result.	-0.34	-3.88	0.00	398
4.3. Re-estimated using weekly returns, idiosyncratic returns are estimated using entire time period, otherwise as in baseline result.	-0.43	-4.42	0.00	412
4.4. Re-estimated using weekly returns, idiosyncratic returns are estimated using rolling 10 year windows, otherwise as in baseline result.	-0.35	-2.54	0.01	254
4.5 Re-estimated using Dimson betas with daily returns of contemporaneous and two days of lags, the three coefficients are added, idiosyncratic returns are estimated using entire time period otherwise as in baseline result.	-1.03	-5.38	0.00	213
4.6 Re-estimated using Fama-French five-factor model to estimate idiosyncratic returns, otherwise as in baseline result.	-0.16	-3.31	0.00	330
4.7 Re-estimated using total stock and currency returns.	-0.07	-1.84	0.07	340
4.8 Drop companies incorporated outside of US	-0.23	-4.12	0.00	387
4.9 Sample only includes stocks added to the index, otherwise as in baseline result.	-0.21	-3.61	0.00	295
4.10 Sample only includes stocks dropped from the index, otherwise as in baseline result. (The difference of inside versus outside of index)	-0.30	-2.37	0.02	103
4.11 Differences in medians and Wilcoxon signed-rank test	-0.07	-2.21	0.02	398

Table 5: Balanced Difference in Differences Event Study Using Matched Firms

The table summarizes the difference in the difference in the sensitivity of firms' idiosyncratic stock returns to a matched currency idiosyncratic return associated with index membership for event firms versus matched control firms. Matched control firms are selected from the 1,000 largest firms not in the S&P500 in the event year and must be idiosyncratically sensitive to the same currency as the event firm. Matching minimizes difference in idiosyncratic currency sensitivities, subject to absolute difference in propensity scores < 0.1. Propensities to be included in (dropped from) the S&P500 index are separately estimated using prior 12 month stock returns and firm size as covariates. Idiosyncratic currency sensitivities are described in Table 2. Differences in sensitivities before versus after the event are winsorized at 10%. The time period is 1990 to 2019. Each triad of rows reports values, *t*-statistics and p-levels.

		Treated	**Control**	**Difference in Difference**
t-test rejecting zero mean difference $\Delta b_{c,i,t}$ in idiosyncratic stock return currency sensitivity in-index minus out-of-index	mean difference	-0.24	-0.01	-0.23
	t-ratio	-4.29	-0.50	-4.07
	p-level	0.00	0.62	0.00
Wilcoxon signed rank test of whether median differences $\Delta b_{c,i,t}$ are zero in idiosyncratic stock return currency sensitivity (in-index minus out-of-index)	z-test	-2.49	-0.18	-3.43
	p-level	0.01	0.86	0.00
	Observations	381	381	381

Table 6: Controlling for Differences in Hedging Activity in Accounting Statements

The table summarizes differences (in-index minus out-of-index) in idiosyncratic currency sensitivity for associated with S&P500 inclusion as described in Table 2 after controlling for differences (in-index minus out-of-index) in financial ratios associated with hedging activity. Panels A and B summarize OLS and WLS regressions, respectively. The sample is S&P500 inclusions and deletions in 1990 through 2019. Each triad of rows reports coefficients, *t*-statistics and p-levels.

proxy for hedging is:		**Absolute Value of Derivatives Unrealized Gain and Loss / Total Assets**	**Absolute Value of Derivatives Unrealized Gain and Loss / Sales**	**Absolute Value of Derivative Gain Losses/ Sales**	**Absolute Value of Derivative Gain Losses/ EBITDA**	**Derivative Assets Current/ Total Assets**	**Derivative Assets Long-Term/ Total Assets**	**Derivative Liabilities Current/ Total Assets**	**Derivative Liabilities Long-Term / Total Assets**	**Absolute Value of Net Derivative Assets / Total Assets**	**All [a]**
Panel A: OLS Regressions		6A.1	6A.2	6A.3	6A.4	6A.5	6A.6	6A.7	6A.8	6A.9	6A.10
Difference in accounting ratio proxy for currency hedging[a]	coefficient	-10.36	-1.85	-2.25	-0.12	-16.13	-41.19	31.76	-6.09	-9.03	
	t-ratio	-1.08	-0.54	-0.63	-0.60	-1.26	-0.87	1.57	-0.41	-0.80	0.69[a]
	p-level	0.28	0.59	0.53	0.55	0.21	0.38	0.12	0.68	0.42	0.72[a]
Difference in idiosyncratic stock return currency sensitivity	coefficient	-0.26	-0.26	-0.25	-0.26	-0.25	-0.25	-0.25	-0.25	-0.25	-0.28
	t-ratio	-4.60	-4.63	-4.53	-4.30	-4.56	-4.58	-4.54	-4.55	-4.57	-4.60
	p-level	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Panel B. WLS Regressions		6B.1	6B.2	6B.3	6B.4	6B.5	6B.6	6B.7	6B.8	6B.9	6B.10
Difference in accounting ratio proxy for currency hedging[a]	coefficient	-4.15	-1.22	-2.68	-0.12	-10.55	-38.80	28.16	-7.39	-6.65	
	t-ratio	-0.63	-0.41	-0.84	-10.84	-1.01	-1.01	1.44	-0.72	-0.84	72.4[a]
	p-level	0.53	0.68	0.40	0.00	0.31	0.31	0.15	0.47	0.40	0.00[a]
Difference in idiosyncratic stock return currency sensitivity	coefficient	-0.25	-0.26	-0.25	-0.26	-0.25	-0.25	-0.25	-0.25	-0.25	-0.28
	t-ratio	-4.53	-4.62	-4.54	-4.30	-4.54	-4.57	-4.54	-4.55	-4.54	-4.56
	p-level	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	Observations	386	384	386	340	386	386	386	386	386	340

[a] F-statistics and p-levels for joint significance of all hedging activity variables.

Table 7: Difference in References to Currency Hedging Given Difference in Index Status

The table display average difference in idiosyncratic currency sensitivity around S&P500 inclusion and deletion events as calculated in Table2 after controlling for differences in mentions of currency hedging in the firm's EDGAR files (10-Ks, 10-K405s, 20-Fs & 40-Fs). We use the same set of keywords and procedure used by Manconi Massa & Zhang (2018) to identify firms that engage in currency hedging. In the first column we control for differences in a dummy variable that indicates whether the firm engages in currency hedging or not. In the second column, we control for differences in the number of mentions of currency hedging. Differences are calculated between the fiscal year end of year -1 and year 1, relative to the event year. The time period is 1995 to 2019 because EDGAR files are only available after 1994. Each triad of rows reports coefficients, *t*-statistics and p-levels.

Panel A: Summary Statistics		7A.1	7A.2	7A.3
Change in Attention to Hedging =	Not in index In index	Attention evident No attention evident	No change	No attention evident Attention evident
Change in idiosyncratic stock return currency sensitivity	Mean	0.11	-0.21	-0.98
	t-ratio	0.67	-3.51	-2.79
	p-level	0.51	0.00	0.01
	Observations	18	297	17

Attention to Hedging proxy(ies)		**Dummy**	**Count**	**Both**[a]	**Both & all in Table 6**[a]
Panel B: OLS Regressions		7B.1	7B.2	7B.3	7B.4
Change in attention proxy for currency hedging[a]	coefficient	-0.54	-0.04		
	t-ratio	-3.03	-2.09	4.94[a]	1.26[a]
	p-level	0.00	0.04	0.01[a]	0.25[a]
Change in idiosyncratic stock return currency sensitivity	coefficient	-0.24	-0.24	-0.24	-0.26
	t-ratio	-4.07	-4.09	-4.10	-4.09
	p-level	0.00	0.00	0.00	0.00
Panel C: WLS Regressions		7C.1	7C.2	7C.3	7C.4
Change in attention proxy for currency hedging[a]	coefficient	-0.41	-0.02		
	t-ratio	-2.80	-3.89	5.63[a]	33.53[a]
	p-level	0.01	0.00	0.00[a]	0.00[a]
Change in idiosyncratic stock return currency sensitivity	coefficient	-0.23	-0.23	-0.24	-0.26
	t-ratio	-4.01	-3.86	-4.05	-3.99
	p-level	0.00	0.00	0.00	0.00
	Observations	332	332	332	290

[a] F-statistics and p values for joint significance of all control variables

Table 8: ChatGPT Interpretation of Currency Hedging

The table display average difference in idiosyncratic currency sensitivity around S&P500 inclusion and deletion events as calculated in Table2 after controlling for differences in currency hedging as determined by ChatGPT. We first identify the currency hedging related words used in Table7 from EDGAR files (10-Ks, 10-K405s, 20-Fs & 40-Fs). We take 50 words before and 50 words after the currency hedging related words as relevant text for hedging. We ask ChatGPT to read all text related to currency hedging and answer the following two questions. Question1: Does the firm hedge its currency risk? [Yes, No]. Question2: Rate the intensity of currency hedging activity by the firm. Use five levels. [Very High, High, Medium, Low, Very Low]. differences in these variables are calculated between the fiscal year end of year -1 and year 1, relative to the event year. The time period is 1995 to 2019 because EDGAR files are only available after 1994. Each triad of rows reports coefficients, *t*-statistics and p-levels.

Panel A: Summary Statistics		8A.1	8A.2	8A.3
Change in Attention to Hedging =	Not in index In index	Attention evident No attention evident	No change	No attention evident Attention evident
Change in idiosyncratic stock return currency sensitivity	Mean	0.05	-0.27	-0.05
	t-ratio	0.24	-4.29	-0.34
	p-level	0.81	0.00	0.81
Observations		25	283	24

ChatGPT Hedging proxy(ies)		**Dummy**	**Hedging Intensity**	**Both[a]**	**Both & all in Table 6 & 7[a]**
Panel B: OLS Regressions		8B.1	8B.2	8B.3	8B.4
Change in proxy for currency hedging[a]	coefficient	-0.05	-0.10		
	t-ratio	-0.35	-1.46	1.16[a]	1.25[a]
	p-level	0.73	0.15	0.32[a]	0.24[a]
Change in idiosyncratic stock return currency sensitivity	coefficient	-0.23	-0.23	-0.22	-0.25
	t-ratio	-3.99	-3.85	-3.81	-3.94
	p-level	0.00	0.00	0.00	0.00
Panel C: WLS Regressions		8C.1	8C.2	8C.3	8C.4
Change in proxy for currency hedging[a]	coefficient	-0.08	-0.10		
	t-ratio	-0.51	-1.41	1.14[a]	157.13[a]
	p-level	0.61	0.16	0.32[a]	0.00[a]
Change in idiosyncratic stock return currency sensitivity	coefficient	-0.23	-0.23	-0.22	-0.25
	t-ratio	-3.99	-3.86	-3.82	-3.86
	p-level	0.00	0.00	0.00	0.00
Observations		332	332	332	290

[a] F-statistics and p values for joint significance of all controls together.

Table 9: Difference in Sensitivity of ROE to Currency Returns Given Difference in Index Status

The table displays the average difference in idiosyncratic stock return sensitivity to currencies around S&P500 inclusion and deletion events as calculated in Table 2 after controlling for differences in idiosyncratic ROE sensitivity to the same currencies. Difference in in idiosyncratic ROE sensitivity to the same currencies are calculated using quarterly data from 5 years before and 5 years after the difference in index status. If the firm has more than one event where event windows overlap, the overlapping time period is allocated to the consecutive event and dropped from the prior event. This ensures that a given time period can only be used for one event. For event to be included in the sample we require at least 12 quarterly (3 years) of observations both before and after the event. The sample period is between 1990-2019. Each triad of rows reports coefficients, *t*-statistics and p-levels.

Panel A: Summary Statistics		9A.1		
Average difference in idiosyncratic ROE currency sensitivity	mean	-0.13		
	t-ratio	-0.51		
	p-level	0.61		
		Return on Equity (ROE)	**ROE and all in Table 6**	**ROE and all in Tables 6, 7 and 8.**
Panel B: OLS Regressions		9B.1	9B.2	9B.3
Change in idiosyncratic ROE currency sensitivity	coefficient	-0.00		
	t-ratio	-0.18	0.29[a]	0.49[a]
	p-level	0.86	0.98[a]	0.93[a]
Change in idiosyncratic stock return currency sensitivity	coefficient	-0.31	-0.30	-0.27
	t-ratio	-4.06	-3.56	-3.10
	p-level	0.00	0.00	0.00
Panel C: WLS Regressions		9C.1	9C.2	9C.3
Change in idiosyncratic ROE currency sensitivity	coefficient	0.00		
	t-ratio	0.14	0.30[a]	0.65[a]
	p-level	0.89	0.98[a]	0.82[a]
Change in idiosyncratic stock return currency sensitivity	coefficient	-0.31	-0.30	-0.27
	t-ratio	-4.03	-3.54	-3.01
	p-level	0.00	0.00	0.00
Observations		221	196	181

[a] F-statistics and p values for joint significance of all controls.

Table 10 Generalization of Results: Other Idiosyncratic Shocks

The Panel A shows differences in stocks weekly idiosyncratic stock return sensitivity to commodities around S&P500 inclusion and deletion events. The list of commodities and commodity indices includes Aluminum Spot Price, Heavy Melting Steel Scrap in Chicago Price, Bloomberg Commodity Index, Live Cattle Spot Price, S&P GSCI Agricultural Index, S&P GSCI Industrial Metals Index, S&P GSCI Livestock Index, CSCE Cocoa Futures Prices, Brazil Santos Arabicas Spot Price, NYCE Cotton Futures Prices, Chicago Yellow Corn No. 2 Spot Price, CME Live Hog Futures, Zinc Special High Grade, CBOT Oat Futures Price, NYMEX Platinum Futures Contract, CSCE Sugar No. 11 Futures Prices, Soybeans Cash Price, West Texas Intermediate Oil Price, Wheat #2 Cash Price, Silver Cash Price, Gold Spot Price-London PM Fixing. The Panel B shows differences in stocks' standard deviation of daily idiosyncratic returns around their inclusions in or deletions from the S&P500 index. The Panel C shows differences in stocks' standard deviation of daily total returns around their inclusions in or deletions from the S&P500 index We drop data in a 2-month exclusion windows around event dates and estimate the stock's idiosyncratic return volatility pre-event in the six months before the exclusion window and its post-event idiosyncratic volatility in the six months after the event. The sample period is from 1990 through 2019. Idiosyncratic stock returns are orthogonal to the value-weighted market index. Differences in standard deviation of daily idiosyncratic returns and raw returns are winsorized at 10% for each sample.

		Difference in variable given difference in passive investment (in-index minus out-of-index)			
		mean	**t-ratio**	**p-level**	**# of obs.**
A	Change in weekly idiosyncratic stock return sensitivity to weekly idiosyncratic commodity returns	-0.06	-3.27	0.00	768
B	Change in stocks' standard deviation of daily idiosyncratic returns	-0.13	-4.49	0.00	911
C	Change in stocks' standard deviation of daily returns	0.03	2.37	0.02	911