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ABSTRACT

Savings increasingly flow to low-cost index funds, which simply buy and hold the stocks in a major index, such as the S&P 500. Increased indexing impedes incorporation of idiosyncratic information into stock prices. We limit endogeneity bias by showing that exogenous idiosyncratic currency shocks induce smaller idiosyncratic moves in the stock prices of currency-sensitive firms in proximate time windows when in the index than when not in it. Increased indexing thus appears to be undermining the efficient markets hypothesis that supports its viability.

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1. Introduction

The rise of passive investment in the half-century since Malkiel (1973) wrote "I have become increasingly convinced that the past records of mutual fund managers are essentially worthless in predicting future success." Malkiel argues this implies the stock market is sufficiently informationally efficient in setting stock prices to fundamental values to render picking stocks pointless. He therefore 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 indexing with undermining the stock market informational efficiency that he argues justifies its existence. As Shiller (2017) 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] This critique has several layers.

Roll (1986) argues that informed traders are largely responsible for bringing information into stock prices because he can associate only some stock price movements with public news. Consequently, he concludes that informed active traders buying underpriced stocks and selling overpriced stocks underlie much price adjustment. Competitive active funds expand until their rising marginal costs of information equal their falling marginal revenues from arbitrage, whereupon their profits are zero and their returns match those of indexes (Grossman and Stiglitz 1980). In this equilibrium, efficiently run active funds match indexes and this does not support Malkiel's (1973) charge that active managers are "essentially worthless".

Rather, active investment has a positive externality for the economy as a whole: keeping stocks priced correctly to provide equilibrium risk-adjusted returns. This not only makes passive

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1 Renshaw and Feldstein (1960) had also suggested a diversified buy-and-hold strategy.
2 Boglel (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, Stephanie. 2017. Passive investing is a 'chaotic system' that could be dangerous, warns Robert Shiller. CNBC Trading nation, Nov 14 2017.

investment viable, but allows savers to buy and hold stocks with minimal information and trading costs (Black 1986). Informed stock price changes also keep firms' costs of capital near equilibrium risk-adjusted rates managers use in capital budgeting decisions and also provide information feedback corporate managers can use in making and revising important decisions. Thus Bond, Edmans and Goldstein (2012) find firms' investment, innovation, strategy and governance decisions reacting to their stock prices.[5]

These considerations coalesce into an argument that vastly expanded indexing untethers stock prices from fundamentals with adverse consequences for investors and the economy. Indeed, *in reductio ad absurdum*, the market capitalizations of stocks in indexes tracked by index funds would sum to, and rise and fall in synch with, aggregate demand for equities. Consistent with index funds and investor sentiment generating demand pressures of this sort, inclusion in a widely tracked index increases a stock's co-movement with the index (Vijh 1994; Barberis et al. 2005; Greenwood 2008; Boyer 2011).

Counterarguments challenge each of these points. Malkiel counters that "Over a 10-year period, roughly 90% of domestic stock funds, for example, are outperformed by the [S&P500] index," and concludes "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." [6] Whether or not the escalating scale of indexing in recent decades has reduced the information content of stock prices is thus an empirical question of considerable importance.

Exploring this question requires distinguishing information-driven from other stock price movements. The recurring stock market manias, panics and crashes that dot financial history are difficult to explain except as markets driven by irrational investor sentiment (Kindleberger 1978).[7] Credible measures of noise trader sentiment, such as market-wide closed-end fund mispricing (Lee, Shleifer and Thaler 1991), correlate with major market moves. Furthermore, stock market index returns exhibit excess volatility (Shiller 1981, 1990), consistent with noise-traders expanding systematic stock market variation (De Long et al. 1990). Collectively, these lines of research build

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[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 Fresard (2012, 2014); and Edmans, Jayaraman and Schneemier (2017).

[6] Quoted in Akst, Daniel. 2022. Fifty Years Later, Burton Malkiel Hasn't Changed His Views on Indexing. Wall Street Journal Nov. 4.

[7] Aliber et al. (2015) update Kindleberger's (1978) analysis, affirming all his basic conclusions.

a compelling case for noise trader sentiment driving stock markets in ways that need not foster efficient capital allocation.[8]

However, Samuelson's dictum (Shiller 2001, p. 243) posits 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." The evidence above is of sentiment-driven stock markets. At the micro-level, stock markets look more efficient (Durnev et al. 2003; Bond et al. 2012). Excess volatility is evident in stock market index returns but not in firm-specific stock returns (Jung and Shiller 2005; Choi et al. 2020). Because individual stocks rise and fall relative to the market on relevant news, event studies (Fama et al., 1969) are useful in finance (Doron and Gurevich, 2014), accounting (Corrado, 2011), operations management (Ding et al., 2018), marketing (Johnston, 2007), international business (El Ghoul et al., 2022), and others. Moreover, web-scraping algorithms link most stock price movements to news (Jeon et al., 2022), suggesting that earlier studies that reported conflicting findings may have relied on a limited number of news sources. Lamont and Stein (2006) find firms treat high stock markets as overvaluations issuing shares and undertaking equity-financed M&A, but do not respond similarly when their stocks prices alone are high. In further alignment with Samuelson's dictum, market-wide stock price changes tend to be transitory (Campbell, 1991), while firm-specific stock price changes tend to be permeant (Vuolteenaho, 2002). Gabaix and Koijen (2022) further argue that demand shocks to aggregate savings swamp information events in explaining market-wide returns, leaving firm-specific price changes to reflect firm-specific information events. Gârleanu and Pedersen (2022) and Glasserman and Mamaysky (2023) derive Samuelson's Dictum in information economics models and provide further background. To explore whether or not escalating indexing has reduced the information content of stock prices, we therefore devise an empirical methodology to highlight firm-specific information events and stock price changes.

Given the paramount importance of this subject, prior research has examined the impact of escalating index investments on proxies for the information content of stock prices. Nevertheless, the existing literature presents a notable divergence of opinions. Many credible theoretical and empirical studies, the latter using a wide range of proxies for indexing and informational

[8] Though see e.g. Morck (2022) on social welfare increasing stock market manias.

efficiency, find that indexing reduces the informational efficiency of the stock market.[9] For example, Bennett, Stulz and Wang (2020), find that, after firms are added to the S&P 500 index, two proxies for the information content of stock prices fall. These are the ratio of idiosyncratic to market-related risk (Veldkamp 2006; Wei and Zhang 2006) and GPIN (Easley et al. 2002). Bennett et al. further show firms' productivity growth slowing after they are added to the S&P 500. These findings are consistent with more index fund investment rendering stocks less accurately priced, with share price changes providing managers with less useful information with which to adjust corporate decision-making (Bond et al. 2012), and with less idiosyncratic information in stock price movements impairing resource allocation efficiency in general (Wurgler 2000; Durnev et al. 2004; Chen et al. 2007; Morck et al. 2013). However, other credible theoretical and empirical studies, the latter again employing various proxies for indexing and informational efficiency, conclude that indexing enhances the informational efficiency of the stock market.[10] Baruch and Zhang (2019) link increased indexing to lower firm-specific informational efficiency and higher market-wide informational efficiency. In contrast, Bond and Garcia (2022) argue for the opposite pattern. Coles et al. (2022) argue that, in equilibrium, indexing does not alter informational efficiency and report evidence consistent with this. In summary, how indexing affects stock market informational efficiency remains debatable.

One debate concerns proxies for informational efficiency. One such proxy is idiosyncratic stock return volatility. 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.[11] Bennet et al. (2002) and many others measure idiosyncratic volatility as a ratio: either as 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 as best reflecting idiosyncratic information. In our context, stocks added to major indexes are known to co-move

[9] See e.g. Goetzmann & Massa (2003); Qin. & Singal (2015); Israel et al. (2017); Ben-David et al. (2018); Broman (2016); Da et al. (2018); Billett, Diep-Nguyen and Garfinkel (2020) and Brown et al. (2021).

[10] See e.g. Boehmer & Kelley (2009); Marshall et al. (2013); Stambaugh (2014); Boone et al. (2015); Madhavan (2016); Madhavan & Sobczyk (2016); Bai et al. (2016); Schmidt & Fahlenbrach (2017); Breugem & Buss (2019); Weissensteiner (2019); Glosten et al. (2021); Huang et al. (2021); Li et al. (2022). French (2008) puts the social value of price discovery by active investment below the aggregate fees active funds charge.

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

more with those indexes (Barberis et al. 2005; Vijh 1994), increasing their systematic volatility and therefore the ratio. Another such proxy, GPIN measures not the information content of stock returns, but the scale of information asymmetry between market makers and other investors (Aktas et al. 2007), which is not the primary concern raised by critics of indexing. Moreover, Bennet et al. (2002a) report their GPIN result attenuating over time as indexing grew more important. Yet another class of proxies include deviations from random walks to proxy for informational inefficiency, which Griffin et al. (2010) dispute. Furthermore, Baltussen et al. (2019) argue that indexing might alter the prominence of various deviations from a random walk without changing overall informational efficiency.

Perhaps encompassing all these concerns is the possibility of endogenous changes in the nature, magnitude, visibility, frequency and characteristics of shocks that a firm experiences after it is included or excluded from an index. For instance, when firms are added to an index, changes in the investor base could introduce changes in sentiment-driven common shocks (Barberis and Shleifer, 2003). Inclusion in an index increases analyst following (Chan et al., 2013; Boone and White, 2015), which may increase the visibility of idiosyncratic shocks. Alternatively, greater prominence after a firm is added to a major index might encourage more conservative management strategies (Bertrand & Mullainathan, 2003; John et al. 2008), potentially making idiosyncratic shocks less common, rather than diminishing the incorporation of idiosyncratic information into stock prices.

Ideally, one should directly assess whether a particular firm-specific information shock, which's magnitude and visibility is exogenous to the firm's inclusion or exclusion from an index, is incorporated differently into stock prices when the firm is part of the index compared to when it is not. That is exactly what we attempt to do in this paper. Our approach differs from the prior literature in two important ways. First, we directly test whether a given information shock is incorporated into stock prices rather than simply measuring whether the relative magnitude of idiosyncratic price movements or their properties change. Directly testing the integration of specific information shocks into stock prices circumvents the discussion about whether idiosyncratic returns are due to information or noise and avoids measurement issues that have plagued the proxies used in the existing literature. Second, we use shocks that are exogenous to any given firms' fundamentals, investor base or information environment, which sidelines endogeneity issues discussed above. Specifically, we use idiosyncratic (unrelated to the US market return) components of foreign currency exchange rate changes as exogenous idiosyncratic shocks to firms that are sensitive to such shocks. The idiosyncratic component of changes in exchange rates is exogenous to a given firm because it is determined in global markets, and is unlikely to be affected by any single firm being added to or dropped from the index. In addition, currency shocks are readily observable by all market participants, and this observability remains unaffected by any changes in the information environment of any given firm. Our tests then see if the idiosyncratic stock returns of exchange rate-sensitive firms that are added to (dropped from) the S&P 500 index[12], and therefore abruptly have more (less) index fund investment, become less (more) sensitive to idiosyncratic exchange rate changes.

We operationalize this approach by estimating correlations of the idiosyncratic components of each stock's returns with the idiosyncratic components of the currencies of major US trading partners. Because exchange rate changes affect different firms differently, and many not at all, we can identify firms whose idiosyncratic stock returns are especially sensitive to idiosyncratic changes in specific countries' exchange rates. Idiosyncratic means orthogonal to US market returns, or alternatively, to Fama and French (2015) five-factor model returns. Highly significant correlations, measured well before (after) (13 to 7 months) a stock is added to (dropped from) the S&P 500 flag stocks as foreign currency sensitive.[13] We find that more stocks are sensitive to the currencies of more important US trading partners. We then test for changes in the sensitivity of these stocks' idiosyncratic returns to idiosyncratic changes in the exchange rates to which they are sensitive in 6-month windows surrounding, but excluding the month when the stock is added to or dropped from the S&P 500.

Our main tests reveal an economically and statistically significant 60% lower (-0.34 point-estimate difference) in stocks' idiosyncratic currency sensitivity when in versus not in the S&P 500, whereas the magnitude of idiosyncratic currency shocks does not change significantly. The result is highly robust: It is evident in stocks added to the index, stocks dropped from the index, and both combined. It is robust across reasonable alternative ways of estimating idiosyncratic returns. Moreover, this difference in point estimate becomes more negative over time in lockstep with plausible proxies for the rising importance of indexing. These results are consistent with

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[12] Some papers use promotions from the Russell 1000 to Russell 2000 index to proxy for increased index fund ownership, but this link is valid only with careful attention to measurement errors (Apple et al. 2020).

[13] This approach mitigates attenuation bias in identifying stocks that are sensitive to currency shocks given that index inclusion may suppress incorporation of idiosyncratic information into stock prices.

indexing impairing the incorporation of firm-specific information into stock prices. This validates Shiller's concerns about indexing, a finding of considerable public policy importance.

Several econometric properties of our tests merit mention. First, Bennett et al. (2020) cogently argue that being added to or dropped from the S&P 500 is an exogenous event. However, Dhillon and Johnson (1991) counter that S&P, a bond rating agency, has inside information about firms' prospects and may select healthier firms for its index. Such considerations might apply to stock price changes associated with being added to or dropped from the index. However, S&P using anticipated abrupt changes in sensitivity to idiosyncratic exchange rates to select firms for its index is implausible.

Second, to preclude our results reflecting unusual macroeconomic conditions or characteristics of firms added to or dropped from the S&P 500, we assemble a control group of placebo firms, matched by idiosyncratic exchange rate sensitivity, past returns, and firm size. These exhibit no significant difference in idiosyncratic currency sensitivities around their matched event firms being added to or dropped from the S&P 500. Moreover, a difference-in-differences event study reveals idiosyncratically exchange rate sensitive event firms to be significantly less sensitive to idiosyncratic exchange rate fluctuations than are their matched placebo firms only when the event firms are in the S&P 500 index. When not in the S&P 500, their idiosyncratic exchange rate sensitivity is not statistically distinguishable from that of their matched placebo controls. This is consistent with being in the S&P 500 index causing idiosyncratically exchange rate sensitive firms' stocks to become less sensitive to idiosyncratic exchange rate changes.

Third, we can reject index firms more intensively hedging exchange rate risk as an alternative explanation of our findings for several reasons. Our main results persist after we control for a range of proxies for changes in currency risk hedging. These are based on: accounting ratios used to report hedging intensity, mentions in firms' documents of terms assembled by Manconi, Massa, and Zhang (2015) to flag exchange rate hedging, measures of foreign currency hedging activity and its intensity constructed using ChatGPT to review pertinent sections of firms' documents, and all the above together. Only 12% to 14% of event firms change their currency hedging significantly around being added to or dropped from the S&P 500 index, with intensified and reduced hedging occurring seemingly randomly among both sorts of event firms.

Fourth, although it is possible that firms that are added to or dropped from S&P 500 may choose policies that reduce their idiosyncratic volatility, we do not expect this to affect our tests.

For example, a firm added to the S&P 500 has likely grown large, and thus able to command greater market power, which could stabilize expected future dividends and reduce firm-specific volatility (Irvine and Pontiff 2009). Also, such a firm may have grown by developing a proprietary technology, and thus be disinclined to invest in self-destructive radical innovation, which could also reduce firm-specific volatility in its stock price (Pastor and Veronesi 2003; Chun et al. 2008, 2011). Our tests isolate idiosyncratic stock price changes due to idiosyncratic currency shocks, and these are unlikely to be affected by changes in overall idiosyncratic volatility due to changes in market power, innovation, or other fundamentals. One possible exception is that market success, crowned by index membership, might lead to reorganized supply chains that reduce firms' fundamentals sensitivity to idiosyncratic currency shocks. Such changes are unlikely to occur immediately, so focusing on short event windows around the index status change date alleviates this concern. In addition, our tests reject firms' idiosyncratic returns on equity (ROE) being differently sensitive to idiosyncratic exchange rate changes when in versus not in the S&P500. Our main results remain after controlling for changes in ROE sensitivity to currencies.

Our findings appear to extend to other idiosyncratic shocks. We observe a significant reduction in the standard deviation of daily idiosyncratic returns when stocks are part of the index relative to when they are not, particularly in the later sample period characterized by increased popularity in index investing.

The econometric tests we employ have potentially broad applicability, as they allow for a direct comparison of the completeness of idiosyncratic information capitalization into stock prices before and after a change in the stock's information environment. In the tests below, that change is the stocks' recently altered S&P 500 index membership status, and the idiosyncratic information events are idiosyncratic exchange rate shocks. Other changes in information environments might include regulatory changes, cross-listings, ownership structure changes, or capital structure changes. Other idiosyncratic information events could involve commodity price changes, weather events, or the like.[14] All that is required is an exogenous change in the information environment (firms cannot opt into the S&P 500 because they foresee fewer or more exchange rate shocks), as well as exogenous and comparably quantifiable information events (exchange rate shocks must be

[14] Faccio et al. (2021) use commodity price-sensitive firms' idiosyncratic stock return sensitivities to idiosyncratic commodity price shocks when in versus not in business groups to quantify shareholders' expectations of extraordinary income sharing (tunneling) in business groups.

economically important to the subject firms' fundamentals and equally so before and after the information environment change).

Our technique lets us conclude that the rise of index investing indeed impairs the capitalization of firm-specific information incorporation into stock prices. Obviously, no econometric tests are perfect but our methodology avoids issues related to the information environment of firms changing when they are added to or dropped from indexes. To obtain clean tests, we focus on idiosyncratic currency shocks. However, our results appear to generalize: idiosyncratic stock return volatility is lower when firms are in the S&P 500 than in proximate time windows when they are not. Index investing that damps index stocks' sensitivity to idiosyncratic information in general compromises both the very market efficiency that justifies indexing and the positive externalities of market efficiency – allocative efficiency (Wurgler 2000) and feedback from stock prices to corporate decision-makers (Bond et al. 2012). Increased passive investment having such effects would also be evidence of active investment having important positive externalities. We welcome further research into these issues.

2. Data and Methodology

2.1 Data Sources

We obtain inclusion and deletion events from the CRSP S&P 500 list, which provides the beginning and end dates of firms that are included in the S&P 500 Index[15]. 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 data is obtained from the Federal Reserve for the largest 15 trade partners of the US, listed in Table 1. Exchange rate returns are calculated relative to the US dollar. For countries that become Eurozone members, we use their local currency prior to their admission to the Eurozone and use the Euro thereafter. Mutual fund portfolio returns are from the CRSP Mutual Fund Dataset and aggregate equity holdings of mutual funds are from FRED.

We match our event firms to EDGAR SIC files to scrape data on hedging-related activities mentioned in 10-Ks, 10-K405s, 20-Fs, and 40-Fs.[16] The EDGAR SEC filings are only available

[15] We drop a few firms that are added to and dropped from the S&P500 the same day. These are new spinoffs of SP500 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.

[16] The last two apply to non-US firms with securities registered in the US. Firms may be dropped from the SP500 after becoming controlled by foreign firms.

from 1994. We establish a mapping between CRSP permnos and SEC CIKs[17]. Since events may be associated with mergers and acquisitions using one CIK per firm-event may result in missing filings before (or after) the event date. For 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 as a replacement. 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.

2.2 Calculating Idiosyncratic Component of Returns

Our goal is to understand whether incorporation of firm specific information changes when a firm is added to or dropped from the S&P 500 Index. Therefore, we calculate idiosyncratic components of both stock returns and currency returns. We then test to see if firm's idiosyncratic stock returns are less attuned to idiosyncratic exchange rate changes when those firms are in the S&P 500 Index than when they are not.

To calculate the idiosyncratic component of returns we use the CAPM with the CRSP value weighed total market return serving as the market return. In our main analysis we allow stock return beta with respect to the market factor to change over time depending on whether the stock is included in S&P 500 or not (based on evidence in Barberis, Shelifer and Wurgler, 2005). Alternatively, in robustness tests, we use different asset pricing models and different ways of calculating factor betas and idiosyncratic returns.

Time variation in beta is allowed by running separate regressions for each period a stock is within or outside of the S&P 500. For example, for a stock added to S&P 500 and then later dropped from S&P 500 we estimate three regressions: before inclusion, during the time the stock is included, and after it is dropped. Firm-specific shocks are the residuals from the regression:

$$R_{i,\tau} = \alpha_i + \beta_i R_{m,\tau} + \varepsilon_{i,\tau}, \qquad [1]$$

where $R_{i,\tau}$ is the daily return of stock *i* at time τ, $R_{m,\tau}$ is the value weighted market return and $\varepsilon_{i,\tau}$ is the firm specific component of stock *i* return at time τ. We use an analogous specification to calculate idiosyncratic component of currency returns:

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

[17] We rely on three different sources: i) Capital IQ , ii) WRDS SEC linking tables , and iii) CRSP/Compustat Merged linking table. In all three data sources, 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.

where $R_{c,\tau}$ is daily return of currency c relative to USD at time τ, $R_{m\tau}$ is the value weighted market return and $\varepsilon_{c\tau,}$ is the idiosyncratic component of currency c return at time τ.

2.3 Matching Firms to Currencies

We first identify idiosyncratically currency-sensitive firms by exploring whether the idiosyncratic components of each firm's stock returns have a statistically significant relationship to the idiosyncratic component of currency returns. We then explore whether firms' idiosyncratic currency-sensitivity differs around the dates their index status changes – that is, the dates they are added to or dropped from the S&P 500 Index, which we denote t. We identify idiosyncratically currency-sensitive stocks added to or dropped from the S&P 500 when those stocks are not in the S&P 500. Thus, matching is done within the 6-month time period spanning 7 to 13 months before (after) the event date t for stocks added to (dropped from) the index. Currency matching is always done when the stock is not in the S&P 500 Index so that any potential reduction in sensitivity to idiosyncratic information due to index membership does not affect the matching. To identify a match between a currency and a firm we use the regression specification

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

where $\varepsilon_{i\tau}$ and $\varepsilon_{c,\tau}$ are the daily idiosyncratic returns of stock i and currency c, respectively, at time τ,. We run the same regression for each firm-currency pair (i, c). We call $b_{i,c,t}$ firm i's *idiosyncratic currency sensitivity* to currency c relevant to event date t.

We declare a match between firm i and currency c if the absolute value of the t-statistic for $b_{i,c,t}$ is larger than or equal to 2. If firm i matches to multiple currencies we pick the currency c whose $b_{i,c,\mathrm{t}}$ has the highest absolute t-statistics. We prefer not to match based on absolute magnitude of $b_{i,c,t}$, which would match based on extreme $b_{i,c,t}$ and could contaminate differences in $b_{i,c,t}$ around the event time due to mechanical mean-reversion associated with measurement error.[18] Below, we adjust currency returns so the expected sign of $b_{i,c,t}$ is always positive.

We have 648 events in which firms matched to currencies, and have stock returns before and after their index status differences from 1970 through 2019. Of these, 463 are added to and 185 are dropped from the S&P 500 Index. We have fewer dropped firms because some are delisted, and therefore do not have stock returns after being dropped from the index. In contrast, S&P

[18] Matching by $b_{i,c,t}$ point estimate absolute magnitudes would risk selecting firm-currency pairs with large same-signed estimation errors. The random nature of estimation errors might then give smaller $b_{i,c,t}$ point estimates in a different time period as a statistical artifact.

selects replacements for these dropped firms from listed firms, so data before and after additions to the index are available.

Table 1 summarizes the distribution of firms matched to currencies. The most matches are to the Chinese Yuan with 138 observations, the Canadian Dollar with 94 observations, and the Japanese Yen with 64 observations. In general, more firm-currency matches are to currencies of larger trading partners of the US. Figure 1 portrays the time series of the number of firms matched to currencies, which varies over years without an apparent time trend.

3. Incorporation of Idiosyncratic Information and Index Investing

After identifying firms matched to a currency, we estimate idiosyncratic stock return sensitivity to idiosyncratic currency returns when the firm is in the index and when it is out of the index. We use the following regression specification for each currency-matched firm and index status-change event:

$$\varepsilon_{i,\tau} = a^{out}_{c,i,t} + b^{out}_{c,i,t} sign(b_{i,c,t})\varepsilon_{c,\tau} + e_{i,\tau}, \;\; \tau < t - t_L \qquad [4]$$

$$\varepsilon_{i,\tau} = a^{in}_{c,i,t} + b^{in}_{c,i,t} sign(b_{i,c,t})\varepsilon_{c,\tau} + e_{i,\tau}, \;\; \tau > t + t_U \qquad [5]$$

where $\varepsilon_{i,\tau}$ is the daily idiosyncratic return of stock i at time τ and $\varepsilon_{c,\tau}$ is the daily idiosyncratic return of currency c at time τ. We multiply idiosyncratic currency returns by $sign(b_{i,c,t})$, the sign of firm i's idiosyncratic sensitivity to c, so the expected $b^{out}_{c,i,t}$ and $b^{in}_{c,i,t}$ are always positive. The estimation is run separately in a pre-event window, running from seven to one month prior to the event, and a post event window, running from one to seven months after the event. This omits a blackout window $[t_L, t_U]$ of one month on either side of firm i's event date t. 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 the difference in beta before and after the event:

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

Table 2 summarizes the difference in idiosyncratic currency sensitivity, $\Delta b_{c,i,t}$, for firms added to or dropped from the S&P 500. 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 -0.28 (t-statistics of -5.58) lower when firms are in the index than when the same firms are not in the index. This corresponds to about 60 percent decline in sensitivity to idiosyncratic currency shocks when the firm is included in the S&P 500 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).

Given that indexing became more prominent after the early 1990s, we re-estimate 2.1 in two subperiods: 1970 to 1990 and 1990 to 2019. Table 4 shows no significant difference in idiosyncratic currency sensitivity around events prior to 1990 and a significant 0.34 (t = -5.54) drop in idiosyncratic currency sensitivity associated with index membership after 1990. In other words, the difference in incorporation of idiosyncratic information around index inclusion/deletion events is driven by the latter subperiod, when index investing is more economically important. For the rest of the analysis, we focus on the latter time period of 1990 through 2019. We refer to column 2.3 of Table 2 as our baseline result.

Table 2 also presents the results of the Wilcoxon signed-rank test, which is more robust to outliers and distributions with fat tails. The results from this test align with our conclusions derived from the t-tests. During the sub-period from 1990 to 2019, among the 459 observations, we observe that the sensitivity to currency exhibited a decrease in 254 instances and an increase in 205 instances when a stock was situated outside of the index compared to when it was within the index. The results of the signed-rank test demonstrate that we can confidently reject the null hypothesis suggesting that the two distributions are the same, with a probability of 0.01.

3.1 Correlation of Results with Index Investing

The difference in incorporation of idiosyncratic information around inclusion and deletion events, especially in the latter period 1990 to 2019, is consistent with index investing reducing incorporation of idiosyncratic information into stocks prices. In this section we analyze whether our results are correlated with various proxies of index investing. We use four different proxies for index investing.

The first proxy for index investing is the ratio of quarterly holdings by S&P 500 Index investor mutual funds in the CRSP mutual fund dataset relative to that of equity investments of all mutual funds from the FRED dataset. An advantage of using mutual funds is that they been around for a long time and their portfolio returns are available, which lets us statistically verify that they are index funds and calculate the ratio for a long time series. A mutual fund is considered an S&P 500 Index investor if the monthly fund returns have a beta between 0.99 and 1.01 with respect to monthly returns of the S&P 500 Index and the R-squared in the same regression is bigger than 0.98 in the entire sample period.

The second index investing proxy is a variation of the first proxy where we use the ratio of quarterly holdings by S&P 500 Index investor mutual funds (as defined above) relative to the holdings of all mutual funds reported in CRSP dataset. The main difference is that the denominator includes all holdings rather than equity holdings of all mutual funds.

The third index augments the second by including S&P 500-indexed ETFs. Easley et al (2021) challenge the common use of total ETF assets as a proxy for passive investment by documenting the rise of ETFs with active trading strategies. We therefore flag S&P 500 indexed ETFs as those whose name include the terms "S&P" and "500" and construct an analog to the second index using both ETFs and mutual funds.

The fourth index investing proxy is from Billett, Garfinkel and Nguyen (2020) who provided us with the quarterly holdings by passive investors and all institutional investors for S&P 500 stocks. The passive investors are defined as funds that invest in a benchmark (Schmidt and Fahlenbrach (2017)) and fund benchmarks are from Cremer & Petajisto (2013) and Morningstar website. Passive investors in this dataset could be using indices other than the S&P 500 as their benchmarks. The data are available between 1996 and 2017. The proxy we use is the ratio of quarterly holdings by passive index investors relative to holdings of all institutional investors equally weighted across all stocks in S&P 500 that quarter.

The final proxy is the Google n-grams (frequency mention) of “index investing”. Essentially this measure shows frequency of “index investing” relative to frequency of all other word pairs in printed and online media. The advantage of using this measure is twofold. First, it provides verification by an entirely different measure, which is not based on portfolio holdings of institutional investors. Second it is available for the entire time period we cover.

Figure 3 plots the time series of Google n-grams for the frequency of mentions of index investing and the quarterly value of equity holdings by S&P 500 index mutual funds as a fraction of the value of equity holdings by all mutual funds.[19] Both indexing proxies are low prior to 1990 and quickly increase after early 1990s.

[19] The time series of the second, third and fourth proxies are not reported in the figure. The second and third proxies are similar to the first one. The fourth proxy is only available for a short period of time.

Table 3 summarizes regressions of event firms' idiosyncratic currency decline associated with index membership on these five proxies of index investing. Larger declines in idiosyncratic currency sensitivity are statistically significantly associated with all five proxies for the importance of indexing. These results suggest the declines in idiosyncratic currency sensitivity are likely driven by the increasing importance of index investing.

3.3 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 as regression 4.0 and then revises these choices as robustness tests.

Table 4 regressions 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 in the main analysis.

Regression 4.3 reruns the baseline using the methodology that Faccio, Morck and Yavuz (2021) employ to estimate idiosyncratic stock return sensitivities to idiosyncratic commodity returns. First, our baseline result is inferred from daily returns. Instead, they use weekly returns to mitigate concerns about different time zones and different liquidities affecting the immediacy of stock price reactions to common idiosyncratic information shocks. Stocks on the threshold of S&P 500 index membership are generally highly liquid and all traded at the same time zone with currency shocks we use. Second, we allow each stock's beta to be different when the stock is in versus out of the index. In contrast, Faccio et al. (2021) estimate idiosyncratic returns across their entire dataset. These differences in methodology could affect the estimation of the idiosyncratic component of the stock return, though we have no a priori reason to believe the difference in methodology bias the estimation. To check this, regression 4.3 repeats our estimation following their methodology. The difference in idiosyncratic currency sensitivity associated with market inclusion is -0.45 with a t-statistic of -4.26, which is very similar both in magnitude and statistical significance to our main results.

Another alternative methodology is 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 betas. Dimson betas may help in capturing possible lead and lag relationships. We use Dimson betas for contemporaneous, one-day, and two-day lagged currency returns. Regression 4.4 show the change in sum of three idiosyncratic currency sensitivity measure to be -1.11, which is larger and more statistically significant (t = -7.02) than the baseline result.

Regression 4.5 revisits the baseline result, but calculates the idiosyncratic components of stock returns and currency returns using Fama and French 5-factor model. Idiosyncratic stock returns are the residuals from the regression:

$$R_{i,t} = \alpha_i + \beta_{i1}(R_{m,t} - r_t) + \beta_{i2} smb_t + \beta_{i3} hml_t + \beta_{i4} rmw_t + \beta_{i5} cma_t + \varepsilon_{i,t}, \qquad [7]$$

where $R_{i,t}$ is the daily return of stock *i* at time *t*, $R_{m,t}$ is the value weighted market return, r_t is the risk free rate, the risk factors smb_t, hml_t, rmw_t and cma_t are as described in Fama and French (2015), and $\varepsilon_{i,t}$ is the idiosyncratic component of return *i* at time *t*. We replace [1] with [7] and its analog for estimating the idiosyncratic component of currency returns [2] with [7]. Regression 4.5 shows these firms on average exhibit a 0.16 lower sensitivity to currency shocks (*t* =-3.52) when in than when not in the S&P 500 index.

The baseline result pools firms added to the S&P 500 index with firms dropped from that index. Regressions 4.6 and 4.7 preserve the methodology of the baseline result, but estimate the average difference in idiosyncratic currency sensitivity for firms added to and dropped from the S&P 500 index separately. Firm's added to the index show a decline in sensitivity to idiosyncratic currency shocks of -0.21 (t = -3.94) while those dropped from the index have a 0.99 (t = 4.33) increase in sensitivity to idiosyncratic currency shocks. Firms are dropped from the index after being taken over and delisted are not included in our sample. We speculate that firms dropped from the index for other reasons might become objects of especially active information discovery.

Overall, while reasonable differences in methodology change the number of firms matching to currencies and the magnitudes of the differences in sensitivity to currency shocks, idiosyncratic stock returns are always significantly less sensitive to idiosyncratic currency returns when stocks are in than not in the S&P 500.

4. 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&P 500 Index. This helps with identification by excluding 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&P 500 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&P 500 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.

4.1. 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 in the S&P 500 index during the event firms' event windows. We assemble this control sample of placebo firms as follows:

For each event, we consider potential matched control firms that are not in S&P 500 index but among the largest 1000 firms by market capitalization as of the end of the year 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 is closest to that of the event firm, and (3) whose propensity score differs in absolute value from that of the event firm by less than 0.1.

Table 6 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 group exhibit no significant difference in idiosyncratic currency sensitivity when the event firms are added to or dropped from the index. As a result, the difference in differences is significant and similar to baseline results. This is inconsistent with our results being an artifact of currency matches arising in periods when firms have abnormally high idiosyncratic currency sensitivity, which then attenuates with distance in time from the currency-matching window because such attenuation is not evident in the control firms.

Table 6 thus excludes the possibility that S&P might systematically add (drop) firms from the S&P 500 index after (before) random spikes in idiosyncratic currency sensitivity. The same tests also exclude the possibility that S&P might systematically add (drop) firms from the S&P 500 index shortly after (before) differences in political, macroeconomic, or other conditions that reduce (increase) idiosyncratically currency sensitive firms' sensitivity to idiosyncratic currency shocks.

A second class of alternative causality scenarios remains possible: firms added to (dropped from the S&P 500 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.

4.2. Controlling for Differences in Hedging Activity in Accounting Statements

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 attempt to directly control for this possibility in three ways. First, we control for differences in indicators of hedging related activity in accounting statements before and after the event. Second, we measure differences in firms' mentions about foreign currency hedging as explained in the next section. Third, we ask ChatGPT to read firm documents and decide whether the firm is hedging its currency risk and its intensity of hedging.

We calculate the difference in balance sheet and income statement-based ratios summarizing hedging activity between the fiscal year -1 and fiscal year +1 where year zero is the event year. Therefore, we need the accounting ratio to be available before and after the event in order to calculate the difference. The ratios 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 the accounting items used in the numerator of the ratios are missing, we assume their values are zero. This is because firms that do not use derivative assets do not report these balance sheet and income statement items.

Each financial ratio above is a measure of general hedging activity and therefore a noisy measure of currency-hedging activity. However, if there is a significant difference in firms' currency risk hedging policies, we expect to capture the policy difference in some of these ratios. We control for differences in the ratios before and after the event using the following regression specification:

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

where $\Delta b_{c,i,t}$ is the difference in the idiosyncratic currency c sensitivity of firm i's stock returns around its time t index status differences from [6] and $\Delta\eta_{h,i,t}$ is the contemporaneous difference in the firm's h^{th} hedging proxy or proxies. The difference in hedging proxies are always calculated when the firm is in the index minus when firm is outside the index, which matches how we calculate $\Delta b_{c,i,t}$. 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 implies 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.

4.3 Controls for Differences in Mentions of Foreign Exchange Hedging Activity

The ratios described in the previous section aggregate derivative positions in foreign exchange, commodities, and interest rates. We are specifically interested in foreign exchange hedging however accounting statements do not identify derivatives used for foreign exchange hedging versus other hedging or speculation. Firms whose foreign exchange hedging activities are more material may highlight this in their communications to investors, and firms that avoid foreign exchange hedging may likewise communicate this. Scraping each event firm's EDGAR files (10-Ks, 10-K405s, 20-Fs, and 40-Fs) before and after their inclusion / deletion events for phrases associated with foreign exchange hedging thus gives us a second approach to assessing differences in hedging. Following Manconi, Massa, and Zhang (2018) we count phrases indicating firm i is[20] and is not[21], respectively, hedging foreign exchange. For each firm we count these phrases twice, denoting counts of phrases indicating currency hedging activity before and after firm i's time t index status as $n_{H,i}^{out}$ and $n_{H,i}^{in}$, respectively; and the analogous counts of phrases indicating no hedging activity as $n_{N,i}^{out}$ and $n_{N,i}^{in}$, respectively;

Using this data, we generate two hedging attention variables. The first is a currency "hedger" firm dummy variable set to one if the firm has at least three instances of the keywords for currency hedging and no instances of keywords that mention that they do not engage in 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.

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

Our first hedging attention difference variable is then

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

Thus, $\Delta H_{1,i,t}$ is plus one for firms that start paying attention to currency hedging when in the index than when not in it, zero for firms whose attention to currency hedging does not change, and minus one for firms that pay markedly less attention to currency hedging when in the index than when not in it.

Panel A of Table 8 presents summary statistics showing no marked hedging attention difference in 88% of events, markedly more attention to hedging in 6% of events and markedly less attention to currency hedging in the remaining 6%. The differences in idiosyncratic currency

[20] 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'.

[21] 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'

sensitivity for each of these groups of events are 0.06, -0.47 and -1.34 with t-statistics of 0.27. -4.77 and -3.11, respectively. This shows firms that attend markedly more to hedging when in the index have statistically significantly more depressed idiosyncratic currency sensitivity when in the index. Therefore, our measure of increased attention to currency hedging does correspond to greater declines in idiosyncratic currency sensitivity. However, the number of firms attending markedly more to currency hedging when in the index is only 22 and the firms doing opposite is 23, rendering changed attention to 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 hedging attention. Next, we control for differences in attention to currency hedging variables around each event and all previous control variables in regressions of the form

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

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]. We find both 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 column C4 affirm that accounting-based hedging proxies and hedging proxies based on keywords are jointly statistically significant. Regardless, of which proxy or proxies for differences in hedging and/or attention to currency hedging are included, the average difference in idiosyncratic currency sensitivity remains negative and highly statistically significant.

4.4 ChatGPT Interpretation of Foreign Exchange 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[22].

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 $G^{T}_{1,i,t} = 1$ for yes answers to the first question and otherwise zero. For the second question, we assign scores starting from $G^{T}_{1,i,t} = 1$ 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

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

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 firm is in the index relative to when it is outside.

Panel A of Table 8 presents summary statistics of $\Delta G_{1,i,t}$. In about 7% of the cases the firms stop hedging currency risk when in the index and hedges when outside. On the other hand, in 7% of the cases firms hedge currency risk when outside of the index but not when in the index. There is no difference in hedging in 86% of cases. The differences in idiosyncratic currency sensitivity for each of these groups of events are 0.00, -0.64 and -0.30, respectively. The firms that stopped hedging when in the index do not experience any difference in sensitivity to currency hedging. While firms that do not change their currency hedging policy experience a significant drop in sensitivity to currency when in the index. The firms that start hedging when in the index have a drop in their sensitivity of currency however this drop is not statistically significant. Again, a relatively small number of firms changing their hedging behavior leaves differences in hedging

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

unlikely to explain our results. 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.

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.

4.5 Controlling for Differences in Fundamentals

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. This concern is partially mitigated by measuring idiosyncratic sensitivity to matched currency within a short window before and after the event. However, differences in the idiosyncratic currency sensitivity of a stock's returns in the short term might still conceivably also reflect long term anticipated differences in fundamentals. Therefore, we control for differences in idiosyncratic fundamental returns with respect to idiosyncratic currency shocks within the window of before and after 5 years of the event.

We proxy for fundamental returns using Return on Equity (ROE), which is net income divided by lagged book equity[23]. We first calculate idiosyncratic components of ROE with respect to the CRSP value-weighted total market return using quarterly financial statements and quarterly market returns. Then we calculate the difference in the sensitivity of the idiosyncratic components of firms' ROEs to the idiosyncratic components of currency returns from 5 years before to 5 years after the event quarter, dropping a quarter on each side of the event quarter. We require at least 12 quarters of observations both before and after the event[24] and lagged book equity to be positive.

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

[24] If the firm has more than one event and the event periods overlap then the overlapping time period is counted for the consequent event.

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 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

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

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 -0.46 to -0.56 and is always highly statistically significant.

4.6 Generalization of Results and Econometric Approach

The econometric tests we utilize are designed to address endogeneity concerns related to a firms' changing information environment around index inclusion and exclusion. We use currency shocks that are determined exogenously in global markets, 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. We test that whether overall idiosyncratic volatility changes around index inclusion and deletion events in Table 10.

Table 10 reports differences in standard deviation of daily idiosyncratic stock returns when the stock is in the index versus when it is not. In these test we use all stocks with index inclusion and deletion events instead of focusing on firms that are sensitive to currency shocks. The average differences in standard deviation of daily idiosyncratic returns when the stock is in the index and when not in the index are slightly negative for the entire sample period between 1970 to 2019. However, the reduction in standard deviation of idiosyncratic returns are entirely driven by the time period after 1990, when index investing became more popular. In fact, during the 1970-1990 time period changes in standard deviation of idiosyncratic returns are slightly positive. These results closely resemble results we obtained from using exogenous shocks to currencies and event firms that are sensitive to currency shocks. This implies that our results are likely to be applicable to all types of idiosyncratic shocks.

Our methodology also possesses broader applicability in various contexts where assessing the integration of exogenous information shocks into stock prices is crucial. We employ the modification in a stock's recently altered S&P 500 index membership status, with idiosyncratic exchange rate shocks as the focal point for our analysis. Additional shifts in information environments may encompass regulatory changes, cross-listings, changes in ownership structure, or adjustments in capital structure. Furthermore, other idiosyncratic information events could encompass changes in commodity prices, weather-related incidents, and similar exogenous shocks that are not directly affected by changes in the firms' information environment.

5. Conclusion and Implications

We conclude that indexing reduces the reactions of stock prices to relevant idiosyncratic information. To be included in our tests, a stock must be added to or dropped from the S&P 500, have sufficient returns data both before and after its transitions into or out of that index, and must, when not in the index, have idiosyncratic (orthogonal to the US market) returns that correlate highly with the idiosyncratic (orthogonal to the US market) currency returns of a major US trading partner. Our conclusion follows from robust findings that the same idiosyncratically foreign currency-sensitive stock's idiosyncratic returns are economically and statistically less correlated with the idiosyncratic returns of the relevant currency when that stock is in the index than when it is not in the index. These conclusions are evident in simple means, in difference-in-difference tests where the control group is other firms idiosyncratically sensitive to the same foreign currencies and matched by prior returns and size to the event firms, and in tests that control for changes in hedging policies.

Our tests advance literature, which previously reached mixed conclusions, in several key 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 use shocks observable by all market participants and exogenous to any given firms' fundamentals, investor base or information environment. Finally, our tests preclude reverse causality (S&P is unlikely to add stocks to the S&P 500 because they are about to become less sensitive to foreign currencies), as well as common latent factors (variables that simultaneously cause S&P to add a firm in its index and that firms' stock to become less sensitive to foreign currency changes). Further tests reject firms hedging foreign currency risk more intensely when in the S&P500 than when not in it and firms' idiosyncratic fundamentals (return on equity) being less sensitive to idiosyncratic foreign currency changes when in the S&P500 than when not in it.

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. 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; Durnev et al. 2004; Chen et al. 2007; Morck et al. 2013).

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Figure 1: Inclusion and Deletion Events of S&P 500 Firms Matched to a Currency

The figure shows the time series of number of firms added to or dropped from S&P 500 index that can also be matched to a currency.

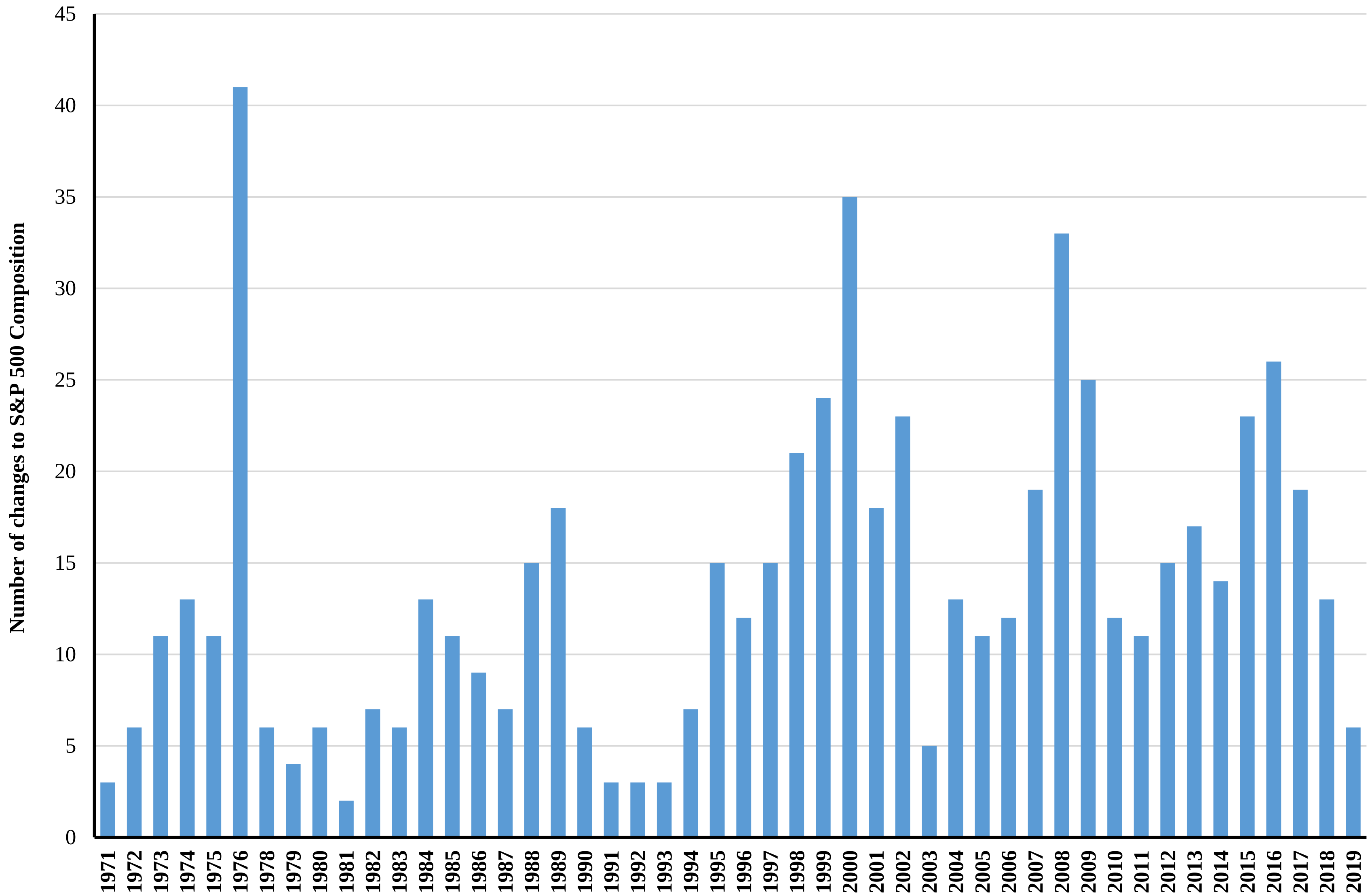

Figure 2. Currency Matching and Idiosyncratic Currency Sensitivity Estimation Windows

This figure provides details about the timeline of currency matching and idiosyncratic currency sensitivity measurement windows for a firm newly included in the S&P 500 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, and twenty trading days after) are dropped. Twenty trading days roughly equal one month. The timeline for deletions from the S&P 500 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, and matching with the currency is estimated in the seventh to thirteenth month after the stock is dropped from the S&P 500 index. This means that in both cases, the currency matching is done while the stock is not in the index.

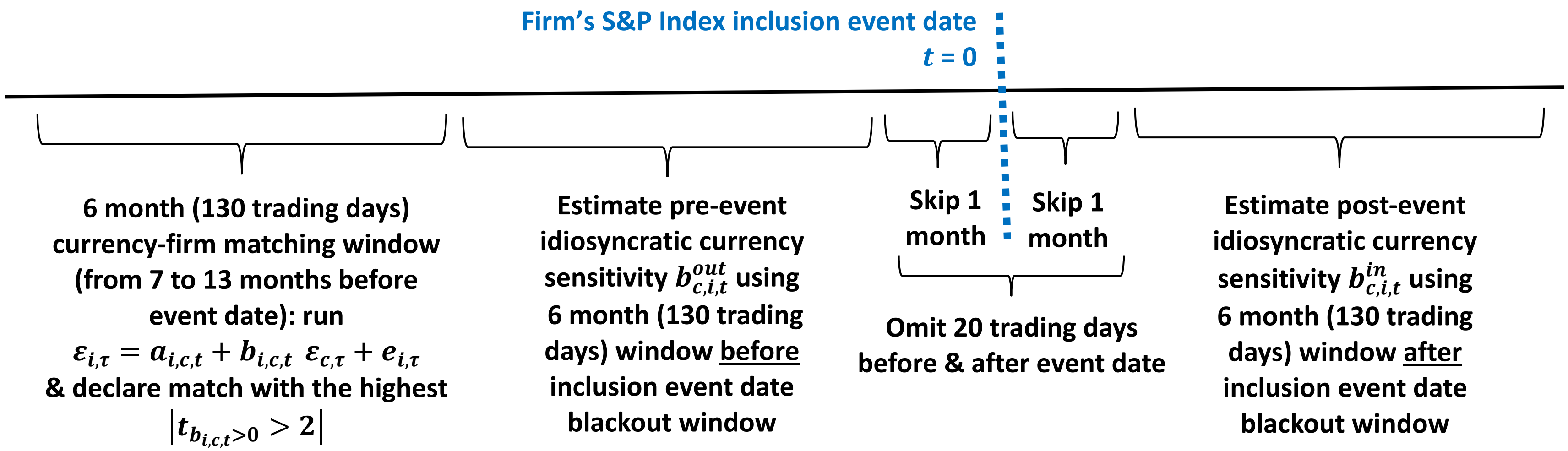

Figure 3. Proxies for the Importance of Index Investing

The figure plots Google frequency mention of "index investing" and the fraction of holdings by S&P 500 Index mutual funds in CRSP relative to all equity holdings of all mutual funds from FRED dataset.

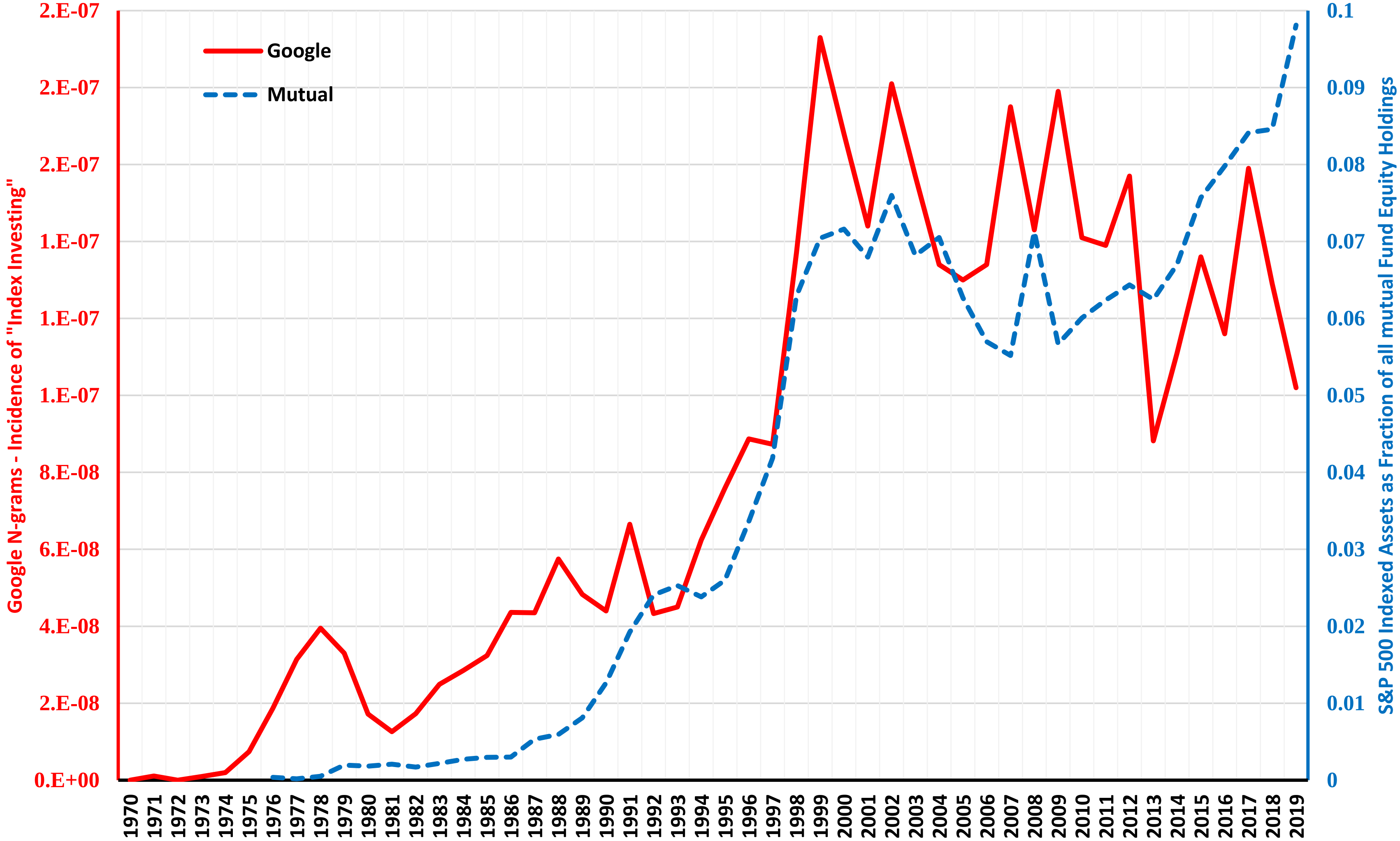

Table 1: Inclusion/deletion Firm matches to Currencies

The Table shows the distribution of firms added to or dropped from S&P 500 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 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	0.06
Canada	94	0.15
China	138	0.21
Eurozone	30	0.05
France	15	0.02
Germany	14	0.02
India	51	0.08
Ireland	16	0.02
Italy	24	0.04
Japan	64	0.10
Mexico	41	0.06
Netherlands	16	0.02
South Korea	26	0.04
Taiwan	31	0.05
United Kingdom	47	0.07
Total	648	100

Table 2: Differences in Incorporation of Idiosyncratic Information

The table shows differences in stocks' idiosyncratic currency sensitivity around their inclusions in or deletions from the S&P 500 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, and 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. Each triad of rows reports values, *t*-statistics and p-levels.

		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	-0.28	-0.12	-0.34
	t-ratio	-5.58	-1.50	-5.54
	p-level	0.00	0.14	0.00
Wilcoxon signed rank test rejecting equal number of positive and negative differences $\Delta b_{c,i,t}$ in idiosyncratic stock return currency sensitivity (in-index minus out-of-index)	number positive	346	92	254
	number negative	302	97	205
	z-test	2.26	-0.22	2.78
	signed-rank test p-level	0.02	0.83	0.01
Observations		648	189	459

Table 3: Index Investing and Differences in Incorporation of Idiosyncratic Information

The table shows regressions of difference in this sensitivity on index investing proxies. Index investing proxies are explained in detail in Section 3.1. Idiosyncratic currency sensitivities are described in Table 2. The coefficient is divided by 1 million in regression 3.5. Clustering is by quarter in regression 1, 2, 3 and 4 and by year in regression 5. Each triad of rows reports coefficients, *t*-statistics and p-levels.

		3.1	3.2	3.3	3.4	3.5
		S&P 500 Index Mutual Fund Holdings as Fraction of Equity Holdings of All Mutual Funds	**S&P 500 Index Mutual Funds Holdings as Fraction of All Holdings of All Mutual Funds**	**S&P 500 Index Mutual Funds and ETF Holdings as Fraction of All Holdings of All Mutual Funds and ETFs**	**Passive Investor Share among S&P 500 Stocks**	**Google n-grams index for the frequency of mentions of index investing**
Time Period		1976 to 2019	1976 to 2019	1976 to 2019	1996 to 2017	1970 to 2019
Correlation with difference in idiosyncratic stock return currency sensitivity (in-index minus out-of-index)	*coefficient*	-1.60	-4.51	-2.62	-41.70	-0.19
	t-ratio	-3.38	-3.10	-2.53	-5.16	-2.33
	p-level	0.05	0.06	0.09	0.02	0.03
	Observations	582	582	582	582	648

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. Regressions 4.1 and 4.2 use no winsorization and winsorization at 5%, respectively. Regression 4.3 uses weekly returns instead of daily returns and estimates idiosyncratic stock returns using the entire dataset assuming that beta with respect to stock market does not change whether the stock is included in the S&P 500 index or not. Regression 4.4 uses daily returns Dimson betas, where idiosyncratic stock returns are regressed on contemporaneous and two days of lagged idiosyncratic currency returns, idiosyncratic returns being calculated using the entire dataset and assuming that beta with respect to stock market does not change whether the stock is included in S&P 500 index or not. Regression 4.5 uses idiosyncratic stock returns and commodity returns calculated using Fama-French five-factor asset pricing model. Regressions 4.6 and 4.7 re-estimate the baseline result for index inclusions and deletions, respectively. 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: Difference in idiosyncratic stock return sensitivity to idiosyncratic currency shocks when in the index minus when not in the index, winsorized at 10%, estimated from daily data using market model betas, pooling stocks added to and dropped from the S&P500 index.	-0.34	-5.54	0.00	459
4.1 Re-estimated with no winsorization, otherwise as in baseline result.	-0.91	-2.67	0.01	459
4.2 Re-estimated winsorizing at 5%, otherwise as in baseline result.	-0.68	-4.04	0.00	459
4.3. Re-estimated using weekly returns, idiosyncratic returns are estimated using entire time period, otherwise as in baseline result.	-0.45	-4.26	0.00	459
4.4 Re-estimated using Dimson betas with daily returns of contemporaneous and two days of lags, the three betas are added, otherwise as in baseline result.	-1.11	-7.02	0.00	376
4.5 Re-estimated using Fama-Frech five-factor model, otherwise as in baseline result.	-0.16	-3.52	0.00	422
4.6 Sample only includes stocks added to the index, otherwise as in baseline result.	-0.24	-3.77	0.00	329
4.7 Sample only includes stocks dropped from the index, otherwise as in baseline result.	0.99	4.33	0.00	130

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&P 500 in the event year and must be idiosyncratically sensitive to the same currency as the event firm. Propensities to be included in (dropped from) the S&P 500 index are separately estimated using prior 12 month stock returns and firm size as covariates. Control firms must have absolute values of propensity scores less than 0.1 different from those of their firms to which they are matched. 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	-0.45	-0.04	-0.40
	t-ratio	-5.42	-1.43	-4.60
	p-level	0.00	0.16	0.00
Wilcoxon signed rank test rejecting equal number of positive and negative differences $\Delta b_{c,i,t}$ in idiosyncratic stock return currency sensitivity in-index minus out-of-index	number positive	196	204	208
	number negative	232	224	220
	z-test	-3.01	-1.41	-2.21
	signed-rank test p-level	0.00	0.16	0.03
	Observations	428	428	428

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&P 500 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&P 500 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**
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	-8.83	-0.84	-2.59	-0.09	-16.77	-51.86	32.39	-8.99	-11.08	
	t-ratio	-0.58	-0.15	-0.45	-0.30	-0.82	-0.68	1.00	-0.38	-0.61	0.37[a]
	p-level	0.56	0.88	0.65	0.77	0.41	0.49	0.32	0.70	0.54	0.95[a]
Difference in idiosyncratic stock return currency sensitivity	coefficient	-0.48	-0.48	-0.47	-0.45	-0.47	-0.48	-0.47	-0.48	-0.48	-0.47
	t-ratio	-5.75	-5.78	-5.72	-5.24	-5.74	-5.75	-5.73	-5.74	-5.75	-5.40
	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		B.1	B.2	B.3	B.4	B.5	B.6	B.7	B.8	B.9	B.10
Difference in accounting ratio proxy for currency hedging[a]	coefficient	-6.23	-1.02	-3.05	-0.08	-14.11	-55.60	30.99	-11.06	-10.99	
	t-ratio	-0.57	-0.22	-0.56	-4.69	-0.79	-0.96	0.98	-0.93	-0.85	29.1[a]
	p-level	0.57	0.83	0.58	0.00	0.43	0.34	0.33	0.35	0.39	0.00[a]
Difference in idiosyncratic stock return currency sensitivity	coefficient	-0.48	-0.48	-0.47	-0.45	-0.47	-0.48	-0.47	-0.48	-0.48	-0.47
	t-ratio	-5.72	-5.77	-5.72	-5.24	-5.73	-5.75	-5.73	-5.74	-5.74	-5.35
	p-level	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	Observations	445	443	445	385	445	445	445	445	445	385

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

Table 7: Difference in References to Currency Hedging

The table display average difference in idiosyncratic currency sensitivity around S&P 500 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, and 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		**Stopped Hedging**	**No difference**	**Started Hedging**
Change in idiosyncratic stock return currency sensitivity	Mean	0.06	-0.47	-1.34
	t-ratio	0.27	-4.77	-3.11
	p-level	0.79	0.00	0.01
	Observations	23	340	22

Attention to Hedging proxy(ies)		**Dummy**	**Count**	**Both**	**Both & all in Table 6**
Panel B: OLS Regressions		7B.1	7B.2	7B.3	7B.4
Change in attention proxy for currency hedging[a]	coefficient	-0.70	-0.07		
	t-ratio	-2.62	-2.90	5.14[a]	0.98[a]
	p-level	0.01	0.00	0.01[a]	0.46[a]
Change in idiosyncratic stock return currency sensitivity	coefficient	-0.49	-0.49	-0.49	-0.48
	t-ratio	-5.37	-5.38	-5.39	-4.95
	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	-0.60	-0.03		
	t-ratio	-2.67	-7.41	7.60[a]	105.8[a]
	p-level	0.01	0.00	0.00[a]	0.00[a]
Change in idiosyncratic stock return currency sensitivity	coefficient	-0.49	-0.47	-0.48	-0.47
	t-ratio	-5.32	-5.13	-5.25	-4.84
	p-level	0.00	0.00	0.00	0.00
	Observations	385	385	385	329

[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&P 500 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, and 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 =		**Stopped Hedging**	**No difference**	**Started Hedging**
Change in idiosyncratic stock return currency sensitivity	Mean	0.00	-0.54	-0.30
	t-ratio	0.01	-5.36	-0.88
	p-level	1.00	0.00	0.39
Observations		27	330	28

ChatGPT Hedging proxy(ies)		**Dummy**	**Hedging Intensity**	**Both**	**Both & all in Table 6 & 7**
Panel B: OLS Regressions		8B.1	8B.2	8B.3	8B.4
Change in proxy for currency hedging[a]	coefficient	-0.15	-0.12		
	t-ratio	-0.61	-1.12	0.63[a]	1.05[a]
	p-level	0.55	0.26	0.54[a]	0.39[a]
Change in idiosyncratic stock return currency sensitivity	coefficient	-0.49	-0.48	-0.48	-0.46
	t-ratio	-5.30	-5.16	-5.15	-4.79
	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	-0.27	-0.13		
	t-ratio	-1.15	-1.19	0.76[a]	15.06[a]
	p-level	0.25	0.23	0.47[a]	0.00[a]
Change in idiosyncratic stock return currency sensitivity	coefficient	-0.49	-0.47	-0.48	-0.46
	t-ratio	-5.32	-5.19	-5.20	-4.75
	p-level	0.00	0.00	0.00	0.00
Observations		385	385	385	329

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

Table 9: Difference in Sensitivity of ROE to Currency Returns

The table displays the average difference in idiosyncratic stock return sensitivity to currencies around S&P 500 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	-0.14		
	t-ratio	-0.54		
	p-level	0.59		
		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	0.04		
	t-ratio	1.27	0.16[a]	0.37[a]
	p-level	0.20	0.99[a]	0.98[a]
Change in idiosyncratic stock return currency sensitivity	coefficient	-0.56	-0.46	-0.46
	t-ratio	-4.69	-3.85	-3.54
	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	0.02		
	t-ratio	0.57	0.14[a]	0.40[a]
	p-level	0.57	0.99[a]	0.97[a]
Change in idiosyncratic stock return currency sensitivity	coefficient	-0.56	-0.46	-0.46
	t-ratio	-4.70	-3.86	-3.52
	p-level	0.00	0.00	0.00
Observations		249	218	199

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

Table 10: Changes in Total Idiosyncratic Volatility

The table shows differences in stocks' standard deviation of daily idiosyncratic returns around their inclusions in or deletions from the S&P 500 index in 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, and 20 trading days after it) and estimate the stock's idiosyncratic return volatility pre-event in the six months (130 trading days) before the exclusion window and its post-event idiosyncratic volatility in the six months (130 trading days) after the event. Idiosyncratic stock 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 standard deviation of daily idiosyncratic are winsorized at 10% for each sample. Each triad of rows reports values, *t*-statistics and p-levels.

		10.1	10.2	10.3
Index status difference events		**All 1970 - 2019**	**Sub-Period 1970 - 1990**	**Sub-Period 1990 - 2019**
t-test rejecting zero mean difference in standard deviation of idiosyncratic daily stock returns(in-index minus out-of-index)	mean difference	-0.043	0.047	-0.13
	t-ratio	-2.17	1.66	-4.49
	p-level	0.03	0.10	0.00
	# of observations	1517	602	911