Cross-Border M&A Flows, Economic Growth, and Foreign Exchange Rates*

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January 9, 2022

Abstract

We uncover a novel source of predictive information, originating from the announcements of cross-border mergers and acquisitions (M&As), that forecasts changes in economic growth and foreign exchange rates. Consistent with the announcements revealing firms' private expectations about economic fundamentals, we find that a country's economic growth accelerates, and its local currency appreciates, following months in which its announced cross-border M&A net inflows are abnormally high. We observe the opposite patterns following abnormally low M&A net inflows. The predictability captures reversals in economic growth and is driven by the acquisition decisions of domestic firms revealing information about their local economic conditions. A currency portfolio that exploits the predictability generates a Sharpe ratio of over 0.70, while the returns are unrelated to other sources of currency return predictability, including carry, value, and momentum.

Keywords: currency returns, cross-border mergers and acquisitions, exchange rate determination, economic growth

JEL Classification: F31, G12, G15

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1 Introduction

One of the most cherished beliefs of international economists is that foreign exchange (FX) rates are intrinsically linked to current and future macroeconomic fundamentals, a relationship that is encapsulated in a broad class of open-economy models of exchange rates (e.g., Engel and West, 2005).[1] An implication of these models is that agents with more accurate expectations of economic fundamentals—than the market's overall expectation—can forecast FX returns. But which economic agents, if any, can more accurately forecast future fundamentals? And how is that information revealed to the market and subsequently embedded into exchange rates?

A common way to address these questions is to study the information contained in aggregate FX trades, i.e., order flow. Analysed in this way, no single agent needs to be consistently better informed. Instead, certain groups of agents may, collectively, be more informed than others, and thus signals can be extracted from observing the actions of particular groups. Providing that at least some agents in the group are better informed, informative expectations about future fundamentals may be revealed through order flow, and thus order flow may predict FX returns. Indeed, evidence shows that the FX market is characterized by a large degree of information asymmetry (Cespa et al., 2021), and that the order flow of non-bank financial firms (e.g., hedge funds) predicts exchange rate movements (Menkhoff et al., 2016; Ranaldo and Somogyi, 2021). This predictability has been attributed to the aggregated orders of these more sophisticated customers revealing informative expectations about future fundamentals—information that is gradually incorporated into market prices (Rime et al., 2010). In contrast, these same studies find that commercial firms' order flow is uninformative about FX returns.

In this paper, we explore a different channel through which information may be revealed to financial markets, by asking whether privately-formed expectations can be expressed *outside* of FX order flow. Why might this be the case? A natural reason is because many agents trade in FX markets for non-profit motives, and thus, plausibly, without fully revealing their information sets. Commercial firms' FX trades, for example, are often mechanical—the outcome of routine daily operations, such as transaction hedging or treasury management, which may be orthogonal to future economic fundamentals. Instead, when making *investment* decisions, all firms—both financial and non-financial—form expectations about future macroeconomic

[1] While the seminal empirical findings of Meese and Rogoff (1983) cast serious doubt on this relationship in the time series, recent studies have demonstrated a far stronger link when explored in the cross-section (Sarno and Schmeling, 2014; Dahlquist and Hasseltoft, 2020; Colacito et al., 2020) or at the security (Lilley et al., 2021) and firm level (Dernaoui and Verdelhan, 2021).

conditions by necessity, since these fundamentals affect the expected cash flows of potential projects. These firms are also not constrained to invest in their domestic market. When opportunities appear more attractive overseas, investment is likely to flow to those markets. Thus, analogous to FX order flow, corporate *investment flow* (the country-level aggregation of corporate investment inflows and outflows) may reveal firm-level expectations about cross-country economic fundamentals and, therefore, provide an alternative exchange rate predictor.

We explore this possibility by asking three research questions: first, is corporate investment flow informative about future macroeconomic fundamentals? Specifically, the hypothesis is that an abnormal number of newly announced investments reveals information about subsequent macroeconomic fundamentals. An abnormally high net investment inflow (more inflows or less outflows than typical) reveals a signal about higher expected domestic economic growth. Vice-versa, an unusually low net investment inflow (less inflows or more outflows than typical) signals weaker domestic growth in the future. Second, if these investment flows are informative, do they provide *incremental* information relative to other well-known predictors of economic activity? And third, if there is novel information about future fundamentals contained in corporate investment flow, can the information be used to forecast exchange rate movements and currency returns, as predicted by open-economy models of exchange rate determination?

The view that corporate investments are driven by expected future growth expectations is consistent with both theory and practice. In a recent survey by the Harvard Business Review, the economy was rated as the number one issue for business leaders: directors factor in expectations about future global growth when deciding upon corporate strategies, merger and acquisition (M&A) activity, and other investment policies.[2] While according to Deloitte, relative cross-country growth prospects are the *main* driver of cross-border M&A investment activity.[3] The forward-looking aspect of investment decision making also has long-standing theoretical underpinnings: in the model of Nickell (1974), for example, firms adjust investment plans based on their expectations of future demand, such that investment stops before demand reaches a peak and resumes after the trough.[4] While, according to international portfolio balance models, demand for foreign assets rises when their returns are relatively more attractive than on domestic assets (Kouri, 1976).

To be clear, we do not assume that international investments are determined *only* by ex-

[2]See "The Political Issues Board Directors Care Most About," Harvard Business Review, February 16, 2016.
[3]See "M&A Insights: Global M&A Drivers," Deloitte, Spring 2016.
[4]See also Arrow (1968) and Bernanke (1983).

pectations of future macroeconomic conditions. Indeed, firms undertake these investments for heterogeneous reasons and no individual project is necessarily informative. Instead, we assume that future macroeconomic fundamentals reflect a common factor in firms' investment decision making, such that the announcements should, in part, reflect firms' heterogeneous beliefs about economic prospects. By aggregating and standardizing announcements, the idiosyncratic components are averaged towards zero and time invariant factors are removed to reveal a more precise signal of firms' combined expectations about future macroeconomic fundamentals.

One potential concern, however, is that commercial firms, unlike hedge funds, are unlikely to reveal predictive information via their investments because, it may be believed, they rely only on publicly available signals. But there are strong theoretical reasons, as well as empirical evidence, to believe firms may have superior information or better information processing capabilities. Domestic firms and investors are, for example, known to have more information about local economic conditions than foreigners (Brennan and Cao, 1997; Van Nieuwerburgh and Veldkamp, 2009), since they are "closer to information" (Frankel and Schmukler, 1996). If so, the changing behaviour of *domestic* firms should be especially revealing about future local economic conditions. In Section 2 we provide further details of these theoretical considerations and outline the theory linking exchange rates to economic fundamentals. In the Appendix we provide a stylized model of exchange rate determination, featuring differences-in-beliefs, in which public investment announcements can forecast exchange rate returns.

A natural way to study international investments is to investigate foreign direct investment (FDI). We choose to do so by studying the largest component of FDI—cross-border M&As. In Section 3 we introduce the data and discuss the appropriateness of M&A data for addressing our research questions. We take the perspective of an American investor, collecting data on all cross-border M&A deals announced for 40 developed and emerging market countries vis-à-vis the United States, from 1994 to 2018. Using this data, we construct monthly measures of "abnormal" cross-border M&A activity for each country, equal to the difference between their announced cross-border M&A net inflows (i.e., the sum of inflows minus the sum of outflows) and its recent median level. To enable a cross-country comparison we then standardize the measure by its volatility.

In Section 4, we turn to our empirical analysis of macroeconomic fundamentals. We investigate changes in economic growth (i.e., economic acceleration) to explore if abnormal levels of announced cross-border M&A deals predict turning points in economic activity. In predictive panel regressions we find, consistent with our hypothesis, that abnormally high M&A net inflows are followed, on average, by higher economic growth, while lower economic growth follows abnormally low M&A net inflows: countries with high (low) M&A net inflows experience growth rates around 1% higher (lower) over the next 60 months. We find these changes reflect *reversals* in economic conditions, that the predictability continues to be observed after controlling for other leading economic indicators, and that the predictability is driven almost entirely by the investment decisions of domestic firms. Overall, the findings support the hypothesis that information contained in cross-border M&A flows can forecast economic fundamentals and may, therefore, provide a source of currency and exchange rate return predictability.

In Section 5, we explore currency return predictability. We do so via a portfolio approach in which higher positive portfolio weight is assigned to countries for which announced M&A net inflows are abnormally high. We implement three portfolio weighting schemes to ensure the results are not driven by one particular choice.[5] The portfolios are rebalanced monthly and have zero net cost. Under the null hypothesis of no predictability, the portfolios should generate zero average returns. Instead, we find all portfolios generate positive and statistically significant returns—indicating that corporate investment flows predict currency returns. The average return of each portfolio is above 4% per annum, t-statistics all exceed 3.50, and the Sharpe ratios range from 0.73 to 0.85. The cumulative portfolio returns all increase steadily over time and remain high even following the global financial crisis (GFC).

Crucially, the currency returns are primarily driven by predicting exchange rate returns, rather than from investing in high interest rate currencies; supporting the economic channel through which improving fundamentals equates to an exchange rate appreciation.[6] Moreover, the exchange rate predictability stems *entirely* from domestic firm decisions. Countries for which local-firm-driven outflows are unusually high, typically experience an annualized exchange rate depreciation of -2.66% over the following month, while an annualized appreciation of 3.94% is observed following an abnormally low outflow. In contrast, foreign-firm-driven inflows provide no exchange rate predictability. Furthermore, we show the portfolio returns are unrelated to the returns of other well-known currency strategies and, in forecasting horse-races, we find that only the M&A portfolio weights can reliably forecast future exchange rate returns.

[5] These include "high-minus-low" that assigns weight to countries with the most extreme M&A signals, "linear" that assigns weight in proportion to the M&A signals' values, and "rank" that assigns weight in proportion to the M&A signals' cross-sectional rankings.

[6] The results support the claim that a source of predictive information is revealed outside of FX order flow. Albuquerque et al. (2008) document a different channel, finding that private information in *equity* order flow forecasts currency returns.

In Section 6, we document additional analysis, finding that: (i) the cross-border M&A portfolios' returns exhibit a permanent, rather than a transitory, component—supporting the claim that the returns are driven by information relating to economic fundamentals; (ii) the predictability of currency returns is stronger when forming signals using the number rather than the dollar value of announced cross-border M&A deals—rejecting an alternative "transaction" hypothesis; (iii) the null hypothesis of no return predictability continues to be rejected in bootstrap tests; and (iv) the economic significance of the return predictability is robust to incorporating transaction costs. In an accompanying Internet Appendix we document a battery of additional robustness checks, which we refer to throughout the main text.

Overall, the study is the first to show that corporate investment flows can predict cross-country changes in economic growth and exchange rate returns. Consistent with firm-level expectations being revealed through the announcement of investment activity, we find that the aggregation of domestic firms' investment activity is especially informative about local economic conditions and exchange rate returns. The paper contributes to a growing literature investigating the ties between economic fundamentals and FX returns, and provides new insights into how price-relevant information is revealed outside of FX order flow.

The results have broad implications: for policy makers, the findings provide a way to extract information from capital flows and to assess the likely impact of capital flows on exchange rates. For academics, the paper contributes to discussions of exchange rate determination and currency market efficiency. For global investors, the documented predictability suggests new ways to identify potential investment opportunities and novel sources of portfolio diversification.

Related literature. The paper is closely related to the studies of information in FX markets and the link between economic fundamentals and exchange rates. Traditionally, public information is thought to be impounded instantaneously into prices so that trading plays no role in price formation. Market microstructure theory suggests, however, that order flow contains private information that was previously dispersed among market participants. The information arises because traders—even with access to the same macroeconomic information—have heterogeneous interpretations of the price implications and differing information processing skills (e.g., Evans and Lyons, 2002, 2005, 2008; Love and Payne, 2008; Menkhoff et al., 2016).[7] Trad-

[7]Evans and Lyons (2005) find that currency markets do not respond to macro news instantaneously. News arrivals induce subsequent currency trading by end-user participants. Love and Payne (2008) show that even for macroeconomic information that is publicly and simultaneously released to all market participants, about one third of the information is impounded into exchange rates via order flow.

ing can therefore serve as a transmission channel by which the market's expectation about future fundamentals is gradually revealed and incorporated into prices.[8]

In this paper, we share with these prior studies the perspective that transactions can reveal informative expectations. Instead of examining order flow, however, we focus an alternative source of information—corporate investment flow. We contribute to the literature by being the first to identify a source of price-relevant information revealed by corporations outside of their FX trading, which is directly relevant for the literature seeking to understanding the importance of macroeconmic fundamentals in exchange rate determination (e.g., Colacito et al., 2020), while also having important implications for both global investors and policy makers.

For global investors, a number of recent studies have found currency return predictability stemming from macroeconomic sources. Dahlquist and Hasseltoft (2020), for example, show that sorting currencies by economic momentum generates a large cross-sectional spread in currency returns. We find that sorting countries by abnormal M&A activity is, however, orthogonal to sorting by economic momentum because it captures a *reversal* in economic growth. The returns are also unrelated, both conceptually and empirically, to various other sources of currency return predictability including carry, value and momentum.[9] The results contribute, therefore, by highlighting a novel source of FX predictability that can help diversify currency portfolios.

From a policy perspective, policy makers are interested in understanding the information content of capital flows, to understand whether those flows will have a permanent or transitory impact on the local exchange rate. The results in this paper help shed light on this issue, by highlighting which intentional corporate investment flows contain information about fundamentals, and are thus likely to have a permanent impact on the local exchange rate.[10]

Finally, the paper is related to the M&A literature. A large body of research has examined the role of firm-specific factors in explaining corporate takeovers.[11] Our investigation more

[8]This information is gradually incorporated into market prices by FX dealers, resulting in FX order flow predicting currency returns (Evans and Lyons, 2006; Osler and Vandrovych, 2009; Ranaldo and Somogyi, 2021).

[9]See, e.g., Lustig et al. (2011), Lustig et al. (2014), Asness et al. (2013); Menkhoff et al. (2016), and Menkhoff et al. (2012); Asness et al. (2013).

[10]Gyntelberg et al. (2018) find that a different subcomponent of capital flows—*informed* international equity flows—also predicts exchange rate returns. Other studies have focussed on the stock position of countries' international accounts. Della Corte et al. (2016) empirically investigate the theoretical model of Gabaix and Maggiori (2015) and find that a cross-sectional spread in currency returns emerges when sorting currencies by their net foreign assets. Gourinchas and Rey (2007) find that the US net international investment position predicts movements in the trade-weighted dollar index, while Della Corte et al. (2012) extend the analysis of Gourinchas and Rey (2007) to forecast bilateral currency pairs.

[11]E.g., the exploitation of complementary assets in the acquirer and target firm (Jovanovic and Braguinsky, 2004), reallocation of corporate liquidity (Almeida et al., 2011), access to productive projects and options for growth (Levine, 2017), management entrenchment (Jensen, 1986), CEO overconfidence (Ferris et al., 2013), and hubris (Roll, 1986; Aktas et al., 2010).

closely mirrors the macroeconomic approach, found in prior studies, that relate fluctuations in aggregate merger activity to various macroeconomic fundamentals.[12] We contribute to this strand of literature by showing that variation in the frequency of cross-border M&A activity is also determined, in part, by firms' expectations of changing macroeconomic fundamentals.

2 Theoretical Framework

In this section, we outline the present value model of exchange rates, which links economic fundamentals and exchange rates. We then turn to discuss the link between investment activity and economic fundamentals before considering the information sets of firms, and why their actions may provide incremental information about future fundamentals. Finally, we turn to FX predictability and discuss why the revelation of this information can forecast exchange rates. We complement the discussion via a simple model of exchange rate determination in which differences-in-beliefs enable public announcements to predict FX returns (see Appendix).

2.1 Exchange rates and economic fundamentals

The present-value model of exchange rates expresses, in its most general form, the log exchange rate (s_t) as a weighted average of current fundamentals and the expected future exchange rate:

$$s_t = (1-\beta)f_t + \beta E_t s_{t+1}, \tag{1}$$

where f_t reflects the value of market fundamentals at time t, β is a discount factor that is less than one, and E_t are market expectations. The general nature of the model enables it to encapsulate a broad class of open economy macroeconomic models of exchange rate determination (see, *inter alia*, Engel and West, 2005; Engel et al., 2007; Sarno and Schmeling, 2014; Bekaert and Hodrick, 2018). Iterating Eq (**1**) forward (and imposing the standard no bubbles condition, $\lim_{q\to\infty} \beta^q E_t s_{t+q} = 0$), the exchange rate equals an infinite sum of discounted fundamentals:

$$s_t = (1-\beta)\sum_{q=0}^{\infty} \beta^q E_t f_{t+q}. \tag{2}$$

Hence the log exchange rate return is a function of changes in current fundamentals and the

[12] E.g., business cycles (Nelson, 1966), economic disturbances (Gort, 1969), capital market conditions (Melicher et al., 1983), industry shocks (Mitchell and Mulherin, 1996), demand shocks (Maksimovic and Phillips, 2002), profitable reallocation opportunities (Jovanovic and Rousseau, 2002), macro-level liquidity (Harford, 2005), and growth opportunities (Rhodes-Kropf et al., 2005).

expectations of future fundamentals:

$$\Delta s_{t+1} = (1-\beta)\sum_{q=0}^{\infty}\beta^q(E_{t+1}f_{t+q+1} - E_t f_{t+q+1}). \tag{3}$$

Through this framework we can begin to understand exchange rate predictability. Agents with more accurate signals about future fundamentals can predict exchange rates as the market adjusts to incorporate the information. That agents have different levels of information is widely accepted in the FX literature: Cespa et al. (2021), for example, find that FX markets are characterized by a substantially higher level of information asymmetry than equity markets, while theoretical contributions have found that various currency market phenomena can be explained by assuming agents have asymmetric information about fundamentals (e.g., Bacchetta and Van Wincoop, 2006; Evans and Lyons, 2006, 2007). We return to predictability below.

2.2 International investment and economic fundamentals

Bernanke (1983) argues that expected changes in fundamentals drive movements in investments. In this paper we focus on cross-border M&A investments, described in detail in Section 3. Because M&A investment is a "*high fixed cost and a low marginal adjustment cost*" activity (Jovanovic and Rousseau, 2002), the public announcement of a bid may signal a firm's confidence in a country's future economic fundamentals. Indeed, M&As often take place simultaneously across firms suggesting that common macroeconomic factors influence investment activity (Nelson, 1966; Melicher et al., 1983; Mitchell and Mulherin, 1996).[13]

Melicher et al. (1983) propose a "merger activity-economic prosperity" theory, which laid a groundwork for understanding the link between fluctuations in aggregate merger activity and macroeconomic fundamentals. According to the theory, managers tie their acquisition decisions, in part, to expected changes in macroeconomic conditions. Declining economic expectations may, for example, induce local firms to look for growth opportunities overseas. Meanwhile deteriorating conditions may discourage inbound M&A flows, as foreign firms decline projects, such as M&As, in an effort to avoid extending the organization into weakening economies.[14] The view echoes that of practitioners, where CEOs embarking on acquisitions are commonly expected to convey confidence about future economic trends.[15]

[13]A large body of research has shown that much of the takeover activity is firm-specific in nature. However, firm-specific characteristics play a minor role in explaining the behavior of aggregate merger activity (Comment and Schwert, 1995).

[14]A competing explanation is that M&A activity takes advantage of systematic overpricing of stocks or transitory appreciation in currencies (Erel et al., 2012). If such a mechanism is at play, however, there is no reason for the investment activity to predict fundamentals or exchange rates.

[15]Recent research by KPMG, for instance, shows that, despite the ongoing COVID-19 pandemic, increased

2.3 Firms' information sets

While firms' collective actions may signal economic fundamentals, why would this signal be incremental to other leading predictors of fundamentals? One argument is that firms make accurate forecasts since they are paramount for capital budgeting decisions. This argument may not, however, be viewed as compelling if firms are not thought to hold informational advantages over, say, professional forecasters or profit-seeking market participants.

Firms are, however, much closer to economic information, especially relating to their own industry and economy, than most market participants—even including sophisticated investors. On a day-to-day basis firms continually observe sales receipts and ongoing expenses, receive feedback on new and existing products, and generate forecasts for product demand and accounting earnings. In essence, firms have a unique real-time perspective on current economic activity, especially as related to their local economic conditions. Indeed, an extant literature has documented differences in information sets across domestic and foreign agents, in which domestic agents have a more precise signal about local economic outcomes, such as asset market payoffs.[16] Frankel and Schmukler (1996), for example, investigate investors' divergent expectations using three Mexican country funds. They show that during the peso crisis in 1994, domestic investors were the first to sell Mexican assets, indicating that domestic investors, who are "closer to information", form more accurate expectations about local economic events. Similarly, Brennan and Cao (1997) present a theoretical model in which domestic investors possess an information advantage over foreign investors due to closer observations of the domestic economy. Overall, therefore, firms have good reasons to be at an informational advantage, and especially domestic firms with regards to their local economic conditions.

It is also feasible, however, that firms learn about foreign market conditions using non-public information. This information can be obtained from exploiting political connections (Schweizer et al., 2019), directors' foreign experience in particular countries (Giannetti et al., 2015), bilateral trade data (Erel et al., 2012; Ahmad et al., 2020), pre-announcement investigations such as target screening, and external expertise of M&A advisors (Lawrence et al., 2021).

confidence and favorable economic outlook have induced a vast majority (87%) of global leaders to bet on growth through M&As, leading to a heightened appetite for deal-making. See "KPMG 2021 CEO Outlook: Media executive summary", KPMG, September 1, 2021.

[16]See, e.g. Kang and Stulz (1997); Coval and Moskowitz (2001); Dvořák (2005); Ivković and Weisbenner (2005); Van Nieuwerburgh and Veldkamp (2009).

2.4 Predictability of foreign exchange rates

The above discussion provides motivation for why firms' investment decision may (i) be a function of future economic conditions and (ii) reflect non-public information. However, while the *investment decision* may be made using non-public information the *announcement* is public. Why then, would announcements of M&A activity provide a source of exchange rate predictability, i.e., why would the foreign exchange market not immediately incorporate this information?

When information is not known by all market participants or, if known, when agents form varying beliefs about its price implications, predictability is easy to demonstrate in, for example, differences-in-beliefs models in which agents place different weight on a common piece of information. The mechanism works through prices only partially responding to information upon release but, through subsequent Bayesian updating, then gradually incorporating the information. To make this channel clear, in the Internet Appendix, we build a simple model of exchange rate determination drawing from the differences-in-beliefs literature (e.g., Banerjee and Kremer, 2010; Jeanneret and Sokolovski, 2021) in which M&A activity provides a signal about the future fundamental (i.e., economic growth) and can therefore predict future exchange rate returns. The model serves to highlight the main theoretical ingredients that enable public information to be a potential source of predictable information and thus a channel for why corporate investments can be used to forecast exchange rates.

Here we highlight the main ingredient—investors have heterogeneous beliefs about a common source of information. In the case of investment announcements, since these are public, the predictability arises because agents either do not symmetrically update their beliefs about exchange rates following the announcements or are unable to extract the signal accurately from public information. Given the wide range of agents trading in currency markets for numerous reasons, both possibilities seem reasonable. Indeed, many agents, e.g., corporations, will have little incentive to accumulate public information prior to trading since there is no profit-motive to their trading. Moreover, this is especially true since the cross-border M&A signals we explore require post-release transformation in order to extract the relevant information and thus, given the expertise required, the information could equally be viewed as private to those with the skills to exploit it. Through the lens of the model, both of these mechanisms are viable.[17]

[17]In the case of order flow, informed agents reveal their FX trades to only a few dealers. Information is therefore diffused through the FX market via dealers acting as information intermediaries (Li and Song, 2021).

3 Data

We collect data on cross-border M&A deals involving the US, announced between December 1973 and December 2018, from the Securities Data Company (SDC) Platinum database.[18] For each deal we obtain the nationality of the acquiror and target firms, the date of the announcement, the form of payment, and the US dollar value of the deal. We exclude deals with missing dollar values to enable a later comparison between the total number and dollar value of the announced transactions. We limit the analysis to major developed and emerging market currencies covering 41 countries, including 20 developed and 21 emerging markets. The countries include (developed countries are denoted in bold): Argentina, **Australia**, **Austria**, **Belgium**, Brazil, Chile, Colombia, Czech Republic, **Denmark**, Estonia, **Eurozone**, **Finland**, **France**, **Germany**, Greece, Hungary, Iceland, India, Indonesia, **Ireland**, **Israel**, **Italy**, **Japan**, Latvia, Lithuania, **Netherlands**, **New Zealand**, **Norway**, Poland, Portugal, Russia, Slovak Republic, Slovenia, South Africa, South Korea, **Spain**, **Sweden**, **Switzerland**, Turkey, the **United Kingdom**, and the **United States**.[19]

In Fig. A.1 of the Internet Appendix, we plot the number of days between cross-border M&A deals for the average developed and emerging market country over a three-year rolling window (each point captures the prior three-year average). The frequency of deals was low in the 1970s and 1980s. Only from the mid 1990s was activity sufficiently high to obtain useful signals of firm-level expectations across both developed and emerging market countries. We therefore restrict the sample to the 25-years (300-months) period beginning in January 1994 and ending in December 2018.

Foreign direct investment. A natural question is why we choose to focus on the announcements of cross-border M&As and not directly on FDI. We do so for four reasons. First, FDI consists of equity investment, inter-company debt, and reinvested earnings; the equity component, which reflects new investment flows such as cross-border M&A and greenfield investment,

[18] Over this period, 142,829 cross-border M&As were announced, totalling $32.27 trillion in deal value. We focus on deals involving the US because it had by far the most active cross-border M&A market. Specifically, the US had: (i) cross-border deals to and from 75% of all other countries; (ii) the largest share of global cross-border M&As, accounting for 31% (38%) of aggregated deals (transaction values); and (iii) the lowest average number of days between two consecutive deals (less than 0.34).

[19] The categorization of countries as developed or emerging is based on the MSCI's classification. China is not included because, while the announced deals are potentially informative, the managed exchange rate makes the currency return less informative. We also exclude Canada and Mexico given their integration with the US economy (all are members of NAFTA), increasing the commonality of macroeconomic shocks and reducing the likely informativeness of announced cross-border M&A deals. In the Internet Appendix we provide evidence, however, that their exclusion does not affect our core findings.

is most likely to carry meaningful information about expected future economic conditions.[20] Second, cross-border M&A accounts for more than half of all FDI, significantly more than greenfield investment, and has been found to provide a close approximation to total FDI dynamics (see, e.g. Baker et al., 2009). Third, FDI flows are typically backward looking and recorded infrequently—either on a quarterly or yearly basis—with the definition and measurement of the non-M&A components of FDI varying across countries while cross-border M&A data is recorded daily and uniformly across deals and countries. Finally, only a small handful of countries report the geographic breakdown of their inward and outward FDI flows—limiting the potential scope of the analysis.[21]

3.1 Descriptive analysis

In Fig. 1, we plot yearly time series of the total number and aggregate dollar value ($ billions) of the cross-border M&As in our dataset. The figure shows a clear clustering of cross-border M&As over time, as observed in prior studies (Xu, 2017; Ahmad et al., 2020). Since the mid-1990's, the total number of cross-border M&As has ranged from a yearly low of around 600 in 1994 to a high of over 1,600 in 2000. In general, the aggregate number of deals has typically averaged around 1,000 per year. The dollar value of the deals has drifted upwards over time, beginning the sample at less than $100 billion before peaking at over $600 billion in 2014.

In Table 1, we present country-level summary statistics. The total number of deals ranges from 12, between the US and Slovenia, to over 5,500 between the US and Eurozone. Hence, the raw M&A activity is not directly comparable across countries, a feature we account for in our standardized M&A measure. In total, more than 86% of deals involve firms from developed market countries, in which the US firm is the target in around 45% of the deals. US firms mainly acquire emerging market firms, although are targets in 40% of deals involving firms from Israel, South Africa, and South Korea. Consistent with the large cross-sectional variation we observe in cross-border M&A activity, we find that the average number of days between deals varies substantially across countries—ranging from less than ten to over 200.

[20]Reinvested earnings are the parent company's claim on their affiliates' undistributed after-tax earnings, while inter-company loans are often used for tax planning purposes. Indeed, it is common for an affiliate in a high-tax jurisdiction to borrow significantly from other parts of the multinational corporation, using the debt to increase their interest expense and reduce their tax liability.

[21]See Erel et al. (2012) for further details.

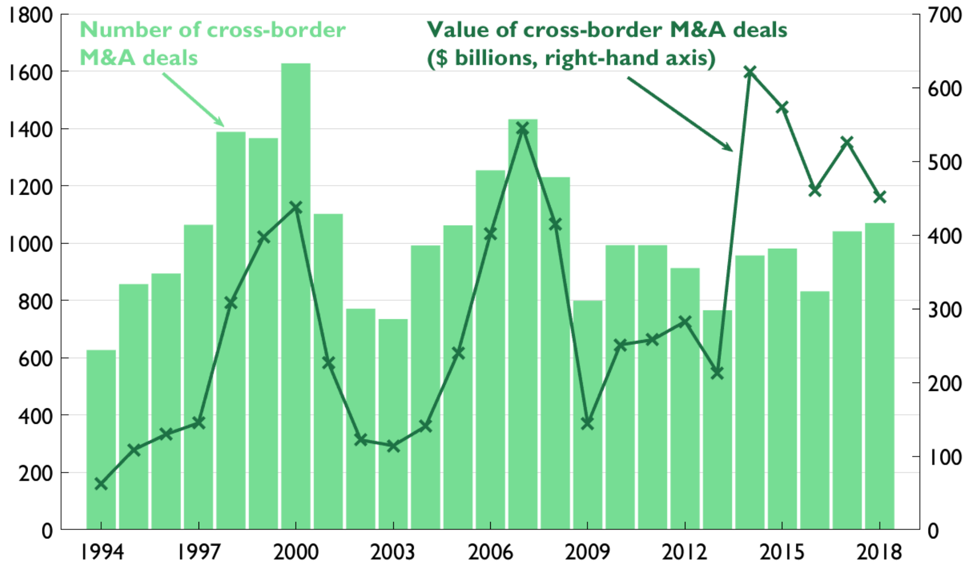

Fig 1. Number and Value of Announced Cross-Border M&As. The figure plots the time series of the total number of cross-border M&A deals in the sample (left-hand axis, bar plot) and the total value of those deals in US dollar billions (right-hand axis, line plot).

3.2 Standardizing merger and acquisition activity

We construct a bilateral monthly measure of cross-border M&A activity between the US and country $i = 1, 2, ..., N-1$ (country N denotes the US). The measure equals the net inflow of cross-border M&A deals, defined as the sum of announced inflows $(In_{i,t})$ *minus* the sum of announced outflows $(Out_{i,t})$ in month t:

$$MA_{i,t} = In_{i,t} - Out_{i,t}. \tag{4}$$

A negative value therefore reflects, for example, that firms in country i announced more acquisitions of US firms during the month than vice versa.[22] We construct an equivalent measure for the United States, aggregated across all other countries, i.e.,

$$MA_{US,t} = \sum_{i=1}^{N-1} In_{i,t} - \sum_{i=1}^{N-1} Out_{i,t}. \tag{5}$$

Our expectation is that changes in M&A net inflows conveys an informative signal about future fundamentals and, by extension, exchange rate returns. Aggregated M&A net inflows can, however, be a simple continuation of a past trend, such that a relatively steady M&A flow

[22]The measure helps to capture *relative* differences in economic conditions. We hypothesize that if firms in country A acquire an unusual high number of firms in country B then, *ceteris paribus*, country A will grow at a relatively slower rate in the future. Aggregating across all deals involving country B would confound the measure. For example, an unusually large net inflow *in aggregate* to country B may mask an unusually *low* net inflow from country A, and thus generate a source of measurement error that we avoid.

is observed between two countries over time because of, for example, time invariant, country-specific factors.[23] Similarly, in some countries there are long periods in which no cross-border M&A deals are announced. Hence, a lack of M&A activity is considered "normal," indicating the absence of new information. When such activity deviates from its recent trend, the deviation becomes informative since it conveys a signal of firms' changing expectations about fundamentals. We therefore define the "normal" M&A activity for each country as the median cross-border M&A net inflow ($\overline{MA}_{i,t}$) over the prior 36 months.[24] To prevent countries with high raw values from dominating the later analysis, we standardize abnormal M&A by its standard deviation ($\sigma_{i,t}$) calculated over the same period.[25] Specifically, our measure of "abnormal" M&A activity is given by,

$$\widetilde{MA}_{i,t} = \frac{MA_{i,t} - \overline{MA}_{i,t}}{\sigma_{i,t}}, \tag{6}$$

which we use to predict economic acceleration and exchange rate returns. Since the standardization requires a prior 36-months history of deals, the first values of $\widetilde{MA}_{i,t}$ are obtained in December 1996, which we use to predict the FX returns in the new month. Thus, while we use data from 1994 onwards, we typically report results as beginning in January 1997 and ending in December 2018. To ensure that we capture predictive information contained in the announcements of cross-border M&A deals, we define non-informative zeros as missing observations.[26]

Our measure is constructed using the number of deals. A potential concern is that the measure does not consider the differential in the size of individual deals, especially if it is believed that the dollar volume of trades better captures the quality or precision of information. As noted earlier, however, a single deal needs not necessarily reflect an expectation of subsequent changes in economic growth if it stems, for example, from managerial self-seeking behavior. Instead, our prediction is that the *occurrence* of multiple cross-border M&A deals towards (or away from) the same country reflects an amplified belief about economic conditions.

Aggregating deal value fails to capture this information. An unusually high deal value could reflect a small number of mega deals undertaken by a small number of firms and thus idiosyncratic drivers of deals will feature more prominently. Moreover, different from currency

[23] Country-specific factors include: accounting standards and investor protection laws (Rossi and Volpin, 2004), geographic distance (Erel et al., 2012), differences in language, religion, and culture (Ahern et al., 2015), and corporate tax rates (Smith and Jean-Marie, 2021).

[24] In our Internet Appendix we explore different standardization windows ranging from 12 to 60 months and find our results remain qualitatively unchanged.

[25] Our results are not sensitive to the choice of alternative estimation windows such as 12, 24, 48 or 60 months.

[26] In the Internet Appendix we show these non-informative zeros do not drive our core results.

trading, transaction size may not be related to the quality of information, as high confidence about the trends in an economy likely increase firms' appetite for deal-making, but not necessarily the size of those deals—the choice of target firms is determined by factors such as asset complementarities and growth potential, instead of the target size alone. Finally, transaction size is heavily influenced by takeover premium that is subject to non-macroeconomic forces such as negotiation skills (Moeller, 2005), competition among bidders (Aktas et al., 2010), and hubris (Roll, 1986). Hence, although deal value should, in principle, provide information about firms' expectations, the number of deals is better suited for capturing the information about fundamentals in which we are interested.[27]

3.3 Macroeconomic fundamentals

We investigate if economic conditions change following M&A deal announcements by studying changes in economic growth (i.e., economic *acceleration*). Economic acceleration is a natural measure to choose since it captures turning points (i.e., economic transitions) as an economy shifts from one growth path to another (see, e.g. Hausmann et al., 2005). It is also a variable that is crucial to policy makers. Indeed, according to Hausmann et al. (2005) "accelerating the process of economic growth is just about the most important policy issue in economics." We measure economic growth following Dahlquist and Hasseltoft (2020). The approach is particularly attractive because it captures different aspects of an economy, providing a more comprehensive picture of economic conditions. Specifically, economic growth is defined as the average (log) growth rate across three macroeconomic series that capture: output (industrial production, IP); consumption (retail sales, RS); and the labor market (*inverse* of unemployment, UE). A higher value therefore indicates stronger economic growth.

We obtain macroeconomic series for each country from the *Organization of Economic Co-operation and Development* (OECD), and calculate the one-year economic growth for country i $(i = 1, ..., N)$ in month t as:[28]

$$g_{i,t} = \frac{1}{3}\left[log\left(\frac{IP_{i,t}}{IP_{i,t-12}}\right) + log\left(\frac{RS_{i,t}}{RS_{i,t-12}}\right) + log\left(\frac{UE_{i,t}}{UE_{i,t-12}}\right)\right]. \tag{7}$$

[27]Our choice is also consistent with earlier work on FX order flow (e.g., Evans and Lyons, 2002; Love and Payne, 2008; Rime et al., 2010), as well as theoretical models that emphasize the number of transactions, not the dollar value, as a determinant of market prices (Easley and O'Hara, 1992; Jones et al., 1994).

[28]To mitigate against outliers unduly influencing the findings, we winsorize the one-year growth in IP, RS, and UE at the 5th and 95th percentiles. In the Internet Appendix we show that this choice is not crucial to our results and that while there are a few large outliers, the core results continue to be observed when winsorizing at either the 1st and 99th percentiles or the 10th and 90th percentiles.

The change in economic growth is then simply:

$$\Delta g_{i,t+s} = g_{i,t+s} - g_{i,t}, \tag{8}$$

which is the difference between one-year growth rates at times $t+s$ and t. In the empirical analysis, we study whether $\widetilde{MA}_{i,t}$ has forecasting power for these changes in economic growth.

3.4 Exchange rates

We collect daily spot and one-month forward foreign exchange rates from WM/Reuters via *Datastream*. The exchange rates are recorded as the US dollar price of one unit of foreign currency. We sample exchange rates on the last trading day of each month to calculate monthly currency excess returns. The returns are from the perspective of a US investor entering a long forward position at time t to buy the equivalent of one US dollar of country i's currency at time $t+1$. Specifically, we calculate currency excess returns as:

$$R_{i,t+1} = \frac{S_{i,t+1} - F^1_{i,t}}{S_{i,t}}, \tag{9}$$

where $S_{i,t}$ and $F^1_{i,t}$ are the spot and one-month forward exchange rates recorded at time t for country i.[29] The euro was launched in January 1999 and 16 countries in our sample have joined the currency zone since its inception. These currencies drop out of the main analysis upon entry into the Eurozone, but we continue to include their cross-border M&As within our measure of *Eurozone* cross-border M&A activity.

4 Empirical Analysis: Economic Growth

In this section we report the first results from our empirical analysis, in which we investigate if abnormal levels of newly announced M&A deals can forecast changes in economic growth.

4.1 Forecasting changes in economic growth

We study the relationship between economic growth and the announcements of cross-border M&A deals in two ways. First, we explore the change in economic growth the five-years prior to and following cross-border M&A announcements, for countries with either unusually high or low levels of M&A net inflows. This test allows us to assess the evolution of economic growth

[29]The availability of foreign exchange rate data varies by country. In Internet Appendix Table A.1, we report the start and end dates of the data for each currency in the sample.

following the M&A announcements to assess the hypothesized predictability while also simultaneously addressing the potential concern that any post-announcement trend is a continuation of the pre-existing trend. Second, we formally investigate the predictability of cross-border M&A announcements in panel regressions, controlling for well-established and publicly available indicators of future economic conditions.

We begin by grouping countries into one of three equally-sized baskets based on their level of abnormal cross-border M&A activity ($\widetilde{MA}_{it}$), defined in Equation (**6**). We denote these baskets as "high", "medium", and "low". We test how economic growth changes, on average, for countries within these baskets by estimating panel regressions in which we regress countries' economic acceleration, $\Delta g_{i,t+s} = g_{i,t+s} - g_{i,t}$, on a dummy variable ($D_{ik,t}$) that is equal to one if country i at time t is in basket k = high, medium, low, and zero otherwise:

$$\Delta g_{i,t+s} = \alpha + \beta D_{ik,t} + \kappa_i + \lambda_{t+s} + \varepsilon_{i,t+s}, \tag{10}$$

where $s = -60, -59, ..., 0, ...59, 60$. When $s < 0$, we study the trend in economic growth *prior* to M&A announcements. Time fixed effects (λ_{t+s}) control for factors varying in time, such as common trends in cross-border M&A activity and global economic conditions, while κ_i denotes country fixed effects, which are included to capture time-invariant determinants of cross-border M&As, such as geographic distance, market size, and cultural differences. The coefficient of interest is β. According to our main hypothesis, abnormally high M&A net inflows signal stronger future economic growth, and vice-versa for abnormally low M&A net inflows. When $s > 0$, we therefore expect $\beta > 0$ if $k = high$ and $\beta < 0$ if $k = low$. In contrast, when $s < 0$, the level of β provides a guide to whether the post-announcement change is a continuation of a pre-existing trend. If so, then we would observe $\beta < 0$ for k = high and $\beta > 0$ for k = low.

In Fig. 2 we plot the estimated β coefficients in relation to s, for $k = high$ and $k = low$. Two standard error bounds are denoted by the shaded region. A striking v-shape pattern emerges for countries with high values of $\widetilde{MA}_{it}$. We observe the opposite pattern for countries with low values of $\widetilde{MA}_{it}$. Turning first to the region in which $s > 0$, the coefficients are found to support the hypothesis that economic growth increases (decreases) following abnormally high (low) cross-border M&A net inflows. Indeed, 60-months following the announcements, high (low) net inflow countries are found to experience growth rates around 1% higher (lower) than at the point of the M&A deal being announced.

On the question as to whether this effect is a continuation of an existing trend, we see

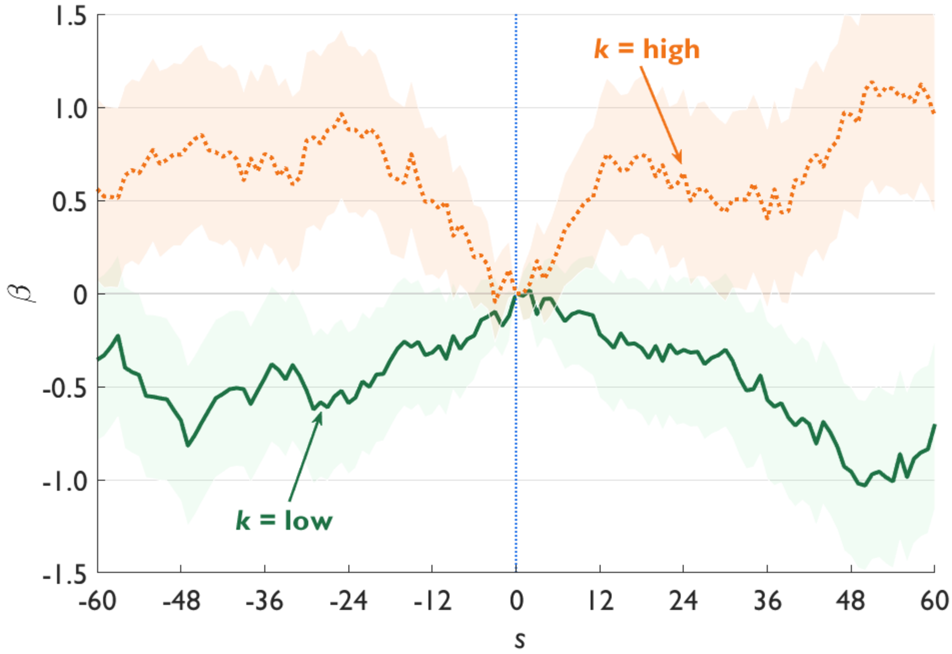

Fig 2. Macroeconomic Acceleration. The figure plots the β coefficients from Equation (10), estimated across values of s for $k = high$ and $k = low$. Two standard error bounds are denoted by the shaded region.

that when $s < 0$ the patterns point instead to *reversals* in economic growth. Countries with high (low) values of $\widetilde{MA}_{it}$ at $s = 0$ experienced higher growth during the previous 60-months. To see this, recall that $\Delta g_{i,t+s} = g_{i,t+s} - g_{i,t}$, and hence if $\Delta g_{i,t+s} > 0$ when $s < 0$ it implies that the economic growth rate was higher prior to the M&A announcement. Strikingly, the month in which the deals are announced appears to almost perfectly capture the point of this economic reversion—providing initial evidence that not only does M&A activity appear to provide a predictive signal, but that the predictability may extend beyond that contained in other leading predictors of economic growth.[30]

4.1.1 Controlling for leading economic indicators

We consider five well-known macroeconomic variables that are well know to predict economic activity, these include: (i) the OECD's composite leading indicators (CLIs), which are a set of monthly indices designed to provide early signals of economic turning points, compiled by combining a comprehensive set of time series components that are, individually, known to predict short-term economic movements. These include expected changes in employment and demand, housing permits, term spreads, consumer confidence, and stock market returns.[31] (ii)

[30]The two series must converge at zero when $s = 0$ but it is *not* mechanical that the point of inflection occurs when $s = 0$, nor that the series would exhibit a v-shape pattern (or inverted v-shape pattern).

[31]We use a 2-month lag of the CLIs to account for the publication delay (see Colacito et al., 2020, for further details).

the term spread, defined as the difference between long-term government bonds and short-term T-bills (Harvey, 1988; Estrella and Hardouvelis, 1991; Hamilton and Kim, 2002); (iii) short-term interest rates measured by the yield on the T-bill (Bernanke and Blinder, 1992); (iv) monthly stock market returns (Fama, 1981); and (v) dividend yields (Fama and French, 1989).

We test if these predictors subsume the information contained in $\widetilde{MA}_{it}$ via a set of predictive panel regressions. The regressions take a similar form to Eq. (**10**), but replace the dummy variables with the actual value of $\widetilde{MA}_{it}$:

$$\Delta g_{i,t+s} = \alpha + \beta \widetilde{MA}_{i,t} + \gamma' X_{i,t} + \kappa_i + \lambda_{t+s} + \varepsilon_{i,t+s}. \tag{11}$$

where $X_{i,t}$ represents the vector of alternative predictors. We focus on the post-announcement period, reporting results for $s = 12, 24, 36, 48, 60$ and controlling for country and time fixed effects. Robust standard errors are double clustered at the country-month level. Given the evidence in Fig. 2, we anticipate the coefficient β will be positive. To test, we estimate two models at each value of s. The first model controls for CLIs, since these indices are specifically designed to incorporate all economic and financial information that forecasts economic growth. The CLIs can be viewed as a mean-reverting index, centered around 100, in which a high value today predicts short-term stronger growth and longer-term economic weakness. In the second model, we replace the CLIs with the alternative sources of economic growth predictability.

Results are reported in Table 2. Pertinently, we find the coefficients on $\widetilde{MA}_{it}$ are highly statistically significant in most cases. Indeed, we observe statistical significance at the 5% significance level when $s = 24$, and at the 1% significance level when $s = 36, 48$, and 60. Consistent with Fig. 2, we also find a positive coefficient when $s = 12$. The magnitudes of the coefficients are also economically significant. A one-standard deviation move above the median value of $MA_{i,t}$, is associated with an economic growth rate that is between 0.24% and 0.45% higher over the following 36 to 60 months. These values are of the same order of magnitude as the average level of economic acceleration over the same period (0.21% and 0.30%). Given these findings, we reject the hypothesis that cross-border M&A activity contain no incremental predictability for future economic growth and thus information appears to be revealed to the market about fundamentals via the announcements of corporate investment activity.[32]

[32] Regarding the other variables, in the first models, the coefficients on the CLIs are all found to be negative and statistically significant at the 1% significance level. In the second models, only the interest rate variables display evidence of predictive content. In particular, a steeper Treasury yield curve predicts an economic acceleration over horizons ranging from 24 to 60 months. Lower short-term interest rates forecast an economic deceleration over 12-months but an economic acceleration over 48 and 60 months—essentially capturing business

4.1.2 Decomposing abnormal M&A activity

When $\widetilde{MA}_{i,t} > 0$ it could be because there are *more* inflows than usual or *less* outflows. Likewise if $\widetilde{MA}_{i,t} < 0$, it may be driven by *more* outflows than normal or *less* inflows.

On the other hand, the distinction *is* revealing. Low M&A net inflows that are driven by *more outflows* than normal, could reflect that domestic firms have observed their local economic conditions and expect future weakness. Equally, high M&A net inflows that are driven by *less outflows*, could reveal domestic firms are expecting a stronger local economy in the future.

We explore the split between foreign-firm inflows and domestic-firm outflows by estimating an equivalent model to that in Eq. (**11**), but replacing $\widetilde{MA}_{i,t}$ with measures constructed using only outflows (denoted $\widetilde{MA}_{i,t}^{out}$) or inflows (denoted $\widetilde{MA}_{i,t}^{in}$):

$$\Delta g_{i,t+s} = \alpha_i + \beta_1 \widetilde{MA}_{i,t}^{in} + \beta_2 \widetilde{MA}_{i,t}^{out} + \gamma' X_{i,t} + \kappa_i + \lambda_{t+s} + \varepsilon_{i,t+s},$$

We report results in Table 3. A clear asymmetric pattern emerges: across all horizons, the outflow-based signal (β_2) is found to be consistently negative and statistical significant, indicating that unusually high (low) outflows translates to slower (faster) future growth. In contrast, the coefficients on the inflow-based signal (β_1) are not statistically different from zero over horizons from 12 to 36 months. The predictability documented in Table 2 is, at least in the shorter term, driven by outflows and thus by the acquisition decisions of domestic firms. To complement this evidence, in Internet Appendix Table A.2, we present estimates of β_1 and β_2 across values of s ranging from -60 to $+60$.[33] The relative importance of the outflow-based measure becomes apparent: countries with relative high outflows exhibit a reversal in economic growth centered $s = 0$. Countries with abnormally high inflows at $s = 0$, however, continue to decelerate in the following months. It is only after 48 months that the economies exhibit faster economic growth than at $s = 0$ and thus, unlike for domestic-firm outflows, the information does not reveal a timely signal about turning points in economic activity.

The results presented in Tables 2 and 3 establish that cross-border M&A activity can be used to extract an informative signal about future economic growth. If currency markets only gradually incorporate this information into their expectations of future economic fundamentals, then the announcements may provide a source of predictability for exchange rate and, potentially, currency returns. We turn to explore these possibilities in the next section.

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cycle variation.

[33] As in Fig. 2, the estimates are obtained without controlling for other publicly available predictors.

5 Empirical Analysis: Foreign Exchange Rates

In this section, we study the predictability of exchange rates and currency returns. In particular, we assess the novelty of $\widetilde{MA}_{i,t}$ as a source of forecastability relative to other, previously documented, predictors of currency returns, and explore the associated diversification benefits.

5.1 Exchange rate and currency return predictability

We explore exchange rate and currency return predictability using a portfolio approach, in which weights are assigned to countries based on their abnormal M&A activity ($\widetilde{MA}_{i,t}$).[34] We adopt three approaches to assigning portfolio weights, denoted as "HML", "linear", and "rank", which we describe below. The portfolios are rebalanced monthly, their weights sum to zero, and they are all both long and short one dollar.

5.1.1 Methods

To obtain HML weights, we sort countries from low to high values of $\widetilde{MA}_{i,t}$, and then group the countries into three equally sized, and equally weighted, portfolios (P_1, P_2, and P_3).[35] HML weights equal P_3 weights and the negative of P_1 weights (countries in P_2 thus receive zero weight in the HML portfolio):

$$w_{i,t}^{hml} = \begin{cases} -1/N_{P_1,t} & \text{if country } i \text{ is in } P_1 \text{ at time } t, \\ 1/N_{P_3,t} & \text{if country } i \text{ is in } P_3 \text{ at time } t, \\ 0 & \text{if country } i \text{ is in } P_2 \text{ at time } t, \end{cases}$$

where $N_{P_1,t}$ and $N_{P_3,t}$ are the number of countries in P_1 and P_3 in month t. The approach therefore assigns weight to the extremes of the distribution but does not allocate higher or lower weights *within* a portfolio. The linear approach, in contrast, assigns weights to all eligible countries in direct proportion to $\widetilde{MA}_{i,t}$:

$$w_{i,t}^{lin} = c_t^{lin} \left(\widetilde{MA}_{i,t} - \mu_t^{lin} \right),$$

[34] Forming currency portfolios to explore return predictability has become a common approach in international finance studies. See, e.g. Lustig and Verdelhan (2007), Lustig et al. (2011), Verdelhan (2018), and Colacito et al. (2020).

[35] The small number of currencies limits the number of portfolios that are typically constructed in currency studies. Mueller, Stathopoulos, and Vedolin (2017) and Ranaldo and Somogyi (2021) also use three portfolios. In the Internet Appendix we show that our results are unaffected when constructing HML portfolios using four or five portfolios, while the use of linear and rank weights helps to mitigate concerns that our results are driven by a particular weighting choice.

where $\mu_t^{lin} = N_t^{-1}\Sigma_{i=1}^{N_t}\widetilde{MA}_{i,t}$ denotes the cross-sectional average of the signal (across all countries, N_t) and c_t^{lin} is a scaling factor that ensures the absolute sum of weights equals two (i.e., $c_t^{lin} = 2/\sum_i |MA_{i,t} - \mu_t^{lin}|$), since the portfolio is long and short one dollar. Signals above the cross-sectional mean receive positive portfolio weights, while signals below the mean receive negative weights. The rank approach is similar, with weight assigned to countries in direct proportion to their cross-sectional *ranking* when sorted by $\widetilde{MA}_{i,t}$, such that:

$$w_{i,t}^{rnk} = c_t^{rnk}\left(\text{rank}(\widetilde{MA}_{i,t}) - \mu_t^{rnk}\right),$$

where $\mu_t^{rnk} = N_t^{-1}\sum_{i=1}^{N_t}\text{rank}(\widetilde{MA}_{i,t})$ denotes the cross-sectional average of the signal and the scaling factor c_t^{rnk} is analogous to that in the linear approach.

5.1.2 Empirical results

Portfolio returns and associated summary statistics are reported in Table 4. In the first three columns we report statistics for the tercile portfolios (P_1, P_2, and P_3). Under the null hypothesis of no return predictability, the average returns equal zero. Instead, we observe a monotonically increasing pattern in the average returns that is consistent with the prediction that improving (deteriorating) fundamentals translate into a currency appreciation (depreciation). Countries experiencing the lowest values of $\widetilde{MA}_{i,t}$ (i.e., P_1 currencies) generate, on average, a negative annualized currency excess return over the following month of -0.89% while, in contrast, P_3 countries earn a positive and highly statistically significant annualized currency return of 3.71%.[36]

The next three columns report statistics for portfolios constructed using HML, linear, and rank weights. The HML portfolio has a positive average annualized return of 4.59% and a Sharpe ratio of 0.85. We find similar results for the linear and rank portfolios. In both cases the currency excess returns are positive, t-statistics are over 3.50, and the associated Sharpe ratios are 0.73 and 0.76, respectively.[37] In Fig. 3, we plot the cumulative returns of the three portfolios. The returns increase steadily over time, are not driven by outliers, and have remained high following the GFC—in contrast to currency carry, value, and momentum signals, which have lost predictive power post-2008 (see, e.g. Ranaldo and Somogyi, 2021).

In the final two rows of Table 4, we report the decomposition of the average returns between

[36]All three portfolios exhibit similar levels of volatility, skewness, and kurtosis, suggesting the differences in returns are unlikely driven by compensation for exposure to higher levels of volatility, downside risk, or kurtosis.
[37]The average correlation among the returns of the three cross-border M&A portfolios is 93%.

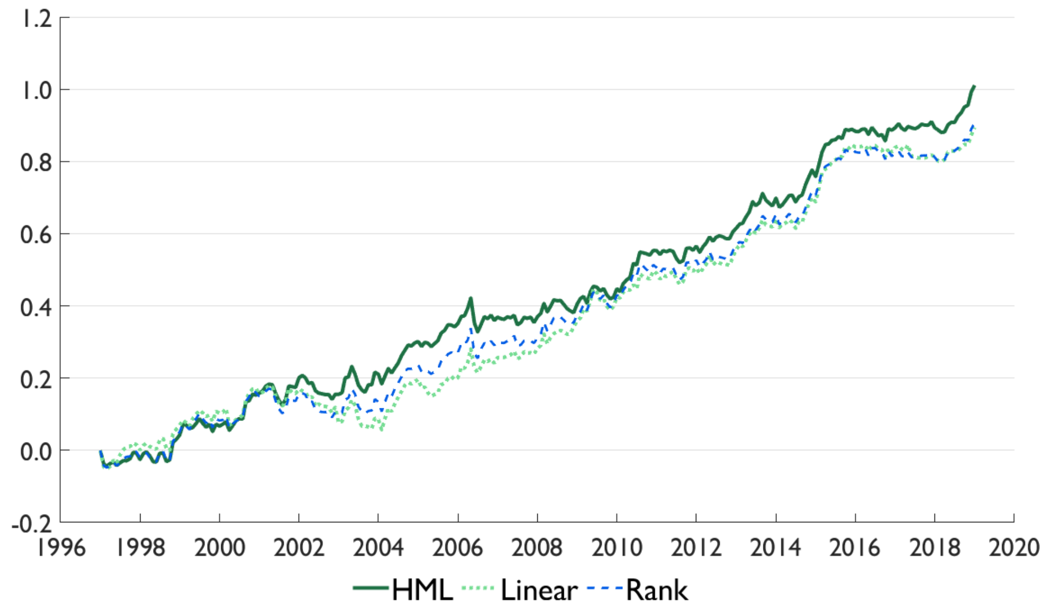

Fig 3. Cumulative Returns of Cross-Border M&A Portfolios. The figure plots the cumulative monthly returns of the three cross-border M&A currency portfolios. The three portfolios include HML (solid line), linear (dotted line), and rank (dashed line). The returns begin in January 1997 and end in December 2018.

the foreign exchange rate (fx) and forward premium (fp) components. Crucially, we find the HML, linear, and rank portfolios all generate positive *exchange rate returns*, which account for around two-thirds of their total average return. The M&A signals can therefore be viewed, consistent with the present-value model of exchange rates, as providing a source of exchange rate return predictability. Turning to the tercile portfolios, we find that P_1 currencies *depreciate*, on average, by 2.44% over the following month (annualized), while P_3 currencies *appreciate*, on average, by 0.84% over the following month (annualized).

In the final two columns, we report the performance of the rank portfolio when limiting the sample to only developed market (Rank_{DM}) or emerging market (Rank_{EM}) currencies.[38] Though more than 85% of the announced cross-border M&A deals in our sample are with developed market firms, our finding is not limited to developed-market currencies. In both cases the average currency excess return and exchange rate return are positive and the Sharpe ratios remain high, albeit slightly lower than those observed in the full sample.

[38] We find similar performance for developed and emerging market currencies for the HML and linear portfolios (see Internet Appendix Table A.2).

5.2 The source of exchange rate return predictability

In Section 4, we observed that the timing of economic growth turning points was principally a domestic-firm effect. This raises a natural question: is the exchange rate predictability we observe also the outcome of domestic-firm-driven outflows? To address this question, we classify all countries entering P_1 and P_3 each month as being allocated to the portfolio because of either an unusual level of inflows or outflows.

Specifically, if country i is allocated to P_1 at time t, we denote it as "domestic-firm-driven" if $|Out_{i,t} - \mu_{Out_{i,t}}| - |In_{i,t} - \mu_{In_{i,t}}| > 0$ and as "foreign-firm-driven" otherwise. The variables $\mu_{Out_{i,t}}$ and $\mu_{In_{i,t}}$ denote the average number of cross-border M&A outflows and inflows for country i over the prior 36-months. A positive value indicates that domestic firms acquisitions were the primary reason that the country was allocated to P_1. Likewise, if country i is allocated to P_3 at time t, we define it as "domestic-firm-driven" if $|Out_{i,t} - \mu_{Out_{i,t}}| - |In_{i,t} - \mu_{In_{i,t}}| < 0$ and as "foreign-firm-driven" otherwise. Across the 264 months, the average percentage of P_1 and P_3 currencies being classified as "domestic-firm-driven" is 60% and 18%, confirming that a high $\widetilde{MA}_{i,t}$ (i.e., a P_3 country) is typically driven by foreign-firm inflows, while a low $\widetilde{MA}_{i,t}$ (i.e., a P_1 country) is usually driven by domestic-firm outflows.

In Table 5, we report the returns and summary statistics for the "more" and "less" portfolios. Interestingly, and reinforcing the insights obtained from Table 3, we find that the exchange rate return predictability is driven *entirely* by the acquisition decisions of *domestic* firms. The annualized monthly foreign exchange return of P_1 countries in the "domestic-firm" portfolio is -2.66%, while the return for countries entering P_3 is 3.94%. In contrast, the analogous results for "foreign-firm" portfolios are only -0.12% and -0.03%. The results therefore support the conclusion that information in domestic-firm driven cross-border M&A *outflows* is the principal driver of the predictability we observe for both economic growth and exchange rate returns.

5.3 A novel source of currency return predictability?

A pertinent question is whether the predictive information we uncover mimics previously identified sources of currency return predictability. There is reason to believe this may be true. For example, Erel et al. (2012) show that an exchange rate depreciation attracts foreign cross-border M&A inflows, since it makes domestic firms relatively cheaper. Similarly, acquiring firms may be thought to be reacting to currently strong economic conditions and thus buying within an already fast growing economy. Additionally, our evidence suggests that the explanatory power in $\widetilde{MA}_{i,t}$ stems from information relating to country-specific fundamentals. However, firms may also react to global shocks to which countries have heterogeneous exposure.

These alternative motivations would be captured by other, previously identified, sources of currency return predictability including (i) currency value (Asness et al., 2013); (ii) currency momentum (Asness et al., 2013); (iii) macroeconomic momentum (Dahlquist and Hasseltoft, 2020), and (iv) inflation momentum (Dahlquist and Hasseltoft, 2020). While the influence of global risk factors would likely overlap with (v) the dollar factor, a proxy for global macroeconomic level risk (Verdelhan, 2018); (vi) the carry factor, which relates to changes in global equity market volatility (Lustig et al., 2011); and (vii) the dollar-carry trade, a proxy for U.S.-specific business cycle variation (Lustig et al., 2014). We construct these portfolios, following the methods of the original studies noted above but for the sample period and currency set used in this study.[39] The portfolios are rebalanced monthly and have zero net cost. Except where noted otherwise, currencies are assigned rank weights for comparability with the cross-border rank-weight M&A portfolio given the conceptually appealing features of rank weighting (see Dahlquist and Hasseltoft, 2020).[40]

Our expectation is that, if the forecasting power of the cross-border M&A portfolios is merely driven by market timing or global risk factors (unrelated to novel information about future economic fundamentals), then the forecastability would not remain after controlling for the alternative sources of predictability.

5.3.1 Comparing sources of currency return predictability

We test if the return predictability that we previously documented is subsumed by the other sources of currency return predictability in two ways. First, we estimate ordinary-least-squares regressions in which we regress the cross-border M&A portfolio's returns, $R^p_{M\&A,t} = \sum_{t=1}^{T} (w^{rnk}_{i,t-1})' R_{i,t}$, on a constant and the returns of each newly constructed portfolio:

$$R^p_{M\&A,t} = \alpha + \sum_k \beta_k R^p_{k,t} + \varepsilon_t, \tag{12}$$

[39] We provide further details about the nature of the portfolio sorts in the Internet Appendix.

[40] We find qualitatively identical results when using the portfolios constructed using either HML or linear weights. The investment performance of the portfolios is presented in Internet Appendix Table A.3. We find that each portfolio generates a positive return, with associated Sharpe ratios ranging from 0.16 (dollar) to 0.83 (carry). Unlike the cross-border M&A portfolio, we find that the currency portfolios are rarely driven by exchange rate return predictability: only dollar-carry and macroeconomic momentum generate positive FX returns, the other portfolios generate positive returns because of investing in higher interest-rate currencies than used to fund the long positions.

where k indexes the newly constructed portfolios and α reflects the component of the returns not explained by the model. The results are presented in Table 6. In the first column we report results for all currencies, while equivalent results for developed- and emerging-market currencies are reported in the second and third columns. The key finding is that the estimates of α are positive and highly statistically significant (at the 1% significance level). For the portfolio constructed using all currencies, the constant equals 3.71% and is thus similar to the total return of 4.12% reported in Table 4—indicating that virtually none of the variation in the M&A portfolio's returns is explained by the other sources of return predictability. The low adjusted-R^2 statistics, ranging between 2% and 4%, further reinforce this finding.

Our second test investigates more directly, via predictive panel regressions, whether the rank weights of the M&A portfolio predict exchange rate and currency returns after controlling for the other sources of currency return predictability. Specifically, we regress one-month currency and foreign exchange rate returns on the rank weights of the cross-border M&A portfolio and all newly constructed portfolios:[41]

$$\begin{aligned} R_{i,t+1} &= \alpha + \beta w^{rnk}_{M\&A,i,t} + \sum_k \gamma_k w^{rnk}_{k,i,t} + \tau_{t+1} + \varepsilon_{t+1} \\ R^{fx}_{i,t+1} &= \alpha + \beta w^{rnk}_{M\&A,i,t} + \sum_k \gamma_k w^{rnk}_{k,i,t} + \tau_{t+1} + \varepsilon_{t+1}, \end{aligned} \tag{13}$$

where $R_{i,t+1}$ is the currency return defined in Equation (**9**) and $R^{fx}_{i,t+1}$ is the exchange rate return, equal to $(S_{i,t+1} - S_{i,t})/S_{i,t}$. We anticipate that the β coefficient is positive in both cases, since higher $\widetilde{MA}_{i,t}$ implies higher exchange rate and currency returns. The question is whether the coefficient is statistically different from zero after controlling for the other sources of return predictability.

We report results in Table 7. The coefficients reflect monthly returns (in percentage points) for a rank weight equal to 1. We find the coefficients on the cross-border M&A portfolio are positive and statistically significant at the 1% level in both cases. Moreover, the coefficient estimates (0.64% and 0.66%) are similar, consistent with the return predictability stemming from the exchange rate component. This contrasts with the carry portfolio that displays a positive relationship with currency returns but a negative relationship with exchange rate returns. Surprisingly, of all the newly constructed portfolios, only the carry rank weights display

[41] We do not obtain rank weights for dollar or dollar-carry but include time fixed effects (τ_t) to control for common dollar movements. The economic and inflation trend portfolios are calculated as in Dahlquist and Hasseltoft (2020). In doing so, rank weights for these portfolios are obtained across all lookback horizons (ranging from one to 60 months) but, for the purposes of this test, we use the 12-month rank weights.

a statistically significant relationship with either exchange rate or currency returns.

We conclude that information contained in the announcements of cross-border M&A deals provides a novel source of exchange rate and currency returns predictability. The results also suggest that the announcements may provide a beneficial source of diversification gains to currency investors, which we now investigate.

5.3.2 Diversification gains

We investigate diversification gains by analyzing the performance of currency portfolios that incrementally introduce different sources of currency return predictability. We view $\widetilde{MA}_{i,t}$ as a source of diversification gains if the addition of a cross-border M&A portfolio increases the broader portfolio's Sharpe ratio. Results from diversification tests are presented in Table 8.

Broad currency portfolios. In Panel A, we present the Sharpe ratios of optimal mean-variance portfolios that exclude the cross-border M&A portfolio. The portfolios are optimized by minimizing the variance at target expected returns varying between 3.50% and 5.50% (increasing in 25 basis points increments). We consider three broad portfolios (BP_1, BP_2, and BP_3) that differ by their investment universe. The first portfolio is limited to only dollar and carry, which are widely viewed as the main return-based factors determining currency returns (see, e.g. Verdelhan, 2018). Sharpe ratios vary between 0.71 and 0.84, increasing as weight is shifted towards carry. The second portfolio expands the investment universe to include value and momentum. At higher target returns, carry is allocated an increasingly higher weight, but at lower returns the diversification gains from including value and momentum are larger—increasing the Sharpe ratio to over 0.90. The third portfolio further expands the investment universe to include dollar-carry, macroeconomic momentum, and inflation momentum. Further investment gains are achieved and the Sharpe ratio increases to 1.17, although the Sharpe ratios of BP_3 are only statistically higher than those of BP_2 at the lowest target returns.[42]

Inclusion of the cross-border M&A portfolio. In Panel B, we present the equivalent results when the cross-border M&A portfolio is added to the investment universe (BP_1^+, BP_2^+, and BP_3^+). In Panel C, we report the corresponding optimal weights allocated to the M&A portfolio ($\omega_{BP_1^+}$, $\omega_{BP_2^+}$, and $\omega_{BP_3^+}$). We find that the addition of the cross-border M&A portfolio

[42]The p-values in the table are based on the Ledoit and Wolf (2008) test for the difference between two Sharpe ratios. The null hypothesis is that the Sharpe ratios are the same. We thank Michael Wolf for making the code available.

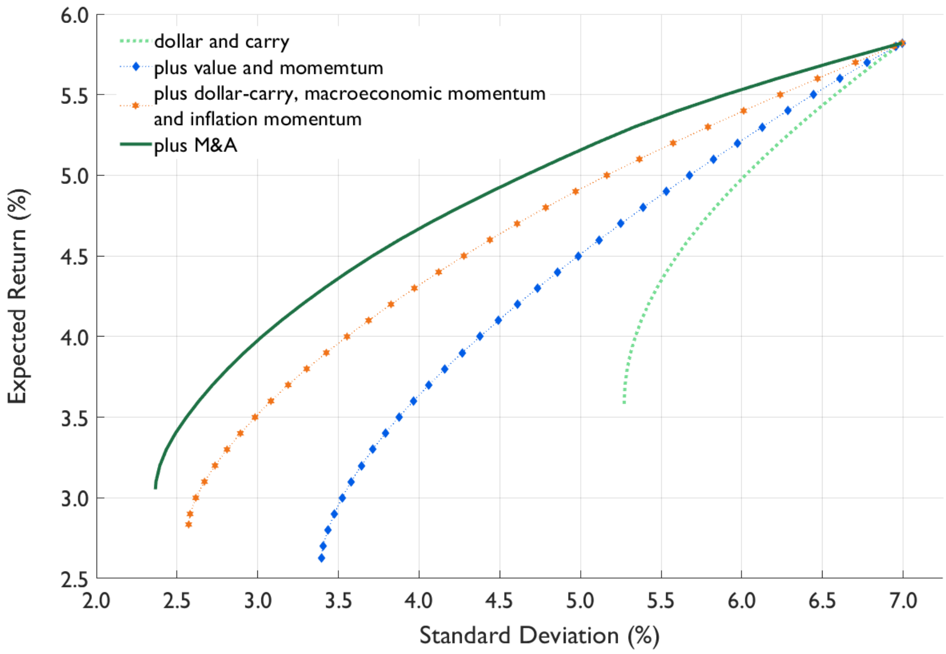

Fig 4. Efficient Frontiers. The figure plots a series of efficient frontiers for various sets of currency portfolios. The dotted line is the efficient frontier when limiting the investment space to only dollar and carry. We add value and momentum (dotted line with diamond markers, four portfolios), dollar-carry, macroeconomic momentum, and inflation momentum (dashed line with star markers, seven portfolios), and the cross-border M&A portfolio (solid line, eight portfolios). The average return vector and covariance matrix are estimated using the full sample of returns from January 1997 to December 2018.

leads to economically large increases in the Sharpe ratio, ranging between 14% and 28%, while the third portfolio (BP_3^+) *always* generates a statistically higher Sharpe ratio than the second (BP_2), increasing to over 1.30 for target returns between 3.5% and 4.0%. To achieve these sizeable diversification gains, an economically large portfolio weight is allocated to the cross-border M&A portfolio of around 33%. Fig. 4 plots the evolution of the efficient frontiers as the investment universe is expanded from the dollar and carry portfolios to include all source of currency return predictability. The figure shows that the cross-border M&A portfolio expands the efficient frontier, even after all other sources of return predictability are made available for investment—reaffirming the conclusion that information contained in the announcements of cross-border M&A deals is novel and provides a beneficial source of diversification gains.

6 Further Analyses

In this section we discuss various robustness tests we conduct and analyze an alternative “transaction” hypothesis to explain our main results.

6.1 The "transaction" hypothesis

The announcement of cross-border M&A deals can plausibly contain information about future FX order flow, providing the transactions will be: (i) completed, and (ii) paid for (at least in part) using cash. M&A deals with large dollar values may therefore impact foreign exchange rates because market participants "front-run" these FX transactions. There are, at least, three reasons this explanation is unlikely to drive our results. First, the announcement dates do not provide precise guidance to the *completion* date, and thus the timing of the future FX transaction is unknown. Second, cross-border M&A is subject to stringent regulations and government interventions—it is thus uncertain whether an M&A deal will ultimately be completed, presenting large risks to perspective front-runners. Third, announced deals do not necessarily result in an FX transaction if it is financed using stock and, in many cases, the payment type is unknown.

If the transaction hypothesis does, however, account for the currency return predictability we observe, then we expect the results of our analysis to be *stronger* when forming signals using the *dollar value* of future transactions, rather than the *number* of announced cross-border M&A deals. Moreover, the predictability should disappear if the analysis is conducted using only deals *without* information about the payment type (around one-third of the deals). We test both hypotheses using the prior portfolio approach and present results in Table 9. When forming portfolios using dollar values (Panel A), the total return drops from 4.12% to 2.66% and the Sharpe ratio falls to 0.54, indicating that a predictive signal is still observed, but it is *not* stronger.

On the second test (Panel B), we find the returns continue to remain statistically significant and the Sharpe ratio is over 0.50, rejecting the hypothesis of no return predictability for deals with missing information about the payment type. In sum, neither conceptually nor after the additional empirical tests do we view the alternative "transaction" hypothesis as a likely driver of the main empirical findings.

6.2 Bootstrap simulations of M&A portfolio returns

A potential concern is that the literature may have been *too* successful in its pursuit of currency return predictability, given the growing number of signals found to predict currency returns in cross-sectional studies. Indeed, standard statistical tests may over-reject the null hypothesis of no predictability (see, e.g. Harvey et al., 2016). We address this concern by conducting

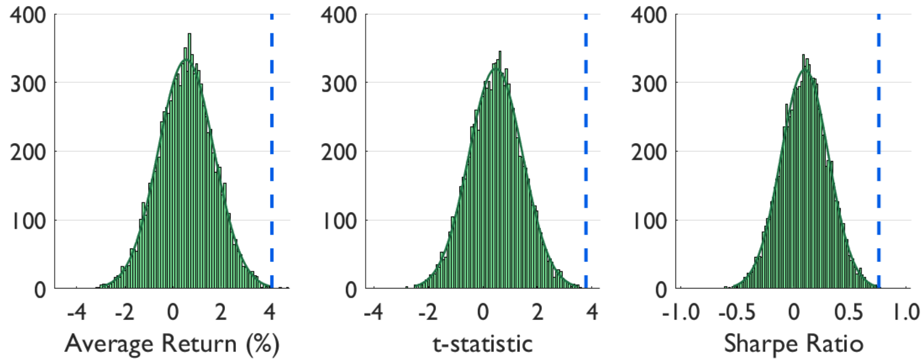

Fig 6. Bootstrapped Distributions with Normal Distribution Fit. The figure plots the histograms of average returns, t-statistics, and Sharpe ratios, calculated using 10,000 bootstrapped samples. The corresponding values for the observed rank-weight M&A portfolio are plotted as dashed lines. A normal distribution fit is overlaid in each sub-figure.

a bootstrap simulation, in which we randomly assign cross-border M&A signals to countries, drawn with replacement from their own vector of observed signals. We generate 10,000 samples and calculate bootstrapped statistics for the rank-weight cross-border M&A portfolio. If the average return of the rank-weight portfolio, documented in Table 4, is *not* different from the average return of the bootstrapped portfolios, then we cannot confidently claim to have uncovered a new source of return predictability. We provide full details of the bootstrap procedure in Internet Appendix Section B.

In Fig. 6, we plot the distributions of the average returns, t-statistics, and Sharpe ratios of the bootstrapped portfolios, overlaid with a normal distribution fit. We find the statistics for the observed rank-weight portfolio are always clear outliers—only a small handful of randomly assigned weights generate equivalent currency return predictability. The p-values are therefore low (below 0.001 in each case), and the average annualized return and Sharpe ratio of the simulated portfolios are only 0.55% and 0.10, compared with 4.12% and 0.76 documented in Table 4. In sum, the announcements of cross-border M&A deals continue to display an economically and statistically informative signal about future currency returns.

6.3 Transaction costs

It is important to ask if the economic benefits from return predictability survive the inclusion of transaction costs. Incorporating transaction costs in currency market studies involves certain complications. The spreads on foreign exchange rates obtained from WM/Reuters are, for example, widely viewed as being larger than the actual spreads paid in financial markets—especially on smaller sized trades (see, e.g. Gilmore and Hayashi, 2011; Melvin et al., 2020). It has thus become common practice to adopt a scaling of spreads, with a 50% rule being adopted in multiple studies (e.g. Menkhoff et al., 2012; Colacito et al., 2020). Even this rule has been found to be too conservative in recent years, during which a 25% scaling has been found to be more appropriate (Cespa et al., 2021). We apply the more conservative 50% scaling and present the results from incorporating transaction costs in Internet Appendix Table A.4. The Sharpe ratios of the cross-border M&A portfolios decline from 0.85, 0.73, and 0.76 for the HML, linear, and rank portfolios, to 0.67, 0.56, and 0.59, respectively. We view this performance as still highly attractive and in line with the performance of leading currency strategies, including the currency carry trade. Therefore, the inclusion of transaction costs—especially for smaller sized trades—does not change the conclusion that information contained in the announcements of cross-border M&A deals provides an economically, as well as statistically, valuable source of currency return predictability.

7 Conclusions

We uncover a novel source of predictive information, originating from the announcements of cross-border M&As, that forecasts economic growth and foreign exchange rate returns. Consistent with the announcements revealing firms' private expectations about economic fundamentals, we find that a country's economic growth accelerates, and their local currency appreciates, following months in which their announced cross-border M&A net inflows are abnormally high. We find the opposite patterns following abnormally low M&A net inflows. The predictability captures reversals in economic growth and is driven principally by the acquisition decisions of domestic firms revealing an informative signal about turning points in local economic growth, which is not subsumed by other publicly available predictors. The results imply that private expectations about future macroeconomic fundamentals are (a) revealed outside of order flow, and (b) able to forecast currency returns when extracted from corporate investment flow.

The results are consistent with theory, in which local agents know more about their domestic economic conditions, and with the notion that firms are "closer to the information" in terms of their private signals about real-time economic information. An aggregate signal, extract from firms' international investments, can therefore help to predict future economic growth. We show, via a simple model of exchange rate determination, that these signals can forecast exchange rate returns if not all investors fully condition on the information when trading, which is easily motivated in the foreign exchange market given the wide range of trading motives.

The paper contributes to growing literatures investigating the links between economic fundamentals and currency returns, and provides a novel approach to studying how private expectations may be revealed to the market and incorporated into prices—connecting to the broader study of information and the determination of exchange rates. The results also have broad practical implications: for policy makers, the findings provide a way to identify informed capital flows, while for global investors, the results highlight a non-traditional source of information that predicts exchange rates. Moreover, the exchange rate predictability can be exploited to form a portfolio that has generated impressive investment returns over a 20-year period and offered a source of large diversification gains.

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Table 1: Summary Statistics

Country	N	%Acq	%Tar	#Days	Country	N	%Acq	%Tar	#Days
Argentina	264	6	94	35	Israel	688	44	56	13
Australia	1,813	44	56	5	Italy	471	29	71	19
Austria	78	36	64	116	Japan	1,175	66	34	8
Belgium	241	39	61	40	Latvia	15	0	100	515
Brazil	504	11	89	18	Lithuania	18	0	100	299
Chile	168	9	91	54	Netherlands	661	44	56	14
Colombia	92	16	84	107	New Zealand	190	28	72	49
Czech Republic	67	0	100	133	Norway	286	37	63	32
Denmark	194	41	59	47	Poland	120	11	89	74
Estonia	16	0	100	558	Portugal	37	19	81	246
Euro Area	5,518	40	60	2	Russian Fed	141	36	64	63
Finland	160	53	48	57	Slovak Rep	13	0	100	361
France	1,265	40	60	7	Slovenia	12	0	100	601
Germany	1,367	37	63	7	South Africa	153	39	61	59
Greece	50	36	64	190	South Korea	634	44	56	14
Hungary	59	12	88	154	Spain	545	32	68	17
Iceland	19	74	26	348	Sweden	488	48	52	19
India	1,127	28	72	8	Switzerland	539	62	38	17
Indonesia	67	7	93	136	Turkey	75	19	81	124
Ireland	501	54	46	18	United Kingdom	5,489	51	49	2
Developed	21,669	45	55	8	Emerging	3,651	24	76	48

The table presents summary statistics on cross-border M&A deals announced between January 1994 and November 2018, across 40 developed and emerging market countries vis-à-vis the United States. For each country, we report the aggregate number of deals (N), the percentage of deals in which the country is the acquiror (%Acq), the percentage of deals in which the country is the target (%Tar), and the average number of days between two consecutive deals being announced (#Days).

Table 2: Forecasting Economic Acceleration

	Dep: $\Delta g_{i,t+12}$		Dep: $\Delta g_{i,t+24}$		Dep: $\Delta g_{i,t+36}$		Dep: $\Delta g_{i,t+48}$		Dep: $\Delta g_{i,t+60}$	
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**	**(9)**	**(10)**
$\widetilde{MA}$	0.082	0.111	0.147**	0.179**	0.238***	0.273***	0.335***	0.409***	0.396***	0.451***
	(0.066)	(0.068)	(0.075)	(0.079)	(0.079)	(0.086)	(0.088)	(0.095)	(0.090)	(0.089)
CLI	–0.893***		–1.575***		–1.715***		–2.002***		–1.585***	
	(0.098)		(0.104)		(0.105)		(0.122)		(0.124)	
Dividend yield		0.139		0.098		–0.022		0.021		0.349
		(0.213)		(0.221)		(0.238)		(0.250)		(0.256)
Stock return		0.031		0.015		0.021		0.009		0.000
		(0.031)		(0.032)		(0.034)		(0.037)		(0.033)
Term spread		0.023		0.465**		0.584***		0.530***		1.271***
		(0.195)		(0.195)		(0.221)		(0.222)		(0.210)
Short rate		–0.438***		–0.173		0.205		0.452***		0.986***
		(0.140)		(0.144)		(0.182)		(0.174)		(0.165)
Country FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Time FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Obs.	2,693	2,386	2,571	2,278	2,439	2,161	2,313	2,055	2,185	1,947
Adj. R^2	0.45	0.47	0.52	0.53	0.49	0.47	0.49	0.46	0.52	0.54

The table presents coefficient estimates from panel regressions of changes in economic growth (i.e., economic acceleration), $\Delta g_{i,t+s}$, for $s = 12, 24, 36, 48$ and 60, on the level of abnormal cross-border M&A activity ($\widetilde{MA}_{i,t}$):

$$\Delta g_{i,t+s} = \alpha_i + \beta \widetilde{MA}_{i,t} + \gamma' X_{i,t} + \kappa_i + \lambda_{t+s} + \varepsilon_{i,t+s},$$

where $X_{i,t}$ denotes control variables that include composite leading indicators (*CLIs*), dividend yields, local stock market returns, term spreads, and short-term interest rates. Country and time fixed effects (κ_i and λ_{t+s}) are included in all regressions. Robust standard errors are double clustered at the country-month level and reported in parentheses. The number of observations (*Obs*) and adjusted R-square statistics (*Adj.* R^2) are reported in the final two rows. Superscripts ***, ** and * denote significance of the coefficients at the 1%, 5% and 10% level, respectively. The sample includes the United States and 40 developed and emerging market countries. The data is monthly, beginning in December 1996 and ending in November 2018.

Table 3: Forecasting Economic Acceleration: Inflows and Outflows

	Dep: $\Delta g_{i,t+12}$		Dep: $\Delta g_{i,t+24}$		Dep: $\Delta g_{i,t+36}$		Dep: $\Delta g_{i,t+48}$		Dep: $\Delta g_{i,t+60}$	
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**	**(9)**	**(10)**
$\widetilde{MA}^{in}$	–0.135	-0.164	–0.143	–0.100	0.036	0.019	0.295**	0.335**	0.530***	0.655***
	(0.099)	(0.104)	(0.107)	(0.113)	(0.113)	(0.127)	(0.122)	(0.132)	(0.127)	(0.130)
$\widetilde{MA}^{out}$	–0.264***	–0.294***	–0.499***	–0.454***	–0.532***	–0.588***	–0.434***	–0.522***	–0.267*	–0.234*
	(0.098)	(0.099)	(0.119)	(0.124)	(0.127)	(0.134)	(0.141)	(0.150)	(0.142)	(0.141)
CLI	–0.885***		–1.557***		–1.700***		–2.002***		–1.598***	
	(0.099)		(0.104)		(0.106)		(0.122)		(0.124)	
Dividend yield		0.132		0.090		–0.030		0.015		0.340
		(0.212)		(0.220)		(0.237)		(0.250)		(0.257)
Stock return		0.031		0.014		0.021		0.009		0.001
		(0.031)		(0.032)		(0.034)		(0.037)		(0.034)
Term spread		–0.005		0.432**		0.552**		0.520**		1.301***
		(0.192)		(0.194)		(0.219)		(0.222)		(0.212)
Short rate		–0.433***		–0.164		0.215		0.453***		0.973***
		(0.138)		(0.143)		(0.180)		(0.174)		(0.165)
Country FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Time FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Obs.	2,693	2,386	2,571	2,278	2,439	2,161	2,313	2,055	2,185	1,947
Adj. R^2	0.45	0.47	0.52	0.53	0.50	0.48	0.49	0.46	0.52	0.54

The table presents coefficient estimates from panel regressions of changes in economic growth (i.e., economic acceleration), $\Delta g_{i,t+s}$, for $s = 12, 24, 36, 48$ and 60, on the level of abnormal cross-border M&A activity constructed using either inflows ($\widetilde{MA}^{in}_{i,t}$) or outflows ($\widetilde{MA}^{out}_{i,t}$):

$$\Delta g_{i,t+s} = \alpha_i + \beta_1 \widetilde{MA}^{in}_{i,t} + \beta_2 \widetilde{MA}^{out}_{i,t} + \gamma' X_{i,t} + \kappa_i + \lambda_{t+s} + \varepsilon_{i,t+s},$$

where $X_{i,t}$ denotes control variables that include composite leading indicators (*CLIs*), dividend yields, local stock market returns, term spreads, and short-term interest rates. Country and time fixed effects (κ_i and λ_{t+s}) are included in all regressions. Robust standard errors are double clustered at the country-month level and reported in parentheses. The number of observations (*Obs*) and adjusted R-square statistics (*Adj.* R^2) are reported in the final two rows. Superscripts ***, ** and * denote significance of the coefficients at the 1%, 5% and 10% level, respectively. The sample includes the United States and 40 developed and emerging market countries. The data is monthly, beginning in December 1996 and ending in November 2018.

Table 4: Cross-Border M&A Portfolios and Currency Return Predictability

	$\mathbf{P_1}$	$\mathbf{P_2}$	$\mathbf{P_3}$	**HML**	**Linear**	**Rank**	$\mathbf{Rank_{DM}}$	$\mathbf{Rank_{EM}}$
mean (%)	–0.89	0.58	3.71	4.59	4.06	4.12	3.01	5.53
t-stat	–0.45	0.33	2.03	4.17	3.61	3.79	2.48	3.24
std (%)	8.07	7.64	8.14	5.43	5.59	5.44	5.65	8.30
SR	–0.11	0.08	0.46	0.85	0.73	0.76	0.53	0.67
skew	–0.22	–0.16	–0.14	–0.19	–0.28	–0.31	0.35	–0.12
kurt	4.32	4.42	4.18	4.34	3.82	4.74	3.92	4.43
ar(1)	0.10	0.04	0.08	0.05	0.02	0.02	0.09	–0.05
mdd (%)	37.1	29.4	15.2	6.62	10.4	6.79	9.34	11.2
fx (%)	–2.44	–0.60	0.84	3.27	2.60	2.88	2.67	4.54
fp (%)	1.55	1.18	2.87	1.32	1.46	1.24	0.34	0.99

The table presents statistics on cross-border merger and acquisition portfolios. Statistics include the average annualized (*mean*) return and associated t-statistic, calculated using Newey and West (1987) standard errors; annualized standard deviation (*std*); Sharpe ratio (*SR*); skewness (*skew*); kurtosis (*kurt*); first-order autocorrelation coefficient (*ar(1)*); and maximum drawdown (*mdd*). The final two rows record the decomposition of the average return between the spot (*fx*) and forward premium (*fp*) components. P_1, P_2, and P_3 denote three portfolios sorted each month from low to high values of $\widetilde{MA}_{i,t}$. HML, *Linear*, and *Rank* denote three zero-cost cross-sectional portfolios. Further details on the portfolio weights can be found in Section 4.3. The sample includes the US and 40 developed and emerging market countries. In the final two columns are statistics for *Rank* portfolios constructed using only developed market ($Rank_{DM}$) and emerging market ($Rank_{DM}$) countries. All statistics are calculated using monthly returns from January 1997 to December 2018.

Table 5: The Sources of Currency Return Predictability

	Domestic Driven Outflows		Foreign Driven Inflows	
	$\mathbf{P_1}$	$\mathbf{P_3}$	$\mathbf{P_1}$	$\mathbf{P_3}$
mean (%)	–1.14	4.06	1.99	3.24
t-stat	–0.55	1.20	0.38	1.61
SR	–0.13	0.44	0.15	0.36
fx (%)	–2.66	3.94	–0.12	–0.03
fp (%)	1.53	0.12	2.11	3.27
$\mu_{\widetilde{MA}_{i,t}}$	–1.30	1.25	–0.96	1.86

The table presents statistics on cross-border merger and acquisition portfolios. Statistics include the average annualized (*mean*) return and associated t-statistic, calculated using Newey and West (1987) standard errors; and the Sharpe ratio (*SR*). The final three rows record the decomposition of the average return between the spot (*fx*) and forward premium (*fp*) components and the average M&A signal of countries in P_1 and P_3 ($\mu_{\widetilde{MA}_{i,t}}$). P_1 and P_3 denote portfolios sorted each month from low to high values of $\widetilde{MA}_{i,t}$. In the left-hand panel ("More"), countries entering P_1 (P_3) experience abnormal M&A activity principally driven by unusually "more" outflows (inflows). In the right-hand panel ("Less"), countries entering P_1 (P_3) experience abnormal M&A activity principally driven by unusually "less" inflows (outflows). HML is a zero-cost cross-sectional portfolio equal to $P_3 - P_1$. Further details on the portfolio weights can be found in Sections 4.3 and 4.4. The sample includes the US and 40 developed and emerging market countries. All statistics are calculated using monthly returns from January 1997 to December 2018.

Table 6: Explaining Cross-Border M&A Portfolio Returns

	All	**DM**	**EM**
α	3.71***	3.56***	5.34***
	(1.24)	(1.29)	(2.02)
Dollar	–0.01	–0.09	0.11
	(0.06)	(0.06)	(0.13)
Carry	0.22**	0.15*	0.18
	(0.11)	(0.09)	(0.15)
Momentum	0.09	0.01	0.13**
	(0.06)	(0.07)	(0.06)
Value	0.16	0.11	–0.16
	(0.14)	(0.09)	(0.16)
$Carry_{USD}$	–0.01	0.01	–0.00
	(0.06)	(0.05)	(0.14)
$Trend_{EC}$	–0.09	–0.17	–0.18
	(0.09)	(0.11)	(0.12)
$Trend_{IN}$	–0.31	–0.32***	–0.07
	(0.20)	(0.14)	(0.23)
Obs.	264	264	264
Adj. R^2	0.023	0.031	0.034

The table presents coefficient estimates from ordinary-least-square regressions of M&A rank portfolio returns on a constant and the returns of other currency portfolios:

$$R^p_{M\&A,t} = \alpha + \sum_k \beta_k R^p_{k,t} + \varepsilon_t,$$

where k indexes the other currency portfolios, k = *Dollar*, *Carry*, ..., and α (the constant) reflects the component of the M&A portfolio returns that is not explained by variation in the other portfolios' returns. Newey and West (1987) standard errors are presented in parentheses. In the first column, the portfolios are constructed using all 40 developed and emerging market countries (*All*). In the second and third columns the portfolios are constructed using only developed market (*DM*) and emerging market (*EM*) countries. All returns are annualized prior to estimation. The number of observations (*Obs*) and adjusted R-square statistics (*Adj.* R^2) are reported in the final two rows. Superscripts ***, ** and * denote significance of the coefficients at the 1%, 5% and 10% level, respectively. The data is monthly, beginning in January 1997 and ending in December 2018.

Table 7: Currency and Exchange Rate Predictability

	Currency Return	FX Return
$w^{rnk}_{M\&A,i,t}$	0.644***	0.662***
	(0.245)	(0.247)
$w^{rnk}_{car,i,t}$	1.672**	–0.672
	(0.717)	(0.716)
$w^{rnk}_{mom,i,t}$	0.510	0.443
	(0.529)	(0.529)
$w^{rnk}_{val,i,t}$	0.921	0.735
	(0.656)	(0.657)
$w^{rnk}_{Trend_{EC},i,t}$	–0.066	0.043
	(0.455)	(0.457)
$w^{rnk}_{Trend_{IN},i,t}$	–0.790	–0.956
	(0.697)	(0.695)
Time FE	YES	YES
Obs.	2,568	2,568
Adj. R^2	0.45	0.45

The table presents coefficient estimates from predictive panel regressions of one-month currency returns (column 1) and exchange rate returns (column 2) at time t+1 on the time-t rank weights from the cross-border M&A portfolio and other currency portfolios (see Section 4.5.2 for details):

$$\begin{aligned} R_{i,t+1} &= \alpha + \beta w^{rnk}_{M\&A,i,t} + \sum_k \gamma_k w^{rnk}_{k,i,t} + \tau_{t+1} + \varepsilon_{t+1} \\ R^{fx}_{i,t+1} &= \alpha + \beta w^{rnk}_{M\&A,i,t} + \sum_k \gamma_k w^{rnk}_{k,i,t} + \tau_{t+1} + \varepsilon_{t+1}, \end{aligned} \tag{14}$$

where $R_{i,t+1}$ is defined in Equation (**9**) and $R^{fx}_{i,t+1} = (S_{i,t+1} - S_{i,t})/S_{i,t}$. Both regressions include time fixed-effects. The number of observations (*Obs*) and adjusted R-square statistics (*Adj.* R^2) are reported in the final two rows. Superscripts ***, ** and * denote significance of the coefficients at the 1%, 5% and 10% level, respectively. The data is monthly, beginning in January 1997 and ending in December 2018.

Table 8: Diversification Gains from the Cross-Border M&A Portfolio

	Expected Return (%)								
	3.50	**3.75**	**4.00**	**4.25**	**4.50**	**4.75**	**5.00**	**5.25**	**5.50**
	Panel A: Sharpe Ratios of Broad Currency Portfolios								
BP_1	–	0.71	0.75	0.78	0.80	0.82	0.83	0.84	0.84
BP_2	0.90	0.91	0.91	0.91	0.90	0.89	0.88	0.87	0.85
BP_3	1.17	1.16	1.13	1.09	1.05	1.01	0.97	0.92	0.88
p-val	[0.06]	[0.07]	[0.10]	[0.15]	[0.19]	[0.20]	[0.18]	[0.18]	[0.25]
	Panel B: Sharpe Ratios after including the M&A Portfolio								
BP_1^+	–	1.01	1.04	1.06	1.06	1.05	1.01	0.93	0.93
BP_2^+	1.08	1.10	1.11	1.10	1.09	1.08	1.05	1.01	0.93
BP_3^+	1.37	1.36	1.32	1.27	1.21	1.14	1.07	1.01	0.93
p-val	[0.02]	[0.02]	[0.02]	[0.02]	[0.03]	[0.03]	[0.04]	[0.08]	[0.06]
	Panel C: Weights Assigned to the M&A Portfolio								
$\omega_{BP_1^+}$	–	0.49	0.50	0.50	0.51	0.48	0.34	0.19	0.19
$\omega_{BP_2^+}$	0.33	0.35	0.38	0.41	0.43	0.46	0.47	0.34	0.19
$\omega_{BP_3^+}$	0.25	0.27	0.30	0.32	0.33	0.34	0.34	0.34	0.19

The table presents portfolio statistics from mean-variance optimized currency portfolios. Panel A reports the optimal Sharpe ratios for three broad portfolios with target returns ranging from 3.5% to 5.5% (BP_1, BP_2, and BP_3). BP_1 contains dollar and carry (2 portfolios). BP_2 adds value and momentum (4 portfolios). BP_3 adds dollar-carry, macroeconomic momentum and inflation momentum (7 portfolios). *p-val* is the p-value from the test that the Sharpe ratio of BP_3 is different to BP_2. Panel B reports the optimal Sharpe ratios once the M&A rank portfolio is included as a potential investment. The *p-val* in Panel B reflects the test that the Sharpe ratio of BP_3^+ is different to the Sharpe ratio of BP_2. Panel C reports optimal weights assigned to the M&A portfolio ($\omega_{BP_1^+}$, $\omega_{BP_2^+}$, and $\omega_{BP_3^+}$). The portfolio weights are restricted to be positive and sum to one. The average return vector and covariance matrix are estimated using the full sample of returns from January 1997 to December 2018.

Table 9: Alternative Cross-Border M&A Signals

Panel A: Dollar Value of M&A Deals	P1	P2	P3	HML	Linear	Rank
Mean (%)	–0.21	1.82	2.49	2.70	4.03	2.66
t-stat	–0.12	0.99	1.45	2.53	2.38	2.68
SR	–0.03	0.22	0.31	0.52	0.49	0.54

Panel B: Missing Payment Information	P1	P2	P3	HML	Linear	Rank
Mean (%)	–1.37	2.93	2.12	3.49	3.14	3.46
t-stat	–0.77	1.91	0.96	2.26	2.31	2.47
SR	–0.18	0.40	0.23	0.49	0.46	0.51

Panel C: Announcement of Unsuccessful Deals	P1	P2	P3	HML	Linear	Rank
Mean (%)	–1.57	0.93	5.18	7.35	6.07	5.64
t-stat	–0.80	0.54	2.63	4.64	3.71	3.54
SR	–0.19	0.13	0.59	0.86	0.71	0.68

Panel D: M&As of Non-financial firms	P1	P2	P3	HML	Linear	Rank
Mean (%)	–0.24	0.65	3.18	3.42	3.12	3.03
t-stat	–0.12	0.38	1.74	3.04	2.68	2.79
SR	–0.03	0.09	0.38	0.57	0.50	0.53

The table presents statistics for currency portfolios sorted by $\widehat{MA}_{i,t}$. The signal is constructed using either the dollar value of M&A deals (Panel A) or using deal without payment information (Panel B). Statistics include the average annualized (*mean*) return and associated t-statistic calculated using Newey and West (1987) standard errors; and the Sharpe ratio (*SR*). P_1, P_2, and P_3 denote three portfolios sorted each month from low to high values of $\widehat{MA}_{i,t}$. HML, *Linear*, and *Rank* denote three zero-cost cross-sectional portfolios. Further details on the portfolio weights can be found in Section 4.3. The sample includes the US and 40 developed and emerging market countries. All statistics are calculated using monthly returns from January 1997 to December 2018.

Internet Appendix
Cross-Border M&A Flows, Economic Growth, and Foreign Exchange Rates

Not for publication

Contents

Table A.11: Transaction Costs
Statistics on cross-border M&A portfolios after including bid-ask spreads.

Table A.12: Transaction Costs
Statistics on cross-border M&A portfolios after including bid-ask spreads.

Table A.13: Transaction Costs
Statistics on cross-border M&A portfolios after including bid-ask spreads.

Table A.14: Transaction Costs
Statistics on cross-border M&A portfolios after including bid-ask spreads.

SECTION B

Details of the bootstrap procedure used to generate results described in Section 5.3.

Section A: A Model of Exchange Rate Predictability

In this section, we present a simple model of exchange rate predictability to demonstrate how publicly available information can generate exchange rate return predictability. The model follows the spirit of a differences-in-belief set-up in which agents "agree to disagree" about publicly available information (e.g., Harrison and Kreps, 1978, Harris and Raviv, 1993; Banerjee and Kremer, 2010; Jeanneret and Sokolovski, 2021) but could equally apply to an "asymmetric information" environment in which certain agents are better at processing (e.g., transforming and modelling) publicly available information in order to extract private signals.

Model set-up

There are three dates, $t = 0, 1, 2$ and two countries (domestic and foreign). In both countries a single risk-free asset is traded. International trade in the securities determines demand for foreign currency. In line with the standard open-economy macroeconomics models, we assume the domestic economy is large, and the foreign economy is small and thus only domestic demand determines exchange rate behavior (see, e.g. Bacchetta and Van Wincoop, 2006; Cespa et al., 2021, and references therein).

In line with present value models of exchange rates, the log-exchange rate at $t = 2$ is equal to its initial level plus a fundamental shock:

$$s_2 = s_0 + f_2, \qquad \text{where } f_2 \sim N(0, \sigma_f^2)$$

where the exchange rate is defined as the domestic price of foreign currency, and thus a higher value of s_2 is consistent with relatively stronger foreign fundamentals. At $t = 0$, therefore, agents all belief that the best predictor the $t = 2$ period exchange rate is simply s_0 and hence that a random-walk model without drift is optimal. This is consistent with the random-walk model being the most difficult forecasting model to beat in forecasting horse races (Rossi, 2013).

All agents in the economy observe s_0 and agree about its level. For simplicity, we abstract from interest rate differentials and assume the risk-free rate is zero in both the domestic and foreign countries. In relation to our empirical analysis, we can therefore think about the fundamental as the change between dates $t = 0$ and $t = 2$ in foreign and domestic economic growth differentials.

Agents

There are three agents in the model. The first is an "informed" agent, denoted I, that seeks out the most accurate signals to predict f_2. We can think of the agent as a smart investor, e.g., a hedge fund. The second agent is a "liquidity" provider or uninformed agent, denoted U, e.g., a dealer in the FX market. FX market dealers have quite different incentives to hedge funds. Dealers are principally interested in balance sheet management (Lyons, 1995) with a stronger emphasis on managing positions over short-term intervals using intra-day technical analysis, rather than focussing on longer-term fundamentals (Menkhoff and Taylor). The third agent is a noise trader, denoted N, e.g., a corporation, which trades randomly to obtain liquidity for day-to-day foreign currency transactions.

Corporate investment flows

At date $t = 1$, an unbiased but noisy signal about the fundamental is revealed to the market:

$$\rho_1 = f_2 + \varepsilon_1, \qquad \text{where } \varepsilon_1 \sim N(0, \sigma_\varepsilon^2)$$

where σ_ε denotes noise in the signal unrelated to the fundamental. Only the informed agent chooses to use this information. Here the distinction between "differences in beliefs" and "asymmetric information" are effectively equivalent. In a differences-in-beliefs interpretation, the informed agent believes the signal is valuable, while the other two agents "agree to disagree" that it is not. In the asymmetric-information interpretation, even though the information is public, only the informed agent can extract the signal, making the signal effectively private.

Both interpretations have merit when applied to the FX market and the specific case of corporate investment flows. As noted above, agents trade for a variety of motives in the FX market and, hence, may choose not to condition on all publicly available information. In the case of cross-border M&A activity, while the M&A activity is publicly announced, not all deals are informative. Only through careful collection and standardization does the signal become informative and hence we could equally view the signal (ρ_1) as being privately revealed to the informed agents who have the technical expertise to extract it.

Demand for foreign risk-free bonds

Trading takes place at $t = 1$. We assume the informed and uninformed agents maximize CARA utility over terminal wealth. We set the risk-aversion parameter equal to unity for simplicity (i.e., $u(W_2) = -e^{-W_2}$). After observing ρ_1 the informed agent updates their conditional expectation and variance of the $t = 2$ spot exchange rate:

$$E_{I,1}[s_2] = s_0 + \rho_1$$
$$Var_{I,1}[s_2] = \sigma_\varepsilon^2$$

In contrast the uninformed agent does not condition on ρ_1 and therefore forms a different expectation and has a less precise signal of the future exchange rate:

$$E_{U,1}[s_2] = s_0$$
$$Var_{U,1}[s_2] = \sigma_f^2$$

Given the assumptions of CARA utility, combined with normally distributed returns, it immediately follows that demand for foreign currency by agent $i = I, U$ at date 1 is given by:

$$x_{i,1} = \frac{E_{i,1}[s_2] - s_1}{Var_{i,1}[s_2]}$$

The noise trader, on the other hand, submits orders $x_{N,1}$ that are normally distributed with mean zero and variance σ_N^2. The purpose of the noise trader's exogenous demand shock is to provide a means through which prices are not fully revealing to the market.[43]

Equilibrium exchange rate

Imposing market clearing at date 1 requires that

$$\omega_I x_{I,1} + \omega_U x_{U,1} + \omega_N x_{N,1} = 0$$

where ω_i is the relative population share of agent $i = I, U, N$ in the market. Given the endogenously determined demands of I and U, the market clearing condition is thus:

$$\begin{aligned} -\omega_N x_{N,1} &= \omega_I \frac{E_{I,1}[s_2] - s_1}{Var_{I,1}[s_2]} + \omega_U \frac{E_{U,1}[s_2] - s_1}{Var_{U,1}[s_2]} \\ &= \omega_I \frac{E_{I,1}[s_2]}{Var_{I,1}[s_2]} + \omega_U \frac{E_{U,1}[s_2]}{Var_{U,1}[s_2]} - \left(\frac{\omega_I}{Var_{I,1}[s_2]} + \frac{\omega_U}{Var_{U,1}[s_2]} \right) s_1 \end{aligned}$$

which can be re-arranged to solve for the exchange rate at date 1:

[43] In the models of Bacchetta and Van Wincoop (2006) and Cespa et al. (2021), an alternative channel is proposed in which informed agents also trade to hedge shocks to a non-traded asset. Both mechanisms prevent a no-trade equilibrium from being attained.

$$
\begin{aligned}
s_1 &= \underbrace{\left(\frac{\omega_I}{Var_{I,1}[s_2]} + \frac{\omega_U}{Var_{U,1}[s_2]}\right)^{-1}}_{\bar{\sigma}^2} \left(\omega_I \frac{E_{I,1}[s_2]}{Var_{I,1}[s_2]} + \omega_U \frac{E_{U,1}[s_2]}{Var_{U,1}[s_2]} + \omega_N x_{N,1}\right) \\
&= \underbrace{\frac{\omega_I \bar{\sigma}^2}{\sigma_\varepsilon^2}}_{0<\lambda<1} E_{I,1}[s_2] + \underbrace{\frac{\omega_U \bar{\sigma}^2}{\sigma_f^2}}_{1-\lambda} E_{U,1}[s_2] + \bar{\sigma}^2 \omega_N x_{N,1}
\end{aligned}
$$

where $\bar{\sigma}^2$ essentially captures a measure of the precision of the conditional variance at date 1 of the informed and uniformed agents. The equation implies that the exchange rate at date-1 is, effectively, a weighted average of the informed and uniformed agent's expectations, plus an additional wedge introduced by the exogenous noise trader demand. Finally, substituting for the expected date-2 exchange rates,

$$
\begin{aligned}
s_1 &= \lambda(s_0 + \rho_1) + (1-\lambda)s_0 + \bar{\sigma}^2 \omega_N x_{N,1} \\
&= s_0 + \lambda\rho_1 + \bar{\sigma}^2 \omega_N x_{N,1}
\end{aligned}
$$

Note that because $\lambda < 1$, the exchange rate does not, on average, fully adjust to incorporate the public information observed at date 1.

7.1 Predictability

The return at date 2 is given by $r_2 = s_2 - s_1$, and is thus equal to:

$$
\begin{aligned}
r_2 &= f_2 - \lambda\rho_1 - \bar{\sigma}^2 \omega_N x_{N,1} \\
&= (1-\lambda)\rho_1 - \varepsilon_1 - \bar{\sigma}^2 \omega_N x_{N,1}
\end{aligned}
$$

and hence the date 1 signal (ρ_1) is informative about the return at date 2

Section A: Additional Results and Further Analyses

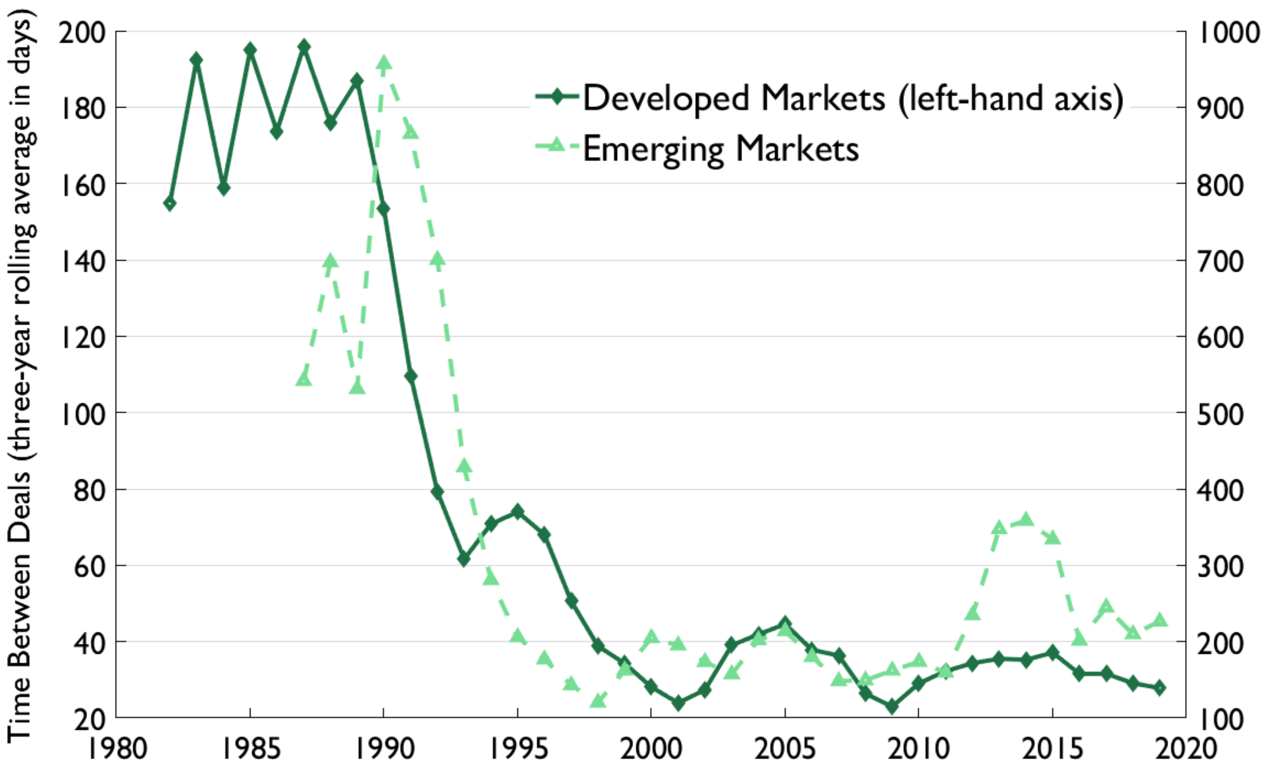

Fig A.1: Frequency of Announced Cross-Border M&As. The figure plots the average number of days between announcements of cross-border M&A deals involving the United States and either developed-market (solid line) or emerging-market (dashed line) countries over the prior 36 months. The 1995 data point, for example, records the average number of days between cross-border M&A deals announced between 1992 and 1994.

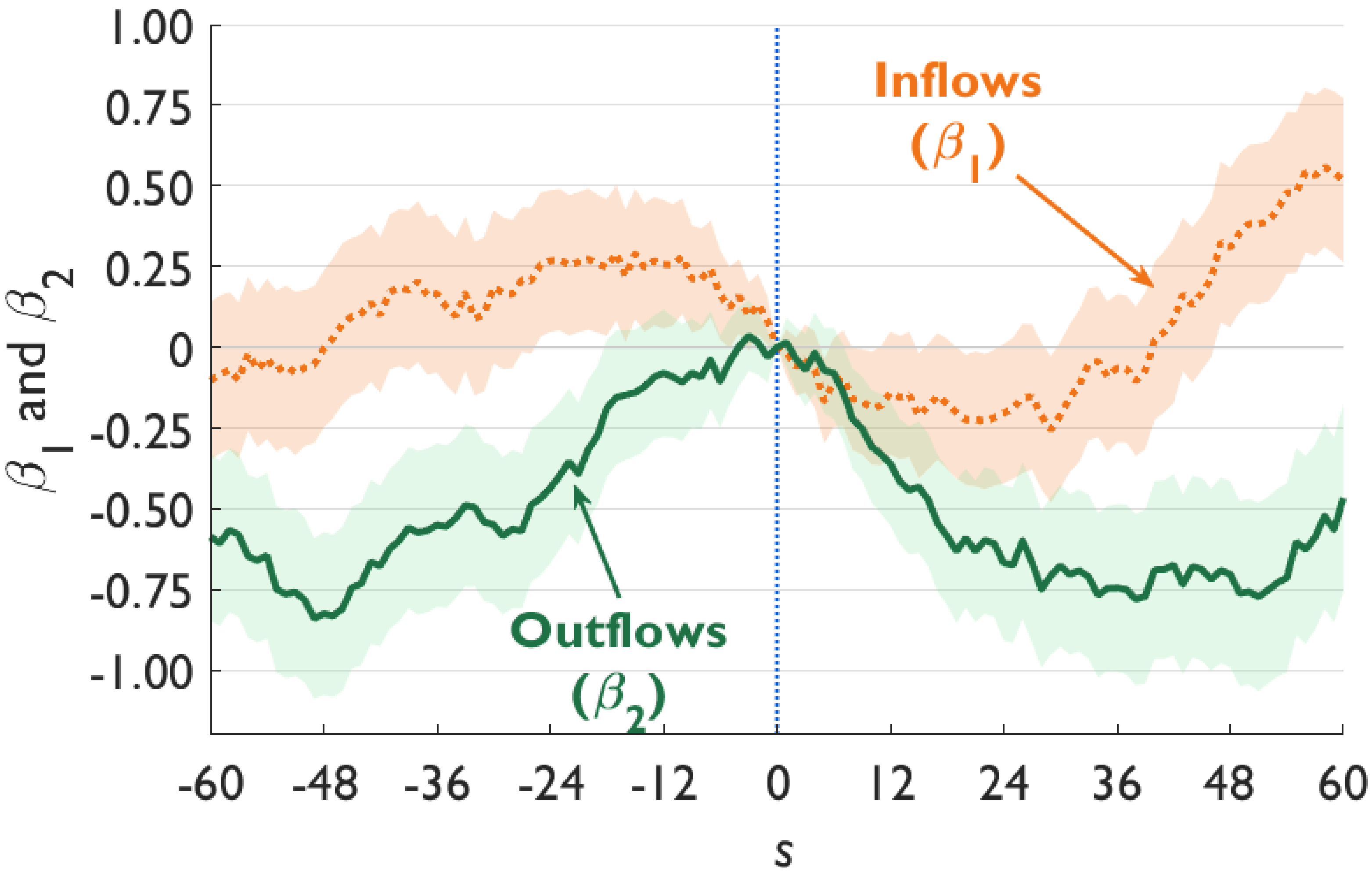

Fig A.2: Macroeconomic Acceleration With Inflows and Outflows. The figure plots β coefficients from panel regressions of changes in economic growth (i.e., economic acceleration), $\Delta g_{i,t+s}$, on the level of abnormal cross-border M&A activity constructed using either inflows ($\widetilde{MA}^{in}_{i,t}$) or outflows ($\widetilde{MA}^{out}_{i,t}$):

$$\Delta g_{i,t+s} = \alpha_i + \beta_1 \widetilde{MA}^{in}_{i,t} + \beta_2 \widetilde{MA}^{out}_{i,t} + \kappa_i + \lambda_{t+s} + \varepsilon_{i,t+s}.$$

Country and time fixed effects (κ_i and λ_{t+s}) are included in all regressions. Robust standard errors are double clustered at the country-month level. Two standard error bounds are denoted by the shaded region. The data is monthly, beginning in December 1996 and ending in November 2018.

Table A.1: Foreign Exchange Data Sources

			DataStream Codes			
Country	**Code**	**Currency**	**Spot**	**1M Forward**	**Start Date**	**End Date**
Argentina	ARS	Peso	ARGPES$	USARS1F	2004-03-31	2018-12-31
Australia	AUD	Dollar	AUSTDOI	USAUD1F	1997-01-31	2018-12-31
Austria	ATS	Schilling	AUSTSC$	USATS1F	1997-01-31	1998-12-31
Belgium	BEF	Franc	BELGLU$	USBEF1F	1997-01-31	1998-12-31
Brazil	BRL	Brazilian real	BRACRU$	USBRL1F	2004-03-31	2018-12-31
Chile	CLP	Peso	CHILPE$	USCLP1F	2004-03-31	2018-12-31
Colombia	COP	Peso	COLUPE$	USCOP1F	2004-03-31	2018-12-31
Czech Republic	CZK	Koruna	CZECHC$	USCZK1F	1997-01-31	2018-12-31
Denmark	DKK	Krone	DANISH$	USDKK1F	1997-01-31	2018-12-31
Estonia	EEK	Kroon	ESTOKR$	USEEK1F	2004-03-31	2010-12-31
Euro Area	EUR	Euro	EUDOLLR	EUDOL1F	1999-01-31	2018-12-31
Finland	FIM	Markka	FINMAR$	USFIM1F	1997-01-31	1998-12-31
France	FRF	Franc	FRENFR$	USFRF1F	1997-01-31	1998-12-31
Germany	DEM	Mark	DMARKE$	USDEM1F	1997-01-31	1998-12-31
Greece	GRD	Drachma	GREDRA$	USGRD1F	1997-01-31	2000-12-31
Hungary	HUF	Forint	HUNFOR$	USHUF1F	1997-10-30	2018-12-31
Iceland	ISK	Krona	ICEKRO$	USISK1F	2004-03-31	2018-12-31
India	INR	Rupee	INDRUP$	USINR1F	1997-10-30	2018-12-31
Indonesia	IDR	Rupiah	INDORU$	USIDR1F	2007-06-30	2018-12-31
Ireland	IEP	Punt	IPUNTEI	USIEP1F	1997-01-31	1998-12-31
Israel	ILS	Shekel	ISRSHE$	USILS1F	2004-03-31	2018-12-31
Italy	ITL	Lira	ITALIR$	USITL1F	1997-01-31	1998-12-31
Japan	JPY	Yen	JAPAYE$	USJPY1F	1997-01-31	2018-12-31
Latvia	LVL	Lats	LATVLA$	USLVL1F	2004-03-31	2013-12-31
Lithuania	LTL	Litas	LITITA$	USLTL1F	2004-03-31	2014-12-31

(Continued overleaf)

			DataStream Codes			
Country	**Code**	**Currency**	**Spot**	**1M Forward**	**Start Date**	**End Date**
Netherlands	NLG	Guilders	GUILDE$	USNLG1F	1997-01-31	1998-12-31
New Zealand	NZD	Dollar	NZDOLLI	USNZD1F	1997-01-31	2018-12-31
Norway	NOK	Krone	NORKRO$	USNOK1F	1997-01-31	2018-12-31
Poland	PLN	Zloty	POLZLO$	USPLN1F	2002-02-28	2018-12-31
Portugal	PTE	Escudo	PORTES$	USPTE1F	1997-01-31	1998-12-31
Russia	RUB	Rouble	CISRUB$	USRUB1F	2004-03-31	2018-12-31
Slovakia	SKK	Koruna	SLOVKO$	USSKK1F	2002-02-28	2008-12-31
Slovenia	SIT	Tolar	SLOVTO$	USSIT1F	2004-03-31	2006-12-31
South Africa	ZAR	Rand	COMRAN$	USZAR1F	1997-01-31	2018-12-31
South Korea	KRW	Won	KORSWO$	USKRW1F	2002-02-28	2018-12-31
Spain	ESP	Preseta	SPANPE$	USESP1F	1997-01-31	1998-12-31
Sweden	SEK	Krona	SWEKRO$	USSEK1F	1997-01-31	2018-12-31
Switzerland	CHF	Franc	SWISSF$	USCHF1F	1997-01-31	2018-12-31
Turkey	TRY	Lira	TURKLI$	USTRY1F	2001-12-31	2018-12-31
United Kingdom	GBP	Pound	UKDOLLR	UKUSD1F	1997-01-31	2018-12-31

The table presents *Datastream* codes and the time periods during which the data are available. Currencies in the Eurozone are included until December 1998, after which they are replaced by the euro.

Table A.2: Cross-Border M&A Portfolios: Developed and Emerging Markets

	Developed Market Countries					Emerging Market Countries				
	P_1	**P_2**	**P_3**	**HML**	**Linear**	**P_1**	**P_2**	**P_3**	**HML**	**Linear**
mean (%)	-0.74	-0.57	2.52	3.26	3.42	0.07	2.74	5.10	5.14	5.05
t-stat	-0.35	-0.34	1.34	2.55	2.78	0.04	1.26	2.85	2.77	3.05
std (%)	8.60	7.68	8.02	5.99	5.86	8.34	9.09	9.22	8.88	8.28
SR	-0.09	-0.07	0.31	0.54	0.58	0.01	0.30	0.55	0.58	0.61
skew	0.08	-0.16	0.27	0.32	0.44	-0.07	-1.00	0.14	0.03	-0.16
kurt	3.80	6.47	3.65	3.98	4.50	7.84	8.79	4.78	4.53	3.80
ar(1)	0.12	-0.01	0.08	0.10	0.11	0.02	0.11	-0.03	-0.04	-0.06
mdd (%)	40.0	26.5	24.1	13.4	10.3	28.0	19.3	9.31	11.18	12.4
fx (%)	-0.81	-0.79	2.15	2.96	3.05	-4.23	-1.42	-0.24	4.06	3.95
fp (%)	0.06	0.21	0.36	0.30	0.37	4.29	4.16	5.34	1.08	1.11

The table presents statistics on cross-border merger and acquisition portfolios. Statistics include the average annualized (*mean*) return and associated t-statistic, calculated using Newey and West (1987) standard errors; annualized standard deviation (*std*); Sharpe ratio (*SR*); skewness (*skew*); kurtosis (*kurt*); first-order autocorrelation coefficient (*ar(1)*); and maximum drawdown (*mdd*). The final two rows record the decomposition of the average return between the spot (*fx*) and forward premium (*fp*) components. P_1, P_2, and P_3 denote three portfolios sorted each month from low to high values of $\widetilde{MA}_{i,t}$. HML and *Linear* denote two zero-cost cross-sectional portfolios. Further details on the portfolio weights can be found in Section 4.3. Results for developed (emerging) market countries are presented in the left (right) panel. All statistics are calculated using monthly returns from January 1997 to December 2018.

Table A.3: Other Sources of Currency Return Predictability

	Dollar	Carry	Momentum	Value	$\mathbf{Carry_{USD}}$	$\mathbf{Trend_{EC}}$	$\mathbf{Trend_{IN}}$
mean (%)	1.13	5.82	2.23	3.67	2.67	2.88	4.45
t-stat	0.66	3.82	1.44	3.01	1.77	2.89	3.68
std (%)	7.29	6.99	7.05	5.78	7.25	4.47	5.61
SR	0.16	0.83	0.32	0.64	0.37	0.64	0.79
skew	–0.15	–0.67	–0.32	–0.57	0.09	–0.20	–0.35
kurt	4.52	6.04	4.08	5.92	4.48	4.53	6.14
ar(1)	0.08	0.12	0.05	0.10	–0.03	0.08	0.12
mdd (%)	25.3	7.23	15.2	6.60	19.7	5.78	6.14
fx (%)	–0.73	–4.28	–0.86	–2.21	1.62	2.13	–3.10
fp (%)	1.86	10.1	3.09	5.89	1.05	0.74	7.55

The table presents statistics on the performance of alternative currency portfolios constructed using rank weights. Statistics include the average annualized (*mean*) return and associated t-statistic, calculated using Newey and West (1987) standard errors; annualized standard deviation (*std*); Sharpe ratio (*SR*); skewness (*skew*); kurtosis (*kurt*); first-order autocorrelation coefficient (*ar(1)*); and maximum drawdown (*mdd*). The final two rows record the decomposition of the average return between the spot (*fx*) and forward premium (*fp*) components. The sample includes the US and 40 developed and emerging market countries. All statistics are calculated using monthly returns from January 1997 to December 2018.

Table A.4: Transaction Costs

	$\mathbf{P_1}$	$\mathbf{P_2}$	$\mathbf{P_3}$	**HML**	**Linear**	**Rank**
mean (%)	–0.47	0.21	3.18	3.64	3.13	3.20
t-stat	–0.24	0.12	1.75	3.30	2.78	2.95
std (%)	8.07	7.64	8.12	5.42	5.59	5.43
SR	–0.06	0.03	0.39	0.67	0.56	0.59
skew	–0.22	–0.17	–0.14	–0.20	–0.30	–0.32
kurt	4.31	4.45	4.19	4.39	3.87	4.77
ar(1)	0.10	0.04	0.06	0.00	–0.02	–0.03
fx (%)	–1.89	–0.64	0.58	2.46	1.84	2.12
fp (%)	1.42	0.86	2.60	1.18	1.29	1.09

The table presents statistics on the performance of cross-border merger and acquisition strategies after incorporating transaction costs. Statistics include the average annualized (*mean*) return and associated t-statistic, calculated using Newey and West (1987) standard errors; annualized standard deviation (*std*); Sharpe ratio (*SR*); skewness (*skew*); kurtosis (*kurt*); first-order autocorrelation coefficient (*ar(1)*); and maximum drawdown (*mdd*). The final two rows record the decomposition of the average return between the spot (*fx*) and forward premium (*fp*) components. P_1, P_2, and P_3 denote three portfolios sorted each month from low to high values of $\widetilde{MA}_{i,t}$. HML, *Linear*, and *Rank* denote three zero-cost cross-sectional portfolios. Further details on the portfolio weights can be found in Section 4.3. The sample includes the US and 40 developed and emerging market countries. All statistics are calculated using monthly returns from January 1997 to December 2018.

Table A.5: Forecasting Economic Acceleration (24 month standardization)

	Dep: $\Delta g_{i,t+12}$		Dep: $\Delta g_{i,t+24}$		Dep: $\Delta g_{i,t+36}$		Dep: $\Delta g_{i,t+48}$		Dep: $\Delta g_{i,t+60}$	
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**	**(9)**	**(10)**
$\widetilde{MA}$	0.075	0.103	0.149*	0.170**	0.158*	0.180**	0.218**	0.292***	0.343***	0.394***
	(0.068)	(0.070)	(0.077)	(0.082)	(0.081)	(0.088)	(0.090)	(0.098)	(0.091)	(0.091)
CLI	–0.897***		–1.596***		–1.764***		–2.126***		–1.645***	
	(0.096)		(0.103)		(0.107)		(0.123)		(0.122)	
Dividend yield		0.100		0.071		0.076		0.026		0.328
		(0.206)		(0.217)		(0.237)		(0.245)		(0.249)
Stock return		0.050		0.038		0.040		0.028		0.025
		(0.031)		(0.031)		(0.034)		(0.037)		(0.032)
Term spread		0.041		0.484**		0.565***		0.518***		1.298***
		(0.195)		(0.195)		(0.221)		(0.222)		(0.210)
Short rate		–0.415***		–0.127		0.191		0.492***		1.061***
		(0.138)		(0.142)		(0.177)		(0.172)		(0.161)
Country FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Time FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Obs.	2,711	2,403	2,587	2,293	2,454	2,178	2,329	2,072	2,200	1,963
Adj. R^2	0.46	0.48	0.52	0.53	0.50	0.48	0.49	0.45	0.52	0.54

The table presents coefficient estimates from panel regressions of changes in economic growth (i.e., economic acceleration), $\Delta g_{i,t+s}$, for $s = 12, 24, 36, 48$ and 60, on the level of abnormal cross-border M&A activity ($\widetilde{MA}_{i,t}$):

$$\Delta g_{i,t+s} = \alpha_i + \beta \widetilde{MA}_{i,t} + \gamma' X_{i,t} + \kappa_i + \lambda_{t+s} + \varepsilon_{i,t+s},$$

where $X_{i,t}$ denotes control variables that include composite leading indicators (*CLIs*), dividend yields, local stock market returns, term spreads, and short-term interest rates. Country and time fixed effects (κ_i and λ_{t+s}) are included in all regressions. Robust standard errors are double clustered at the country-month level and reported in parentheses. The number of observations (*Obs*) and adjusted R-square statistics (*Adj.* R^2) are reported in the final two rows. Superscripts ***, ** and * denote significance of the coefficients at the 1%, 5% and 10% level, respectively. The sample includes the United States and 40 developed and emerging market countries. The data is monthly, beginning in December 1996 and ending in November 2018.

Table A.6: Forecasting Economic Acceleration (48 month standardization)

	Dep: $\Delta g_{i,t+12}$		**Dep: $\Delta g_{i,t+24}$**		**Dep: $\Delta g_{i,t+36}$**		**Dep: $\Delta g_{i,t+48}$**		**Dep: $\Delta g_{i,t+60}$**	
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**	**(9)**	**(10)**
$\widetilde{MA}$	0.076	0.0+2	0.219***	0.226***	0.311***	0.326***	0.397***	0.483***	0.392***	0.504***
	(0.065)	(0.068)	(0.073)	(0.078)	(0.078)	(0.085)	(0.087)	(0.094)	(0.088)	(0.088)
CLI	–0.914***		–1.575***		–1.735***		–2.038***		–1.644***	
	(0.098)		(0.105)		(0.105)		(0.120)		(0.123)	
Dividend yield		0.046		0.050		–0.009		0.014		0.353
		(0.214)		(0.223)		(0.240)		(0.253)		(0.257)
Stock return		0.031		0.011		0.024		–0.000		–0.005
		(0.032)		(0.032)		(0.035)		(0.037)		(0.034)
Term spread		0.072		0.552***		0.673***		0.640***		1.397***
		(0.196)		(0.197)		(0.223)		(0.221)		(0.212)
Short rate		–0.419***		–0.110		0.262		0.549***		1.073***
		(0.141)		(0.145)		(0.181)		(0.170)		(0.164)
Country FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Time FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Obs.	2,692	2,386	2,570	2,278	2,440	2,164	2,314	2,056	2,189	1,951
Adj. R^2	0.45	0.46	0.52	0.53	0.50	0.48	0.49	0.46	0.52	0.55

The table presents coefficient estimates from panel regressions of changes in economic growth (i.e., economic acceleration), $\Delta g_{i,t+s}$, for $s = 12, 24, 36, 48$ and 60, on the level of abnormal cross-border M&A activity ($\widetilde{MA}_{i,t}$):

$$\Delta g_{i,t+s} = \alpha_i + \beta \widetilde{MA}_{i,t} + \gamma' X_{i,t} + \kappa_i + \lambda_{t+s} + \varepsilon_{i,t+s},$$

where $X_{i,t}$ denotes control variables that include composite leading indicators (*CLIs*), dividend yields, local stock market returns, term spreads, and short-term interest rates. Country and time fixed effects (κ_i and λ_{t+s}) are included in all regressions. Robust standard errors are double clustered at the country-month level and reported in parentheses. The number of observations (*Obs*) and adjusted R-square statistics (*Adj.* R^2) are reported in the final two rows. Superscripts ***, ** and * denote significance of the coefficients at the 1%, 5% and 10% level, respectively. The sample includes the United States and 40 developed and emerging market countries. The data is monthly, beginning in December 1996 and ending in November 2018.

Table A.7: Forecasting Economic Acceleration (60 month standardization)

	Dep: $\Delta g_{i,t+12}$		Dep: $\Delta g_{i,t+24}$		Dep: $\Delta g_{i,t+36}$		Dep: $\Delta g_{i,t+48}$		Dep: $\Delta g_{i,t+60}$	
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**	**(9)**	**(10)**
$\widetilde{MA}$	0.129**	1.34**	0.283***	0.293***	0.394***	0.433***	0.438***	0.549***	0.399***	0.534***
	(0.065)	(0.068)	(0.073)	(0.078)	(0.078)	(0.084)	(0.085)	(0.093)	(0.087)	(0.087)
CLI	–0.931***		–1.587***		–1.780***		–2.080***		–1.678***	
	(0.097)		(0.103)		(0.103)		(0.120)		(0.122)	
Dividend yield		0.001		–0.003		–0.078		–0.065		0.308
		(0.209)		(0.217)		(0.235)		(0.246)		(0.251)
Stock return		0.009		–0.001		0.017		–0.005		–0.005
		(0.031)		(0.032)		(0.034)		(0.037)		(0.034)
Term spread		0.093		0.605***		0.704***		0.736***		1.480***
		(0.194)		(0.195)		(0.220)		(0.220)		(0.211)
Short rate		–0.408***		–0.094		0.292		0.605***		1.123***
		(0.142)		(0.145)		(0.179)		(0.171)		(0.164)
Country FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Time FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Obs.	2,697	2,381	2,575	2,273	2,446	2,159	2,319	2,052	2,190	1,943
Adj. R^2	0.45	0.47	0.53	0.54	0.50	0.48	0.50	0.47	0.53	0.55

The table presents coefficient estimates from panel regressions of changes in economic growth (i.e., economic acceleration), $\Delta g_{i,t+s}$, for $s = 12, 24, 36, 48$ and 60, on the level of abnormal cross-border M&A activity ($\widetilde{MA}_{i,t}$):

$$\Delta g_{i,t+s} = \alpha_i + \beta \widetilde{MA}_{i,t} + \gamma' X_{i,t} + \kappa_i + \lambda_{t+s} + \varepsilon_{i,t+s},$$

where $X_{i,t}$ denotes control variables that include composite leading indicators (*CLIs*), dividend yields, local stock market returns, term spreads, and short-term interest rates. Country and time fixed effects (κ_i and λ_{t+s}) are included in all regressions. Robust standard errors are double clustered at the country-month level and reported in parentheses. The number of observations (*Obs*) and adjusted R-square statistics (*Adj. R^2*) are reported in the final two rows. Superscripts ***, ** and * denote significance of the coefficients at the 1%, 5% and 10% level, respectively. The sample includes the United States and 40 developed and emerging market countries. The data is monthly, beginning in December 1996 and ending in November 2018.

A.8: Cross-Border M&A Portfolios and Currency Return Predictability

	$\mathbf{P_1}$	$\mathbf{P_2}$	$\mathbf{P_3}$	**HML**	**Linear**	**Rank**
			24 month standardization			
mean (%)	–0.30	1.00	3.81	4.11	3.71	3.48
t-stat	–0.15	0.58	2.01	3.46	3.28	3.38
SR	–0.04	0.13	0.45	0.68	0.67	0.68
fx (%)	–1.65	–0.11	1.00	2.64	2.30	2.29
fp (%)	1.35	1.10	2.82	1.47	1.42	1.19
			48 month standardization			
mean (%)	0.12	–0.77	4.52	4.39	3.91	3.69
t-stat	0.06	–0.44	2.16	3.15	3.43	3.45
SR	0.01	–0.10	0.51	0.68	0.70	0.69
fx (%)	–1.22	–1.84	1.75	2.98	2.39	2.41
fp (%)	1.34	1.07	2.77	1.42	1.52	1.28
			60 month standardization			
mean (%)	–0.25	0.38	4.50	4.75	3.86	3.71
t-stat	–0.12	0.23	2.22	3.46	3.34	3.30
SR	–0.03	0.05	0.52	0.76	0.69	0.70
fx (%)	–1.60	–0.76	1.67	3.28	2.38	2.44
fp (%)	1.35	1.14	2.83	1.47	1.48	1.27

The table presents statistics on cross-border merger and acquisition portfolios. Statistics include the average annualized (*mean*) return and associated *t*-statistic, calculated using Newey and West (1987) standard errors; annualized standard deviation (*std*); Sharpe ratio (*SR*); skewness (*skew*); kurtosis (*kurt*); first-order autocorrelation coefficient (*ar(1)*); and maximum drawdown (*mdd*). The final two rows record the decomposition of the average return between the spot (*fx*) and forward premium (*fp*) components. P_1, P_2, and P_3 denote three portfolios sorted each month from low to high values of $\widetilde{MA}_{i,t}$. HML, *Linear*, and *Rank* denote three zero-cost cross-sectional portfolios. Further details on the portfolio weights can be found in Section 4.3. The sample includes the US and 40 developed and emerging market countries. In the final two columns are statistics for *Rank* portfolios constructed using only developed market ($Rank_{DM}$) and emerging market ($Rank_{DM}$) countries. All statistics are calculated using monthly returns from January 1997 to December 2018.

Table A.9: Forecasting Economic Acceleration (with Mexico and Canada)

	Dep: $\Delta g_{i,t+12}$		**Dep: $\Delta g_{i,t+24}$**		**Dep: $\Delta g_{i,t+36}$**		**Dep: $\Delta g_{i,t+48}$**		**Dep: $\Delta g_{i,t+60}$**	
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**	**(9)**	**(10)**
$\widetilde{MA}$	0.108*	0.129**	0.133*	0.148**	0.251***	0.268***	0.318***	0.382***	0.367***	0.415***
	(0.063)	(0.065)	(0.070)	(0.074)	(0.073)	(0.079)	(0.082)	(0.086)	(0.083)	(0.082)
CLI	–0.845***		–1.439***		–1.655***		–2.033***		–1.573***	
	(0.091)		(0.099)		(0.101)		(0.116)		(0.118)	
Dividend yield		0.206		0.154		–0.006		0.140		0.407
		(0.211)		(0.220)		(0.238)		(0.248)		(0.249)
Stock return		0.031		0.009		0.019		0.014		0.005
		(0.030)		(0.031)		(0.032)		(0.034)		(0.032)
Term spread		0.031		0.267		0.511**		0.274		1.024***
		(0.186)		(0.190)		(0.207)		(0.213)		(0.201)
Short rate		–0.502***		–0.406***		0.144		0.265		0.783***
		(0.133)		(0.145)		(0.170)		(0.167)		(0.157)
Country FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Time FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Obs.	3,129	2,746	2,989	2,621	2,836	2,485	2,691	2,363	2,543	2,238
Adj. R^2	0.46	0.48	0.52	0.54	0.52	0.50	0.52	0.49	0.54	0.56

The table presents coefficient estimates from panel regressions of changes in economic growth (i.e., economic acceleration), $\Delta g_{i,t+s}$, for $s = 12, 24, 36, 48$ and 60, on the level of abnormal cross-border M&A activity ($\widetilde{MA}_{i,t}$):

$$\Delta g_{i,t+s} = \alpha_i + \beta \widetilde{MA}_{i,t} + \gamma' X_{i,t} + \kappa_i + \lambda_{t+s} + \varepsilon_{i,t+s},$$

where $X_{i,t}$ denotes control variables that include composite leading indicators (*CLIs*), dividend yields, local stock market returns, term spreads, and short-term interest rates. Country and time fixed effects (κ_i and λ_{t+s}) are included in all regressions. Robust standard errors are double clustered at the country-month level and reported in parentheses. The number of observations (*Obs*) and adjusted R-square statistics (*Adj.* R^2) are reported in the final two rows. Superscripts ***, ** and * denote significance of the coefficients at the 1%, 5% and 10% level, respectively. The sample includes the United States and 40 developed and emerging market countries. The data is monthly, beginning in December 1996 and ending in November 2018.

A.10: Cross-Border M&A Portfolios and Currency Return Predictability (with Mexico and Canada)

	$\mathbf{P_1}$	$\mathbf{P_2}$	$\mathbf{P_3}$	**HML**	**Linear**	**Rank**
mean (%)	–0.44	0.60	4.02	4.46	3.22	3.25
t-stat	–0.23	0.38	2.15	3.71	2.93	3.18
std (%)	8.08	7.09	8.23	5.79	5.20	5.09
SR	–0.05	0.08	0.49	0.77	0.62	0.64
skew	–0.40	–0.16	–0.19	–0.26	–0.16	–0.24
kurt	5.33	4.78	4.66	3.92	3.54	4.28
ar(1)	0.09	0.01	0.04	–0.03	0.01	–0.01
mdd (%)						
fx (%)	–2.21	–0.62	1.12	3.33	2.03	2.25
fp (%)	1.76	1.21	2.90	1.13	1.19	1.00

The table presents statistics on cross-border merger and acquisition portfolios. Statistics include the average annualized (*mean*) return and associated t-statistic, calculated using Newey and West (1987) standard errors; annualized standard deviation (*std*); Sharpe ratio (*SR*); skewness (*skew*); kurtosis (*kurt*); first-order autocorrelation coefficient (*ar(1)*); and maximum drawdown (*mdd*). The final two rows record the decomposition of the average return between the spot (*fx*) and forward premium (*fp*) components. P_1, P_2, and P_3 denote three portfolios sorted each month from low to high values of $\widetilde{MA}_{i,t}$. HML, *Linear*, and *Rank* denote three zero-cost cross-sectional portfolios. Further details on the portfolio weights can be found in Section 4.3. The sample includes the US and 40 developed and emerging market countries. In the final two columns are statistics for *Rank* portfolios constructed using only developed market ($Rank_{DM}$) and emerging market ($Rank_{DM}$) countries. All statistics are calculated using monthly returns from January 1997 to December 2018.

Table A.11: Forecasting Economic Acceleration (1st and 99th percentile winsorization)

	Dep: $\Delta g_{i,t+12}$		Dep: $\Delta g_{i,t+24}$		Dep: $\Delta g_{i,t+36}$		Dep: $\Delta g_{i,t+48}$		Dep: $\Delta g_{i,t+60}$	
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**	**(9)**	**(10)**
$\widetilde{MA}$	0.076	0.113	0.133	0.141	0.261***	0.278***	0.378***	0.432***	0.454***	0.501***
	(0.074)	(0.076)	(0.085)	(0.089)	(0.093)	(0.101)	(0.102)	(0.109)	(0.107)	(0.107)
CLI	–1.093***		–1.858***		–2.108***		–2.397***		–1.854***	
	(0.113)		(0.117)		(0.121)		(0.137)		(0.142)	
Dividend yield		0.100		0.007		–0.107		–0.081		0.264
		(0.247)		(0.258)		(0.274)		(0.299)		(0.309)
Stock return		0.045		0.029		0.027		0.016		0.014
		(0.035)		(0.037)		(0.040)		(0.043)		(0.040)
Term spread		0.064		0.512**		0.612**		0.553**		1.277***
		(0.227)		(0.227)		(0.254)		(0.248)		(0.243)
Short rate		–0.414***		–0.159		0.251		0.573***		1.153***
		(0.161)		(0.168)		(0.208)		(0.193)		(0.188)
Country FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Time FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Obs.	2,693	2,386	2,571	2,278	2,439	2,161	2,313	2,055	2,185	1,947
Adj. R^2	0.52	0.54	0.57	0.58	0.54	0.52	0.53	0.50	0.56	0.57

The table presents coefficient estimates from panel regressions of changes in economic growth (i.e., economic acceleration), $\Delta g_{i,t+s}$, for $s = 12, 24, 36, 48$ and 60, on the level of abnormal cross-border M&A activity ($\widetilde{MA}_{i,t}$):

$$\Delta g_{i,t+s} = \alpha_i + \beta \widetilde{MA}_{i,t} + \gamma' X_{i,t} + \kappa_i + \lambda_{t+s} + \varepsilon_{i,t+s},$$

where $X_{i,t}$ denotes control variables that include composite leading indicators (*CLIs*), dividend yields, local stock market returns, term spreads, and short-term interest rates. Country and time fixed effects (κ_i and λ_{t+s}) are included in all regressions. Robust standard errors are double clustered at the country-month level and reported in parentheses. The number of observations (*Obs*) and adjusted R-square statistics (*Adj.* R^2) are reported in the final two rows. Superscripts ***, ** and * denote significance of the coefficients at the 1%, 5% and 10% level, respectively. The sample includes the United States and 40 developed and emerging market countries. The data is monthly, beginning in December 1996 and ending in November 2018.

Table A.12: Forecasting Economic Acceleration (10th and 90th percentile winsorization)

	Dep: $\Delta g_{i,t+12}$		Dep: $\Delta g_{i,t+24}$		Dep: $\Delta g_{i,t+36}$		Dep: $\Delta g_{i,t+48}$		Dep: $\Delta g_{i,t+60}$	
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**	**(9)**	**(10)**
$\widetilde{MA}$	0.078	0.106*	0.141**	0.179***	0.206***	0.247***	0.291***	0.369***	0.336***	0.397***
	(0.057)	(0.059)	(0.065)	(0.069)	(0.068)	(0.074)	(0.076)	(0.083)	(0.078)	(0.078)
CLI	–0.707***		–1.282***		–1.384***		–1.645***		–1.313***	
	(0.081)		(0.089)		(0.089)		(0.103)		(0.103)	
Dividend yield		0.119		0.058		–0.061		0.010		0.226
		(0.181)		(0.195)		(0.208)		(0.216)		(0.220)
Stock return		0.020		0.005		0.018		0.002		–0.010
		(0.026)		(0.028)		(0.030)		(0.032)		(0.028)
Term spread		0.035		0.421**		0.560***		0.496**		1.173***
		(0.167)		(0.170)		(0.193)		(0.193)		(0.182)
Short rate		–0.371***		–0.147		0.188		0.363**		0.850***
		(0.118)		(0.122)		(0.156)		(0.152)		(0.142)
Country FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Time FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Obs.	2,693	2,386	2,571	2,278	2,439	2,161	2,313	2,055	2,185	1,947
Adj. R^2	0.40	0.41	0.46	0.47	0.45	0.42	0.44	0.41	0.48	0.49

The table presents coefficient estimates from panel regressions of changes in economic growth (i.e., economic acceleration), $\Delta g_{i,t+s}$, for $s = 12, 24, 36, 48$ and 60, on the level of abnormal cross-border M&A activity ($\widetilde{MA}_{i,t}$):

$$\Delta g_{i,t+s} = \alpha_i + \beta \widetilde{MA}_{i,t} + \gamma' X_{i,t} + \kappa_i + \lambda_{t+s} + \varepsilon_{i,t+s},$$

where $X_{i,t}$ denotes control variables that include composite leading indicators (*CLIs*), dividend yields, local stock market returns, term spreads, and short-term interest rates. Country and time fixed effects (κ_i and λ_{t+s}) are included in all regressions. Robust standard errors are double clustered at the country-month level and reported in parentheses. The number of observations (*Obs*) and adjusted R-square statistics (*Adj.* R^2) are reported in the final two rows. Superscripts ***, ** and * denote significance of the coefficients at the 1%, 5% and 10% level, respectively. The sample includes the United States and 40 developed and emerging market countries. The data is monthly, beginning in December 1996 and ending in November 2018.

A.13: Cross-Border M&A Portfolios and Currency Return Predictability

	$\mathbf{P_1}$	$\mathbf{P_2}$	$\mathbf{P_3}$	$\mathbf{P_4}$	**HML**	**Linear**	**Rank**
mean (%)	–0.20	–0.06	2.35	4.21	4.19	4.06	4.12
t-stat	–0.09	–0.03	1.23	2.19	2.71	3.61	3.79
std (%)	9.22	7.87	8.02	8.98	7.31	5.59	5.44
SR	–0.02	–0.01	0.29	0.47	0.57	0.73	0.76
skew	–0.28	–0.23	–0.08	0.06	–0.30	–0.28	–0.31
kurt	4.52	4.90	4.93	3.76	4.40	3.82	4.74
ar(1)							
mdd (%)							
fx (%)	–1.64	–0.99	0.86	1.15	2.55	2.59	2.86
fp (%)	1.44	0.94	1.49	3.06	1.64	1.47	1.26

The table presents statistics on cross-border merger and acquisition portfolios. Statistics include the average annualized (*mean*) return and associated t-statistic, calculated using Newey and West (1987) standard errors; annualized standard deviation (*std*); Sharpe ratio (*SR*); skewness (*skew*); kurtosis (*kurt*); first-order autocorrelation coefficient (*ar(1)*); and maximum drawdown (*mdd*). The final two rows record the decomposition of the average return between the spot (*fx*) and forward premium (*fp*) components. P_1, P_2, and P_3 denote three portfolios sorted each month from low to high values of $\widetilde{MA}_{i,t}$. HML, *Linear*, and *Rank* denote three zero-cost cross-sectional portfolios. Further details on the portfolio weights can be found in Section 4.3. The sample includes the US and 40 developed and emerging market countries. In the final two columns are statistics for *Rank* portfolios constructed using only developed market ($Rank_{DM}$) and emerging market ($Rank_{DM}$) countries. All statistics are calculated using monthly returns from January 1997 to December 2018.

A.14: Cross-Border M&A Portfolios and Currency Return Predictability

	$\mathbf{P_1}$	$\mathbf{P_2}$	$\mathbf{P_3}$	$\mathbf{P_4}$	$\mathbf{P_5}$	**HML**	**Linear**	**Rank**
mean (%)	–0.46	–1.17	0.70	3.11	5.53	5.95	4.06	4.12
t-stat	–0.21	–0.56	0.43	1.57	2.41	3.32	3.61	3.79
std (%)	9.39	8.64	7.63	8.59	10.12	8.42	5.59	5.44
SR	–0.05	–0.14	0.09	0.36	0.55	0.71	0.73	0.76
skew	–0.32	–0.17	0.12	–0.20	0.36	0.04	–0.28	–0.31
kurt	4.73	5.05	4.05	4.77	4.90	4.15	3.82	4.74
ar(1)	0.07	0.09	0.00	0.09	0.00	0.00	–0.02	–0.03
mdd (%)	37.1	29.4	15.2	6.62	10.4	6.79		
fx (%)	–1.82	–2.34	–0.18	1.22	2.18	3.93	2.60	2.88
fp (%)	1.36	1.16	0.88	1.89	3.35	2.02	1.47	1.26

The table presents statistics on cross-border merger and acquisition portfolios. Statistics include the average annualized (*mean*) return and associated t-statistic, calculated using Newey and West (1987) standard errors; annualized standard deviation (*std*); Sharpe ratio (*SR*); skewness (*skew*); kurtosis (*kurt*); first-order autocorrelation coefficient (*ar(1)*); and maximum drawdown (*mdd*). The final two rows record the decomposition of the average return between the spot (*fx*) and forward premium (*fp*) components. P_1, P_2, and P_3 denote three portfolios sorted each month from low to high values of $\widetilde{MA}_{i,t}$. HML, *Linear*, and *Rank* denote three zero-cost cross-sectional portfolios. Further details on the portfolio weights can be found in Section 4.3. The sample includes the US and 40 developed and emerging market countries. In the final two columns are statistics for *Rank* portfolios constructed using only developed market ($Rank_{DM}$) and emerging market ($Rank_{DM}$) countries. All statistics are calculated using monthly returns from January 1997 to December 2018.

Section B: Bootstrap Procedure

We begin with a balanced panel, consisting of $N = 41$ countries and $T = 264$ months (i.e., $T \times N = 10,824$ observations). Each country contains one M&A signal ($\widetilde{MA}_{i,t}$) per month from December 1996 to November 2018. *Uninformative* signals, i.e., $MA_{i,t} = \overline{MA}_{i,t} = 0$, are set to missing but are included within the panel. Uninformative signals from a forecasting perspective *are* informative for the simulation, since countries with relatively little M&A activity have a higher probability of randomly drawing a non-informative signal.

We form bootstrap samples independently across countries. The procedure is as follows:

1. For country i in month t, randomly draw with replacement an M&A signal $\widetilde{MA}^*_{i,t}$, from the vector of observed signals $\widetilde{MA}_i$.
2. Repeat Step **1**, for each month $t = 1, 2, ..., T$.
3. Repeat Steps **1** and **2**, across all countries $i = 1, 2, ..., N$.
4. Form rank-weight cross-border M&A portfolios as described in Section 4.3 using the $T \times N$ bootstrapped dataset.
5. Compute the average annualized currency return, t-statistic, and Sharpe ratio of the rank-weight portfolio.
6. Repeat Steps **1-5**, 10,000 times to form a distribution of the portfolios' average returns, t-statistics and Sharpe ratios.