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

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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 abnormal acquisition activity of domestic firms signalling turning points in their local economic conditions. A currency portfolio that exploits the predictability generates a Sharpe ratio of over 0.70, is primarily driven by a positive exchange rate return component, and is unrelated to other sources of return predictability.

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

JEL Classification: F31, E22, E32, G12, G15, G34

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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 combined actions of particular groups. 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. 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. However, because of their dynamic nature, real decisions by firms often rely directly on their expectations for future micro and macroeconomic conditions (e.g., Gennaioli et al., 2016; Coibion et al., 2018). For instance, when making international *investment* decisions, all firms—both financial and non-financial—form expectations about the future states of the domestic and foreign macroeconomies

[1]While the seminal empirical findings of Meese and Rogoff (1983) cast doubt on this relationship, 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) and at the security (Lilley et al., 2021) and firm level (Adams and Verdelhan, 2021).

by necessity, since these fundamentals are key determinants of the relative returns on potential projects. An expectation of strengthening domestic economic conditions raises the demand for home assets, whereas declining economic expectations push both home and foreign firms to pursue more attractive investment opportunities elsewhere. 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 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 economic 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 international portfolio balance models predict that demand for foreign assets rises when their returns become relatively attractive (Kouri, 1976).

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

[2] "The Political Issues Board Directors Care Most About," Harvard Business Review, February 16, 2016.
[3] "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 (i.e., firm-specific, industry-wide, or economy-wide 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 investment announcements should, in part, reflect firms' heterogeneous beliefs about economic prospects. By aggregating and standardizing announced investment flows, 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, reveal no incremental 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 have superior information or better information processing capabilities. Domestic firms and investors are, for example, known to have more accurate information about local economic conditions than foreigners (Brennan and Cao, 1997; Van Nieuwerburgh and Veldkamp, 2009; Tille and van Wincoop, 2014), 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 also provide a simple model of exchange rate determination, featuring differences-in-beliefs, in which investment announcements provide a signal about future economic fundamentals and thereby help to predict 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 announced cross-border M&A net inflows to a country (i.e., the sum of inflows minus the sum of outflows) and their median level, standardized by 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. Specifically, 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, and that the predictability continues to be observed after controlling for other leading economic indicators. Decomposing abnormal M&A net inflows into foreign-driven inflows and domestic-driven outflows, we further show that the predictability is driven almost entirely by the abnormal acquisition activity of domestic firms that naturally enjoy an information advantage regarding local economic conditions. 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 0.76. 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 −2.99% over the following month, while an annualized appreciation of 5.48% is

[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 indicate a source of predictive information revealed outside of FX order flow. Albuquerque et al. (2008) document a different channel, finding that *equity* order flow forecasts currency returns.

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.

In Section 6, we document additional analysis, finding that 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. Similarly, we show that a new measure of abnormal M&A activity, constructed using dollar values relative to the size of the economy, is uninformative about changes in economic growth when orthogonalized relative to our main measure, but the reverse is not true. To the extent that the new measure captures the potential causal effect of M&As on the real economy, the finding indicates that abnormal M&A net inflows predict rather than *cause* the change in economic growth, supporting the information channel we propose. To support this evidence, we find that even uncompleted M&A deals forecast changes in economic growth. Our analysis also rules out endogeneity concern arising from the possibility that past exchange rate movements drive our results. We show that measures of currency momentum and value are unrelated to our measure of abnormal M&A activity and that our returns are unrelated to the returns of momentum and value portfolios. 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 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 the academic literature on exchange rate determination by documenting a relationship between economic fundamentals and FX returns, and provides new insights into how price-relevant information is revealed to the market outside of FX order flow. The results also have broad practical implications: for policy makers, the findings provide a way to extract the information content from foreign direct investment and to therefore assess its likely impact on the local exchange rate. For global investors, the documented predictability suggests new ways to identify price relevant information that can lead to potential investment opportunities and novel sources of portfolio diversification.

Related literature. The paper is closely related to studies of information flows in FX markets and of the relationship 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] Trading can therefore serve as a transmission channel by which the market's expectation about future fundamentals is gradually revealed and incorporated into prices by FX dealers.

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 on 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 to the literature seeking to understanding if macroeconomic fundamentals are important for exchange rate determination (e.g., Colacito et al., 2020), while also having practical 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.[8] 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,

[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 public announcements, around one-third of information is impounded into exchange rates via order flow.

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

and are thus likely to have a permanent impact on the local exchange rate.[9]

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.[10] Our investigation more closely mirrors the macroeconomic approach, found in prior studies, that relate fluctuations in aggregate merger activity to various macroeconomic fundamentals.[11] 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 relationship 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 discuss why FX predictability might arise from corporate announcements.

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

[9]Gyntelberg et al. (2018) find that *informed* international equity flows also predicts exchange rate returns. Other studies have focussed on the external stock position. Della Corte et al. (2016) find that a cross-sectional spread in currency returns when sorting currencies by their net foreign assets, consistent with the theory of Gabaix and Maggiori (2015). Gourinchas and Rey (2007) find that the US net international investment position predicts movements in the trade-weighted dollar index, which Della Corte et al. (2012) extend to bilateral pairs.

[10]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).

[11]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).

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 the change in both current fundamentals and the expectation 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 than the market can predict exchange rates. 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).

In the context of our study, and through the lens of the present-value model, we obtain three necessary conditions for exchange rate predictability: (1) international investment announcements contain information about future fundamentals; (2) the information is incremental to other public information known to predict fundamentals, and therefore the announcements reveal new (previously private) information; and (3) the exchange rate does not immediately incorporate this information, leading to FX predictability. In the following sections, we discuss these three conditions.

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 takeover 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 the aggregate deal activity (Nelson, 1966; Melicher et al., 1983; Mitchell and Mulherin, 1996).[12]

[12]A large body of research has shown that much of the takeover activity is firm-specific in nature. However,

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 the expected changes in macroeconomic conditions. Declining economic expectations may, for example, induce local firms to look for growth opportunities overseas. Meanwhile deteriorating domestic 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.[13] The view echoes that of practitioners, where CEOs embarking on acquisitions are commonly expected to convey confidence about future economic trends.[14]

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 (Andrade et al., 2021). 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.[15] 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

firm-specific characteristics play a minor role in explaining the behavior of aggregate merger activity (Comment and Schwert, 1995).

[13]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.

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

[15]A recent study by McKinsey & Company shows that many of the firms it surveyed run more than one type of forecasting process and that they have reams of data at their fingertips, including internal financial data and external market information, to create informed estimates such as sales growth or predictions for aggregate economic conditions. See "Bringing a real-world edge to forecasting," McKinsey & Company, March 13, 2020.

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, firms have good reasons to be at an informational advantage, and especially domestic firms regarding their local economic conditions.

It is also feasible 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).

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 Appendix, we build a simple model of exchange rate determination drawing from the differences-in-beliefs literature (e.g., Harrison and Kreps, 1978; Harris and Raviv, 1993; Banerjee and Kremer, 2010; Jeanneret and Sokolovski, 2021), in which agents place different weight on the importance of M&A activity for understanding future fundamentals. In the model, M&A activity provides an informative signal about the future fundamental (i.e., economic growth) and predicts future exchange rate returns. The model serves

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

to highlight the main theoretical ingredients that enable public information to be a potential source of predictable information.

In the interest of space, we highlight here the main theoretical ingredient—investors have heterogeneous beliefs about a common source of information. In the case of investment announcements, although these are public, the predictability arises because agents either do not form symmetric beliefs about public signals or are unable to extract signals from public information. Since exchange rates reflect the average expectations of investors, the exchange rate does not fully update to incorporate the signal. Only when the fundamental is revealed do prices fully update, leading to a source of predictability. Given the wide range of agents trading in currency markets for various reasons, both differences-in-beliefs and asymmetric information are reasonable. Indeed, many agents, e.g., corporations, have little incentive or find it expensive to accumulate public information prior to trading. Moreover, careful analysis is necessary to transform the raw data into useful M&A signals we explore in the study, which presents a barrier to obtaining the information. The information could, therefore, equally be viewed as private to those with the information-processing skills to exploit it.[17]

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.[19] 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**,

[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).

[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]In our main analysis, we include cross-border M&As by both financial and non-financial firms. However, as shown in Internet Appendix Table A.14, our results continue to hold when we exclude financial firms which generally may be thought to have superior abilities to collect and process information.

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**.[20]

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, is most likely to carry meaningful information about expected future economic conditions.[21] 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. In comparison, 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.[22]

[20] 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 exclude Canada and Mexico given their integration with the US economy (all are members of NAFTA), since *a priori* it increases the commonality of macroeconomic shocks and reduces the likely informativeness of announced cross-border M&A deals. In Internet Appendix Tables A.8 and A.9 we provide evidence, however, that their exclusion does not affect our main findings.

[21] 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.

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

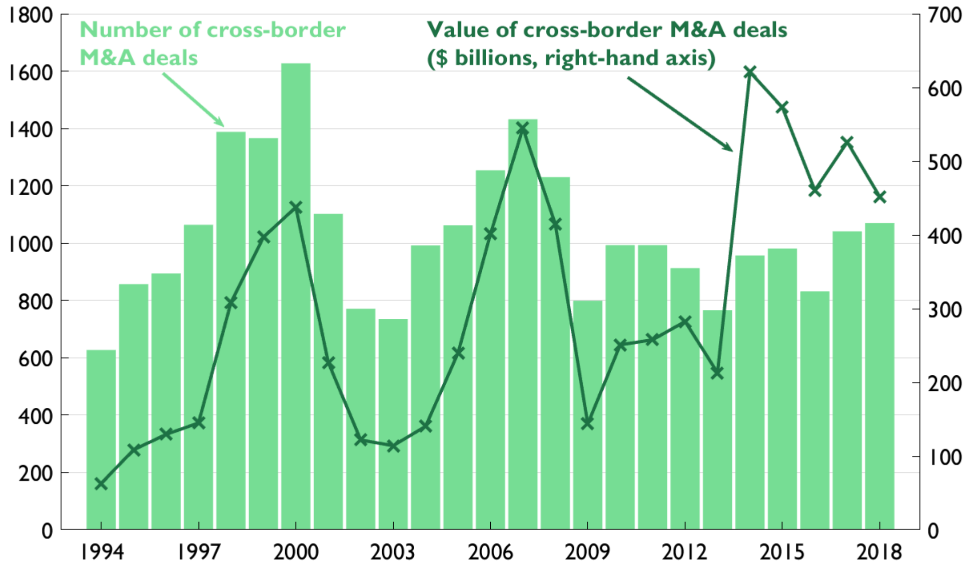

Fig 1. Number and Value of Announced Cross-Border M&As. The figure plots the time series of the total number of cross-border M&A deals in the sample (left-hand axis, bar plot) and the total value of those deals in US dollar billions (right-hand axis, line plot).

3.1 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.

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.[23] 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 is observed between two countries over time because of, for example, time invariant, country-specific factors.[24] 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 in that 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.[25] 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. Specifically, our measure of "abnormal" M&A activity is given by,

[23]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.

[24]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).

[25]In Internet Appendix Tables A.5 to A.7, we explore different standardization windows ranging from 12 to 60 months and find our results remain qualitatively unchanged. The predictability of economic acceleration becomes stronger than in our main result when the window is extended and slightly weaker when it is reduced. However, there is little quantitative difference for the exchange rate and currency return predictability across windows.

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

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 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 trading, transaction size may not be related to the quality of information, as high confidence about the trends in an economy likely increases 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, e.g., 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]

[26] In Internet Appendix Table A.13 we show these non-informative zeros do not drive our core results.

[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).

3.3 Macroeconomic fundamentals

We investigate if the aggregate M&A net inflow contains information about future economic fundamentals 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 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]

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

The change in economic growth is then given by:

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

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

[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 Internet Appendix Tables A.10 and A.11 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.

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.

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 in 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 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 investigate the predictability of cross-border M&A announcements in panel regressions, controlling for well-established and publicly available indicators of future economic conditions.

4.1 Forecasting changes in economic growth

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 $\Delta g_{i,t+s} = g_{i,t+s} - g_{i,t}$, on a dummy variable ($D_{ik,t}$) that is equal to one if country i at time t is in basket k

[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.

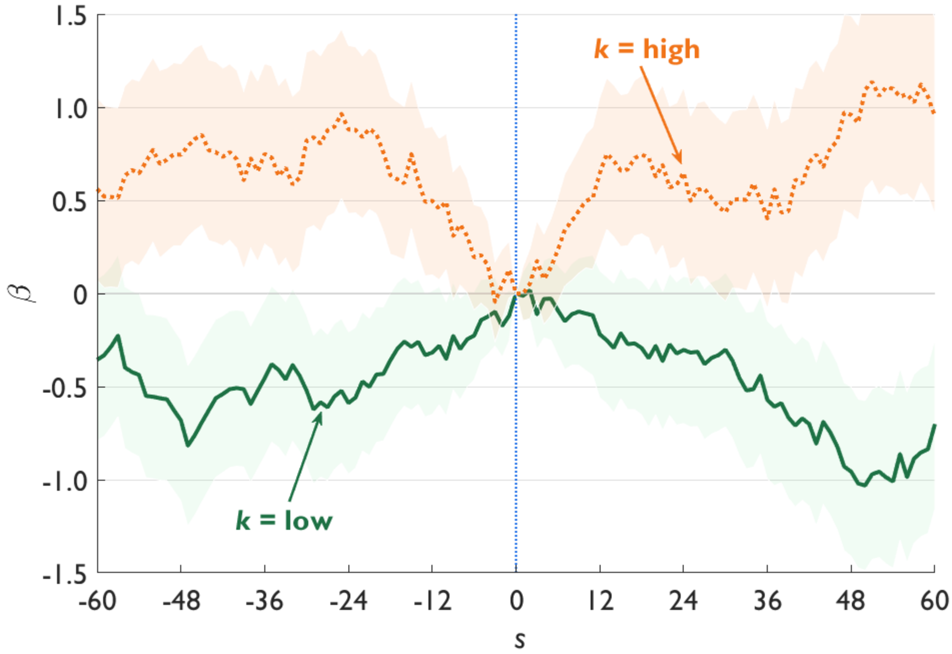

Fig 2. Macroeconomic Acceleration. The figure plots the β coefficients from Equation (**10**), estimated across values of s for $k = high$ and $k = low$. Two standard error bounds are denoted by the shaded region.

= 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 change in economic growth *prior* to the 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. That is, economic acceleration ($\Delta g_{i,t+s}$) would be trending upward over time when $k = high$, such that the pre-announcement economic growth is lower but the post-announcement level is higher than the growth at $s = 0$. The mirror image would be observed 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 that when $s < 0$ the patterns point instead to *reversals* in economic growth. Countries with high (low) values of $\widetilde{MA}_{it}$ at $s = 0$ started with higher (lower) growth during the previous 60-months, which then declined (increased) steadily towards teh growth level at $s = 0$.[30] 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, which we examine next.[31]

4.1.1 Controlling for leading economic indicators

We consider five well-known macroeconomic variables that are well known 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, including expected changes in employment and demand, housing permits, term spreads, consumer confidence, and stock market returns.[32] (ii) 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

[30]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.

[31]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).

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

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. 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. In the second model, we replace the CLIs with the alternative sources of economic growth predictability. Given the evidence in Fig. 2, we anticipate the coefficient β will be positive.

Results are reported in Table 2. Pertinently, we find the coefficients on $\widetilde{MA}_{it}$ are all positive and 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. 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 economic growth change over the same period (0.21% and 0.30%). Given these findings, we contend that announcements of corporate investment activity appear to reveal new information to the market about changes in economic growth.

4.1.2 Decomposing abnormal M&A activity

To try and better understand the source of the predictive information, we return to the theoretical motivations underpinning the analysis, described in Section 2. As noted in Section 2.3, firms may have superior information, especially about local economic conditions, through the real-time feedback on sales and general business conditions they observe. As we noted, however, there are also channels through which firms may have more precise insights into foreign economic conditions. In this section, we therefore explore whether the predictive information we observe is stemming principally from the decisions of either domestic or foreign firms.

When our main signal $\widetilde{MA}_{i,t}$ is positive, it could be due to more foreign-firm-driven inflows than usual or less domestic-firm-driven outflows. Likewise if $\widetilde{MA}_{i,t}$ is negative, it may be driven by *more* domestic-firm-driven outflows than normal or less foreign-firm-driven inflows. It follows that if low M&A net inflows are driven mainly by more outflows than normal, it may reflect that domestic firms have observe deterioration in their local economic conditions and expect lower future growth. Equally, high M&A net inflows driven by less outflows, may reveal that domestic firms expect stronger local economic conditions in the future—curtailing their international investments.

To explore whether predictability is driven primarily by domestic or foreign firm investment decisions, we construct two alternatively measures of "abnormal" M&A activity using only inflows (denoted *in*) or outflows (denoted *out*), in which for $k = in, out$, the abnormal activity is given as in Equation (**6**) by:

$$\widetilde{MA}_{i,t}^{k} = \frac{MA_{i,t}^{k} - \overline{MA}_{i,t}^{k}}{\sigma_{i,t}^{k}}, \tag{12}$$

where, for example, $MA_{i,t}^{in}$ are the inflows into country i from the US in month t and $\overline{MA}_{i,t}^{in}$ is the median level of inflows from the US to country i over the prior 36 months. If predictability emerges from $MA_{i,t}^{in}$, it would suggest a foreign-firm-driven effect, while more predictability stemming from $MA_{i,t}^{out}$ indicates a domestic-firm-driven source of predictability.

We investigate which effect appears to dominate by estimating an equivalent model to that in Eq. (**11**), but replacing $\widetilde{MA}_{i,t}$ with $\widetilde{MA}_{i,t}^{in}$ and $\widetilde{MA}_{i,t}^{out}$:

$$\Delta g_{i,t+s} = \alpha_i + \beta_1 \widetilde{MA}_{i,t}^{in} + \beta_2 \widetilde{MA}_{i,t}^{out} + \gamma' X_{i,t} + \kappa_i + \lambda_{t+s} + \varepsilon_{i,t+s}, \tag{13}$$

We report results in Table 3. A clear asymmetric pattern emerges: across all horizons, the domestic-firm-driven outflow 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 foreign-firm-driven inflow signal (β_1) are not statistically different from zero over most horizons. The predictability documented in Table 2 is, at least in the shorter term, driven principally therefore by outflows and thus by the investment decisions of domestic firms. To complement this evidence, in Internet Appendix Fig. 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 domestic-firm-driven outflows becomes more apparent: countries with relative high outflows exhibit a reversal in economic growth centered at $s = 0$. Countries with abnormally high inflows at $s = 0$ continue, however, to decelerate in the following months. It is only after 48 months that these economies exhibit faster economic growth than observed at $s = 0$. It follows that, unlike for domestic-firm outflows, the information in inflows does *not* reveal a timely signal about

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

turning points in local 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 currency returns. We turn to explore this possibility in the next section.

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.

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] The HML weights are equal to the P_3 weights and the negative of P_1 weights (countries in P_2 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

[34]Forming currency portfolios to explore return predictability is a common method in exchange rate 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 et al. (2017) and Ranaldo and Somogyi (2021) also use three portfolios. In Internet Appendix Table A.12, we show that our results are unaffected when constructing HML portfolios using five portfolios, while the use of linear and rank weights further mitigates any concerns that our results are driven by a particular weighting scheme.

lower weights *within* a portfolio. The linear approach, in contrast, assigns weights to all eligible countries in direct proportion to $\widetilde{MA}_{i,t}$:

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

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.

5.1.1 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 −0.86% while, in contrast, P_3 countries earn a positive and highly statistically significant annualized currency return of 3.43%.[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 4.29% and a Sharpe ratio of 0.76. 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

[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%.

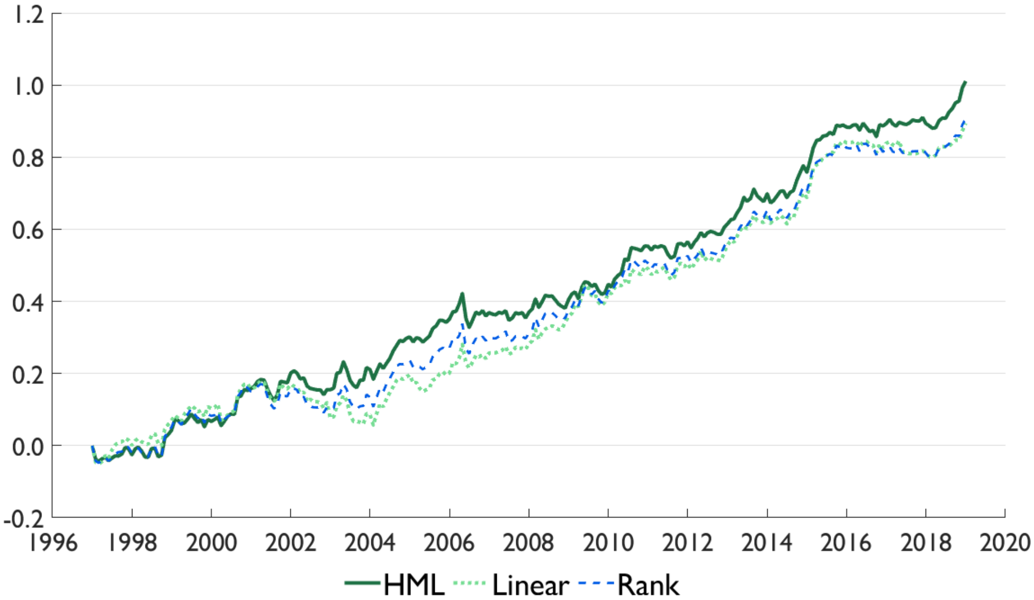

Fig 3. Cumulative Returns of Cross-Border M&A Portfolios. The figure plots the cumulative monthly returns of the three cross-border M&A currency portfolios. The three portfolios include HML (solid line), linear (dotted line), and rank (dashed line). The returns begin in January 1997 and end in December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

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 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 0.52% 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

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

remain high, albeit slightly lower than those observed in the full sample.

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 entering the portfolio because of either an unusual level of foreign-firm-driven inflows or domestic-firm-driven 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 value for $\widetilde{MA}_{i,t}$ (i.e., a P_3 country) is typically driven by foreign-firm inflows, while a low value for $\widetilde{MA}_{i,t}$ (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 "domestic-driven-outflows" and "foreign-driven-inflows" 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-driven-outflows" portfolio is -5.07%, while the return for countries entering P_3 is 5.02%. The spread in foreign exchange rate returns between P_3 and P_1 in the domestic-driven-outflows portfolio (i.e., HML) is therefore economically large (10.09% per annum) and highly statistically significant. In contrast, the analogous results for P_1 and P_3 in the "foreign-driven-inflows" portfolio are only -1.11% and -0.11%, yielding a statistically insignificant spread of 1%. We find these results are also reflected in the spreads in currency excess returns (8.47% versus 2.85%) and in the Sharpe ratios of the HML portfolios (0.82 versus 0.34).

Overall, the results suggest that not all cross-border M&A flows are equally informative about future exchange rate returns. Instead, domestic driven M&A outflows generate more precise signals, consistent with domestic firms having more accurate information to infer a timely signal about changes in their local economic conditions. 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 FX 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

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

[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.

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:

$$R^p_{M\&A,t} = \alpha + \sum_k \beta_k R^p_{k,t} + \varepsilon_t, \tag{14}$$

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 4.13% 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]

$$\begin{aligned} R_{i,t+1} &= \alpha + \beta w^{rnk}_{M\&A,i,t} + \sum_k \gamma_k w^{rnk}_{k,i,t} + \tau_{t+1} + \varepsilon_{t+1} \\ R^{fx}_{i,t+1} &= \alpha + \beta w^{rnk}_{M\&A,i,t} + \sum_k \gamma_k w^{rnk}_{k,i,t} + \tau_{t+1} + \varepsilon_{t+1}, \end{aligned} \tag{15}$$

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,

[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.

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 (0.65% 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 a statistically significant relationship with either exchange rate returns or currency returns.

We conclude that information contained in the announcements of cross-border M&A deals provides a novel source of predictability for exchange rate and currency returns. The results also suggest that the announced M&A flows 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 in-

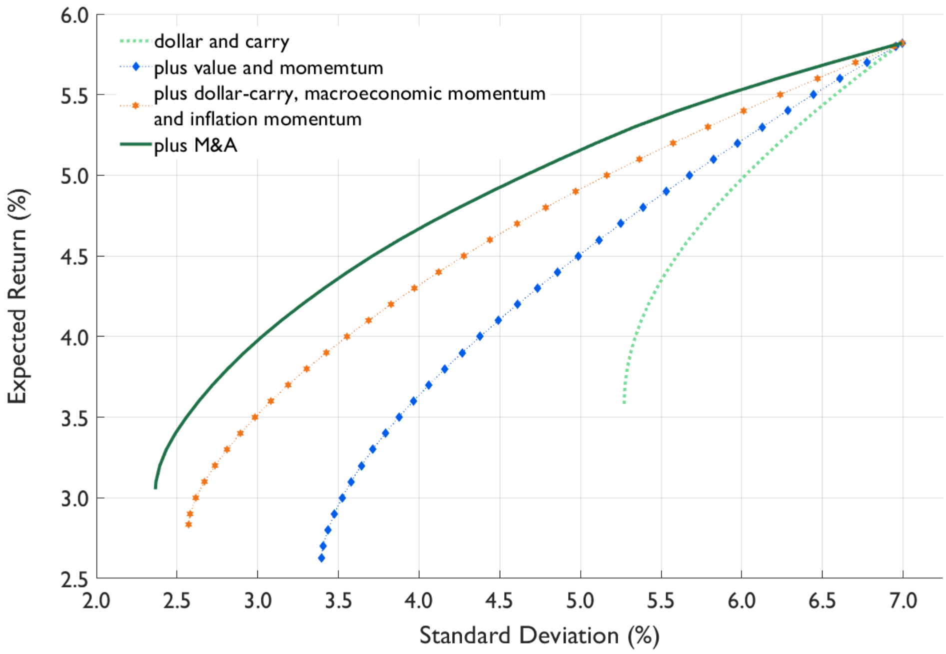

Fig 4. Efficient Frontiers. The figure plots a series of efficient frontiers for various sets of currency portfolios. The dotted line is the efficient frontier when limiting the investment space to only dollar and carry. We add value and momentum (dotted line with diamond markers, four portfolios), dollar-carry, 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.

clude 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 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

[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 code available.

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.

5.4 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 0.76, 0.73, and 0.76 for the HML, linear, and rank portfolios, to 0.59, 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.

6 Further Analyses

In this section we discuss the robustness of the currency predictability and analyze an alternative "transaction" hypothesis that might also explain our core results. We also consider whether M&A activity *drives* changes in economic growth and consider the endogeneity concern that abnormal levels of M&A activity are driven by exchange rate movements.

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 M&A 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 4.13% 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 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 Does abnormal M&A activity drive changes in economic growth?

Central to the interpretation of our results is that abnormal M&A activity provides a signal about changes in economic growth. The signal reflects an aggregation of private expectations that are revealed to the market. A competing hypothesis is that, instead of revealing private information about turning points in economic activity, abnormal M&A net inflows may have a *causal* effect on local economic growth through production gains, job creation (Toews and

Vezina, 2020), and diffusion of new technologies (Aitken and Harrison 1999).

If this economic channel is the main driver of our results, then we would expect to observe faster economic growth in countries experiencing abnormally high dollar volumes of M&A net inflows relative to the size of the economy.

To explore this possibility, we compute, for each country and month, the net inflow-to-GDP ratio, defined as the aggregate dollar value of announced cross-border M&A net inflow divided by the last year's GDP:

$$MA^{\$}_{i,t} = \frac{MA^{\$,in}_{i,t} - MA^{\$,out}_{i,t}}{GDP_{i,t-12}} \tag{16}$$

where $MA^{\$,in}_{i,t}$ and $MA^{\$,out}_{i,t}$ denote the dollar volume of monthly cross-border M&A inflows and outflows for country i in month t. As before, we standardize $MA^{\$}_{i,t}$ by its median ($\overline{MA}^{\$}_{i,t}$) and standard deviation ($\sigma^{\$}_{i,t}$) over the prior 36 months:

$$\widetilde{MA}^{\$}_{i,t} = \frac{MA^{\$}_{i,t} - \overline{MA}^{\$}_{i,t}}{\sigma^{\$}_{i,t}}, \tag{17}$$

Higher values of $\widetilde{MA}^{\$}_{i,t}$ therefore indicate that country i receives higher than usual M&A investments as a percentage of the country's GDP in month t and consequently, should experience faster economic growth in the future.

To examine whether the announced cross-border M&As predict or drive future economic growth, we construct an orthogonalized version of our main measure of abnormal M&A activity $\perp \widetilde{MA}_{i,t}$, defined as the residuals obtained from the country-specific regressions of $\widetilde{MA}_{i,t}$ on $\widetilde{MA}^{\$}_{i,t}$. This variable is designed to capture the unique predictive power of the abnormal number of net inflow, unrelated to the abnormal dollar volume that may potentially drive growth. We construct a similar version of orthogonalized $\perp \widetilde{MA}^{\$}_{i,t}$ using the residuals from the country-specific regressions of $\widetilde{MA}^{\$}_{i,t}$ on $\widetilde{MA}_{i,t}$.

In Internet Appendix Table A.15, we present results from re-estimating the panel regression analysis as in Equation (11), replacing $\widetilde{MA}_{i,t}$ with $\perp \widetilde{MA}_{i,t}$ in Panel A and with $\perp \widetilde{MA}^{\$}_{i,t}$ in Panel B. The coefficients on $\perp \widetilde{MA}_{i,t}$ are all positive and highly statistically significant at the 1% level over most horizons, indicating that the abnormal number of M&A net inflow continues to be a strong predictor of future growth even after removing the potential causal effect of dollar volume on the real economy. In contrast, $\perp \widetilde{MA}^{\$}_{i,t}$ exhibits a negative relationship or positive but statistically insignificant relationship in most cases. Overall, the findings suggest that announced cross-border M&As contain predictive information about changes in economic growth, and that the predictivity stems from the unexplained component of deal numbers revealing private expectations, rather than the real effect of M&A driving economic growth.

To complement this analysis, we also investigate a second test to understand whether changes in economic growth can be predicted by M&A signals constructed using only uncompleted deals that should have little effect on the real economy. The results are presented in Internet Appendix Table A.16. We find that the abnormal level of uncompleted net inflows continues to be a strong predictor of future economic growth, again consistent with the predictive information contained in M&A announcements, rather than the M&As themselves, explaining the link between deal activity and future economic conditions.

6.3 An endogeneity concern: do exchange rates drive $\widetilde{MA}$?

In Section 5, we showed that the returns of the zero-cost M&A portfolios are unrelated to other sources of currency return predictability. It might be thought, however, that the transformation of the information from underlying signals to portfolio weights distorts the magnitude of the differences and hence, that the signals are not meaningfully different. Erel et al. (2012) make an important contribution to the literature on cross-border M&A flows, showing that exchange rate movements are a factor driving M&A activity across borders. The economic mechanism is intuitive: companies which have experienced a recent exchange rate appreciation have relatively more buying power in foreign markets. Alternatively, firms located in countries with presently undervalued currencies (e.g., relative to purchasing power parity), become more attractive to foreign buyers. We therefore take an alternative look at whether the information in our main signal is simply a reflection of firms taking advantage of favourable prices.

It should be noted that Erel et al. (2012) use average measures of value over their 18-year sample and focus on the total number of cross-border deals rather than the *abnormal* level of deals. However, if the abnormal level of deals is related to exchange rate movements then it potentially undermines the economic channel we claim lies behind our core finding. To address this concern, we follow the approach of Asness et al. (2013) and construct monthly measures of currency value and momentum. Currencies that are either more undervalued or have experienced a recent currency appreciation, have higher values. If this alternative explanation has validity, then we expect to observe a positive relationship between $\widetilde{MA}_{i,t}$ and our measure of value (undervalued currencies attract investment) and a negative relationship between $\widetilde{MA}_{i,t}$ and momentum (stronger currencies make firms less attractive to foreign buyers).

In Internet Appendix Table A.17, we present the results from estimating panel regressions of $\widetilde{MA}_{i,t}$ on our measures of currency value and momentum:

$$\widetilde{MA}_{i,t} = \alpha_i + \beta_1 VAL_{i,t} + \beta_2 MOM_{i,t} + \kappa_i + \lambda_t + \varepsilon_{i,t}, \tag{18}$$

where $VAL_{i,t}$ and $MOM_{i,t}$ represent the levels of undervaluation and exchange rate momentum for currency i at time t and κ_i and λ_t are currency and time fixed effects. In the first column of Table A.17 we limit attention to value signals, we investigate momentum signals in column 2. In column 3, we include both value and momentum signals.

Across the regressions, we find that neither value nor momentum signals are statistically different from zero, while the coefficient on currency momentum has the wrong sign for the transaction price mechanism to drive our findings. It should be noted that these results are not in contradiction to Erel et al. (2012), who focus principally on understanding the average number of deals between countries, whereas we focus on abnormal levels of deal activity, which do not appear to be driven by valuation or momentum effects.

6.4 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 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 C.

In Fig. 5, 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

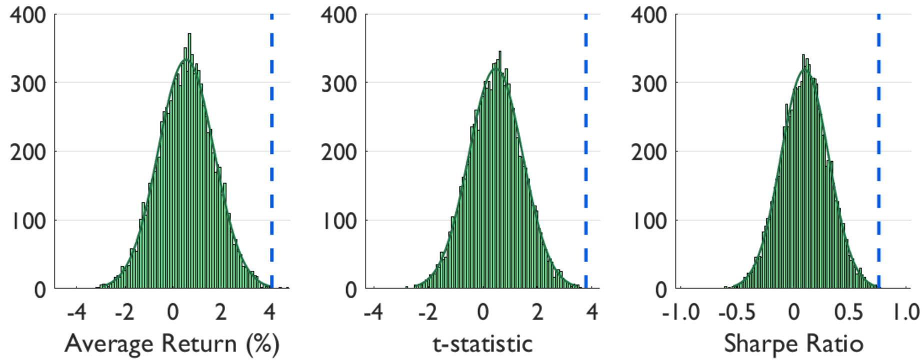

Fig 5. Bootstrapped Distributions with Normal Distribution Fit. The figure plots the histograms of average returns, t-statistics, and Sharpe ratios, calculated using 10,000 bootstrapped samples. The corresponding values for the observed rank-weight M&A portfolio are plotted as dashed lines. A normal distribution fit is overlaid in each sub-figure.

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 4.13% 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.

7 Conclusions

We uncover a novel source of predictive information, originating from the announcements of cross-border M&As, that forecasts changes in 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 a more accurate signal about turning points in local economic growth, which is not subsumed by other publicly available predictors. The results imply that corporate investments are related to future economic fundamentals, that private expectations about future macroeconomic fundamentals are revealed outside of order flow, and that the revealed information can be used to forecast exchange rate returns.

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, extracted 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 have broad practical implications: for policy makers, the findings provide a way to identify informed capital flows, while for global investors, the documented predictability suggests new ways to identify price relevant information that can lead to potential investment opportunities and novel sources of portfolio diversification.

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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 Changes in Economic Growth

	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-squared 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 Changes in Economic Growth: 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

	$\mathbf{P_1}$	$\mathbf{P_2}$	$\mathbf{P_3}$	**HML**	**Linear**	**Rank**	$\mathbf{Rank_{DM}}$	$\mathbf{Rank_{EM}}$
mean (%)	–0.86	1.19	3.43	4.29	4.06	4.13	3.01	6.01
t-stat	–0.44	0.68	1.89	3.76	3.61	3.79	2.48	3.25
std (%)	8.08	7.57	8.23	5.61	5.59	5.44	5.65	8.95
SR	–0.11	0.16	0.42	0.76	0.73	0.76	0.53	0.67
skew	–0.22	–0.19	–0.13	–0.24	–0.28	–0.31	0.35	0.04
kurt	4.31	4.59	4.19	5.18	3.82	4.74	3.92	4.51
ar(1)	0.10	0.06	0.05	0.01	–0.02	–0.03	0.07	–0.06
mdd (%)	44.1	26.0	21.6	10.3	12.3	8.3	11.1	16.5
fx (%)	–2.41	–0.07	0.52	2.93	2.60	2.89	2.67	5.04
fp (%)	1.55	1.26	2.91	1.36	1.46	1.24	0.33	0.97
$\mu_{\widetilde{MA}_{i,t}}$	–1.13	0.41	1.80					

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*), average spot return (*fx*) and forward premium (*fp*). The final row reports the average value of the $\widetilde{MA}_{it}$ variable in P_1, P_2, and P_3, which denote the 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 Source of Foreign Exchange Rate Predictability

	Domestic Driven Outflows			Foreign Driven Inflows		
	$\mathbf{P_1}$	$\mathbf{P_3}$	**HML**	$\mathbf{P_1}$	$\mathbf{P_3}$	**HML**
mean (%)	–2.99	5.48	8.47**	0.74	3.59	2.85
SR	–0.27	0.65	0.82	0.07	0.37	0.34
fx (%)	–5.07	5.02	10.09***	–1.11	–0.11	1.00
fp (%)	2.08	0.47	–1.62***	1.85	3.70	1.85***
$\mu_{\widetilde{MA}_{i,t}}$	–1.27	1.29		–0.76	1.90	

The table presents statistics on cross-border merger and acquisition portfolios. Statistics include the average annualized ($mean$) return, Sharpe ratio (SR), average spot return (fx) and forward premium (fp). The final row reports the average value of the $\widetilde{MA}_{it}$ variable in P_1 and P_3, which denote two of the portfolios sorted each month from low to high values of $\widetilde{MA}_{i,t}$. In the left-hand panel, countries entering P_1 and P_3 experience abnormal M&A activity principally driven by domestic-firm-driven outflows. In the right-hand panel, countries entering P_1 and P_3 experience abnormal M&A activity principally driven by foreign-firm-driven inflows. HML is a zero-cost cross-sectional portfolio equal to $P_3 - P_1$. Superscripts ***, ** and * denote significance of the HML returns at the 1%, 5% and 10% level, respectively. 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
$w^{rnk}_{M\&A,i,t}$	0.646***	0.656***
	(0.248)	(0.249)
$w^{rnk}_{car,i,t}$	1.672**	–0.683
	(0.751)	(0.749)
$w^{rnk}_{mom,i,t}$	0.510	0.422
	(0.540)	(0.539)
$w^{rnk}_{val,i,t}$	0.921	0.896
	(0.666)	(0.661)
$w^{rnk}_{Trend_{EC},i,t}$	–0.066	0.069
	(0.467)	(0.468)
$w^{rnk}_{Trend_{IN},i,t}$	–0.789	–1.131
	(0.698)	(0.693)
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):

$$\begin{aligned} R_{i,t+1} &= \alpha + \beta w^{rnk}_{M\&A,i,t} + \sum_k \gamma_k w^{rnk}_{k,i,t} + \tau_{t+1} + \varepsilon_{t+1} \\ R^{fx}_{i,t+1} &= \alpha + \beta w^{rnk}_{M\&A,i,t} + \sum_k \gamma_k w^{rnk}_{k,i,t} + \tau_{t+1} + \varepsilon_{t+1}, \end{aligned} \tag{19}$$

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

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.

Appendix: A Model of Exchange Rate Determination

In this section, we present a simple model of exchange rate determination 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 (e.g., Kim and Verrecchia, 1994; Bacchetta and Van Wincoop, 2006; Cespa et al., 2021).

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 risk-free securities determines the 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 infinitesimally 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 date 2 is equal to its initial level plus a fundamental shock:

$$s_2 = s_0 + f_2, \qquad \text{where } f_2 \sim N(0, \sigma_f^2) \tag{A.1}$$

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. All agents in the economy are aware of the distribution of s_2 and so at date 2, therefore, agents all believe that the best predictor of the date 2 exchange rate is simply s_0, and hence that a random-walk model without drift is optimal. This set-up is consistent with the random-walk model being the most difficult forecasting model to beat in forecasting horse races (Meese and Rogoff, 1983; 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 in foreign and domestic economic growth differentials between the two dates.

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, 2007). The third agent is a noise FX trader, denoted N, e.g., a corporation, who makes exogenously determined random trades.

Corporate investment flows

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

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

where ρ_1 can be interpreted as the country-level aggregation of M&A net inflows; ε denotes noise in the signal unrelated to the fundamental. Only the informed agent chooses to use this information.[43] Here the distinction between "differences-in-beliefs" and "asymmetric information" is an interesting theoretical discussion but is not crucial to demonstrating predictability. In a differences-in-beliefs interpretation, the informed agent believes the signal is valuable, while the other agents "agree to disagree" that it is not. In this situation, all agents are aware about the different views that exist in the market. In the asymmetric-information interpretation, however, even though the information is public, only the informed agent has the information processing skills to extract the signal, making the signal effectively private.[44]

Both of these interpretations are plausible when applied to the FX market and to the specific case of corporate investment flows. As noted above, agents trade for a variety of motives in the FX market, including a variety of liquidity rationales and, hence, may choose not to condition

[43] The noise in the signal reflects the fact that firms pursue M&As for a wide range of reasons, some of which are unrelated to macroeconomic fundamentals, e.g., market timing (Erel et al., 2012), firm-specific reasons (e.g., Jovanovic and Braguinsky, 2004; Almeida et al., 2011), and managers' self-interest seeking behavior (e.g., Jensen, 1986). Consequently, not every deal is informative. Aggregation and standardization are therefore needed for skilled agents to exact useful macroeconomic information from ρ_1.

[44] Kim and Verrecchia (1994) introduce a similar mechanism in which a public signal—earnings announcements—reveal more information to some participants than others, driven by different levels of information processing skill.

on all publicly available information even if a signal is known to carry information about future fundamentals. In the case of cross-border M&A activity, while the M&A activity is publicly announced, not all deals are informative since no single deal necessarily reveals information about future economic conditions. It is only through careful collection and standardization that the signal becomes informative, and hence we could equally view the signal as privately obtained by informed agents with the technical expertise to extract it. Indeed, Cespa et al. (2021) find strong evidence of large asymmetric information in foreign exchange markets, which is argued from the perspective of the large degree of heterogeneity in investor types, in which certain agents extract a stronger signal about future fundamentals.

Demand for foreign risk-free bonds

Trading takes place at date 1. We assume the informed and uninformed agents maximize CARA utility over terminal wealth, in which 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 uses Bayesian updating to form a conditional expectation and conditional variance of the date 2 spot exchange rate as follows:

$$\begin{aligned} E_{I,1}[s_2] &= s_0 + \rho_1 \\ Var_{I,1}[s_2] &= \sigma_\varepsilon^2 \end{aligned} \tag{A.3}$$

In contrast the uninformed agent does not condition on ρ_1 and therefore forms a different expected spot exchange rate and less precise signal of the next period exchange rate:

$$\begin{aligned} E_{U,1}[s_2] &= s_0 \\ Var_{U,1}[s_2] &= \sigma_f^2 > \sigma_\varepsilon^2 \end{aligned} \tag{A.4}$$

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

$$x_{i,1} = \frac{E_{i,1}[s_2] - s_1}{Var_{i,1}[s_2]} \tag{A.5}$$

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.[45]

[45]In the models of Bacchetta and Van Wincoop (2006) and Cespa et al. (2021), an alternative channel is

Equilibrium exchange rate

Imposing market clearing at date 1 requires that

$$\omega_I x_{I,1} + \omega_U x_{U,1} + \omega_N x_{N,1} = 0 \tag{A.6}$$

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:

$$\begin{aligned} -\omega_N x_{N,1} &= \omega_I \frac{E_{I,1}[s_2] - s_1}{Var_{I,1}[s_2]} + \omega_U \frac{E_{U,1}[s_2] - s_1}{Var_{U,1}[s_2]} \\ &= \omega_I \frac{E_{I,1}[s_2]}{Var_{I,1}[s_2]} + \omega_U \frac{E_{U,1}[s_2]}{Var_{U,1}[s_2]} - \left(\frac{\omega_I}{Var_{I,1}[s_2]} + \frac{\omega_U}{Var_{U,1}[s_2]} \right) s_1 \end{aligned} \tag{A.7}$$

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

$$\begin{aligned} s_1 &= \underbrace{\left(\frac{\omega_I}{Var_{I,1}[s_2]} + \frac{\omega_U}{Var_{U,1}[s_2]} \right)^{-1}}_{\bar{\sigma}^2} \left(\omega_I \frac{E_{I,1}[s_2]}{Var_{I,1}[s_2]} + \omega_U \frac{E_{U,1}[s_2]}{Var_{U,1}[s_2]} + \omega_N x_{N,1} \right) \\ &= \underbrace{\frac{\omega_I \bar{\sigma}^2}{\sigma_\varepsilon^2}}_{\lambda} E_{I,1}[s_2] + \underbrace{\frac{\omega_U \bar{\sigma}^2}{\sigma_f^2}}_{1-\lambda} E_{U,1}[s_2] + \bar{\sigma}^2 \omega_N x_{N,1} \end{aligned} \tag{A.8}$$

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 stochastic component introduced by the exogenous noise-trader demand. Substituting for the expected date 2 exchange rates in Equations (**A.3**) and (**A.4**), the spot exchange rate at date 1 can be further simplified,

$$\begin{aligned} s_1 &= \lambda(s_0 + \rho_1) + (1 - \lambda)s_0 + \bar{\sigma}^2 \omega_N x_{N,1} \\ &= s_0 + \lambda \rho_1 + \bar{\sigma}^2 \omega_N x_{N,1} \end{aligned} \tag{A.9}$$

The exchange rate at date 1 therefore incorporates information from the informative signal but, because $\partial s_1 / \partial \rho_1 = \lambda$, and since $0 < \lambda < 1$, the exchange rate does not fully adjust to incorporate the information, resulting in a source of exchange rate predictability at date 1.

proposed in which informed agents also trade to hedge shocks to a non-traded asset. Both mechanisms serve to prevent the no-trade outcome (e.g., Milgrom and Stokey, 1982) from being attained.

Exchange rate predictability

To see the nature of the exchange rate predictability, note that the return at date 2 is given by $r_2 = s_2 - s_1$, and recalling from Equation (**A.1**) that $s_2 = s_0 + f_2$, we can state the return at date 2 as:

$$\begin{aligned} r_2 &= f_2 - \lambda\rho_1 - \bar{\sigma}^2\omega_N x_{N,1} \\ &= (1-\lambda)\rho_1 - \varepsilon_1 - \bar{\sigma}^2\omega_N x_{N,1} \end{aligned} \tag{A.10}$$

and thus since $\partial r_2/\partial\rho_1 = 1-\lambda > 0$, it follows that the information revealed at date 1 provides a predictive signal about the return at date 2, in which a positive signal (a higher abnormal level of M&A net inflows from the perspective of our empirical investigation) predicts an appreciation of the local exchange rate.

The purpose of this stylized model is to highlight that, in presence of heterogeneous agents, information stemming from corporate investment announcements, which are publicly revealed to the market, are unlikely to be immediately absorbed into prices. The central assumption of heterogeneity across FX market participants is well supported by both the theoretical and empirical literatures on foreign exchange markets and, furthermore, the additional assumption that M&A activity provides a noisy signal about future fundamentals, receives strong support within this study. Extensions of the model could consider the quantitative aspects of the model, such as time required for market prices to fully incorporate fundamental information, in a dynamic setting with multiple intermediaries. Indeed, Banerjee et al. (2009) show how dynamic models of differences-in-beliefs can only generate a price drift by also incorporating asymmetric information. Empirical work could seek to understand whether market participants appear to trade on the basis of information in corporate investment activity and, if so, whether they choose to obscure the information they reveal by trading with multiple dealers or choose to provide more precise signals through one-off large trades.

Overall for the purposes of this study, we focus our attention on Equations (**A.2**) and (**A.10**) and investigate whether the signal we construct in Equation (**6**) of the main paper, which proxies for ρ_1 in the model, contains information for forecasting future fundamentals and exchange rate returns.

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

Not for publication

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SECTION B
Details of the alternative sources of currency return predictability outlined in Section 5.3.

SECTION C
Details of the bootstrap procedure used to generate results described in Section 6.2.

Section A: Additional Results and Further Analyses

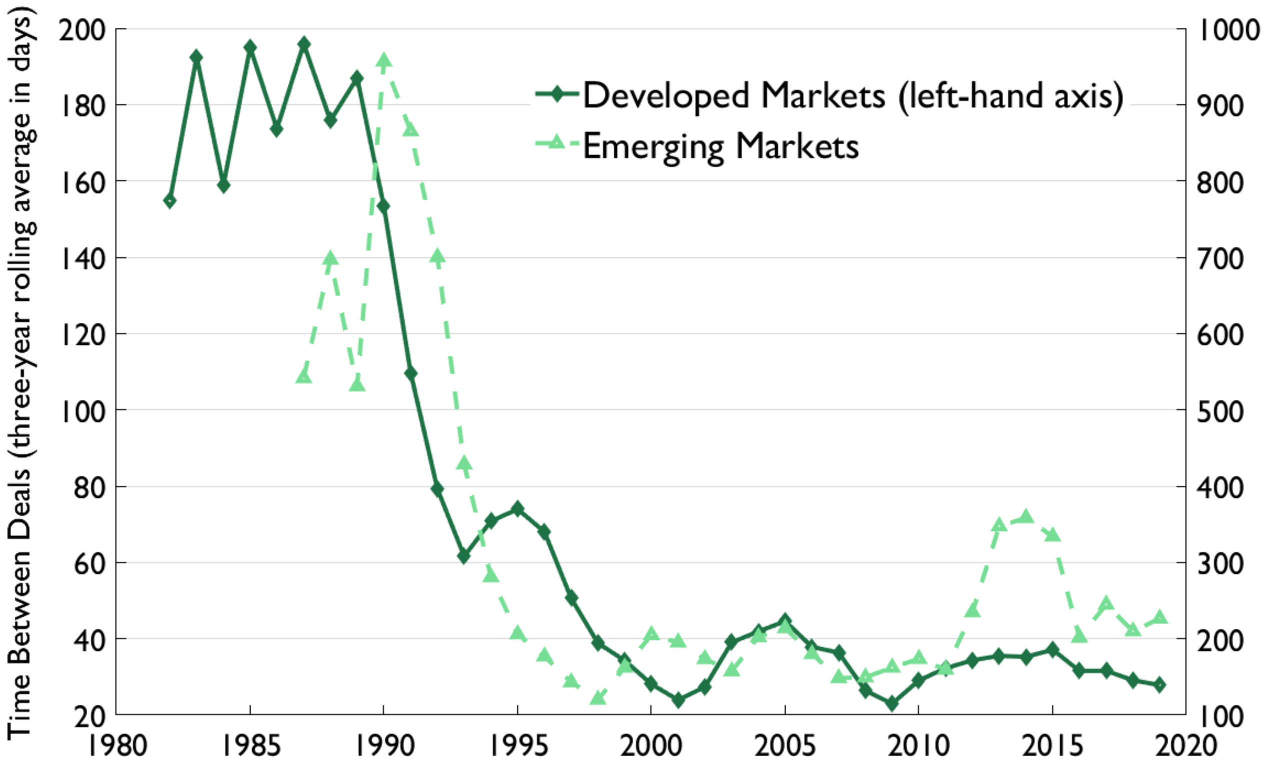

Fig A.1: Frequency of Announced Cross-Border M&As. The figure plots the average number of days between announcements of cross-border M&A deals involving the United States and either developed-market (solid line) or emerging-market (dashed line) countries over the prior 36 months. The 1995 data point,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

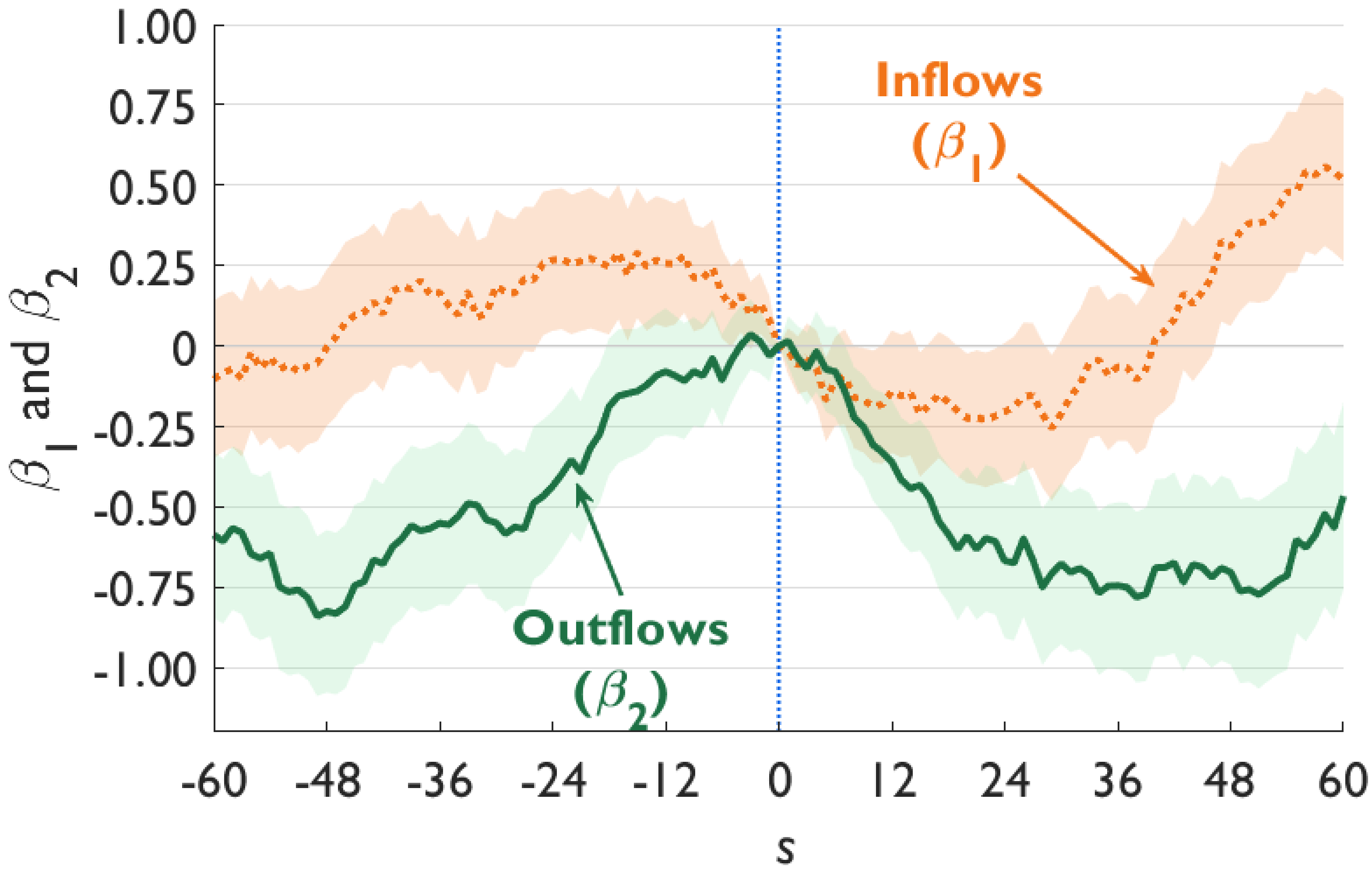

Fig A.2: Macroeconomic Acceleration With Inflows and Outflows. The figure plots β coefficients from panel regressions of changes in economic growth (i.e., economic acceleration), $\Delta g_{i,t+s}$, on the level of abnormal cross-border M&A activity constructed using either inflows ($\widetilde{MA}_{i,t}^{in}$)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

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

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

Country	Code	Currency	DataStream Codes: Spot	DataStream Codes: 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
Netherlands	NLG	Guilders	GUILDE$	USNLG1F	1997-01-31	1998-12-31

(Continued overleaf)

Country	Code	Currency	DataStream Codes Spot	 1M Forward	Start Date	End Date
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				
	$\mathbf{P_1}$	$\mathbf{P_2}$	$\mathbf{P_3}$	**HML**	**Linear**	$\mathbf{P_1}$	$\mathbf{P_2}$	$\mathbf{P_3}$	**HML**	**Linear**
mean (%)	-0.95	-0.32	2.23	3.17	3.42	0.17	3.05	7.46	7.43	5.15
t-stat	-0.45	-0.19	1.15	2.37	2.78	0.09	1.36	3.73	3.39	2.82
std (%)	8.50	7.66	8.20	6.20	5.86	8.07	9.16	10.45	10.12	8.97
SR	-0.11	-0.04	0.27	0.51	0.58	0.02	0.33	0.71	0.73	0.57
skew	0.07	-0.19	0.19	0.18	0.44	-0.33	-1.11	0.15	0.01	-0.11
kurt	3.76	6.56	3.51	4.34	4.50	7.51	10.37	4.98	4.13	3.75
ar(1)	0.11	-0.01	0.09	0.06	0.08	0.02	0.16	-0.11	-0.04	-0.05
mdd (%)	53.1	26.3	23.1	17.1	11.4	37.5	34.9	14.8	15.8	14.8
fx (%)	-1.02	-0.54	1.87	2.89	3.05	-4.35	-1.75	1.60	6.07	4.12
fp (%)	0.07	0.23	0.36	0.29	0.37	4.52	4.80	5.86	1.36	1.03
$\mu_{\widetilde{MA}_{i,t}}$	–1.10	0.23	1.43			–0.84	0.86	2.19		

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*), average spot return (*fx*) and forward premium (*fp*). The final row reports the average value of the $\widetilde{MA}_{it}$ variable in P_1, P_2, and P_3, which denote the 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	$\text{Carry}_{\text{USD}}$	Trend_{EC}	Trend_{IN}
mean (%)	1.07	5.82	2.23	3.67	2.63	2.88	4.45
t-stat	0.62	3.82	1.44	3.01	1.73	2.89	3.68
std (%)	7.31	6.99	7.05	5.78	7.28	4.47	5.61
SR	0.15	0.83	0.32	0.64	0.36	0.64	0.79
skew	–0.14	–0.67	–0.32	–0.57	0.09	–0.20	–0.35
kurt	4.50	6.04	4.08	5.92	4.47	4.53	6.14
ar(1)	0.08	0.12	0.05	0.10	–0.03	0.08	0.12
mdd (%)	25.6	7.23	15.2	6.60	20.5	5.78	6.14
fx (%)	–0.61	–4.28	–0.86	–2.21	1.61	2.13	–3.10
fp (%)	1.68	10.1	3.09	5.89	1.02	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 (%)	–0.44	0.81	2.89	3.33	3.13	3.21
t-stat	–0.22	0.46	1.60	2.92	2.78	2.95
std (%)	8.08	7.57	8.22	5.61	5.59	5.43
SR	–0.05	0.11	0.35	0.59	0.56	0.59
skew	–0.21	–0.20	–0.14	–0.26	–0.30	–0.32
kurt	4.30	4.61	4.20	5.24	3.87	4.77
ar(1)	0.10	0.06	0.05	0.01	–0.02	–0.03
mdd (%)	42.4	28.2	21.8	10.8	15.3	9.5
fx (%)	–2.07	–0.37	0.07	2.14	1.85	2.14
fp (%)	1.63	1.18	2.82	1.19	1.28	1.07

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: Alternative Measures of $\widetilde{MA}$

	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)**
$\widetilde{MA}_{12}$	0.051	0.032	0.181**	0.132	0.082	0.102	0.035	0.071	0.183**	0.240***
	(0.071)	(0.072)	(0.081)	(0.085)	(0.084)	(0.089)	(0.091)	(0.098)	(0.092)	(0.092)
$\widetilde{MA}_{24}$	0.073	0.105	0.148*	0.172**	0.157*	0.185**	0.216**	0.293***	0.341***	0.394***
	(0.067)	(0.069)	(0.077)	(0.082)	(0.080)	(0.088)	(0.089)	(0.097)	(0.090)	(0.090)
$\widetilde{MA}_{48}$	0.075	0.091	0.218***	0.228***	0.309***	0.328***	0.393***	0.480***	0.391***	0.503***
	(0.065)	(0.068)	(0.073)	(0.078)	(0.078)	(0.084)	(0.086)	(0.093)	(0.088)	(0.087)
$\widetilde{MA}_{60}$	0.128**	1.36**	0.283***	0.293***	0.391***	0.434***	0.433***	0.544***	0.400***	0.532***
	(0.064)	(0.067)	(0.072)	(0.077)	(0.077)	(0.084)	(0.084)	(0.092)	(0.087)	(0.087)

The table presents coefficient estimates of $\widetilde{MA}$ based on four sets of estimates of Equation (**11**) of the main paper. The results from the original baseline estimates are shown in Table 2. We alter the construction of $\widetilde{MA}_{it}$ from the original 36-month rolling-window estimate (see Equation (**6**)) to a 12-month, 24-month, 48-month, and 60-month rolling window. 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: Alternative Measures of $\widetilde{MA}^{in}$ and $\widetilde{MA}^{out}$

	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)**
$\widetilde{MA}^{in}_{12}$	–0.105	–0.186*	–0.080	-0.238**	–0.199*	-0.234*	–0.166	–0.226*	0.156	0.187
	(0.104)	(0.106)	(0.110)	(0.115)	(0.117)	(0.124)	(0.125)	(0.134)	(0.125)	(0.131)
$\widetilde{MA}^{in}_{24}$	–0.098	–0.126	–0.141	-0.159	–0.058	-0.101	0.178	0.164	0.425***	0.478***
	(0.100)	(0.105)	(0.109)	(0.116)	(0.115)	(0.127)	(0.123)	(0.137)	(0.125)	(0.132)
$\widetilde{MA}^{in}_{48}$	–0.146	–0.145	–0.026	0.054	0.155	0.188	0.438***	0.565***	0.490***	0.807***
	(0.097)	(0.102)	(0.106)	(0.113)	(0.111)	(0.124)	(0.118)	(0.128)	(0.126)	(0.128)
$\widetilde{MA}^{in}_{60}$	–0.074	–0.020	0.023	0.171	0.234**	0.390***	0.401***	0.677***	0.451***	0.853***
	(0.096)	(0.101)	(0.105)	(0.111)	(0.109)	(0.122)	(0.117)	(0.126)	(0.124)	(0.127)
$\widetilde{MA}^{out}_{12}$	–0.178*	–0.226**	–0.265**	–0.335***	–0.279**	–0.342**	–0.159	–0.278*	0.058	–0.000
	(0.105)	(0.105)	(0.125)	(0.130)	(0.128)	(0.139)	(0.143)	(0.155)	(0.145)	(0.144)
$\widetilde{MA}^{out}_{24}$	–0.161	–0.226**	–0.387***	–0.397***	–0.377***	–0.453***	–0.193	–0.343**	–0.117	–0.163
	(0.105)	(0.105)	(0.125)	(0.130)	(0.128)	(0.139)	(0.143)	(0.155)	(0.145)	(0.144)
$\widetilde{MA}^{out}_{48}$	–0.301***	–0.315***	–0.560***	–0.492***	–0.588***	–0.618***	–0.455***	–0.520***	–0.293**	–0.210
	(0.096)	(0.099)	(0.116)	(0.121)	(0.125)	(0.134)	(0.136)	(0.147)	(0.140)	(0.139)
$\widetilde{MA}^{out}_{60}$	–0.307***	–0.291***	–0.589***	–0.482***	–0.596***	–0.561***	–0.499***	–0.477***	–0.334**	–0.195
	(0.094)	(0.096)	(0.113)	(0.118)	(0.119)	(0.129)	(0.134)	(0.144)	(0.136)	(0.135)

The table presents coefficient estimates of $\widetilde{MA}^{in}$ and $\widetilde{MA}^{out}$ based on four sets of estimates of Equation (**13**) of the main paper. The results from the original baseline estimates are shown in Table 3. We alter the construction of $\widetilde{MA}^{in}$ and $\widetilde{MA}^{out}$ from the original 36-month rolling-window estimate (see Equation (**6**)) to a 12-month, 24-month, 48-month, and 60-month rolling window. 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: Alternative Foreign Exchange Rate Predictability

	P_1	P_2	P_3	HML	Linear	Rank
			12 month standardization			
mean (%)	–0.38	0.65	4.00	4.38	3.66	3.53
t-stat	–0.19	0.38	2.21	3.95	3.42	3.33
SR	–0.05	0.09	0.47	0.77	0.66	0.66
fx (%)	–2.11	–0.64	1.25	3.36	2.53	2.59
fp (%)	1.73	1.29	2.75	1.02	1.13	0.93
			24 month standardization			
mean (%)	0.42	0.36	3.53	3.11	3.71	3.49
t-stat	0.21	0.21	1.88	2.68	3.28	3.39
SR	0.05	0.05	0.42	0.57	0.67	0.68
fx (%)	–1.17	–0.95	0.65	1.82	2.29	2.29
fp (%)	1.58	1.32	2.88	1.30	1.43	1.20
			48 month standardization			
mean (%)	–0.14	0.03	4.11	4.25	3.91	3.69
t-stat	–0.07	0.02	2.19	3.70	3.43	3.45
SR	–0.02	0.00	0.49	0.74	0.70	0.69
fx (%)	–1.70	–1.25	1.19	2.89	2.42	2.44
fp (%)	1.56	1.28	2.92	1.37	1.49	1.24
			60 month standardization			
mean (%)	–0.57	1.36	3.80	4.38	3.86	3.71
t-stat	–0.30	0.76	2.07	3.61	3.34	3.30
SR	–0.07	0.18	0.46	0.76	0.69	0.70
fx (%)	–2.06	–0.10	0.90	2.95	2.43	2.49
fp (%)	1.48	1.46	2.91	1.42	1.43	1.22

The table presents statistics on cross-border merger and acquisition portfolios, based on abnormal M&A activity constructed over different standardization windows ranging from 12 to 60 months. Statistics include the average annualized (*mean*) return and associated t-statistic, calculated using Newey and West (1987) standard errors; Sharpe ratio (*SR*); average return spot return (*fx*) and forward premium (*fp*). 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. 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.8: Including Canada and Mexico: Economic Growth

	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)**
$\widetilde{MA}$	0.107*	0.128**	0.131*	0.147**	0.250***	0.271***	0.317***	0.383***	0.365***	0.417***
	(0.062)	(0.064)	(0.070)	(0.073)	(0.073)	(0.079)	(0.081)	(0.086)	(0.083)	(0.082)
CLI	–0.824***		–1.417***		–1.632***		–1.994***		–1.543***	
	(0.091)		(0.099)		(0.101)		(0.116)		(0.119)	
Dividend yield		0.194		0.151		–0.024		0.129		0.390
		(0.210)		(0.219)		(0.236)		(0.247)		(0.247)
Stock return		0.031		0.009		0.019		0.013		0.004
		(0.029)		(0.030)		(0.032)		(0.034)		(0.032)
Term spread		0.035		0.252		0.502**		0.239		0.976***
		(0.185)		(0.189)		(0.207)		(0.212)		(0.200)
Short rate		–0.502***		–0.428***		0.125		0.224		0.740***
		(0.132)		(0.144)		(0.171)		(0.168)		(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 42 developed and emerging market countries. The data is monthly, beginning in December 1996 and ending in November 2018.

Table A.9: Including Canada and Mexico: Foreign Exchange Rates

	$\mathbf{P_1}$	$\mathbf{P_2}$	$\mathbf{P_3}$	**HML**	**Linear**	**Rank**
mean (%)	–0.08	0.36	3.87	3.95	3.22	3.26
t-stat	–0.04	0.22	2.22	3.58	2.93	3.18
std (%)	7.87	7.23	7.94	5.36	5.20	5.09
SR	–0.01	0.05	0.49	0.74	0.62	0.64
skew	–0.20	–0.27	–0.24	–0.25	–0.16	–0.24
kurt	4.51	4.75	4.87	4.31	3.54	4.28
ar(1)	0.10	0.05	0.04	0.01	0.01	–0.01
mdd (%)	43.1	29.0	20.3	12.5	19.2	14.3
fx (%)	–1.95	–1.11	1.00	2.95	2.02	2.25
fp (%)	1.87	1.48	2.88	1.01	1.20	1.01
$\mu_{\widetilde{MA}_{i,t}}$	–1.18	0.33	1.73			

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*), average spot return (*fx*) and forward premium (*fp*). The final row reports the average value of the $\widetilde{MA}_{it}$ variable in P_1, P_2, and P_3, which denote the 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 42 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.10: 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. The one-year growth in IP, RS, and UE is winsorized at the 1st and 99th percentiles (as opposed to the 5th and 95th percentiles). 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.11: 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. The one-year growth in IP, RS, and UE is winsorized at the 10th and 90th percentiles (as opposed to the 5th and 95th percentiles). 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: 5 Portfolios

	P_1	P_2	P_3	P_4	P_5	HML	Linear	Rank
mean (%)	–0.55	–1.49	0.53	3.90	4.23	4.78	4.06	4.12
t-stat	–0.27	–0.72	0.31	1.80	2.11	3.01	3.61	3.79
std (%)	8.71	8.22	7.87	8.73	9.63	7.75	5.59	5.44
SR	–0.06	–0.18	0.07	0.45	0.44	0.62	0.73	0.76
skew	–0.31	–0.19	–0.09	–0.41	0.33	0.26	–0.28	–0.31
kurt	4.40	5.00	5.40	4.95	4.11	4.92	3.82	4.74
ar(1)	0.07	0.11	0.01	0.12	–0.03	0.00	–0.02	–0.03
mdd (%)	51.2	40.4	34.7	35.1	19.4	11.8	12.3	8.3
fx (%)	–2.33	–2.64	–0.62	1.67	0.84	3.17	2.60	2.89
fp (%)	1.78	1.15	1.15	2.23	3.39	1.61	1.46	1.24
$\mu_{\widetilde{MA}_{i,t}}$	–1.44	–0.43	0.45	1.21	2.21			

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*), average spot return (*fx*) and forward premium (*fp*). The final row reports the average value of the $\widetilde{MA}_{it}$ variable in P_1, P_2, P_3, P_4, and P_5 which denote the 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.13: Including Zeros

	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)**
$\widetilde{MA}_{12}^{in}$	–0.143	–0.127	–0.118	-0.193*	–0.219**	-0.183*	–0.079	–0.126	0.056	0.050
	(0.090)	(0.092)	(0.100)	(0.102)	(0.105)	(0.108)	(0.112)	(0.117)	(0.113)	(0.112)
$\widetilde{MA}_{24}^{in}$	–0.142	–0.127	–0.141	-0.180*	–0.090	-0.079	0.161	0.105	0.275**	0.235**
	(0.087)	(0.094)	(0.095)	(0.104)	(0.102)	(0.110)	(0.110)	(0.116)	(0.112)	(0.113)
$\widetilde{MA}_{48}^{in}$	–0.154*	–0.100	–0.007	0.059	0.092	0.239**	0.365***	0.488***	0.338***	0.569***
	(0.082)	(0.091)	(0.092)	(0.099)	(0.099)	(0.105)	(0.106)	(0.109)	(0.109)	(0.108)
$\widetilde{MA}_{60}^{in}$	–0.103	–0.007	0.029	0.169*	0.145	0.392***	0.346***	0.608***	0.312***	0.608***
	(0.083)	(0.092)	(0.092)	(0.099)	(0.099)	(0.105)	(0.105)	(0.108)	(0.110)	(0.108)
$\widetilde{MA}_{12}^{out}$	–0.208**	–0.204**	–0.178	–0.219*	–0.245**	–0.267**	–0.099	–0.203	–0.053	–0.038
	(0.101)	(0.097)	(0.118)	(0.120)	(0.120)	(0.124)	(0.134)	(0.141)	(0.141)	(0.134)
$\widetilde{MA}_{24}^{out}$	–0.202**	–0.197**	–0.351***	–0.352***	–0.367***	–0.383***	–0.257*	–0.370**	–0.279**	–0.232*
	(0.098)	(0.096)	(0.112)	(0.117)	(0.121)	(0.125)	(0.136)	(0.144)	(0.142)	(0.137)
$\widetilde{MA}_{48}^{out}$	–0.353***	–0.280***	–0.504***	–0.410***	–0.527***	–0.445***	–0.513***	–0.465***	–0.440***	–0.213
	(0.094)	(0.093)	(0.107)	(0.112)	(0.120)	(0.125)	(0.132)	(0.140)	(0.136)	(0.130)
$\widetilde{MA}_{60}^{out}$	–0.340***	–0.266***	–0.505***	–0.383***	–0.503***	–0.375***	–0.482***	–0.375***	–0.429***	–0.195
	(0.094)	(0.092)	(0.106)	(0.111)	(0.119)	(0.124)	(0.131)	(0.140)	(0.135)	(0.129)

The table presents coefficient estimates of $\widetilde{MA}^{in}$ and $\widetilde{MA}^{out}$ based on four sets of estimates of Equation (**13**) of the main paper, where non-informative zeros ($\widetilde{MA}_{i,t} = 0$) are included. The results from the original baseline estimates are shown in Table 3. We alter the construction of $\widetilde{MA}^{in}$ and $\widetilde{MA}^{out}$ from the original 36-month rolling-window estimate (see Equation (**6**)) to a 12-month, 24-month, 48-month, and 60-month rolling window. 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.14: Cross-Border M&A Portfolios and Currency Return Predictability (financial and non-financial firms)

	$\mathbf{P_1}$	$\mathbf{P_2}$	$\mathbf{P_3}$	**HML**	**Linear**	**Rank**	$\mathbf{P_1}$	$\mathbf{P_2}$	$\mathbf{P_3}$	**HML**	**Linear**	**Rank**
	Non-financial firms						*Financial firms*					
mean (%)	–0.24	0.65	3.18	3.42	3.12	3.03	0.04	0.98	2.24	2.19	1.58	2.10
t-stat	–0.12	0.38	1.74	3.04	2.68	2.79	0.03	0.56	1.18	1.54	1.23	1.59
std (%)	8.02	7.41	8.29	6.05	6.24	5.71	8.09	7.36	8.86	8.04	7.46	7.51
SR	–0.03	0.09	0.38	0.57	0.50	0.53	0.01	0.13	0.25	0.27	0.21	0.28
skew	0.03	0.08	0.01	0.40	–0.19	0.29	–0.05	0.05	–0.08	0.01	–0.17	–0.16
kurt	4.13	4.61	5.01	5.13	4.59	4.80	5.72	6.27	4.01	4.33	4.79	4.72
ar(1)	0.11	0.05	0.02	–0.08	–0.09	–0.07	0.05	0.09	–0.01	–0.12	–0.11	–0.11
mdd (%)	36.8	22.5	22.6	8.2	14.3	10.4	38.7	24.8	26.5	27.7	26.7	25.6
fx (%)	–1.41	–0.28	0.40	1.81	1.55	1.59	–1.52	–0.42	–0.21	1.31	0.74	1.34
fp (%)	1.17	0.93	2.78	1.61	1.57	1.44	1.57	1.40	2.45	0.88	0.84	0.76
$\mu_{\widetilde{MA}_{i,t}}$	–1.28	0.25	1.72				–1.16	0.68	2.34			

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*), average spot return (*fx*) and forward premium (*fp*). The final row reports the average value of the $\widetilde{MA}_{it}$ variable in P_1, P_2, and P_3, which denote the 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 deals involving financial firms (SIC codes 6000-6999) are presented in the right panel. The left panel reports the results for deals involving non-financial firms. All statistics are calculated using monthly returns from January 1997 to December 2018.

Table A.15: Using $\widetilde{MA}^{\$}$ to Forecast Changes in Economic Growth

Panel A: Orthogonalizing $\widetilde{MA}$ Relative to $\widetilde{MA}^{\$}$

	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)**
$\perp \widetilde{MA}$	0.133*	0.207***	0.166**	0.189**	0.184**	0.273***	0.270***	0.307***	0.352***	0.334***
	(0.071)	(0.073)	(0.0.079)	(0.082)	(0.086)	(0.090)	(0.093)	(0.100)	(0.096)	(0.096)

Panel B: Orthogonalizing $\widetilde{MA}^{\$}$ Relative to $\widetilde{MA}$

	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)**
$\perp \widetilde{MA}^{\$}$	–0.131**	–0.174**	–0.101	–0.066	–0.032	–0.061	0.131	0.115	0.199**	0.209**
	(0.066)	(0.068)	(0.078)	(0.082)	(0.082)	(0.089)	(0.087)	(0.092)	(0.092)	(0.089)

The table presents coefficient estimates of $\perp \widetilde{MA}$ and $\perp \widetilde{MA}^{\$}$ based on two estimates of Equation (**11**) of the main paper. The results from the original baseline estimates are shown in Table 2. In Panel A, we alter the construction of $\widetilde{MA}$ from the original 36-month rolling-window estimate (see Equation (**6**)) by orthogonalizing the measure relative to $\widetilde{MA}^{\$}$ (Equation (**17**)). In Panel B, we orthogonalize $\widetilde{MA}^{\$}$ relative to our original measure $\widetilde{MA}$ and use it to replace $\widetilde{MA}$ in Equation (**11**). 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.16: Uncompleted Deals

	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)**
$\widetilde{MA}$	0.128*	0.144*	0.058	0.027	0.204**	0.192*	0.266***	0.285**	0.349***	0.312**
	(0.078)	(0.079)	(0.081)	(0.090)	(0.093)	(0.102)	(0.102)	(0.118)	(0.108)	(0.122)
CLI	–1.207***		–1.854***		–1.923***		–2.118***		–1.940***	
	(0.163)		(0.162)		(0.176)		(0.184)		(0.196)	
Dividend yield		0.632		–0.055		0.056		0.230		1.091*
		(0.478)		(0.477)		(0.565)		(0.654)		(0.636)
Stock return		0.010		0.032		0.009		–0.016		0.003
		(0.055)		(0.062)		(0.068)		(0.072)		(0.071)
Term spread		0.105		0.617*		0.441		0.576		1.221***
		(0.311)		(0.368)		(0.408)		(0.405)		(0.430)
Short rate		–0.686***		–0.348		–0.165		0.105		0.454
		(0.230)		(0.274)		(0.337)		(0.323)		(0.323)
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.	1,214	1,129	1,147	1,065	1,070	992	1,008	932	940	872
Adj. R^2	0.50	0.51	0.59	0.57	0.52	0.48	0.50	0.44	0.53	0.51

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 an alternative measure of abnormal cross-border M&A activity, constructed using the number of announced deals that are uncompleted ($\widetilde{MA}^{*}_{i,t}$):

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

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.17: Explaining Abnormal M&A Activity with Value and Momentum

	Dependent variable: $\widetilde{MA}_{i,t}$		
$VAL_{i,t}$	0.171		0.175
	(0.173)		(0.192)
$MOM_{i,t}$		0.545	0.535
		(0.345)	(0.356)
constant	1.066	–1.205***	–0.441
	(1.316)	(0.199)	(0.461)
Country FE	YES	YES	YES
Time FE	YES	YES	YES
Obs.	3,030	2,974	2,833
Adj. R^2	0.12	0.14	0.13

The table presents coefficient estimates from panel regressions of abnormal cross-border M&A activity ($\widetilde{MA}_{i,t}$) on contemporaneous currency value ($VAL_{i,t}$) and momentum ($MOM_{i,t}$) signals:

$$\widetilde{MA}_{i,t} = \alpha_i + \beta_1 VAL_{i,t} + \beta_2 MOM_{i,t} + \kappa_i + \lambda_t + \varepsilon_{i,t},$$

where κ_i and λ_t denote country and time fixed effects. 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.

Section B: Sources of Currency Return Predictability

We construct seven alternative currency portfolios based on the recent currency market literature. The portfolios are:

1. **Dollar.** Equally weighted long position in all currencies against the US dollar. The portfolio has been shown to offer a small positive return, on average, that could account for the special role of the US dollar in the international monetary system (Maggiori, 2017). It is also the main currency factor (i.e., the market factor) explaining bilateral foreign exchange returns (Verdelhan, 2018).
2. **Carry.** Buys currencies that are trading at the largest forward discount (i.e., highest interest rate) and sells currencies trading at a forward premium (Lustig et al., 2011).
3. **Momentum.** Buys "winner" currencies and sells "loser" currencies. We follow the approach of Asness et al. (2013), and calculate momentum over a 12-month period, implementing the portfolio using a 1-month formation period.
4. **Value.** Buys "undervalued" currencies and sells "overvalued" currencies. We follow Asness et al. (2013) and calculate currency value as the difference between the 60-month inflation differential and the FX return over the same period.
5. **Dollar-Carry.** Either entirely long or short the US dollar against other currencies, conditional on the average forward discount against the US dollar (Lustig et al., 2014).

6/7. **Macroeconomic and inflation growth momentum.** Buys (sells) currencies issued by countries with the strongest (weakest) macroeconomic growth and inflation momentum. The two strategies are constructed following Dahlquist and Hasseltoft (2020).

Section C: 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.