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

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Abstract

We extract expectations about future economic growth from firms' cross-border merger and acquisition (M&A) announcements, and show they predict changes in economic growth rates and foreign exchange rate returns. The predictability is driven by the cross-border M&A announcements of cyclical domestic firms, which signal turning points in local economic conditions. The findings are motivated via a simple model of exchange rate determination with heterogeneous expectations and support the theorized connection between foreign exchange rates and macroeconomic fundamentals. The results provide new tools for policy makers concerned with predicting economic activity and offer global investors a novel source of portfolio diversification.

Keywords: exchange rate determination, foreign exchange predictability, cross-border mergers and acquisitions, 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 expectations about future macro fundamentals, such as economic growth—a relationship that is encapsulated in a broad class of present-value models (e.g., Engel and West, 2005). If macro fundamentals are predictable, then the theorized relationship implies that the local exchange rate should appreciate when new information necessitates an upward revision to those expectations. Moreover, the appreciation should not be entirely instantaneous if agents form heterogeneous expectations about macro fundamentals—a common assumption in models of exchange rate determination (Bacchetta and Van Wincoop, 2006; Cespa et al., 2022). One potential approach to empirically test these theoretical implications is, therefore, to study if changes in the market's expectations about future macro fundamentals can predict subsequent exchange rate returns. The econometrician faces an empirical challenge, however, in adopting this approach because the market's expectations about future macro fundamentals are unobservable.

In this paper we aim to overcome this challenge, in an effort to shed new light on exchange rate determination. While the econometrician cannot observe market-wide expectations, she can observe agents' *actions*. When agents in the economy undertake actions, which are conditioned on private information they hold about future macro fundamentals, they reveal a noisy predictive signal about those fundamentals to the market—impacting market-wide expectations. Therefore, by studying the predictive signals emerging from the actions of informed agents, the econometrician can indirectly learn about the market's changing expectations, providing a novel means to test the theorized relationship between macroeconomic fundamentals and foreign exchange rates.

An important question arises: which economic agents *are* privately informed about future macro fundamentals? While various economic agents may obtain private signals, the group that is most closely tied to economic activity and which routinely undertakes observable actions, conditional on private information, are *firms*. Firms have a special place in the economy since they observe real-time data about their own and their industry's economic activity, providing them with private information to use when taking corporate actions (see, e.g. Andrade et al., 2022).[1,2] Since most firms are not profit-seeking in the FX market, their information sets are unlikely

[1] 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 considerable data at their fingertips, including internal financial data and external market information, to create informed estimates about, *inter alia*, sales growth and aggregate economic conditions. See "Bringing a real-world edge to forecasting," McKinsey & Company, March 13, 2020.

[2] Governments (including central banks) and households may also obtain private signals, either through collecting information about firms in the economy or through the provision of their labour, respectively. In both cases, however, it is unclear what actions are routinely undertaken that are conditional on this information. One possibility is to explore the information contained in unexpected central bank decisions. However, there is limited information about those underlying market-wide expectations across a large cross-section of countries.

to be fully revealed through FX trading but instead through key corporate activities such as investments.[3] Indeed, firms have a clear incentive to form expectations when selecting investment opportunities, since aggregate economic output impacts both the cash flows and discount rates associated with a potential project (e.g., Gennaioli et al., 2016; Coibion et al., 2018).

Therefore, when a firm announces a new investment, it plausibly reveals private information about the future state of the economy. When a firm announces a new *international* investment, it plausibly reveals private information about the future state of both the local and foreign economies. The economic mechanism is intuitive: when making investment decisions, multinational firms are not obliged to invest in their domestic market, especially if prospects appear to be deteriorating domestically or improving in a foreign economy. An *abnormally* high net investment inflow (more inflows or less outflows than typical) at the country level may thus reveal information that local growth is expected to rise, while unusually low net investment inflows (less inflows or more outflows than typical) may signal weaker future growth. If the international investment activity of firms does predict the changing state of the economy, then it validates those actions as providing important signals that affect market-wide expectations about future economic growth—leading to the tantalizing prospect that the signals also predict exchange rate returns, supporting the link between macroeconomic fundamentals and foreign exchange rates.

While firms undertake investments for a variety of reasons, our central proposition is that the aggregation of investment flows helps to synthesize the dispersed private signals that firms observe about future economic conditions. Thus, by studying the peaks and troughs of this aggregate economic behavior, we can learn about the relative direction and strength of those signals. In Section 2, we discuss the related literatures in exchange rate economics and corporate investments, while also expanding upon the theoretical foundations motivating our study. Moreover, in the Appendix, we present a simple model of exchange rate determination that serves to make precise the core economic mechanisms. In summary, there are three central ingredients: (i) exchange rates are determined by the markets' expectation about a future fundamental; (ii) the fundamental contains a predictable component; and (iii) agents in the economy form heterogeneous expectations about the fundamental. Armed with these three ingredients we show that the exchange rate can be forecast using the same information that changes expectations about the fundamental. The central empirical task of this paper is to devise a method to extract this information from agents' actions, and thus indirectly study whether exchange rates respond over time to the market's changing beliefs about future macro fundamentals.

[3] Corporate FX trades are often mechanical—the outcome of routine daily operations, such as transaction hedging or treasury management, which are unlikely to be driven by expectations about macro fundamentals.

We study firms' real international investment activity, i.e., foreign direct investment (FDI), using data on the largest component of FDI—cross-border mergers and acquisitions (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 a monthly measure of "abnormal" cross-border M&A activity for each country that is designed to capture the predictive signals revealed by firms. We construct the measure as the difference between the sum of recently announced cross-border M&A net inflows to a country (i.e., the sum of inflows minus the sum of outflows) and the long-run trend in its level, standardized by volatility.

In Section 4, we turn to study the predictability of economic growth using our newly formed measure. In particular, we evaluate whether abnormal levels of announced cross-border M&A deals predict turning points in economic growth. In predictive panel regressions we find that abnormally high M&A net inflows are followed, on average, by higher economic growth rates, while lower economic growth rates follow 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 the predictability extends beyond other leading economic indicators, implying that new information is revealed to the market through cross-border M&A announcements. Furthermore, the changes in economic growth reflect *reversals* in economic conditions: abnormally high M&A net inflows capture, on average, the turning point at which economic growth shifts from a declining to an increasing trend, and vice-versa for abnormally low M&A net inflows.

The predictability we uncover supports the claim that firms reveal private information that provides a signal about future economic growth. It is natural to ask, therefore, how these signals are obtained and which firms are most likely to obtain them. We conjecture that through their day-to-day operations, firms receive private signals about their *local* economic conditions. Indeed, domestic firms and investors are known to have more accurate information about local economic conditions than foreigners, since they are "closer to the information" (see, e.g. Frankel and Schmukler, 1996; Brennan and Cao, 1997; Van Nieuwerburgh and Veldkamp, 2009; Tille and van Wincoop, 2014). We therefore test whether *domestic* firms are especially revealing about local economic conditions. Decomposing abnormal net inflows into foreign M&A *in*flows and domestic M&A *out*flows, we find the predictability of an economic growth reversal is driven entirely by the acquisition activity of domestic firms. While domestic firms may have an informational advantage over foreign firms, there is also reason to think that *within* the set of domestic firms, some would be more likely to obtain superior signals about changing economic conditions than others. In particular, firms operating in cyclical industries are more exposed to real-time data about the economy's growth rate. And indeed, when we further decompose our measure by the cyclicality of the industry, we find the predictability we observe is obtained from the cross-border M&A announcements of domestic firms operating in cyclical industries.

Having established the link between the main measure and changes in economic growth, we turn, in Section 5, to explore the central issue of exchange rate predictability. Historically, exchange rate predictability has been virtually unobservable in time-series studies at horizons under one year (Meese and Rogoff, 1983; Rossi, 2013). Recent studies have turned, with far greater success, to the cross-section via the construction of currency portfolios (Lustig and Verdelhan, 2007). The approach exploits the fact that exchange rates tend to co-vary with one another over time in predictable ways (Lustig et al., 2011; Verdelhan, 2018). Thus, while a signal may not precisely predict bilateral exchange rates, it may provide information about *relative* exchange rate returns. Put differently, the fact that a country's signal is "high" may be less informative than whether it is *higher* than other countries' signals. The approach is also conceptually attractive for this study because our main measure serves as a noisy proxy for changing market-wide expectations. By grouping countries, the cross-sectional approach reduces the impact of measurement error by testing if countries with rising (falling) expectations tend to appreciate (depreciate) *on average*.

We follow this literature by building currency portfolios in which higher positive portfolio weight is assigned to countries for which announced M&A net inflows are abnormally high.[4] Under the null hypothesis of no *currency* return predictability, the portfolios should generate zero average returns. Instead, we find the portfolios generate positive and statistically significant returns. This initial finding is important for global currency investors, given the impressive risk-return profiles of the portfolios (Sharpe ratios range from 0.73 to 0.76) and because the returns are unrelated to other currency strategies—providing a novel source of portfolio diversification.

Crucially, from the perspective of exchange rate determination, we find the currency returns are primarily driven by predicting exchange rate returns and not from simply recreating a "carry trade" strategy. Consistent with the hypothesized present-value relationship, currencies associated with the most abnormally high level of net investment inflows appreciate on average over the following month, while those exposed to the lowest abnormal net investment inflows depreciate. Supporting the earlier results obtained on the predictability of economic growth, we find that 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

[4]We implement three portfolio weighting schemes: "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.

depreciation of 5.07% over the following month, while an annualized *appreciation* of 5.02% is observed following an abnormally low outflow. Moreover, among domestic firms, the strength of the exchange rate predictability is highest for cyclical firms. For example, the size of the currency depreciation, following an abnormally large cross-border M&A outflow, is found to be over 2% larger if driven by cyclical, rather than non-cyclical, firm outflows.

In Section 6, we document additional analysis. We find that the predictability of exchange rate returns is stronger when forming our main measure using the *number* rather than the *dollar value* of announced cross-border M&A deals—rejecting an alternative "transaction" hypothesis. In addition, we construct an alternative measure using dollar values relative to gross domestic product (GDP), to capture the potential causal effect of M&A activity on the real economy. We show that this alternative measure is uninformative about changes in economic growth when orthogonalized relative to our main measure, but the reverse is not true. The finding indicates that abnormal M&A net inflows *predict* rather than *cause* changes in economic growth—supporting the information channel we propose. Finally, our analysis rules out endogeneity concerns arising from the possibility that past exchange rate movements, macroeconomic forces, or political factors, drive our results. Specifically, we show that the residuals from regressing our measure on a variety of determinants continues to generate our main result. In the Internet Appendix, we document a battery of additional robustness checks.

Overall, the study provides novel evidence on the determination of exchange rates that supports the widely theorized, but fleetingly observed, connection between macroeconomic fundamentals and foreign exchange rates. The connection is established via the predictability of exchange rate returns, which we find to be driven by the international investment activity of domestic firms operating in cyclical industries. The evidence also provides broad support to theoretical literatures, in which agents are modelled as forming heterogeneous expectations about macro fundamentals, and in which domestic agents are assumed to hold more precise expectations than foreigners about domestic economic conditions.

The results have broad practical implications: for policy makers, the findings provide a new way to assess the informativeness of FDI and provide an additional variable for forecasting economic growth, while for global investors, the predictability can be used to construct a novel currency investment strategy that offers a beneficial source of portfolio diversification.

2 Theoretical Framework and Literature Review

The paper is primarily related to various strands of foreign exchange literature. Most notable is the literature on the "disconnect" between macroeconomic fundamentals and exchange rates (Obstfeld and Rogoff, 2000). The surprising lack of an observable relationship between economic fundamentals and exchange rate returns dates back to the seminal findings of Meese and Rogoff (1983). One potential explanation for the weak link is that exchange rates are determined in a present-value framework by an infinite stream of fundamentals—expectations about *future* fundamentals are critical.[5] If those fundamentals are themselves unpredictable, then a lack of a relationship with the exchange rate can be easily rationalized (Engel et al., 2007).

In this paper, we take an alternative approach by exploring the implications of macro fundamentals having a predictable component that is not uniformly interpreted by all currency market agents (i.e., heterogeneous expectations, see e.g., Bacchetta and Van Wincoop, 2006; Cespa et al., 2022; Jeanneret and Sokolovski, 2021).[6] Currency market participants can form different expectations for a variety of reasons. Some agents choose to be better informed than others because they trade for a profit motive, whereas a large proportion of currency trading, for example by central banks and corporations, is for liquidity reasons. In this case, public information is processed in different ways—some agents rationally choose to develop better models than others. Indeed, Cespa et al. (2022) find that the currency market exhibits a high degree of asymmetric information, far higher than observed in equity markets. Even among professional forecasters, disagreement about future fundamentals is widespread (Della Corte and Krecetovs, 2019) and hence, whether via asymmetric information or heterogeneous beliefs, there is strong support for

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

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

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

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

[6]A recent literature has found evidence of a stronger relationship when macroeconomic fundamentals are explored in the cross-section (Sarno and Schmeling, 2014; Dahlquist and Hasseltoft, 2020; Colacito et al., 2020) or using microeconomic information at the security (Lilley et al., 2021) or firm level (Adams and Verdelhan, 2021). Some time-series evidence exists on a link between macroeconomic fundamentals and exchange rates at either much longer or shorter horizons. Mark (1995), for example, finds that macroeconomic fundamentals can predict exchange rate returns at horizons greater than one year, while Andersen et al. (2003) find that economic announcements impact the exchange rate in the minutes following their release.

the assumption that agents form heterogeneous expectations about future fundamentals.

In the Appendix, we present a simple model of exchange rate determination that serves to highlight the main theoretical mechanisms described above. We begin from a present-value framework, in which a fundamental (e.g., the growth rate of the economy) determines the level of the exchange rate. In the model, public information is exogenously revealed that provides a noisy predictive signal about the fundamental, changing market-wide expectations. The key testable implication is that the exchange rate should be predictable using the same signal that forecasts the fundamental if agents form heterogeneous expectations about the fundamental. Therefore, if the signal reveals "good" economic news, the local exchange rate continues to appreciate following the release of the signal, and continues to depreciation in the case of "bad" news.

The key innovation in this paper is to quantitatively extract signals about future macro fundamentals from firms' cross-border M&A announcements. As market expectations react to public signals, we indirectly study if changing market expectations about macro fundamentals are connected to subsequent exchange rate movements, for which we find strong empirical support. Moreover, finding a difference in the predictive content of domestic and foreign M&A flows implies that agents form heterogeneous beliefs, and supports the theoretical literature in which domestic agents have a more precise signal about local economic outcomes. Brennan and Cao (1997), for example, present a theoretical model in which domestic investors possess an information advantage over foreign investors due to closer observations of the domestic economy. In other empirical work, Frankel and Schmukler (1996) show that during the Mexican peso crisis in 1994, domestic investors were the first to sell Mexican assets, indicating that domestic investors, who are "closer to the information," form more accurate expectations about local economic events.[7]

The paper also has links with the foreign exchange literature on order flow. If a group of economic agents are privately informed about future fundamentals then their FX trading may reveal that information. Indeed, evidence shows that FX order flow helps to predict exchange rate returns and has been linked to future fundamentals (Rime et al., 2010).[8] We consider a quite different source of information that is revealed by firms outside of their FX trading. Indeed, the FX trades of commercial firms are unrelated to future exchange rates (Menkhoff et al., 2016; Ranaldo and Somogyi, 2021), further highlighting the novelty of the channel we propose.

Finally, in the exchange rate literature, the paper is related to work on currency investment strategies. 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

[7]See also, *inter alia*, Kang and Stulz (1997); Coval and Moskowitz (2001); Dvořák (2005); Ivković and Weisbenner (2005); Van Nieuwerburgh and Veldkamp (2009).

[8]Albuquerque et al. (2008) find that *equity* order flow forecasts currency returns.

countries by their abnormal cross-border M&A activity is orthogonal to sorting by economic momentum because it captures a reversal, rather than momentum, in economic growth. The returns are also unrelated, both conceptually and empirically, to various other sources of currency return predictability including carry, value, and momentum.[9]

2.1 Corporate investments

In the corporate investments literature, the forward-looking aspect of investment decision making has long-standing theoretical underpinnings: Bernanke (1983) shows that expected changes in fundamentals affect investment decisions, while in the model of Nickell (1974), firms adjust investment plans based on their expectations about future demand—investment stops before demand reaches a peak and resumes after the trough.[10] Melicher et al. (1983) propose a theory for understanding the link between aggregate merger activity and macroeconomic fundamentals. According to the theory, managers tie acquisition decisions, in part, to expected changes in macroeconomic conditions. Declining economic expectations may, therefore, encourage local firms to invest overseas and discourage inbound M&A flows, as foreign firms avoid extending their organization into weakening economies.[11] The view echoes that of practitioners. 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, M&A activity, and other investment policies.[12] While according to Deloitte, relative cross-country growth prospects are the main driver of cross-border M&A investment activity.[13]

We contribute to this literature by showing that fluctuations in aggregate cross-border M&A activity serve as a transmission mechanism through which dispersed private information held by firms is synthesized and revealed to the public. We focus on *aggregate* cross-border M&A activity since international investments are not determined *only* by expectations about future macro fundamentals. Indeed, firms undertake these investments for heterogeneous reasons and no individual project is necessarily informative. But by aggregating and standardizing the announced investment flows, the idiosyncratic motivations are averaged out, and the time invariant factors are removed, to reveal a more precise signal about the information driving firms' actions and the impact those actions have on market-wide expectations.

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

[10]See also Arrow (1968).

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

[12]"The Political Issues Board Directors Care Most About," Harvard Business Review, February 16, 2016.

[13]"M&A Insights: Global M&A Drivers," Deloitte, Spring 2016.

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.[14] 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.[15,16] We limit the analysis to major developed and emerging market currencies covering 41 countries, including 20 developed and 21 emerging markets. The countries include (developed countries are denoted in bold): Argentina, **Australia**, **Austria**, **Belgium**, Brazil, Chile, Colombia, Czech Republic, **Denmark**, Estonia, **Eurozone**, **Finland**, **France**, **Germany**, Greece, Hungary, Iceland, India, Indonesia, **Ireland**, **Israel**, **Italy**, **Japan**, Latvia, Lithuania, **Netherlands**, **New Zealand**, **Norway**, Poland, Portugal, Russia, Slovak Republic, Slovenia, South Africa, South Korea, **Spain**, **Sweden**, **Switzerland**, Turkey, the **United Kingdom**, and the **United States**.[17]

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. The frequency of deals was low in the 1970s and 1980s. Only from the mid 1990s was activity sufficiently high to obtain informative signals 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—a subset of FDI—and not directly on aggregate FDI itself. We do so for four reasons. First, aggregate FDI consists of equity investment, inter-company debt,

[14]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).

[15]In our main analysis, we include cross-border M&As by both financial and non-financial firms. However, we find our results continue to hold when we exclude financial firms. See Section 6.4 for further details.

[16]Excluding deals with missing values is also appropriate because 68% of those deals are found to have delayed announcements, i.e., the effective date of completion occurs on or before the announcement date, and thus these deals are likely to weaken the informativeness of our main measure.

[17]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 the Internet Appendix we provide evidence, however, that their exclusion does not affect our main findings. See Section 6.4 for further details.

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.[18] 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.[19]

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 that we account for in our main 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.

[18]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.

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

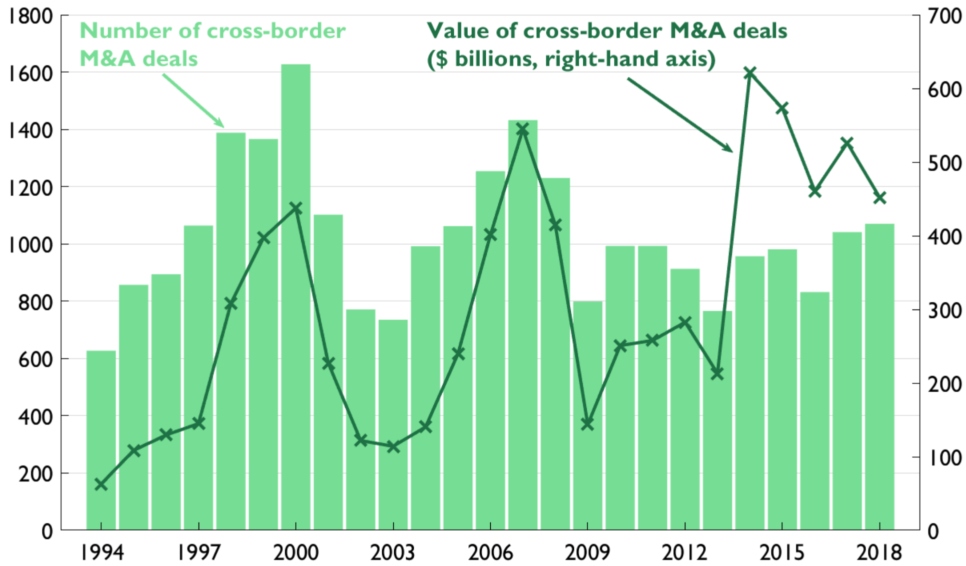

Fig 1. Number and Value of Announced Cross-Border M&As. The figure plots the time series of the total number of cross-border M&A deals in the sample (left-hand axis, bar plot) and the total value of those deals in US dollar billions (right-hand axis, line plot).

3.2 Constructing the main measure

Our main measure is designed to capture information revealed by firms about changing economic conditions that impact the market's expectations about future economic growth rates. To construct the main measure, we begin by calculating the cross-border M&A activity between the US and country $i = 1, 2, ..., N-1$ (country N denotes the US) as the sum of announced inflows ($MA^{in}_{i,t}$) *minus* the sum of announced outflows ($MA^{out}_{i,t}$) in month t:

$$MA_{i,t} = MA^{in}_{i,t} - MA^{out}_{i,t}. \tag{3}$$

A negative value therefore reflects, for example, that firms in country i announced more acquisitions of US firms during the month than vice versa.[20] We make an equivalent calculation for the United States that aggregates across all other countries, i.e.,

$$MA_{US,t} = \sum_{i=1}^{N-1} MA^{in}_{i,t} - \sum_{i=1}^{N-1} MA^{out}_{i,t}. \tag{4}$$

The value of $M\&A_{i,t}$ may be high, in absolute terms, simply because two countries are closely connected because of, for example, time invariant, country-specific factors.[21] Similarly, some

[20]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.

[21]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).

countries will experience long periods in which no cross-border M&A deals are announced and thus a lack of M&A activity is "normal" and not indicative of any new information. It is only when activity deviates from its trend that the announcements convey a useful signal. We therefore define "normal" M&A activity for each country as its trend level, that we set equal to its median level over the prior 36 months ($\overline{MA}_{i,t}$).[22] Furthermore, to prevent countries with high raw values from dominating the later analysis, we standardize the measure by its standard deviation ($\sigma_{i,t}$) calculated over the same period. Thus, our main measure is defined as,

$$\widetilde{MA}_{i,t} = \frac{MA_{i,t} - \overline{MA}_{i,t}}{\sigma_{i,t}}. \tag{5}$$

Since the standardization requires estimating a trend, the first values of $\widetilde{MA}_{i,t}$ are obtained in December 1996, and thus the first forecasts are for January 1997. 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 new information revealed by cross-border M&A deals, we define the main measure as missing when it equals zero, since it implies that no information has been revealed to the market (i.e., $MA_{i,t} = \overline{MA}_{i,t}$).[23]

Our measure is constructed using the *number* of deals. A potential concern is that the measure does not account for the *dollar size* of individual deals, especially if the dollar volume 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 dollar values, on the other hand, fails to capture this information. An unusually high deal value could reflect, for example, a mega deal undertaken by a single firm, and thus the idiosyncratic drivers of deals will feature more prominently. Moreover, quite different from foreign exchange trading, the 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. Indeed, 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 the 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,

[22] In the Internet Appendix, we explore different standardization windows ranging from 12 to 60 months and find our results remain qualitatively unchanged. See Section 6.4 for further details.

[23] In the Internet Appendix we show that these non-informative zeros do not drive our results. See Section 6.4 for further details.

in principle, provide a signal about firms' information, the number of deals is better suited to capturing the signal revealed by the announcements.[24]

3.3 Economic growth

We study changes in the economic growth rate (i.e., economic acceleration) using the measure proposed by Dahlquist and Hasseltoft (2020).[25] Their measure is particularly suitable because it captures different aspects of an economy, providing a more comprehensive picture of economic conditions that is broadly applicable across countries. 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), in which a higher value 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:[26]

$$g_{i,t} = \frac{1}{3}\left[log\left(\frac{IP_{i,t}}{IP_{i,t-12}}\right) + log\left(\frac{RS_{i,t}}{RS_{i,t-12}}\right) + log\left(\frac{UE_{i,t-12}}{UE_{i,t}}\right)\right]. \tag{6}$$

The change in economic growth is then given by:

$$\Delta g_{i,t+s} = g_{i,t+s} - g_{i,t}, \tag{7}$$

which is the difference between one-year growth rates at times $t+s$ and t.

3.4 Exchange rates

We collect daily spot and one-month forward foreign exchange rates from WM/Reuters via *Datastream.* The exchange rates are recorded as the US dollar price of one unit of foreign currency. We sample exchange rates on the last trading day of each month to calculate monthly currency excess returns and foreign exchange rate returns. The currency excess 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

[24]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).

[25]Changes to the economic growth rate are of enormous significance to policy makers. Indeed, Hausmann et al. (2005) note that "*accelerating the process of economic growth is just about the most important policy issue in economics.*"

[26]To mitigate against outliers unduly influencing the findings, we winsorize the one-year growth in IP, RS, and UE at the 5th and 95th percentiles. In the Internet Appendix we show that this choice is not crucial to our results and that while there are a few large outliers, the core results continue to be observed when winsorizing at either the 1st and 99th percentiles or the 10th and 90th percentiles. See Section 6.4 for further details.

of country i's currency at time t+1. Specifically, we calculate currency excess returns as:

$$r_{i,t+1} = \frac{S_{i,t+1} - F^1_{i,t}}{S_{i,t}}, \tag{8}$$

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, while spot exchange rate returns are defined as:[27]

$$e_{i,t+1} = \frac{S_{i,t+1} - S_{i,t}}{S_{i,t}}. \tag{9}$$

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 Part I: Economic Growth

We study the relationship between changes in economic growth and our main measure of abnormal cross-border M&A activity ($\widetilde{MA}_{it}$, defined in Equation (**5**)), in two ways. First, we investigate changes in economic growth in the five-years prior to and following the signals' release for the groups of countries with the highest and lowest signals each month. The test allows us to obtain a first look at the average evolution of economic growth following the cross-border M&A announcements and to address the potential concern that any post-announcement trend is simply a *continuation* of a pre-existing trend. Second, we investigate the predictability of our main measure in a more formal setting, via predictive panel regressions. We then turn to the source of information by investigating which firms reveal predictive signals to the market.

4.1 Changes in economic growth

We begin by grouping countries into one of three equally-sized baskets based on their value of $\widetilde{MA}_{it}$. We denote these baskets as "high", "medium", and "low". To test how economic growth changes on average, we regress $\Delta g_{i,t+s}$, on a dummy variable ($D_{ik,t}$), equal to one if country i at time t is in basket k = high, medium, low, and zero otherwise:

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

[27] 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.

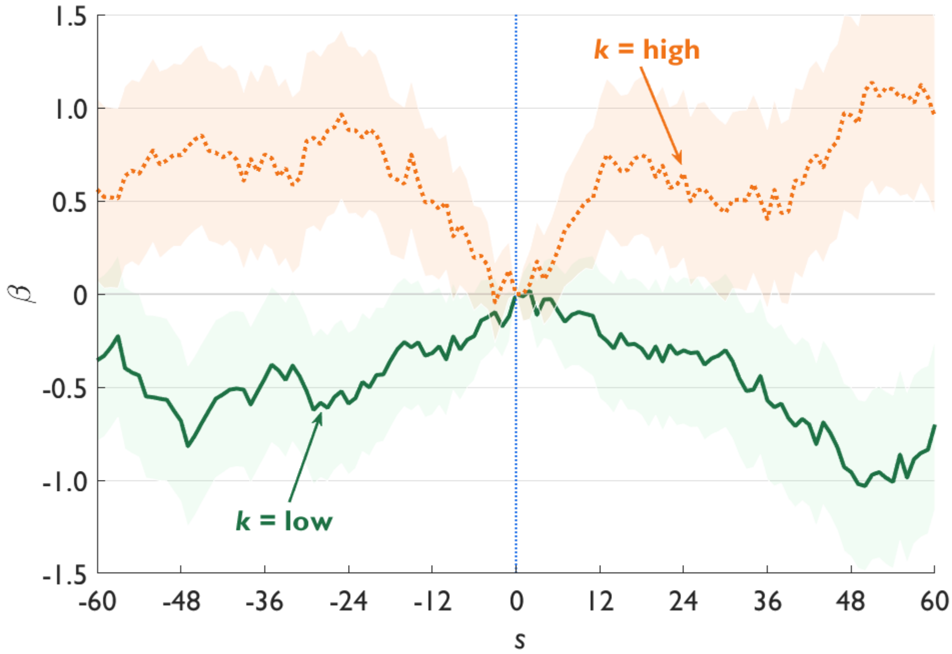

Fig 2. Change in Economic Growth. The figure plots the β coefficients from Equation (**10**), estimated across values of s for $k = high$ and $k = low$. Two standard error bounds are denoted by the shaded region.

where $s = -60, -59, ..., 0, ...59, 60$. Thus, when $s < 0$, the change in economic growth is relative to a point *prior* to the signal's release and hence a positive value of $\Delta g_{i,t+s}$ indicates that the growth rate has fallen in the run-up to the signal being announced (i.e., the growth rate was previously higher than observed at $s = 0$). 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 that may also affect changes in economic growth, such as legal origin and developed or emerging status.

The coefficient of interest is β. According to our main hypothesis, abnormally high (low) M&A net inflows signal stronger (weaker) future economic growth. When $s > 0$, we therefore expect $\beta > 0$ if $k =$ high and $\beta < 0$ if $k =$ low. In Fig. 2 we plot the estimated β coefficients. We denote two-standard-error bounds by the shaded regions. Strikingly, a v-shape pattern emerges for countries with high values of $\widetilde{MA}_{it}$, centred almost exactly at $s = 0$, while we observe the mirror-image, inverted v-shape pattern, for countries with low values of $\widetilde{MA}_{it}$. These patterns imply that the economic growth rate increases (decreases) following abnormally high (low) values of the $\widetilde{MA}_{it}$ signal, consistent with our main hypothesis. Indeed, over the 60-months following the cross-border M&A announcements, high (low) net inflow countries see their growth rates increase (decrease) by around 1% on average. And these trends are not a simple continuation of a pre-existing pattern. Instead, they point to a *reversal* in economic growth rates. To see this, observe that the economic growth rate for k = high countries is *declining* prior to the signal's release (positive coefficient when $s < 0$) but increases almost immediately thereafter (positive coefficient when $s > 0$), while the opposite pattern of increasing growth rate followed by decreasing growth rate is observed for k = low countries. Thus, the signals' release to the market almost perfectly coincides with turning points in economic conditions.[28]

4.2 Predictive panel regressions

We implement a more rigorous test by estimating predictive panel regressions in which we regress the change in economic growth on $\widetilde{MA}_{it}$, while controlling for various alternative predictors of economic activity ($X_{i,t}$):

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

We focus on the post-announcement period, reporting results for $s = 12, 24, 36, 48, 60$, while also controlling for country and time fixed effects. Robust standard errors are double clustered at the country-month level. The control variables 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;[29] (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 estimate two models for each value of s. The first model controls for CLIs, since these indices are specifically designed to incorporate a comprehensive set of economic and financial information. In the second model, we replace the CLIs with the alternative sources of economic growth predictability. Results are reported in Table 2. We observe that the coefficients on $\widetilde{MA}_{it}$ are all positive and highly statistically significant in the majority of cases. Indeed, statistical significance is found 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: when the $MA_{i,t}$ signal is one-standard deviation above its median level the economic growth rate is between 0.24% to 0.45% higher over the following 36 to 60 months, which is the same order of magnitude as the average change in economic growth over the same period.

[28] 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).

[29] 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).

4.3 Which firms reveal predictive signals?

To investigate the source of the predictive signals, we return to the theoretical motivations underpinning the analysis. Firms may have superior information about future economic conditions due to obtaining real-time information about sales, interacting with local suppliers and customers, and observing business and industry conditions on a day-to-day basis. This information is likely to be related, on average, to the local economy—firms do not observe this information for *all* foreign economies. Even for foreign economies in which MNCs are active, firms face the "liability of foreignness" owing to language barriers, physical distance, and possible lack of a local information network. If true, the predictive signals we observe are most likely to be the outcome of domestic firms revealing predictive information about their local economy.

To test this hypothesis, we construct an equivalent measure to our main measure (defined in Equation (**5**)) but using *only* inflows or outflows:

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

where $k = out, in$, $MA^{k}_{i,t}$ reflects the domestic-firm outflows or foreign-firm inflows into/from country i in month t, $\overline{MA}^{k}_{i,t}$ is the trend level, and $\sigma_{i,t}$ is the standard deviation. To investigate whether it is domestic or foreign firm announcements that matter for predictability, we estimate an equivalent predictive model to that defined in Equation (**11**), replacing $\widetilde{MA}_{i,t}$ with $\widetilde{MA}^{out}_{i,t}$ and $\widetilde{MA}^{in}_{i,t}$:

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

Results are reported in Table 3. We observe a clear asymmetric pattern: across all horizons, the outflow measure, signifying the predictability stemming from domestic firms (β_1), is consistently negative and statistically significant—indicating that unusually high (low) outflows translate to lower (higher) future growth rates. In contrast, the β_2 coefficients, which capture predictability stemming from foreign firm announcements, are only statistically different from zero at longer horizons and thus do not capture the timely reversal effect that we document in Fig 2. We make this point clearer in Fig. A.2 of the Internet Appendix by presenting estimates of β_1 and β_2 across values of s.[30] The relative importance of the domestic-firm outflows are apparent: countries with relative high outflows exhibit an inverted v-shape reversal in economic growth that is centered at $s = 0$, while the effect is not observed for foreign-firm inflows, implying that those flows are not capturing the turning points in local economic activity that we previously observed.

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

Cyclical firms. While domestic firms appear to be endowed with an informational advantage about local economic conditions, some firms may be more highly exposed to timely information about the state of the economy if they happen to operate in industries that are more sensitive to economic fluctuations. Thus, one might anticipate that if the predictability we document is truly attributable to an information channel, it would be detected primarily among domestic firms operating in the most *cyclical* industries.

To investigate this possibility, we follow Sharpe (1994) and construct a measure of cyclicality for each industry-country pair, measured by the median covariance between the log sales growth of firms within a particular industry (defined at the two-digit SIC code level) and the country's log GDP growth rate.[31] Acquiring firms are then divided into high and low cyclicality groups, in which "high" reflects an above median covariance level. Following our prior approach, we further cut the data by disaggregating inflows and outflows between high and low cyclicality firms to yield four alternative measures of abnormal M&A activity:

$$\widetilde{MA}_{i,t}^{k,c} = \frac{MA_{i,t}^{k,c} - \overline{MA}_{i,t}^{k,c}}{\sigma_{i,t}} \tag{14}$$

where $k = out, in$ and $c = high, low$. Once again we estimate predictive panel regressions, replacing $\widetilde{MA}_{i,t}$ with the four new measures:

$$\Delta g_{i,t+s} = \alpha_i + \beta_1 \widetilde{MA}_{i,t}^{out,high} + \beta_2 \widetilde{MA}_{i,t}^{out,low} + \beta_3 \widetilde{MA}_{i,t}^{in,high} + \beta_4 \widetilde{MA}_{i,t}^{in,low} + \gamma' X_{i,t} + \kappa_i + \lambda_t + \varepsilon_{i,t+s}. \tag{15}$$

Results are reported in Table 4. We observe that among the four types of M&A flows, the abnormal outflows of the most cyclical domestic firms carry the strongest predictive information for subsequent changes in economic growth. Compared to abnormal outflows by less cyclical domestic firms, high cyclicality domestic firms exhibit stronger predictive power at all horizons, in terms of both the magnitude and statistical significance of the estimated coefficients. Moreover, the abnormal inflows of foreign firms (either high or low cyclicality) have generally weak forecasting power and do not detect the short-term reversal pattern previously observed in economic growth.

In sum, this section documents strong evidence that the main measure we construct provides a source of predictive information about changes in economic growth and thus sends an important signal to the market for forming expectations. Recalling our theoretical motivation: if exchange rates are a function of changing expectations about future macro fundamentals, then the signal should also predict exchange rate returns—a proposition that we investigate in the next section.

[31] We obtain annual sales data for all listed firms included in the Compustat (US) and Compustat Global (non-US) databases.

5 Empirical Analysis Part II: Foreign Exchange Rates

We explore foreign exchange rate return and currency excess return predictability using a cross-sectional methodology via the construction of currency portfolios. The method follows the pioneering work of Lustig and Verdelhan (2007), who were the first to adopt a portfolio approach within the exchange rate literature. Exchange rates are noisy and have been notoriously difficult to predict in time-series studies at horizons under one year,[32] even when the econometrician is given perfect foresight of the fundamentals thought to determine exchange rates (Meese and Rogoff, 1983). Predicting the *point estimate* of the exchange rate is thus an arduous task and the random walk without drift model has remained an indelibly difficult benchmark to beat in time-series studies. The conceptual advantage of the cross-sectional methodology, however, is that it changes the benchmark for predictability. Rather than aim to predict the precise point estimate, the approach asks whether a relatively high value of the predictor variable translates to a higher (or lower) exchange rate return on average.[33] Cross-sectional predictability thus provides important information about the drivers of the foreign exchange factor structure and offers a clearer measure about the economic significance of predictability that is highly relevant for most practitioners. Indeed, many market participants do not require a precise point estimate as part of their decision making—knowing whether an exchange rate is likely to be above or below the forward rate is sufficient, especially when investing or hedging in currency markets.

We build currency portfolios by assigning weight to currencies based on our main measure ($\widetilde{MA}_{i,t}$), using three alternative approaches: "HML," "linear," and "rank," which we describe below. The portfolios are rebalanced monthly, their weights sum to zero, and they are all long and short one dollar. To obtain HML weights, we sort currencies from low to high values of $\widetilde{MA}_{i,t}$, and group the currencies into three equally sized, and equally weighted, portfolios (P_1, P_2, and P_3).[34] HML weights are equal to P_3 weights and the negative of P_1 weights (P_2 currencies are allocated 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 assigns

[32] See the survey by Rossi (2013) for further details

[33] See also Lustig and Verdelhan (2007), Lustig et al. (2011), Verdelhan (2018), and Colacito et al. (2020).

[34] 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.2, we show that our results are unaffected, however, 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.

weight to the extremes of the distribution but does not allocate higher or lower weights *within* a portfolio. The linear approach, in contrast, assigns weights to all eligible countries in direct proportion to their signal's value:

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

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 to the linear approach, with weight assigned to all countries, but this time in direct proportion to the cross-sectional *ranking* of their signal, 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 Currency excess returns

Portfolio returns and associated summary statistics are reported in Table 5. 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 currency excess return predictability, the average returns should equal zero. But instead,we observe a monotonically increasing pattern: countries with the lowest values of $\widetilde{MA}_{i,t}$ (i.e., P_1 currencies) generate, on average, annualized currency excess returns 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%.[35]

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 all cases the currency excess returns are positive, t-statistics are over 3.50, and the associated Sharpe ratios are over 0.70.[36] In Fig. 3, we plot the cumulative currency excess returns of the three portfolios. The returns increase steadily over time, are not driven by outliers, and have remained high following the global financial crisis (GFC)—in contrast to currency carry, value, and momentum signals,

[35] 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.

[36] The average correlation of the returns across the three portfolios is 93%.

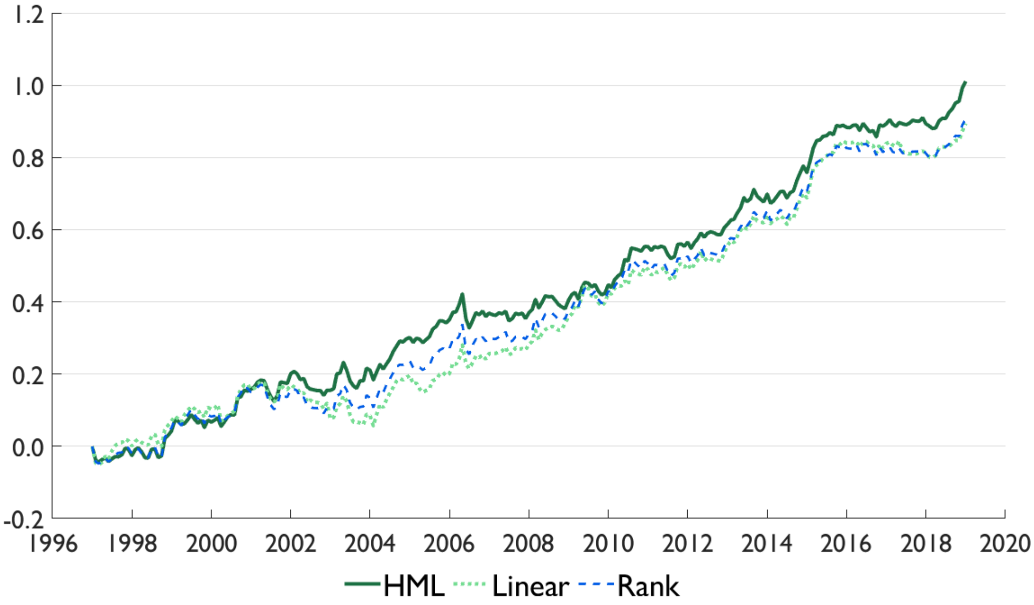

Fig 3. Cumulative Returns of Cross-Border M&A Portfolios. The figure plots the cumulative monthly returns of the three cross-border M&A currency portfolios. The three portfolios include HML (solid line), linear (dotted line), and rank (dashed line). The returns begin in January 1997 and end in December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

which have lost predictive power post-2008 (see, e.g. Ranaldo and Somogyi, 2021). 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. 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 is positive and the Sharpe ratios is high, albeit slightly lower than those observed in the full sample.[37]

These initial findings on currency excess return predictability are important for global currency investors as they point towards a source of return that may be beneficial as part of broader currency portfolio. Later in this section we return to investigate whether the returns are unrelated to other investment strategies and thus whether they offer a beneficial source of portfolio diversification. But first we turn to our central question, and explore whether the observed currency excess return predictability also translates to exchange rate return predictability.[38]

[37]In Internet Appendix Table A.3, we document similar performance for the HML and linear portfolios.

[38]In Internet Appendix Section B, we further explore currency excess return predictability. In particular, we show via a bootstrap procedure that the predictability is quite different from what would be obtained by randomly assigning signal values to currencies, and that the returns continue to be economically sizeable when controlling for transaction costs.

5.2 Foreign exchange rate returns

In the final two rows of Table 5, we report the decomposition of the average currency excess returns between the foreign exchange rate (fx) and forward premium (fp) components. Our central prediction is that a high value of our main measure, $\widetilde{MA}_{i,t}$, is associated with a subsequent exchange rate appreciation, and hence we anticipate that the monotonic pattern we observed earlier for currency excess returns is primarily the result of exchange rate movements. If, on the other hand, interest rate differentials are the principal driver, it would be evidence against the main hypothesis. 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 2.41% over the following month (annualized), while P_3 currencies *appreciate*, on average, by 0.52% per annum.

In the earlier analysis, on the predictability of changes in economic growth, we found the predictability to be principally driven by the cross-border M&A announcements of cyclical domestic firms. If the economic mechanisms proposed in this paper are to be supported, then the exchange rate predictability we observe should also be driven by cyclical domestic firms. In the next section, we therefore turn to investigate the split between domestic and foreign firms, before further disaggregating the data to study cyclical and non-cyclical firms.

5.2.1 Domestic versus foreign firms

We classify all countries entering P_1 and P_3 each month as having entered the portfolio because of either an unusual level of foreign firm *in*flows or domestic firm *out*flows. Specifically, if country i is allocated to P_1 at time t, i.e., $\widetilde{MA}_{i,t}$ is negative, it could be because domestic firms are moving more capital offshore, or because foreign firms have chosen to reduce their investments in the local economy, or both. Likewise, if country i is allocated to P_3 at time t, i.e., $\widetilde{MA}_{i,t}$ is positive, it may be because foreign firms are investing more in the local economy, or because domestic firms are investing less overseas, or both. We denote the country as "domestic driven" if $|MA^{out}_{i,t} - \overline{MA}^{out}_{i,t}| - |MA^{in}_{i,t} - \overline{MA}^{in}_{i,t}| > 0$ and as "foreign driven" otherwise. A positive value therefore indicates that domestic firms' announcements were the primary reason that the country was allocated to P_1 (more outflows than usual) or P_3 (less outflows than usual). Across the sample, 60% and 18% of P_1 and P_3 currencies are classified as "domestic driven," confirming that a high value for $\widetilde{MA}_{i,t}$ (i.e., a P_3 country) is typically driven by foreign inflows, while a low value for $\widetilde{MA}_{i,t}$ (i.e., a P_1 country) is usually driven by domestic outflows.

In Table 6, we report the returns and summary statistics for the "domestic driven" and "foreign driven" portfolios. Interestingly, and reinforcing the insights obtained from Table 3, we find that the exchange rate return predictability is driven *entirely* by the cross-border M&A announcements of *domestic* firms. The annualized monthly exchange rate return for P_1 countries in the "domestic driven" 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 (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" portfolio are only -1.11% and -0.11%, yielding a statistically insignificant spread of 1%. These results are also observed for 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 support the earlier evidence that information stemming from domestic firm announcements is where the predictive signal emerges—consistent with domestic firms conveying more accurate information about changes in their local economic conditions. Next, we turn to consider whether the strength of this predictability increases when further disaggregating the predictive signal by the cyclicality of the industry.

5.2.2 Cyclical firms

In Table 7, we reclassify countries entering P_1 and P_3 each month based on the four disaggregated M&A flows defined in Equation (**14**). Specifically, for countries that are denoted as "domestic driven" at time t, i.e., $|MA_{i,t}^{out} - \overline{MA}_{i,t}^{out}| > |MA_{i,t}^{in} - \overline{MA}_{i,t}^{in}|$, we also classify them as "high cyclicity" if the absolute value of the abnormal outflows of cyclical industries is greater than the absolute value of abnormal outflows in less cyclical industries, i.e., $|\widetilde{MA}^{out,high}| > |\widetilde{MA}^{out,low}|$ and as "low cyclicity" otherwise. A similar method is employed to split "foreign driven" countries each month between "high cyclicity" and "low cyclicity."

Consistent with our earlier results, we find that the outflows of highly cyclical domestic firms are the most informative about future exchange rate behavior. Currencies entering P_1 because of unusually high outflows of domestic cyclical firms experience an exchange rate depreciation of 3.72% per annum, while countries entering P_3, because of less outflows than typical among cyclical domestic firms, appreciate by 8.13% (annualized) over the following month.[39] In comparison, the equivalent exchange rate returns of P_3 and P_1 for "low cyclicity" domestic firms are -1.51% and 2.68%, respectively. Moreover, the substantial difference in predictive information stemming from domestic and foreign firms is further underscored by the *negative* annualized foreign exchange rate

[39]By disaggregating the data there are relatively few months in which *both* P_1 and P_3 contain at least one currency necessary for the construction of the HML portfolio. Hence, summary statistics on HML are omitted but are available upon request.

returns for countries entering both P_3 and P_1 of the "foreign driven" portfolios.

Overall, these results suggest that not all cross-border M&A flows are equally informative about future exchange rate returns. Domestic cyclical driven M&A outflows generate more precise signals, consistent with domestic firms in the most cyclical industries having more accurate information about changes in their local economic conditions. The results therefore support the conclusion that information revealed through the cross-border M&A announcements of domestic cyclical firms is the primary driver of the predictability we observe for both economic growth rates and exchange rate returns.

5.3 Novelty of the predictability and portfolio diversification

A pertinent question is whether the predictive information we uncover mimics previously identified sources of cross-sectional return predictability. There are reasons to believe this may be true. For example, Erel et al. (2012) find that an exchange rate depreciation attracts cross-border M&A inflows, especially if the currency is already undervalued, as 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. These alternative motivations would be captured by other, previously identified, sources of cross-sectional return predictability including currency value (Asness et al., 2013); currency momentum (Asness et al., 2013); and macroeconomic momentum (Dahlquist and Hasseltoft, 2020).

We therefore construct these alternative sources of return predictability plus others from the exchange rate literature, including the dollar factor, a proxy for US domestic risk (Verdelhan, 2018); the carry factor, which relates to changes in global market risk (Lustig et al., 2011); the dollar-carry trade, which is known to predict variation in the US business cycle (Lustig et al., 2014) and inflation momentum (Dahlquist and Hasseltoft, 2020). We do so following the methods of the original studies using the sample period and currencies employed in this study. 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 M&A rank-weight portfolio, given the conceptually appealing features of rank weights (see Dahlquist and Hasseltoft, 2020).[40]

[40]We provide further details about the construction in Internet Appendix Section C. 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 C.1. We find that each portfolio generates a positive return, with associated Sharpe ratios ranging from 0.15 (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.

5.3.1 Comparing sources of return predictability

We test if the return predictability previously documented is subsumed by other sources of return predictability using predictive panel regressions and hence, by doing so, we also explore exchange rate predictability in the time series. Specifically, we test if the weights in the rank weight portfolio continue to predict exchange rate returns and currency excess returns, after controlling for the equivalent rank weights on currencies in the alternative portfolios:[41]

$$
\begin{aligned}
r_{i,t+1} &= \alpha + \beta w^{rnk}_{M\&A,i,t} + \sum_k \gamma_k w^{rnk}_{k,i,t} + \tau_{t+1} + \varepsilon_{t+1}, \\
e_{i,t+1} &= \alpha + \beta w^{rnk}_{M\&A,i,t} + \sum_k \gamma_k w^{rnk}_{k,i,t} + \tau_{t+1} + \varepsilon_{t+1}.
\end{aligned}
\tag{16}
$$

Results are reported in Table 8. The coefficients reflect monthly returns (in percentage points) for a rank weight equal to unity. We find the coefficients on the rank weights in the cross-border M&A portfolio are positive and highly statistically significant at the 1% level. 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 trade portfolio that displays a positive relationship with currency returns but a negative relationship with exchange rate returns. Surprisingly, of all the alternative portfolios, only the carry trade rank weights also exhibit a statistically significant relationship with currency returns.

We conclude that information contained in the announcements of cross-border M&A announcements provides a novel source of return predictability, implying that the predictability may also provide a beneficial source of diversification gains to global currency investors. We investigate the extent of this diversification benefit in the next section.[42]

5.3.2 Diversification gains

We investigate diversification gains by analyzing the performance of currency portfolios that incrementally introduce different sources of return predictability. We view the predictive signal, $\widetilde{MA}_{i,t}$, as a source of diversification gains if the addition of a cross-border M&A portfolio increases the broader portfolio's Sharpe ratio. Results are presented in Table 9.

[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.

[42] In Internet Appendix Table C.2, we present results from an alternative test in which we regress the returns of the M&A rank-weight portfolio on the returns of all other strategies. We find that the R-square of the regression is only 2.3% and the "alpha" is over 3.7%, similar to the unconditional return of 4.1%, documented in Table 5.

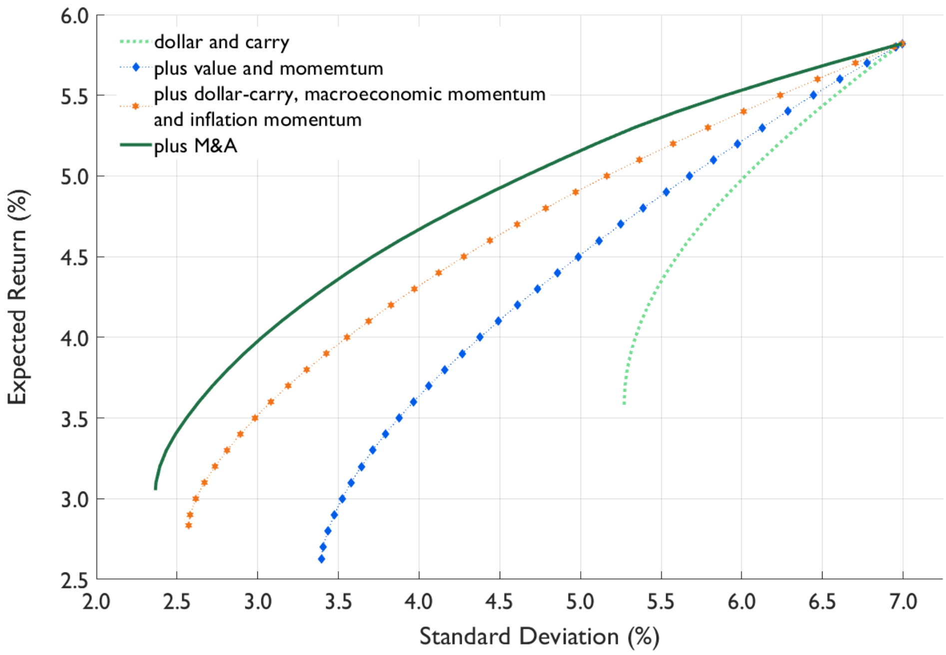

Fig 4. Efficient Frontiers. The figure plots a series of efficient frontiers for various sets of currency portfolios. The dotted line is the efficient frontier when limiting the investment space to only dollar and carry. We add value and momentum (dotted line with diamond markers, four portfolios), dollar-carry,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

Broad currency portfolios. In Panel A, we present the Sharpe ratios of optimal mean-variance portfolios that exclude the cross-border M&A portfolio. The portfolios are optimized by minimizing the variance at target expected returns varying between 3.50% and 5.50% (increasing in 25 basis points increments). We consider three broad portfolios (BP_1, BP_2, and BP_3) that differ by their investment universe. The first portfolio is limited to only dollar and carry, which are widely viewed as the main return-based factors determining currency returns (see, e.g. Verdelhan, 2018). Sharpe ratios vary between 0.71 and 0.84, increasing as weight is shifted towards carry. The second portfolio expands the investment universe to include value and momentum. At higher target returns, carry is allocated an increasingly higher weight, but at lower returns the diversification gains from including value and momentum are larger—increasing the Sharpe ratio to over 0.90. The third portfolio further expands the investment universe to include dollar-carry, macroeconomic momentum, and inflation momentum. Further investment gains are achieved and the Sharpe ratio increases to 1.17, although the Sharpe ratios of BP_3 are only statistically higher than those of BP_2 at the lowest target returns.[43]

[43] 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.

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 sources of currency return predictability. The figure shows that the cross-border M&A portfolio expands the efficient frontier, even after all other sources of return predictability are made available for investment—reaffirming the conclusion that information contained in the announcements of cross-border M&A deals is novel and provides a beneficial source of portfolio diversification.

6 Further Analyses

In this section we present the results from further analyses. We begin by investigating an alternative "transaction" motivation for why exchange rates may appreciate following the announcements of cross-border M&As. Next, we study if unusual levels of cross-border M&A activity might *cause* the changing levels in economic growth we observe, thus negating the information channel we propose. Finally, we investigate potential endogeneity concerns that other macroeconomic, political, and financial variables drive both exchange rates and abnormal cross-border M&A flows.

6.1 Do agents "front run" M&A order flow?

The announcement of cross-border M&A deals can plausibly contain information about future foreign exchange order flow, providing the transactions are: (i) completed, and (ii) paid for (at least in part) using cash. Cross-border M&A deals with large dollar values may therefore predict subsequent exchange rate returns because market participants "front run" these foreign exchange 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 future foreign exchange transactions are unknown. Second, cross-border M&A is subject to stringent regulations and government interventions—it is thus uncertain whether an M&A deal will be completed, presenting large market 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 account for the exchange rate predictability we observe, then the results of our analysis would most likely be *stronger* when forming signals using the *dollar value* of cross-border M&A transactions, rather than the *number* of announced cross-border M&A deals. Moreover, the predictability would presumably disappear when the analysis is conducted using deals *without* payment information (around one-third of the deals). We test both hypotheses using the cross-sectional portfolio approach.

Results are reported in Table 10. When forming portfolios using dollar values (Panel A), the total returns to the rank-weighted portfolio 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 also remains over 0.50, rejecting the hypothesis of no return predictability for deals with missing payment information. In sum, neither conceptually nor following additional empirical tests do we view the alternative "transaction" hypothesis as the likely driver of the observed predictability.

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

One of the main results in the paper is that abnormal M&A activity provides a predictive signal about changes in future economic growth rates. We interpret this signal as capturing firms' private information that is revealed to the market when they announce new international investments. A competing hypothesis, however, is that instead of revealing private information, abnormal cross-border M&A activity may *cause* a change in subsequent economic growth rates through production gains, job creation (Toews and Vézina, 2020), and diffusion of new technologies (Aitken and Harrison, 1999). If so, we would anticipate observing faster economic growth in countries that experience abnormally high dollar volumes of cross-border M&A net inflows *relative to the size of the economy.*

To explore this alternative explanation, we compute, for each country and every month, the net cross-border M&A inflow-to-GDP ratio, defined as the aggregate dollar value of announced cross-border M&A net inflows divided by the last year's gross domestic product (GDP):

$$MA^{\$}_{i,t} = \frac{MA^{\$,in}_{i,t} - MA^{\$,out}_{i,t}}{GDP_{i,t-12}}, \tag{17}$$

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 with the main measure, we standardize $MA^{\$}_{i,t}$ by its median

($\overline{MA}^{\$}_{i,t}$) and standard deviation ($\sigma^{\$}_{i,t}$) over the prior 36 months:

$$\widetilde{MA}^{\$}_{i,t} = \frac{MA^{\$}_{i,t} - \overline{MA}^{\$}_{i,t}}{\sigma^{\$}_{i,t}}. \tag{18}$$

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.

To understand whether the main measure (the "information channel") or the alternative ("economic activity channel") are the primary source of predictive information, we begin by constructing an orthogonalized version of our main measure $\perp \widetilde{MA}_{i,t}$, equal to the residuals from regressing $\widetilde{MA}_{i,t}$ on $\widetilde{MA}^{\$}_{i,t}$ for each country. This variable is designed to capture the unique predictive power of the main measure that is unrelated to dollar volumes and GDP. Moreover, we construct an equivalent $\perp \widetilde{MA}^{\$}_{i,t}$ using the residuals from regressing $\widetilde{MA}^{\$}_{i,t}$ on $\widetilde{MA}_{i,t}$.

In Table 11, we present results from re-estimating the earlier panel regressions (Equation (**11**)), replacing $\widetilde{MA}_{i,t}$ with both $\perp \widetilde{MA}_{i,t}$ (Panel A) and $\perp \widetilde{MA}^{\$}_{i,t}$ (Panel B). We find that the coefficients on $\perp \widetilde{MA}_{i,t}$ are all positive and highly statistically significant at the 1% level at most horizons, indicating that the abnormal number of M&A net inflow continues to be a strong predictor of future economic growth changes even after removing information about dollar volumes and GDP. In contrast, $\perp \widetilde{MA}^{\$}_{i,t}$ exhibits a weak relationship with future changes to economic growth. In some cases the coefficient has the wrong sign (indicating a negative relationship) or exhibits a positive coefficient but one that is statistically indistinguishable from zero. Overall, therefore, the results go against the alternative hypothesis and support the information channel we propose.[44]

6.3 Do other factors drive predictability?

Cross-border M&A activity may be determined by other macroeconomic, financial, and political variables. These other factors may, therefore, be responsible for driving both the predictability of economic growth and exchange rate returns. For example, if the local investment environment improves for either political or economic reasons, capital may flow into the country and appreciate the local exchange rate, while the economic prospects independently improve. While not part of our sample, this would perhaps be most evident for many eastern European economies that transitioned to market-based economies during the 1990s. Furthermore, past changes in exchange rates, regulations, and local stock market valuations are all potential drivers of cross-border M&As

[44]To complement this analysis, we also implement 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.4. We find that the abnormal level of uncompleted net inflows continues to be a strong predictor of future economic growth, again consistent with predictive information being revealed through cross-border M&A announcements.

that may affect exchange rates and future economic growth.

It is important to therefore rule out the possibility that the predictive signal we uncover is not subsumed by alternative factors that drive both exchange rates and economic growth. To do so, we purge the main measure, $\widetilde{MA}_{i,t}$, of various factors to obtain a cleaner measure of the predictive information revealed through the announcements of M&A activity. To do so, we begin by running cross-sectional panel regressions of $\widetilde{MA}_{i,t}$ on a set of country-level, time-varying variables ($x_{i,t}$):

$$\widetilde{MA}_{i,t} = \alpha + \beta x_{i,t} + \kappa_i + \lambda_t + \varepsilon_{i,t}, \tag{19}$$

where κ_i represents country fixed effects that absorb time-invariant, country-specific characteristics, e.g., language, religion, geographical distance, and legal origin, while year fixed effects (λ_t) absorb global shocks affecting the cross-section of countries in a given month. We double cluster standard errors at the country-month level.

We include several explanatory variables ($x_{i,t}$) in the regressions. First, we control for valuation effects, measured by changes in local stock market valuations and monthly exchange rate returns (Erel et al., 2012). Second, we control for the level of openness of an economy using its bilateral trade openness, defined as the maximum of bilateral imports and exports between country i and the US (Ferreira et al., 2010; Erel et al., 2012).[45] Third, La Porta et al. (1997) show that investor protection and, more generally, the quality of institutions and legal enforcement, can help to explain cross-country differences in financial markets development. Moreover, political risk—driven by policy shifts in tax regulations, restrictions on FDI, and other changing government actions—is likely a key factor affecting inward foreign investment (Bekaert et al., 2007). We therefore control for: (i) a time-varying index measuring the quality of institutions in country i, complied from the *International Country Risk Guide* (ICRG) political risk subcomponents: corruption, law and order, and bureaucratic quality; and (ii) a time-varying index of investment profile measuring the state of country i's investment environment, compiled from the ICRG political risk subcomponents reflecting the risk of expropriation, contract viability, payment delays, and repatriation of profits. Higher scores indicate better institutional quality and lower overall risk. Finally, we control for macroeconomic conditions as proxied by the log of country i's GDP, GDP per capita, and the GDP growth rate.[46]

[45] Imports (exports) are computed as the value of imports (exports) from country i to (from) the US as a fraction of total imports (exports) from country i in month t. The data are obtained from the *United Nations Commodity Trade Statistics* database.

[46] Results from these initial regressions are presented in Internet Appendix Table A.5. Among the explanatory variables, we find that macroeconomic conditions are the most important determinants of abnormal M&A activity. Both market size (measured by GDP) and economic growth positively and statistically significantly affect the aggregate abnormal net inflows. The finding is consistent with larger, faster growing economies attracting more foreign investments because they are associated with more profitable niche investment opportunities (Globerman

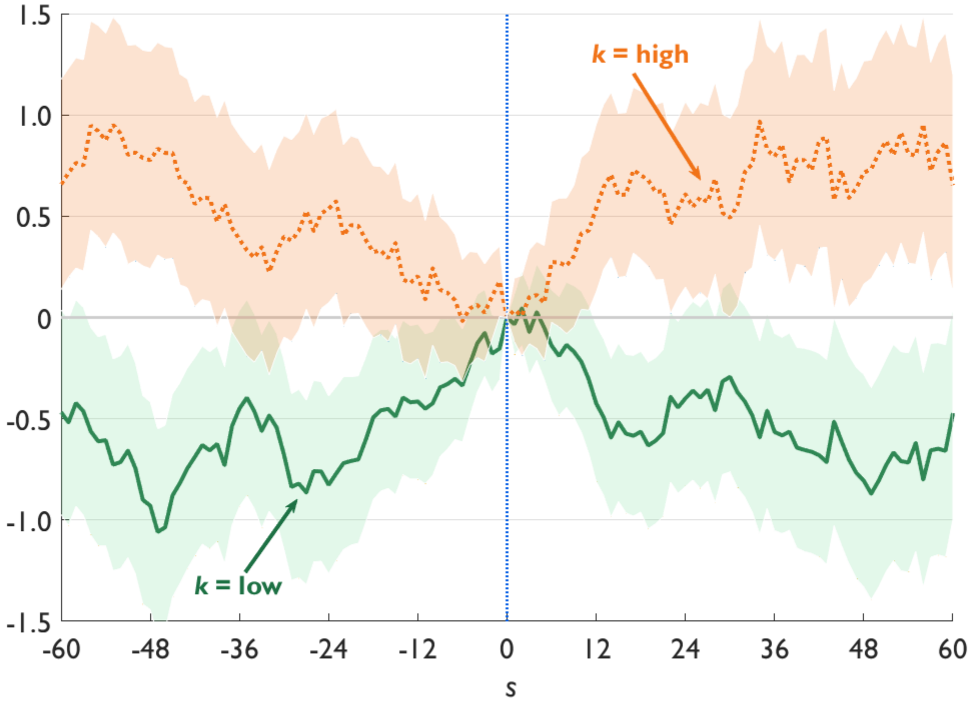

Fig 5. Change in Economic Growth. The figure plots the β coefficients from Equation (**10**), estimated across values of s for $k = high$ and $k = low$ values of $\varepsilon_{i,t}^{MA}$. Two standard error bounds are denoted by the shaded region.

From these initial regressions we collect the residual values ($\varepsilon_{i,t}^{MA}$), which serve as an alternative measure of the main predictive signal. Fig. 5 plots the β coefficients from re-estimating Equation (**10**) with these residual values. As in Fig. 2, we observe a clear v-shaped pattern for countries with high values of $\varepsilon_{i,t}^{MA}$, and an inverted v-shaped pattern for countries experiencing low values of $\varepsilon_{i,t}^{MA}$. Thus, even after adjusting $\widetilde{MA}_{i,t}$ for confounding factors, we continue to observe a predictable turning point in economic growth. We also re-estimate predictive panel regressions (Equation (**11**)), replacing the main measure with $\varepsilon_{i,t}^{MA}$. Results are reported in Table 12. We see that $\varepsilon_{i,t}^{MA}$ remains a strong predictor of changes in economic growth—the coefficients on $\varepsilon_{i,t}^{MA}$ are positive at all horizons, and statistically significant at the 1% level in nine of the ten specifications.

Finally, we test the economic value of the above predictive relationship in a portfolio setting. Table 13 presents the returns and summary statistics for the HML, linear, and rank portfolios constructed using $\varepsilon_{i,t}^{MA}$. Reinforcing the insights gained from the panel regressions, we find that all three portfolios deliver statistically significant positive currency excess returns, with t-statistics exceeding 3.0 and Sharpe ratios ranging from 0.62 to 0.67. The slightly weaker returns, relative to Table 5, are driven almost entirely by lower interest rate differentials. Indeed, we find that the exchange rate component remains high, ranging from 2.58% to 3.25%, and accounts for more

and Shapiro, 1999). The coefficient on GDP per capita is negative and significant at the 5% level, suggesting that firms are more likely to invest in countries with lower GDP per capita to take advantage of relative lower labour costs for production (di Giovanni, 2005). Other variables, including past exchange rate returns and the investment profile do not, however, have a statistically significant relationship with the main measure we construct.

than 90% of the total excess returns, indicating that the exchange rate predictability we initially observe is not subsumed by information in the explanatory variables.

Overall, the findings continue to support the claim that the exchange rate predictability we observe is the result of predictive signals that are revealed through cross-border M&A announcements, and is unrelated to a battery of alternative economic, political, and financial forces driving M&As.

6.4 Other analyses

We undertake a battery of additional robustness checks and report results in a supplemental Internet Appendix. Here we briefly summarize the core findings. In Table A.6 we find that our main results continue to hold when we exclude financial firms; in Tables A.7 and A.8 we provide evidence that the results are unaffected through the inclusion of NAFTA members; in Tables A.9 and A.10 we show that our main results are qualitatively unchanged when we explore different standardization windows for our main measure, ranging from 12 to 60 months; in Table A.11 we show that non-informative zeros do not drive our core results; finally in Tables A.12 and A.13 we explore alternative winsorization choices for economic growth, and find that our core results are unaffected when winsorizing at either the 1st and 99th percentiles or the 10th and 90th percentiles.

7 Conclusions

Exchange rates and macroeconomic fundamentals have a long, chequered, history. While many macroeconomic models predict that exchange rate returns are a function of expected future macro fundamentals, the empirical evidence for such a relationship has been weak. One possible explanation for this weak relationship is that testing these macroeconomic models is fraught with difficulty, given the latent nature of the market's expectations. In this paper, we propose a method to measure the market's changing expectations. Since the market responds to public signals, we contend that observable actions, which are undertaken based on private information about the future state of the economy, reveal predictive signals to the market that shift expectations. Therefore by studying those actions, the econometrician can indirectly test the relationship between changing market expectations and subsequent foreign exchange rate returns.

Constructing a country-level measure of abnormal M&A activity to reflect the predictive signal, we show that it strongly predicts changes in economic growth by capturing turning points in economic activity. According to the theoretical literature on heterogeneous expectations, this same predictive signal should also predict exchange rate returns if agents do not form symmetric beliefs about the future fundamental—a point we make precise via a simple model of exchange rate determination. We thus turn to exchange rate return predictability and find clear evidence that both currency excess returns and foreign exchange returns can be forecasted in a cross-sectional setting. In all cases, the predictability we observe is found to be driven by domestic firms operating in cyclical industries—consistent with domestic firms having an informational advantage over foreign firms about the local economy. The results have three broad implications for the foreign exchange literature: (i) they provide new support for the link between macroeconomic fundamentals and foreign exchange rates; (ii) they support theoretical models that assume currency market agents form heterogeneous expectations about future fundamentals; and (iii) they provide evidence for a novel source of currency excess return and exchange rate return predictability.

The results also have important implications for policy makers and global currency investors. For policy makers, the results provide a new variable that can be used to forecast future economic growth and to monitor the informativeness of FDI flows. For global investors, the documented currency return predictability implies a novel portfolio strategy that has offered historically high volatility-adjusted returns, even following the global financial crisis—a period in which many other currency strategies have struggled. Moreover, the strategy returns are unrelated to other popular currency strategies, and thus provide a beneficial source of portfolio diversification.

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Appendix: A Toy 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 closely 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 is also very closely related 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., 2022).

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., 2022, 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 0, therefore, agents all believe that the best predictor of the date 2 exchange rate is simply s_0, and hence 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.[47]

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.[48] 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.[49]

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

[47] It is important to clarify the role of corporations given the empirical analysis focusses on extracting predictive signals from *informed* corporate actions. The important distinction is that corporations' foreign exchange trades are known, in aggregate, to have no relationship with future foreign exchange rate returns (Menkhoff et al., 2016; Ranaldo and Somogyi, 2021). This outcome is not surprising, however, if firms are not seeking to profit from exchange rate movements, e.g., managing their treasury of foreign cash positions. In contrast, corporations' real investment decisions may reveal information since these actions are the outcome of a profit-seeking motive.

[48] 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.

[49] 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. (2022) 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.[50]

[50] In the models of Bacchetta and Van Wincoop (2006) and Cespa et al. (2022), an alternative channel is 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.

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.

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, is unlikely to be immediately absorbed into prices. The central assumption of heterogeneous expectations 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 (**5**) of the main paper, which proxies for ρ_1 in the model, contains information for forecasting future macro fundamentals and foreign exchange rate returns.

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: Domestic and Foreign Firms

	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)**
$\widetilde{MA}^{out}$	–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)
$\widetilde{MA}^{in}$	–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)
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 outflows ($\widetilde{MA}^{out}_{i,t}$) or inflows ($\widetilde{MA}^{in}_{i,t}$):

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

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: **Forecasting Changes in Economic Growth: Cyclical and Non-Cyclical Industries**

	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)**
$\widetilde{MA}^{out,high}$	-0.341^{**}	-0.401^{**}	-0.825^{***}	-0.707^{***}	-0.774^{***}	-0.840^{***}	-0.465^{**}	-0.571^{***}	-0.252	-0.136
	(0.152)	(0.156)	(0.184)	(0.181)	(0.197)	(0.205)	(0.206)	(0.217)	(0.205)	(0.209)
$\widetilde{MA}^{out,low}$	-0.203	-0.216	-0.394^{**}	-0.432^{**}	-0.468^{**}	-0.533^{**}	-0.454^{**}	-0.525^{**}	-0.215	-0.239
	(0.164)	(0.162)	(0.184)	(0.204)	(0.200)	(0.215)	(0.222)	(0.245)	(0.229)	(0.237)
$\widetilde{MA}^{in,high}$	0.129	0.040	0.074	0.022	0.231	0.157	0.344^{**}	0.361^{**}	0.564^{***}	0.487^{***}
	(0.125)	(0.131)	(0.144)	(0.148)	(0.153)	(0.161)	(0.165)	(0.173)	(0.172)	(0.170)
$\widetilde{MA}^{in,low}$	-0.112	0.005	-0.005	0.120	0.023	-0.071	0.415^{**}	0.411^{**}	0.610^{***}	0.900^{***}
	(0.152)	(0.172)	(0.160)	(0.176)	(0.166)	(0.196)	(0.184)	(0.209)	(0.190)	(0.195)
Controls	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
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 four disaggregated abnormal M&A flows defined in Equation (14):

$$\Delta g_{i,t+s} = \alpha_i + \beta_1 \widetilde{MA}_{i,t}^{out,high} + \beta_2 \widetilde{MA}_{i,t}^{out,low} + \beta_3 \widetilde{MA}_{i,t}^{in,high} + \beta_4 \widetilde{MA}_{i,t}^{in,low} + \gamma' X_{i,t} + \kappa_i + \lambda_{t+s} + \varepsilon_{i,t+s},$$

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 5: 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 5. 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 6: The Source of Return Predictability: Domestic and Foreign Firms

	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 outflows. In the right-hand panel, countries entering P_1 and P_3 experience abnormal M&A activity principally driven by foreign-firm 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 7: The Source of Return Predictability: Cyclical and Non-Cyclical Industries

	High Cyclicality Outflows		**Low Cyclicality Outflows**		**High Cyclicality Inflows**		**Low Cyclicality Inflows**	
	$\mathbf{P_1}$	$\mathbf{P_3}$	$\mathbf{P_1}$	$\mathbf{P_3}$	$\mathbf{P_1}$	$\mathbf{P_3}$	$\mathbf{P_1}$	$\mathbf{P_3}$
mean (%)	–2.41	9.62**	−0.35	3.10	0.78	1.85	−5.00	0.54
SR	–0.27	0.98	−0.13	0.91	0.07	0.19	−0.49	0.05
fx (%)	–3.72	8.13*	–1.51	2.68	–1.14	–1.30	–6.56	–3.04
fp (%)	1.30	1.49***	1.14	0.41	1.92	3.15***	1.57	3.58***
$\mu_{\widetilde{MA}_{i,t}}$	–1.33	1.36	–1.37	1.22	–0.78	1.88	–0.60	1.86
Obs	190	39	166	35	117	232	65	172

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 first two panels, countries entering P_1 and P_3 experience abnormal M&A activity principally because of unusual outflows by domestic firms operating in highly and less cyclical industries. In the last two panels, countries entering P_1 and P_3 experience abnormal M&A activity principally driven by unusual inflows of foreign firms in highly and less cyclical industries (see Section 5.2.2 for details). 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 8: 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 5.3.1 for details):

$$r_{i,t+1} = \alpha + \beta w^{rnk}_{M\&A,i,t} + \sum_k \gamma_k w^{rnk}_{k,i,t} + \tau_{t+1} + \varepsilon_{t+1}$$

$$e_{i,t+1} = \alpha + \beta w^{rnk}_{M\&A,i,t} + \sum_k \gamma_k w^{rnk}_{k,i,t} + \tau_{t+1} + \varepsilon_{t+1},$$

where $r_{i,t+1}$ and $e_{i,t+1}$ are defined in Equations (**8**) and (**9**), respectively. 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 9: 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 10: 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
fx (%)	–1.62	0.44	–0.03	1.59	2.24	1.49
fp (%)	1.41	1.39	2.52	1.11	1.79	1.17
$\mu_{\widehat{MA}_{i,t}}$	–0.75	0.07	1.27			

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
fx (%)	–2.52	1.67	–0.44	2.08	1.80	2.23
fp (%)	1.16	1.26	2.57	1.41	1.34	1.23
$\mu_{\widehat{MA}_{i,t}}$	–1.23	0.43	1.97			

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; Sharpe ratio (*SR*) average spot return (fx) and forward premium (fp). The final row reports the average value of the $\widehat{MA}_{i,t}$ variable in P_1, P_2, and P_3, which 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 5. 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 11: 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 (**5**)) by orthogonalizing the measure relative to $\widetilde{MA}^{\$}$ (Equation (**18**)). 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 12: 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)**
$\varepsilon_{i,t}^{MA}$	0.179**	0.212***	0.250***	0.285***	0.304***	0.368***	0.340***	0.433***	0.389***	0.437***
	(0.077)	(0.079)	(0.087)	(0.093)	(0.095)	(0.101)	(0.110)	(0.114)	(0.114)	(0.115)
CLI	–0.832***		–1.296***		–1.460***		–1.746***		–1.301***	
	(0.110)		(0.110)		(0.116)		(0.137)		(0.135)	
Dividend yield		0.159		0.193		0.169		–0.027		0.385
		(0.228)		(0.234)		(0.258)		(0.278)		(0.279)
Stock return		0.046		0.035		0.041		0.026		0.008
		(0.038)		(0.038)		(0.041)		(0.045)		(0.044)
Term spread		–0.373		0.060		–0.117		–0.091		0.439
		(0.238)		(0.248)		(0.292)		(0.305)		(0.315)
Short rate		–0.695***		–0.559***		–0.489**		–0.120		0.227
		(0.169)		(0.190)		(0.228)		(0.239)		(0.256)
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.	2,116	1,887	1,994	1,779	1,863	1,662	1,738	1,556	1,610	1,448
Adj. R^2	0.48	0.50	0.57	0.59	0.52	0.51	0.48	0.46	0.53	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 residuals ($\varepsilon_{i,t}^{MA}$) from regressing abnormal M&A activity ($\widetilde{MA}_{i,t}$) on a set of economic, financial, and political factors (see Section 6.3 for details):

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

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 13: Cross-Border M&A Portfolios Sorted on $\varepsilon_{i,t}^{MA}$

	$\mathbf{P_1}$	$\mathbf{P_2}$	$\mathbf{P_3}$	**HML**	**Linear**	**Rank**
mean (%)	0.71	3.47	4.23	3.52	3.04	2.81
t-stat	0.32	1.80	1.99	3.40	3.26	3.28
std (%)	8.26	7.39	8.53	5.27	4.91	4.56
SR	0.09	0.47	0.50	0.67	0.62	0.62
skew	–0.43	–0.27	–0.05	–0.04	0.11	0.00
kurt	4.79	5.92	4.16	3.10	4.97	4.37
ar(1)	0.09	0.05	0.02	–0.09	–0.06	–0.07
mdd (%)	39.6	21.4	22.7	9.0	8.7	8.4
fx (%)	–1.42	–1.22	1.83	3.25	2.81	2.58
fp (%)	2.13	2.25	2.40	0.27	0.22	0.23
$\mu_{\varepsilon_{i,t}^{MA}}$	–1.25	0.17	1.30			

The table presents statistics on cross-border merger and acquisition portfolios sorted by $\varepsilon_{i,t}^{MA}$. 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 $\varepsilon_{i,t}^{MA}$ variable in P_1, P_2, and P_3, which denote the three portfolios sorted each month from low to high values of $\varepsilon_{i,t}^{MA}$. HML, *Linear*, and *Rank* denote three zero-cost cross-sectional portfolios. Further details on the portfolio weights can be found in Section 5. The sample includes the US and 40 developed and emerging market countries. All statistics are calculated using monthly returns from January 1997 to December 2018.

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

Not for publication

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B.2: Transaction Costs
A discussion of the issues relating to the incorporation of transaction costs in foreign exchange studies.

Table B.1: Transaction Costs
Statistics on the tercile, HML, Linear, and Rank portfolios after incorporating transaction costs.

SECTION C

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

Table C.1: Other Sources of Currency Return Predictability
Statistics on currency portfolios sorted using other sources of currency return predictability including carry, value, momentum, dollar-carry, and economic momentum.

Table C.2: Explaining Cross-Border M&A Portfolio Returns
Explaining the returns of the rank-weight cross-border M&A portfolio by regressing on the returns of the alternative sources of currency return predictability.

Section A: Additional Results and Further Analyses

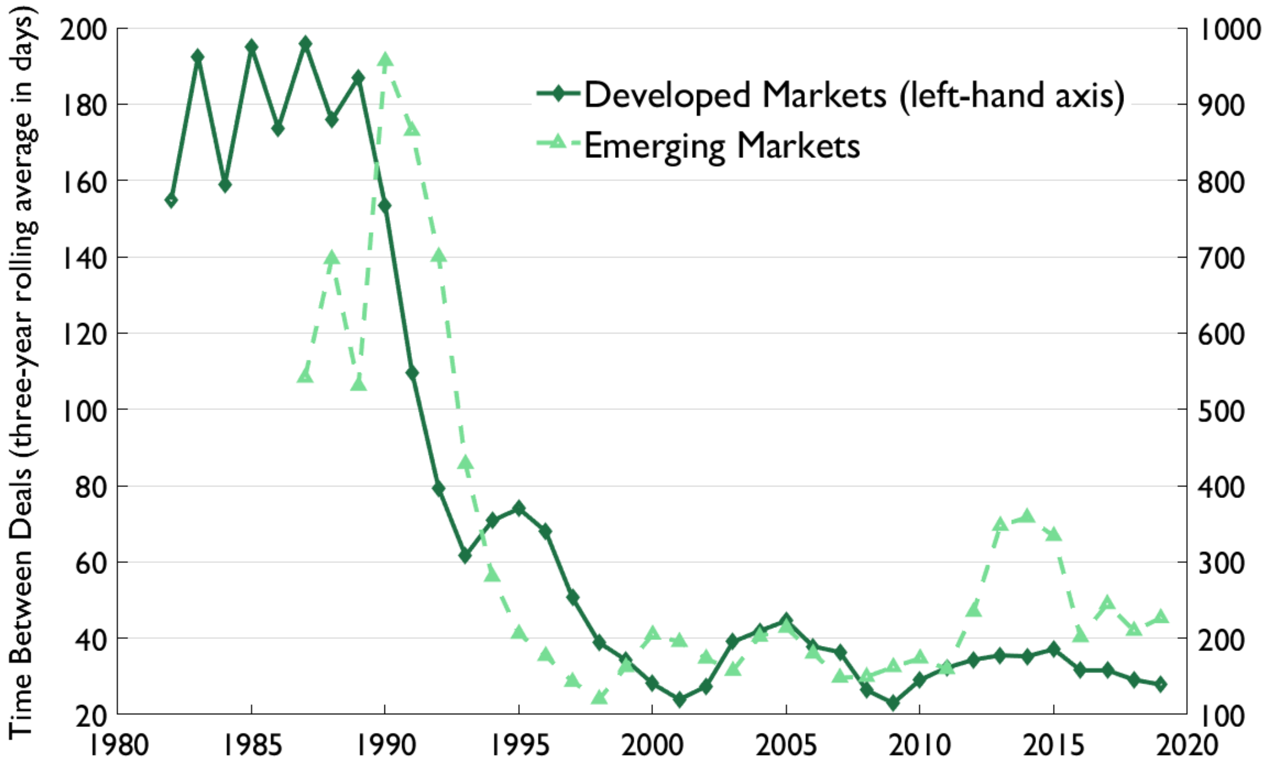

Fig A.1: Frequency of Announced Cross-Border M&As. The figure plots the average number of days between announcements of cross-border M&A deals involving the United States and either developed-market (solid line) or emerging-market (dashed line) countries over the prior 36 months. The 1995 data point,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

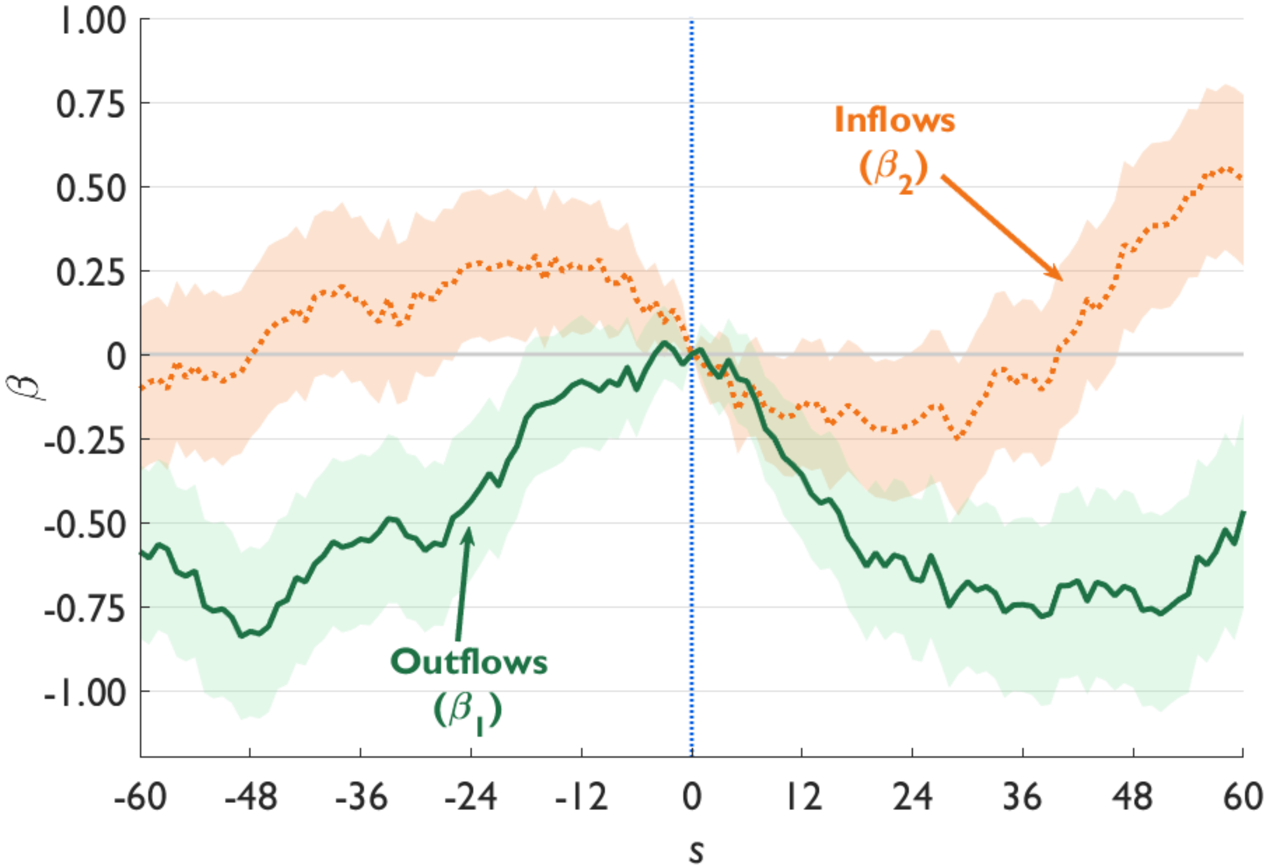

Fig A.2: Macroeconomic Acceleration With Inflows and Outflows. The figure plots β coefficients from panel regressions of changes in economic growth (i.e., economic acceleration), $\Delta g_{i,t+s}$, on the level of abnormal cross-border M&A activity constructed using either outflows ($\widetilde{MA}^{out}_{i,t}$)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

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

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

Table A.1: Foreign Exchange Data Sources

			DataStream Codes			
Country	**Code**	**Currency**	**Spot**	**1M Forward**	**Start Date**	**End Date**
Argentina	ARS	Peso	ARGPES$	USARS1F	2004-03-31	2018-12-31
Australia	AUD	Dollar	AUSTDOI	USAUD1F	1997-01-31	2018-12-31
Austria	ATS	Schilling	AUSTSC$	USATS1F	1997-01-31	1998-12-31
Belgium	BEF	Franc	BELGLU$	USBEF1F	1997-01-31	1998-12-31
Brazil	BRL	Brazilian real	BRACRU$	USBRL1F	2004-03-31	2018-12-31
Chile	CLP	Peso	CHILPE$	USCLP1F	2004-03-31	2018-12-31
Colombia	COP	Peso	COLUPE$	USCOP1F	2004-03-31	2018-12-31
Czech Republic	CZK	Koruna	CZECHC$	USCZK1F	1997-01-31	2018-12-31
Denmark	DKK	Krone	DANISH$	USDKK1F	1997-01-31	2018-12-31
Estonia	EEK	Kroon	ESTOKR$	USEEK1F	2004-03-31	2010-12-31
Euro Area	EUR	Euro	EUDOLLR	EUDOL1F	1999-01-31	2018-12-31
Finland	FIM	Markka	FINMAR$	USFIM1F	1997-01-31	1998-12-31
France	FRF	Franc	FRENFR$	USFRF1F	1997-01-31	1998-12-31
Germany	DEM	Mark	DMARKE$	USDEM1F	1997-01-31	1998-12-31
Greece	GRD	Drachma	GREDRA$	USGRD1F	1997-01-31	2000-12-31
Hungary	HUF	Forint	HUNFOR$	USHUF1F	1997-10-30	2018-12-31
Iceland	ISK	Krona	ICEKRO$	USISK1F	2004-03-31	2018-12-31
India	INR	Rupee	INDRUP$	USINR1F	1997-10-30	2018-12-31
Indonesia	IDR	Rupiah	INDORU$	USIDR1F	2007-06-30	2018-12-31
Ireland	IEP	Punt	IPUNTEI	USIEP1F	1997-01-31	1998-12-31
Israel	ILS	Shekel	ISRSHE$	USILS1F	2004-03-31	2018-12-31
Italy	ITL	Lira	ITALIR$	USITL1F	1997-01-31	1998-12-31
Japan	JPY	Yen	JAPAYE$	USJPY1F	1997-01-31	2018-12-31
Latvia	LVL	Lats	LATVLA$	USLVL1F	2004-03-31	2013-12-31
Lithuania	LTL	Litas	LITITA$	USLTL1F	2004-03-31	2014-12-31
Netherlands	NLG	Guilders	GUILDE$	USNLG1F	1997-01-31	1998-12-31

(Continued overleaf)

			DataStream Codes			
Country	**Code**	**Currency**	**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: Five Portfolios

	$\mathbf{P_1}$	$\mathbf{P_2}$	$\mathbf{P_3}$	$\mathbf{P_4}$	$\mathbf{P_5}$	**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 five 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 5. 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.3: **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 5. 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.4: 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.5: Explaining Abnormal M&A Activity

	$\widetilde{MA}$
Stock return	0.009
	(0.008)
Exchange rate return	0.539
	(1.159)
Max(import,export)	–0.063
	(0.220)
Log(GDP)	3.542**
	(1.456)
Log(GDP per capita)	–3.667**
	(1.577)
Investment profile	0.011***
	(0.004)
Quality of institutions	0.023
	(0.067)
Country FE	YES
Time FE	YES
Obs.	2532
Adj. R^2	0.16

The table presents the coefficient estimates from panel regressions of abnormal cross-border M&A activity ($\widetilde{MA}$) on a set of country-level, time-varying variables defined in Section 6.3 as well as 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.

Table A.6: 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, *Linear* and *Rank* denote three zero-cost cross-sectional portfolios. Further details on the portfolio weights can be found in Section 5. 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.7: 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.8: 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 5. The sample includes the US and 42 developed and emerging market countries. All statistics are calculated using monthly returns from January 1997 to December 2018.

Table A.9: 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 (**5**)) 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.10: Alternative Foreign Exchange Rate Predictability

	$\mathbf{P_1}$	$\mathbf{P_2}$	$\mathbf{P_3}$	**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.11: 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)**
$\widetilde{MA}$	0.061	0.097	0.104	0.123	0.142*	0.205**	0.313***	0.340***	0.386***	0.358***
	(0.067)	(0.070)	(0.075)	(0.080)	(0.081)	(0.085)	(0.089)	(0.092)	(0.091)	(0.089)
CLI	–1.079***		–1.601***		–1.674***		–1.866***		–1.533***	
	(0.080)		(0.083)		(0.087)		(0.102)		(0.091)	
Dividend yield		–0.003		0.136		–0.024		–0.004		0.114
		(0.123)		(0.136)		(0.135)		(0.149)		(0.157)
Stock return		0.029		0.038*		0.012		0.014		0.005
		(0.021)		(0.022)		(0.023)		(0.026)		(0.025)
Term spread		–0.026		0.804***		0.922***		0.900***		1.130***
		(0.113)		(0.108)		(0.112)		(0.124)		(0.141)
Short rate		–0.288***		0.383***		0.699***		0.975***		1.003***
		(0.082)		(0.081)		(0.091)		(0.101)		(0.115)
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.	4,989	4,154	4,737	3,952	4,485	3,752	4,234	3,553	3,982	3,352
Adj. R^2	0.43	0.47	0.52	0.55	0.49	0.53	0.46	0.49	0.51	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 ($\widetilde{MA}_{i,t}$) including non-informative zeros (results from the original baseline estimates are shown in Table 2):

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

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 A.12: 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.13: 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.

Section B: Economic Significance of Return Predictability

B.1: 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 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.

If the average return of the rank-weight portfolio, documented in Table 5, 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. In Fig. B.1, we plot the distributions of the average returns, t-statistics, and Sharpe ratios of the bootstrapped portfolios, overlaid with a normal distribution fit. We find the statistics for the observed rank-weight portfolio are always clear outliers—only a small handful of randomly assigned weights generate equivalent currency return predictability. The p-values are therefore low (below 0.001 in each case), and

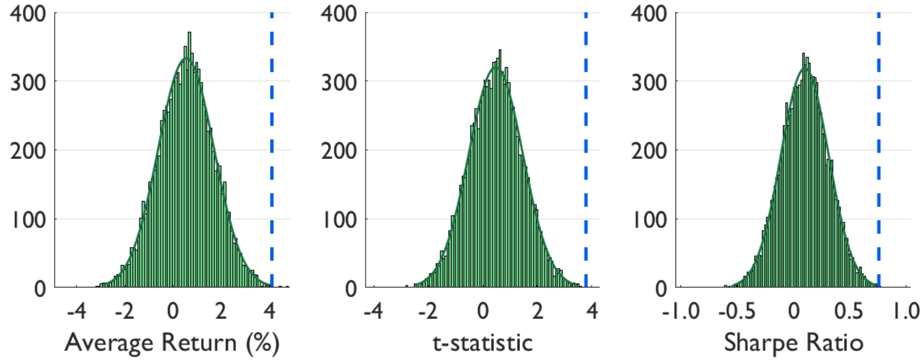

Fig B.1: Bootstrapped Distributions with Normal Distribution Fit. The figure plots the histograms of average returns, t-statistics, and Sharpe ratios, calculated using 10,000 bootstrapped samples. The corresponding values for the observed rank-weight M&A portfolio are plotted as dashed lines. A normal distribution fit is overlaid in each sub-figure.

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 5. In sum, the announcements of cross-border M&A deals continue to display an economically and statistically informative signal about future currency returns.

B.2: 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., 2022). We apply the more conservative 50% scaling and present the results from incorporating transaction costs in Table B.1. 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.

Table B.1: 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 5. 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.

Section C: 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).

Table C.1: Other Sources of Currency Return Predictability

	Dollar	**Carry**	**Momentum**	**Value**	**Carry$_{\mathbf{USD}}$**	**Trend$_{\mathbf{EC}}$**	**Trend$_{\mathbf{IN}}$**
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 C.2: 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.