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Investors' Limited Attention and the Supply-Chain Return Predictability: Evidence from Emerging Markets

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Resumo

A persistência de anomalias no mercado acionista levou autores a desafiar os pressupostos da hipótese dos mercados eficientes (HME). Alguns desses estudos focaram-se na evidência empírica de que os investidores não precificam títulos eficientemente, pois devido à atenção limitada e à quantidade de informação pública disponível, não é possível reunir e processar essa informação. Além disso, a globalização gerou interesse na disseminação dos eventos idiossincráticos entre empresas relacionadas e como são afetados os preços dos ativos.

Esta dissertação encontra evidência empírica de que informação relevante não é imediatamente incorporada nos preços das ações de empresas fornecedoras, levando à previsibilidade dos retornos. Analisámos 10 economias emergentes: China, India, Brasil, Rússia, México, Indonésia, Turquia, Tailândia, África do Sul e Malásia, o que expande a cobertura geográfica de estudos relacionados, que se focaram nos mercados desenvolvidos, principalmente nos EUA. Usando uma amostra de 5,962 empresas e 844,390 observações mensais, construímos um portfólio "long-short" que gera retornos em excesso ao mercado.

Para obter as relações fornecedor-cliente, usámos os dados "input-output" de 2021 da OCDE que, pelo nosso conhecimento, nunca foram usados para estudar o efeito "lead-lag". Para obter os dados das empresas, usámos a Refinitiv Eikon. O período escolhido foi entre 1995 e 2018. Segundo a maioria dos autores (Anexo I), as melhores metodologias para o estudo são as regressões em painel e Fama-MacBeth (1973).

O alfa mensal do portfólio ponderado foi de 0.40 por cento, traduzindo-se num prémio anual de 4.80 por cento. Posteriormente, aprofundámos a análise para perceber se os resultados foram induzidos por empresas pequenas e ilíquidas. Os resultados mantêm-se independentemente do tamanho. A regressão Fama-MacBeth (1973) demonstrou que os resultados não são induzidos pelas variáveis de controlo incluídas.

Este estudo desafia a HME ao demonstrar que o efeito "lead-lag" é resultado da lenta difusão de informação. Os resultados implicam que, dado que os investidores não consideram as relações cliente-fornecedor, um portfólio de compra ou venda de empresas fornecedoras, de acordo com os retornos mensais defasados das clientes, produz retornos anuais em excesso.

Palavras-chave: Previsibilidade de Retorno da Cadeia de Abastecimento, Atenção Limitada, Efeito "Lead-Lag"

Códigos JEL: G40, G41

Abstract

The persistence of anomalies in the stock market led researchers to challenge the assumptions of the efficient market hypothesis (EMH). Some of this research focused on finding empirical evidence that investors are not capable of efficiently pricing securities, since combining the human's limited attention with the vast amount of public information available, it is not possible to gather and process all public information. Moreover, the increasing globalisation drove a growing interest on studying how idiosyncratic events spread through firms' connections and how that impacts asset pricing.

This dissertation finds empirical evidence that relevant information is not instantly incorporated into stock prices of supplier companies, leading to supply-chain return predictability. We analysed 10 emerging markets: China, India, Brazil, Russia, Mexico, Indonesia, Turkey, Thailand, South Africa and Malaysia, which expands the geographical coverage of related studies that mainly focused on developed markets, particularly the U.S. Using a supplier sample of 5,962 companies, representing 844,390 company-month observations, we built a long-short portfolio yielding abnormal returns.

To obtain the supplier-customer relationships, we used the 2021 OECD inter-country input-output (ICIO) database, which, to the extent of our knowledge, was never used to study the lead-lag effect. To retrieve the companies' information, we used the Refinitiv Eikon database. The study period is between 1995 and 2018. According to most authors (Appendix I), the best methodologies for this study were panel and Fama-MacBeth (1973) regressions.

The value-weighted portfolio's monthly alpha retrieved was 0.40 percent, which converts into an annual abnormal return of 4.80 percent. Subsequently, we furthered our analysis to understand if the results were induced by very small and highly illiquid companies. The results indicate a lead-lag effect of returns between firms, regardless of their size. Using a Fama-MacBeth (1973) regression, we also found evidence that these results are not being driven by other control variables which are correlated with contemporaneous stock returns.

Hence, this study challenges the EMH by demonstrating that the lead-lag effect is the result of the slow diffusion of information. Our results imply that investors can buy or sell supplier firms, according to monthly lagged customer returns, to get annual abnormal returns.

Keywords: Supply-Chain Return Predictability, Limited Attention, Lead-Lag Effect

JEL-Codes: G40, G41

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1. Introduction

An assumption of the efficient market hypothesis is that investors are capable of pricing securities in an efficient manner since they gather and process all public information (Fama, 1970; Fama, 1991). However, recently, there is a growing amount of empirical evidence and theoretical research that is challenging markets' efficiency, thus relaxing some of its strict assumptions, specifically the investors' ability to gather and process all information (Menzly & Ozbas, 2010; Shahrur et al., 2010).

Relaxing this assumption is consistent with the vast research around human's attention, where it has been demonstrated a limit to the brain's cognitive-processing capability. Combining this finding with the large amount of financial information available, it is inevitable that limited attention plays a role in the investors' decision-making process (Hou et al., 2009; Kahneman, 1973). In fact, Barber and Odean (2008) confirm that significant events, such as stocks in the news, influence investors' decisions, and Hou et al. (2009) suggest that investors ignoring a company's earnings announcement, due to their attention limitation, delineates a much more clear-cut post-earnings-announcement drift, as they are unable to quickly reflect the information on prices.

Moreover, in an increasingly globalised world, researchers have been focusing on how idiosyncratic events spread more easily through the established connections between firms, whether they are supplier-customer relationships, strategic alliances, or any other kind of explicit contracted agreement, and how that affects the asset pricing in financial markets (Zareei, 2021).

Therefore, intra and inter-industry supply-chain effects and the confirmation that investors' lack of attention to public information may lead to the predictability of returns has been a recent area of interest for researchers conducting studies in empirical asset pricing (Li et al., 2020; Shahrur et al., 2010).

In fact, Cohen and Frazzini (2008) focused on studying this customer-supplier effect, using data from companies listed on the NYSE, AMEX and NASDAQ exchanges. In their research, they found out evidence of "customer momentum", that is, the customer companies' returns in a certain month would predict the supplier companies' returns in the following month and, consequently, a monthly portfolio based on a long-short strategy could provide annual abnormal returns.

Hence, considering the research done by these two authors and the results they provided, we replicated this study on the companies listed in emerging markets. We decided to study these markets since, to the extent of our knowledge, there is a gap in the existing literature.

To obtain the supplier-customer relationships, we used the 2021 OECD inter-country input-output (ICIO) database, and, to retrieve the companies' data for our sample formation, we used Refinitiv Eikon's database. The period of the study is limited by the amount of data available in both databases, which is between 1995 and 2018.

Thus, our research question is: Are there any available investment opportunities in companies with a supplier-customer relationship that generate abnormal returns, considering the stock price underreaction to negative (positive) news involving connected firms, and the consequent negative (positive) price drifts, coming from investors' attention restrictions?

In fact, the results we retrieved were in line with our hypothesis. The value-weighted portfolio's monthly alpha obtained for the whole supplier sample was 0.40 percent, which converts into an annual abnormal return of 4.8 percent. Subsequently, we furthered our analysis to understand if the results were induced by very small and highly illiquid companies. The results indicate a lead-lag effect of returns between firms, regardless of their size. Using a Fama-MacBeth (1973) regression, we also found evidence that these results are not being driven by other control variables which are correlated with contemporaneous stock returns.

The implications of our study are challenging for the market's efficiency, specifically for those who argue that prices reflect all available information. Indeed, Cohen and Frazzini (2008) indicate that investors' limited attention is responsible for failing to take the necessary customer-supplier relationships into account, thus affecting asset prices and leading to return predictability along the supply-chain. The evidence supporting our research question means that investors are able to build a portfolio that generates abnormal returns.

The present dissertation is divided in five chapters. Following this introduction, next chapter presents the literature review: the main concepts and empirical evidence about traditional finance, the Efficient Market Hypothesis, investors' limited attention and research related to economic links and predictable returns. Then, in chapter 3, we present the research question, and describe the data analysis and the applied methodology. In chapter 4, we report and discuss the empirical results. Lastly, the final chapter contains the main findings and conclusions.

2. Literature Review

2.1 Traditional Finance

Until the 1970s, the focus of research on the finance field was on studying what should be the investors' decision-making process behind investment decisions, and developing theories based on this framework (Joo & Durri, 2015).

The period of traditional finance research can be split in two stages. The first stage lasted until 1952, which was ruled by the traditional finance framework. In 1738, Bernoulli introduced the expected utility theory, that stated utility was used as a measure of humans' satisfaction for consuming goods or services. Accordingly, in the decision-making process of risky options, economic agents would compare the utility values provided by each available alternative (Bernoulli, 2011; Kapoor & Prosad, 2017; Von Neumann & Morgenstern, 2007). Subsequently, Mill (1874) presented the "*homo economicus*" or the rational economic man, who always strives to maximise his utility. There are some underlying assumptions regarding the characteristics of this economic agent: (1) perfect rationality; (2) perfect self-interest; (3) perfect information. These assumptions became the three main pillars of traditional or standard finance (Joo & Durri, 2015; Kapoor & Prosad, 2017).

Accordingly, a rational economic man should always correctly update their beliefs with new information, while maximising his satisfaction (Barberis et al., 2003). Hence, in traditional finance theory, investors are not impacted by their emotions, and act rationally, considering all available information in the investment decision-making process. Besides the *homo economicus*, standard finance also assumes that, in an efficient market, prices of securities immediately adjust to new information and current prices already incorporate all available information (Joo & Durri, 2015).

In 1952, Markowitz contributed to the traditional finance theory with the portfolio selection model, a process applied by investors to build the optimal portfolio, combining various risky assets and a risk free asset (Markowitz, 1952). In fact, this was also a major input for the development of what would become one of the most important asset pricing models in finance, the Capital Asset Pricing Model (CAPM) (Kapoor & Prosad, 2017; Merton, 1973).

The second phase, between the 1960s and the 1970s, was dominated by the neoclassical finance, whose major contributions relied on the CAPM, the Arbitrage Pricing Theory (APT) and the Efficient Market Hypothesis (EMH). The CAPM or "Sharpe-Lintner-Mossin meanvariance equilibrium model of exchange" provides a theoretical relationship between the risk of an asset and its expected return, which is seen as a fair return, considering the benchmark (Kapoor & Prosad, 2017; Lintner, 1965; Merton, 1973; Mossin, 1966; Sharpe, 1964). Over the years, the model was heavily criticised, both empirically and theoretically. Since CAPM is based on the Markowitz theory, it suffers from all its criticism as well, but some other objections are added considering the additional assumptions that it requires, such as the homogeneous expectations of economic agents (Fama & French, 1992; Fama & French, 2004).

The three-factor model was developed by Fama and French (1992), which argued that CAPM did not have full explanatory power over cross-sectional variation in equity returns, but that adding size and book-to-market value of equity as variables would provide such explanation (Faff, 2001; Merton, 1973). Hence, supporters of traditional finance would rather use the three-factor model instead of the CAPM, since the model produced inconsistencies regarding market efficiency (Kapoor & Prosad, 2017; Merton, 1973). The APT, established by Ross (1976), uses the same linear relationship between the expected return and risk of an asset as the CAPM, but it is a multi-factor model, meaning there are several macroeconomic variables that depict systematic risk (Roll & Ross, 1980).

However, the past academic work provided extensive analysis but had little theory to back it up. Therefore, Fama (1970) formalised the Efficient Market Hypothesis and organised the existing and growing empirical evidence.

2.2 Efficient Market Hypothesis

The Efficient Market Hypothesis was widely acknowledged by academic economists until the eighties, when it reached its highest point of popularity (Shiller, 2003). Since then, the theory has been discussed, but still remains relevant (Ţiţan, 2015).

The hypothesis was formalised in 1970, when Eugene Fama published the definition of markets' efficiency and the three forms of efficiency: weak, semi-strong and strong efficiency (Ţiţan, 2015). According to Fama (1970), an efficient market is one where prices always promptly incorporate existing information. Hence, this definition had several implications on the academics' perspective of how the market operates. When new information arrived in the market, it was immediately incorporated into prices. Therefore, the best strategy for investors to follow is a passive investment, that is, holding a well-diversified portfolio of stocks. Consequently, technical analysis (the analysis of past stock prices to infer future prices) or fundamental analysis (the assessment of a companies' financial information to determine the stock price), would not reveal fruitful for investors, as it would not allow them to obtain higher returns (Malkiel, 2003).

Fama (1970) distinguished three forms of markets' efficiency: weak, semi-strong and strong efficiency. The weak form of efficiency refers that current stock prices already incorporate all historical information (e.g., previous prices, trading volume, etc) that explained price changes in the past, implying a "random walk" behaviour of prices. Given that information is immediately incorporated in prices, then tomorrow price changes can only be explained by tomorrow's news and, thus, they are not affected by today's price changes. Since news are impossible to predict, it is logical to infer that price changes are random, that investors are not able to yield excess return in the market and that technical analysis reveals not fruitful (Degutis & Novickytė, 2014; Malkiel, 2003; Ţiţan, 2015).

The semi-strong form of efficiency incorporates the propositions assumed by the weak form, but it adds that prices also change immediately and correctly to include all currently released public information (e.g., acquisitions, distributed dividends, changes in accounting policies, etc.). Consequently, semi-strong efficiency of markets leads both technical and fundamental analysis not to be of great utility for investors in the pursuance of risk-weighted excess returns. The strong efficiency of markets presumes prices incorporate all available information in the market, complementing the weak and semi-strong form by stating that all private information should also be included. The immediate effect is that trading on insider information is a strategy that does not provide excess returns (Degutis & Novickytė, 2014; Fama, 1970; Ţiţan, 2015).

Afterwards, several researchers have dedicated their work to test all three types of efficiency, which have formed divergent opinions regarding capital markets' efficiency. Studies conducted on the observation of the weak form of efficiency led to a divergence of opinions. However, to what concerns the semi-strong and strong forms of EMH, most researchers have found no financial data that supported this type of market efficiency, thus discrediting both of them (Ţiţan, 2015).

Moreover, some market anomalies have occurred throughout the years, which cannot be fully explained by the traditional financial theory and the underlying EMH (Kapoor & Prosad, 2017). Hence, during the 1980s, people started doubting whether the propositions assumed by standard finance theorists were reasonable. This theory fails to comprehend, for example, the reasons behind individual investor trading, their portfolio selection and performance, and why returns change for non-risk related causes (Joo & Durri, 2015). In general, people started questioning whether financial agents really were rational or, instead, if they were affected by their own emotions of fear and greed, which would uncover the irrationality and inconsistency of choices under uncertainty (Bernstein, 1998; Kapoor & Prosad, 2017).

Therefore, it all culminated in the emergence of a new field of finance, the Behavioural Finance, which focused on providing behavioural explanations to the aforementioned anomalies (Joo & Durri, 2015; Kapoor & Prosad, 2017).

2.3 Investors' Limited Attention and Return Predictability

Essentially, the concept of market efficiency implies investors must allocate full attention to available information and to constantly update, process and reflect it in the decision-making process (Chen et al., 2020; Peng & Xiong, 2006).

In reality, as pointed out by Kahneman (1973), attention is a non-effortless scarce cognitive resource and, thus, it must be selective, meaning is not humanly possible to fulfil standard finance's requirements because people suffer from limited attention (Da et al., 2011). In fact, limited attention is a necessary consequence of the concept of bounded rationality, which states that human's rationality is limited by certain cognitive boundaries (Corwin & Coughenour, 2008; Uzar & Akkaya, 2013). Kahneman (1973) also states that significant empirical evidence suggests that humans are constrained in terms of performing multi-tasking.

Regarding financial decisions, investors' time and processing restrictions and the vast amount of information circulating in the financial environment result in investors being unable to analyse several types of information at the same time. Therefore, investors are forced to be selective on the information they pay attention to (Chen et al., 2020; Corwin & Coughenour, 2008; Hirshleifer et al., 2011; Hirshleifer & Teoh, 2003; Kahneman, 1973; Peng & Xiong, 2006).

Furthermore, Hirshleifer and Teoh (2003) go deeper and argue that humans' attention is directed towards salient stimuli. The salience of an information, whether it comes from its "'prominence', tendency to 'stand out', or its degree of contrast with other stimuli in the environment", has the power to facilitate how people encode some ideas, in exchange of others (Hirshleifer & Teoh, 2003, p. 342). To what concerns "conscious thought", the availability heuristic defined by Tversky and Kahneman (1974) is significant since the way attention will be directed to processing ideas will depend on how easily some memories are accessed and, as discussed above, this easiness is related with more salient information. Accordingly, it follows that people neglect "abstract, statistical, and base-rate information" (Hirshleifer & Teoh, 2003, p. 342).

Several studies have found evidence of a significant role of limited attention on investor behaviour, which is determinant in establishing asset prices, thus leading to return predictability, as, in the end, information is only incorporated in prices if investors actually pay attention to it (Hirshleifer et al., 2011; Peng & Xiong, 2006).

Throughout time, market responses to earnings and earnings components have been a puzzle that researchers have not yet been able to decipher (Hirshleifer et al., 2011). Post-earnings announcement drift (PEAD) is one of the strongest anomalies that have been systematically recorded (Ke & Ramalingegowda, 2005). It refers to the subsequent extension of abnormal returns towards the signal of earnings surprises, after the earnings announcement has happened, meaning that, on average, prices under react to unexpected earnings (Bernard & Thomas, 1989; Hirshleifer et al., 2011; Ke & Ramalingegowda, 2005). Therefore, abnormal returns tend to continue to drift up in the case of "good news" and to drift down for "bad news" (Bernard & Thomas, 1989). Foster et al. (1984) found out a profitable strategy in a 60-day span, after a certain earnings announcement, which consisted in a long position in firms with earnings surprises in the highest decile and a short position in firms with earnings surprises in the lowest decile. Without considering transaction costs, this strategy generated an annual abnormal return of 25 percent.

Limited attention has been pointed out as a possible explanation for the post-earnings announcement drift (Chen et al., 2020). Indeed, a significant amount of empirical evidence demonstrates under reaction of stock prices to public news events or earnings announcements, which suggests investors fail to react instantly to those announcements (Hirshleifer & Teoh, 2003). Francis et al. (1992) found that market reactions to earnings announcements in nontrading hours were much slower when compared to the markets' response in trading hours, taking several days to gradually incorporate that information into the price. DellaVigna and Pollet (2009) made a similar analysis with different weekdays, comparing the reaction of the market to earnings announcements done on Friday to the response on other weekdays. The results showed Friday announcements came with a higher delayed response, lower trading volume and a stronger drift (Chen et al., 2020; DellaVigna & Pollet, 2009). Hirshleifer et al. (2009) focused on testing whether the release of a load of information to the markets would be responsible for PEAD. The authors found out that PEAD is much stronger when multiple earnings announcements are made throughout a single day (Chen et al., 2020; Hirshleifer et al., 2009). Hirshleifer et al. (2011) developed a model in which they demonstrate PEAD increases with the amplitude of the earnings surprise and that the proportion of investor inattentiveness is inversely related with the markets' quickness of reaction to a certain earnings surprise.

Furthermore, limited attention also provides a potential explanation for the accrual and cash flow anomalies. These anomalies were first reported by Sloan (1996), who argues that investors focus too much on earnings, thus failing to fully incorporate information embedded in the accrual and cash flow components of earnings into prices, at least until it actually impacts future earnings. Hence, the author showed these anomalies coexist and are negatively related, meaning there is a tendency for companies with high levels of accruals (low levels of free cash flows) to be overpriced, thus providing low future abnormal returns, and companies with low levels of accruals to be under-priced (Hackel et al., 2000; Sehgal et al., 2012; Sloan, 1996).

Hirshleifer et al. (2011) argue that institutional investors should pay more attention to earnings components than retail investors, which is coherent with the finding of Collins et al. (2003) that the accrual anomaly is more robust around stocks with lower institutional ownership. Teoh and Wong (2002) suggest that analysts neglect accruals data while providing their forecasts to the market and Chen et al. (2002) state that there is no evidence of the existence of the accrual anomaly when accrual information is released at the same time as the earnings announcement, which suggests the anomaly is caused by investors who do not pay attention to the subsequent reporting of accruals. Moreover, managers use accounting discretion to capitalise on investors' disregard of accruals information and different accounting methods to make the most of fixated investors' assessments (Degeorge et al., 1999; Kothari, 2001; Libby et al., 2002; Teoh et al., 1998).

2.4 Research on Firms' Linkages and Return Predictability

In the current globalised world, firms are linked to each other due to various reasons and through different types of economic relationships, whether they are supplier-customer relationship, strategic alliances, or any other type of contractual agreement (Zareei, 2021). Given the slow diffusion of information and investor limited attention, researchers have been focusing on studying how idiosyncratic shocks spread across companies, and how the price reacts to those events, leading to return predictability (Zareei, 2021). Our study relates to the strand of literature that focuses not only on cross-predictability of returns, where a stock may, at times, be leading a stock and, at other times, be lagging that stock, but also on lead-lag predictability of returns, where a stock always leads or lags another one (Zareei, 2021).

Lo and MacKinlay (1990) provided the first piece of evidence of lead-lag predictability between intra-industry companies, where it was found that small stocks lagged returns of large stocks. Hou (2007) confirmed that this lead-lag effect is typically an intra-industry anomaly, meaning returns on big firms lead returns on small firms in the same industry. Brennan et al. (1993) demonstrated that portfolio returns of firms followed by fewer analysts lag portfolio returns of firms followed by several analysts. Badrinath et al. (1995) showed that returns of high-institutional ownership portfolios lead returns of portfolios with lower institutional ownership. Menzly and Ozbas (2006) documented cross-predictability among industries in the same supply-chain. Hong et al. (2007) suggested that, due to the slow diffusion of information, the returns of a substantial number of industries are able to predict the returns of the stock market up to two months.

Cohen and Frazzini (2008) and Menzly and Ozbas (2010) extended the work on the intra-industry predictability anomaly, studying the lead-lag effect in economically linked firms, with a customer-supplier relationship. Cohen and Frazzini (2008) supposed that, given the slow diffusion of information and if two firms are economically linked, then there must be correlation between their performance, leading to return predictability. In their hypothesis, news regarding the customer company should also have an effect on the supplier's stock price, meaning there is a lead-lag effect between both companies (Cohen & Frazzini, 2008).

Therefore, the authors found out evidence of what they termed as "customer momentum", referring that customer companies' returns in a certain month predict the supplier companies' returns in the following month and, consequently, a monthly portfolio based on a long-short strategy could provide annual abnormal returns of 18.4 percent (Cohen &

Frazzini, 2008). Menzly and Ozbas (2010) performed a similar link analysis at the industry-level and observed that there is cross-predictability among returns of economically linked stocks, through industry customer-supplier relationships, and that the robustness of this cross-predictability reduced according to the number of more informed and professional investors, such as analysts and institutional investors. Shahrur et al. (2010) extended this work by analysing the customer-supplier lead-lag effect in international equity markets, providing evidence that customer companies lead returns of supplier companies.

Albuquerque et al. (2015) documented return predictability of companies with high trade credit links, based on the returns produced by the customer company. Scherbina and Schlusche (2015a) suggested that firms which appear on important news lead returns of firms that relate to the news. Scherbina and Schlusche (2015b) demonstrate that news' information content reveals underlying economic linkages between companies, leading to monthly return cross-predictability. Cao et al. (2016) found that a long-short portfolio based on predictability among alliance partners would provide a monthly return of 89 basis points. Regarding technology-linked companies, Qiu et al. (2018) presented a long-short portfolio providing returns of 105 basis points based on a lead-lag effect. Jin and Li (2020) verify predictability of returns between geographically linked companies, particularly revealing a lag effect of focal firms regarding their geographical peers. Li et al. (2020) studied the intra-industry supply-chain effect in the Chinese market, identifying return predictability.

Zhang et al. (2020) demonstrated return predictability in Chinese industries increased in a bull market and identified returns in the banking, real estate, leasing and information technology industries were positively correlated with market returns and returns in conventional industries were negatively correlated with market returns. Bai et al. (2020) provide evidence of intra-industry return predictability on companies with overlapping offshore sales activities. In a different framework, Chen et al. (2020) analyse the lessor-lessee relationship in real estate markets, observing that the future returns of real estate investment trusts (REITs) are higher for the best performing tenants leasing the properties. Zareei (2021) also built a long-short portfolio based on cross-momentum propagation of shocks between economically linked firms, yielding significant returns.

3. Data and Methodology

Our research question is: Are there any available investment opportunities in companies with a supplier-customer relationship that generate abnormal returns, considering the stock price underreaction to negative (positive) news involving connected firms, and the consequent negative (positive) price drifts, coming from investors' attention restrictions?

To answer the question, as suggested by Yin (2009), we resorted to quantitative methodologies to assess the causality effect between investors' limited attention and the consequent underreaction, leading to a profitable investment opportunity. The extant empirical literature on the subject confirms the adequacy of such option (see Appendix I).

According to the majority of the authors, the best methodologies to analyse the lead-lag effect and the profitability of the strategic portfolio are panel and Fama-MacBeth (1973) regressions.

3.1 Data

Considering the previous studies around supply-chain return predictability, we replicated them on the largest emerging markets, between 1995 and 2018. The preference for studying emerging markets is, to the extent of our knowledge, due to the existing gap in the literature. Nevertheless, we are aware that Li et al. (2020) have already analysed supply-chain return predictability in China, the largest emerging economy. Therefore, we extend this study to other emerging markets.

According to the International Monetary Fund (IMF), Dow Jones, Russell, Standard & Poor's and Morgan Stanley Capital International (MSCI)[1], the compiled list of emerging markets includes Brazil, Chile, China, Colombia, Hungary, Indonesia, India, Malaysia, Mexico, Peru, Philippines, Russia, South Africa, Thailand and Turkey. From this list, we selected the 10 largest emerging economies by gross domestic product (GDP), ranked by the IMF (2018): China, India, Brazil, Russia, Mexico, Indonesia, Turkey, Thailand, South Africa and Malaysia.

[1] https://www.ig.com/uk/news-and-trade-ideas/other-news/top-10-emerging-market-economies-190117

3.1.1 Sample companies

To build our set of sample companies, we used Refinitiv Eikon database to determine the stocks that were listed on the corresponding exchanges of the aforementioned countries. Similar to Shahrur et al. (2010) and Li et al. (2020), we imposed restrictions in order to eliminate potential errors and very small companies. Using data from the last day of our sample period (December 31st, 2018), first, we excluded all financial firms (NAICS code starting with 52) due to the challenge that capturing their customers represents. Second, we only included companies with total assets and total revenues above $5 million. Third, we removed a stock if, during the research period, any of its monthly return was greater than or equal to 100 percent. Lastly, we only included companies with a price-to-book ratio below or equal to 50.

Following these criteria, the "overall sample" was composed of 5,981 companies. This sample was then used to compute customer returns and build the "supplier sample". The "supplier sample", the sample of our interest regarding the study, is composed uniquely of companies from which customers returns are available. Applying this last restriction, we obtained a sample of 5,962 companies, with 844,390 company-month observations.

Table 1 illustrates descriptive statistics for the last day in our sample period, December 31st, 2018, and is divided into panel A, which demonstrates the statistics for our overall sample, and panel B, which shows the same statistics for our supplier sample. Since the return data was available for almost all of our companies in the first sample, the statistics in both panels are very similar.

Regarding panel A, the average market value of equity (MVE) was $1.642 billion and the median was $314 million. Chinese stocks represented the largest proportion of the sample, both in terms of number of companies (48.05 percent) and market value of equity (55.14 percent). Moreover, the overall sample included 370 industries.

As previously mentioned, since the customer return data was highly available, the supplier sample represented 98.12 percent of the overall sample in terms of market value of equity. The average market capitalisation of panel B was $1.645 billion and the median was $314 million. This indicates that, on average, the supplier and customer companies are of similar size.

Table 1. Descriptive Statistics, December 2018

Market	Nº of companies	Mean MVE ($bn)	Median MVE ($bn)	Market MVE ($bn)	% of total MVE	Nº of Industries
A. Overall sample						
China	2,874	1.502	0.591	4,315.511	55.14	**38**
India	1,202	1.078	0.063	1,294.280	16.54	**38**
Brazil	146	2.637	0.579	384.973	4.92	**38**
Russia	106	3.951	0.364	410.914	5.25	**38**
Mexico	89	2.938	0.846	258.574	3.30	**38**
Indonesia	240	0.853	0.150	204.690	2.62	**38**
Turkey	167	0.359	0.058	59.644	0.76	**38**
Thailand	439	0.757	0.090	332.296	4.25	**38**
South Africa	160	1.865	0.350	294.700	3.77	**38**
Malaysia	558	0.484	0.049	269.696	3.45	**28**
Total	5,981	1.642	0.314	7,825.279	100.00	**370**
B. Supplier sample						
China	2,869	1.503	0.591	4,312.587	55.13	**38**
India	1,199	1.079	0.063	1,294.238	16.55	**38**
Brazil	145	2.653	0.585	384.651	4.92	**38**
Russia	104	3.951	0.364	410.914	5.25	**38**
Mexico	88	2.938	0.846	258.574	3.31	**38**
Indonesia	240	0.853	0.150	204.690	2.62	**38**
Turkey	166	0.359	0.058	59.644	0.76	**38**
Thailand	438	0.759	0.090	332.253	4.25	**38**
South Africa	158	1.865	0.350	294.700	3.77	**38**
Malaysia	555	0.486	0.049	269.626	3.45	**28**
Total	5,962	1.645	0.314	7,678.077	100.00	**370**

Comparing our samples with the ones obtained by Shahrur et al. (2010), our study of reference, we observe that, after applying the aforementioned restrictions, we retrieved a larger supplier sample (5,962 vs 3,942 companies). Since the study of reference started with a larger overall sample (5,981 vs 9,437 companies), we can conclude that this is due to the high availability of customer return data in our sample. Regarding the number of unique IO industries, our supplier sample is also larger (370 vs 223 industries). To what concerns the median and average MVE, we also retrieved larger figures (0.314 vs 0.146 billion dollars and 1.645 vs 1.490 billion dollars, respectively).

Additionally, we can observe that our sample is more concentrated in terms of market capitalisation and number of companies, since Chinese stocks account for about 55 percent (vs 20 percent in Japanese stocks in the study of reference) and about 48 percent (vs 37 percent in Japanese stocks in the study of reference), respectively.

3.1.2 Customer-supplier linkages

To identify the customer-supplier relationships, similarly to Li et al. (2020), we relied on the yearly input-output tables as they argue it is a superior method compared to the principal customer identification used by Cohen and Frazzini (2008). However, instead of the World Input-Output database (WIOD), we used the OECD inter-country input-output (ICIO) database, which presented a wider coverage regarding the number of emerging markets and the period of time. To the extent of our knowledge, this is the first study that used the OECD input-output table (2021 edition) as a source for identifying the customer-supplier relationships.

Since the input-output use table states the estimated value of the supplier industry's output that is used in the production of the customer industry's output, for each supplier industry we were able to determine which were their customer industries and the weight of each one on the total output of the supplier industry.

To identify the customer industries for each supplier industry and, consequently, separate the supplier companies from the customer companies, we first gathered the International North American Industry Classification System (NAICS) code for the companies in our sample (available in the Refinitiv Eikon database), to classify them by industry. Subsequently, given that the ICIO tables used a different code system to identify each industry, we converted each NAICS code to its equivalent one in the use table. After the conversion, we were able to identify the supplier companies and their portfolio of customer companies.

Furthermore, we restricted our final sample of supplier industries based on the use that was given to their output. Suppliers' output can either have an intermediate use by other companies (to produce another product) or it can have a final demand. In the last case, the supplier company sells its output to a final user such as households and, thus, there are no companies from which we can retrieve return data, which would not be feasible for the study we want to conduct. Moreover, there is also the case where the output could be sold to intermediate users, but there are no publicly traded companies. Hence, the final sample only included supplier industries that sold at least 25 percent of its output to publicly traded companies, for which return data was constructible.

Performance persistence studies, such as the one we are carrying out, usually suffer from the look-ahead bias. The look-ahead bias is inherent in the methodology used in these studies, referring to the use of information that was not yet available during the period of the study. In this type of studies, two periods may be recognized: the ranking period, in which companies' stocks are ranked at the end of the first period according to their performance and grouped in portfolios; and the evaluation period, in which the portfolios' average performance are determined, with the underlying condition that the stocks remain in the same ranks at the end of the second testing period (Brown et al., 1992; Daniel et al., 2009; Ter Horst et al., 2001). Thus, to avoid look-ahead bias when we build our portfolios and compare their performance with other return factors, we selected the ICIO tables of the previous year for the stock data of the actual year.

3.2 Customer return index

Following Shahrur et al. (2010), to verify whether there is a customer-supplier lead-lag effect, we built the customer return variable for the *i*th supplier industry as indicated below:

$$\mathit{Customer\ return}_{i,t-1} = \sum_{\substack{j=1 \\ j \neq i}}^{n} CR_{j,t-1}\ (\mathit{Industry\ percentage\ sold}_{ij})$$

Where:

- n is the number of customer industries;
- CR_j represents the average return of the portfolio of companies that belong to the jth customer industry, weighted by the *Industry percentage sold*$_{ij}$;
- *Industry percentage sold*$_{ij}$ is computed as the percentage of the ith supplier industry that is sold to each jth customer industry;

Overall, the variable *Customer return*$_{t-1}$ is the return average of the portfolio of customer industries of each supplier industry, weighted by the *Industry percentage sold*$_{ij}$, which measures the relevance of each customer industry to their supplier industry, in terms of sold output. Intuitively, *Customer return*$_{t-1}$ will be high if relevant customer industries in the supplier industry's portfolio exhibit significant positive returns in that month.

Furthermore, it is important to mention that we took into account all customers when computing *Industry percentage sold*$_{ij}$, meaning that we included industries with no publicly traded companies and final demand, such as households. Since the returns of customer industries for which we did not have available customer return data was equal to zero, the logic behind this approach was to penalise the returns of customer industries that were irrelevant buyers of the supplier's output. Finally, it is also important to note that we computed the variable *Customer return*$_{t-1}$ only using customer industries belonging to the same country as the supplier industry. Since the consequences of new information that impacts customers might be country specific, the construction of this variable was made at the country level and not at the universal level.

3.3 Long-short portfolio formation

The central research question of this study lies on the supply-chain predictability of returns. To verify for this lead-lag relationship, our aim is to test whether a strategy of buying or selling supplier firms, depending on the previous monthly lagged customer returns, would yield abnormal returns. Accordingly, for each month t, we started by setting a rank of supplier industries in ascending order, contingent on the previously computed *Customer return*$_{t-1}$.

Considering the ranked list of supplier industries, we built five quintile portfolios, from Q1, which includes the industries with the lowest *Customer return*$_{t-1}$, to Q5, which holds the industries with the highest *Customer return*$_{t-1}$. Subsequently, we formed a long-short (L-S) portfolio based on the strategy of holding the Q5 and shorting the Q1 supplier industries. Therefore, if the supplier and customer returns exhibit a lead-lag effect, our constructed long-short portfolio should generate abnormal returns.

We estimated portfolio abnormal returns using the market model, based on the return of a portfolio composed of stocks in 26 emerging markets, and the four-factor model, which is the Fama and French (1993) three-factor model extended by Carhart (1997) momentum factor. The *Market, HML, SML and MOM* factors were obtained in Kenneth French's website[2], which were constructed using different portfolios of stocks of emerging markets.

Hence, following Shahrur et al. (2010), we estimated the subsequent model for each supplier portfolio:

$$Supplier\ portfolio\ excess\ return_t = a + \beta_1 Market_t + \beta_2 HML_t + \beta_3 SMB_t + \beta_4 MOM_t$$

Where:

- *Supplier portfolio excess return*$_t$ is the equally or value-weighted monthly excess return on the supplier industry portfolio;
- $Market_t$ is the monthly excess return on the emerging markets' value-weighted portfolio of stocks;
- HML_t is the monthly difference between the average return on two value portfolios and the average return on two growth portfolios;
- SMB_t is the monthly difference between the average return on nine small stock portfolios and the average return on nine big stock portfolios;
- MOM_t is the monthly equally-weighted difference between the average for two winner portfolios and the average return for two loser portfolios;

Following Fama (1998), to compute excess portfolio returns (portfolio returns minus the risk-free rate), we use the U.S. one-month Treasury bill rate as a proxy for the risk-free rate.

Moreover, despite having performed an analysis at the country level for the variable *Customer return*$_{t-1}$, our focus on this study was to assess the customer-supplier return predictability in

[2] https://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html

the global sample of stocks in emerging markets. Therefore, we conducted our subsequent tests at the universal level, meaning that, to build the quintiles, the long-short portfolio and the four risk factors, we used data corresponding to the whole universe of emerging markets in our study.

Additionally, we analysed separately a sample containing only Chinese companies, since they represented about 55 percent of our supplier sample.

3.4 Fama-MacBeth (1973) regression model

In our final approach to this study, we tested for the possibility that the previous findings from the L-S portfolio were being driven by other variables which are correlated with contemporaneous stock returns. Thus, we used a Fama-MacBeth (1973) regression methodology to analyse whether the L-S strategy still holds after controlling for these variables.

Contrary to the previous methods used on the study, the regression model is estimated at the supplier-company level, and not at the industry level, to control for determinants of contemporaneous stock returns that are specific to the company.

Therefore, in the following model, for every calendar month of our study period, we regressed the stock returns of supplier companies on the customer returns and control variables:

$$\begin{aligned}&\textit{Supplier firm return}_t = a + \beta_1 \textit{Customer return}_{t-1} + \beta_2 \textit{Return}_{t-1} + \beta_3 \textit{Return}_{t-12,t-2} + \\ &\beta_4 \textit{Industry return}_{t-1} \textit{ or } (\beta_5 \textit{Large-size industry return}_{t-1} + \beta_6 \textit{Medium-size industry return}_{t-1} + \\ &\beta_7 \textit{Small-size industry return}_{t-1}) + \beta_8 \textit{ Industry return}_{t-12,t-2} + \beta_9 \textit{MVE}_{t-1} + \beta_{10} \textit{PTB}_{t-1} + \mu\end{aligned}$$

Where:

- Return refers to the supplier company's return. While $Return_{t-1}$ controls for the reversal effect of Jegadeesh (1990), $Return_{t-12,t-2}$ controls for the momentum effect of Jegadeesh and Titman (1993);
- Industry return is computed as the value-weighted return of the companies' 2-digit ISIC Rev. 4 industry code, weighted by each company's market capitalisation. Both

Industry Return$_{t-1}$ and *Industry Return$_{t-12,t-2}$* are included in the regression to control for the industry-level momentum effect (Moskowitz & Grinblatt, 1999);

- Similar to the industry return control variables, *small-, medium-, and large-size industry returns$_{t-1}$* represent the value-weighted return of the companies' 2-digit ISIC Rev. 4 industry code, divided in portfolios of different percentile ranges of market value of equity (MVE): one portfolio of small-industry companies between the 0 to 30th percentile of MVE; one portfolio of medium-industry companies between the 30th to 70th percentile of MVE; and one portfolio of large-industry companies between the 70th to 100th percentile of MVE. These control variables were included to control for the intra-industry lead-lag effect (Hou, 2007);
- *MVE$_{t-1}$* represents the market value of equity of a company;
- *PTB$_{t-1}$* is the price-to-book ratio of a company, i.e., the ratio between the market value of equity and the book value of equity;

Since the supplier and customer companies conduct their operations in linked industries, we must emphasize that the *Industry return* control variable is specifically important because it is most likely that the lagged customer return is correlated with the lagged supplier return.

β_1 coefficient in the model represents the aim of our research question. Thus, we can build a hypothesis regarding the result of this coefficient: if we confirm our research question and, indeed, there is a lead-lag effect coming from the supplier-customer relationship, then β_1 must be positive and statistically significant.

4. Empirical results

4.1 Supplier Portfolio's Abnormal Returns

Table 2 represents the results for the constructed quintile portfolios of stocks, using the market model. Panel A demonstrates the results using equally-weighted monthly returns, which were calculated by computing each supplier industry's average return and, subsequently, the average return for the industries considered in the quintile. Panel B reports the results using value-weighted monthly returns, which were weighted by the stocks' market capitalisations.

Table 2. Supplier Portfolio's Abnormal Returns: Market Model, January 1996-December 2018

	Q1 (low)	Q2	Q3	Q4	Q5 (high)	L-S
A. Equally-weighted monthly returns						
Intercept (%)	-0.15***	-0.03***	0.01***	0.06***	0.25***	0.38***
	(-26.55)	(-15.83)	(6.38)	(22.18)	(22.51)	(30.05)
Market	0.01691***	0.01007***	0.00905***	0.00100***	0.01632***	-0.00059
	(18.74)	(28.87)	(30.42)	(21.97)	(9.92)	(-0.29)
Adjusted R^2	56.03%	75.17%	77.07%	63.66%	26.15%	-0.33%
B. Value-weighted monthly returns						
Intercept (%)	-0.15***	-0.03***	0.02***	0.07***	0.24***	0.39***
	(-24.40)	(-12.29)	(7.42)	(21.92)	(22.27)	(29.19)
Market	0.01637***	0.01002***	0.00911***	0.00989***	0.01615***	-0.00022
	(17.04)	(25.22)	(25.86)	(19.69)	(9.23)	(-0.10)
Adjusted R^2	51.27%	69.79%	70.83%	58.44%	23.43%	-0.36%

Note: The sample includes 844,390 company-month observations for 5,962 unique companies. The market model includes the value-weighted excess return on a market index.

t-statistics in parentheses.

*Significant at the 10 percent level.

***Significant at the 1 percent level.

Regarding panel A, the supplier industries with the worst performance (Q1) have an intercept, i.e. monthly alpha, of -0.15 percent, statistically significant at the 1 percent level (t-statistic is -26.55). The fifth quintile (Q5), that includes the supplier industries with the highest performance, has an intercept of 0.25 percent, also statistically significant at the 1 percent level (t-statistic is 22.51).

Therefore, the analysed long-short portfolio strategy of buying stocks in Q5 and shorting stocks in Q1 yields a monthly alpha of 0.38 percent, which is statistically significant at the 1 percent level (t-statistic is 30.05). Hence, the L-S strategy generates an annual abnormal return of 4.56 percent. Additionally, the results presented in Table 2 demonstrate that the monthly alpha continuously increases across the five quintiles and, overall, the results are aligned with our hypothesis that the returns of supplier and customer industries exhibit a lead-lag effect.

To what concerns panel B, we retrieved similar results. The strategy generates a monthly alpha of 0.39 percent, statistically significant at the 1 percent level, with a t-statistic of 29.19, which converts into an annual abnormal return of 4.68 percent.

Comparing with the results retrieved by Shahrur et al. (2010), we observe that the equally-weighted monthly returns are higher, amounting to 1.28 percent monthly abnormal returns, which translates into 15.36 percent annually. However, if we consider the value-weighted monthly returns, the L-S strategy yields a return of 0.35 percent (statistically insignificant), which is smaller than ours.

Table 3 also represents the results for the constructed quintile portfolios of stocks, but following the four-factor model. Comparing the results with the ones retrieved in Table 2, we can observe that they are very similar, meaning that adding the three extra factors does not have a significant impact in our results. The monthly alpha of the L-S strategy only increased by 0.01 percent in both equally and value-weighted monthly returns. Hence, for the following tables, we have only reported the results retrieved using the four-factor model.

The comparison to the study of Shahrur et al. (2010) is similar to the one from Table 2: a higher abnormal return (1.23 percent) considering the equally-weighted monthly returns and a statistically insignificant premium return of 0.34 percent, when considering the value-weighted returns.

Subsequently, we built a trimmed supplier sample by applying liquidity constraints, to analyse whether the results we retrieved were induced by very small and highly illiquid companies. Therefore, firstly, we removed from the sample companies that were below the 10^{th}

Table 3. Supplier Portfolio's Abnormal Returns: Four-Factor Model, January 1996-December 2018

	Q1 (low)	Q2	Q3	Q4	Q5 (high)	L-S
A. Equally-weighted monthly returns						
Intercept (%)	-0.15***	-0.04***	0.01***	0.07***	0.25***	0.39***
	(-24.21)	(-15.73)	(5.87)	(21.81)	(22.25)	(28.68)
Market	0.01777***	0.01074***	0.00939***	0.01009***	0.01565***	-0.00212
	(18.14)	(29.51)	(30.27)	(21.25)	(8.94)	(-0.97)
SMB	0.00619*	0.00567***	0.00458***	0.00525***	0.00827	0.00207
	(2.14)	(5.26)	(4.99)	(3.74)	(1.60)	(0.32)
HML	-0.00273	0.00073	0.00119	0.00059	-0.00559	-0.00285
	(-1.05)	(0.76)	(1.44)	(0.47)	(-1.20)	(-0.49)
MOM	0.00113	0.00072	-0.00104	-0.00377***	-0.01372***	-0.01486***
	(0.56)	(0.94)	(-1.62)	(-3.81)	(-3.76)	(-3.26)
Adjusted R^2	56.56%	77.30%	79.11%	66.84%	29.81%	2.43%
B. Value-weighted monthly returns						
Intercept (%)	-0.15***	-0.03***	0.02***	0.07***	0.26***	0.40***
	(-22.35)	(-11.58)	(6.62)	(20.44)	(21.53)	(27.78)
Market	0.01648***	0.01026***	0.00911***	0.00961***	0.01455***	-0.00193
	(15.65)	(23.63)	(23.73)	(17.73)	(7.71)	(-0.83)
SMB	-0.00143	0.00177	0.00122	0.00104	-0.00150	0.00007
	(-0.46)	(1.38)	(1.08)	(0.65)	(-0.27)	(-0.01)
HML	0.00003	0.00078	0.00132	0.00186	-0.00322	-0.00325
	(0.01)	(0.68)	(1.30)	(1.29)	(-0.64)	(-0.53)
MOM	0.00210	0.00056	-0.00086	-0.00291*	-0.01246***	-0.01456***
	(0.96)	(0.61)	(-1.07)	(-2.57)	(-3.17)	(-3.02)
Adjusted R^2	50.93%	69.74%	70.97%	59.43%	25.38%	1.85%

Note: The sample includes 844,390 company-month observations for 5,962 unique companies. The market model includes the value-weighted excess return on a market index.

t-statistics in parentheses.

*Significant at the 10 percent level.

***Significant at the 1 percent level.

percentile of market capitalisation and trading turnover. The latter was computed as the average daily trading volume over the previous three months divided by the total number of shares outstanding. Secondly, we excluded companies with a stock price below 1 dollar, registered at the last day of our sample period. Establishing these criteria resulted in a trimmed supplier sample of 2,386 companies, with 314,537 company-month observations.

The results for the trimmed supplier sample are reported in **Table A.1**, which was included in the appendix II due to the low adjusted R^2 that we retrieved. Nevertheless, the L-S strategy remains relevant as the portfolio provides a statistically significant (at the 1 percent level) monthly alpha of 0.50 percent, which translates into a 6 percent annual premium.

Moreover, from the trimmed supplier sample, we furthered our analysis to check whether the results were driven by small companies and constructed four subsamples of stocks based on the companies' market capitalisation (MVE): micro-cap sample (with a MVE lower than 250 million dollars), small-cap sample (with a MVE between 250 million dollars and 1 billion dollars), mid-cap sample (with a MVE between 1 billion dollars and 5 billion dollars) and large-cap sample (with a MVE higher than 5 billion dollars). Establishing these MVE thresholds resulted in the following subsamples: the micro-cap subsample includes 399 companies, representing 56,304 company-month observations; the small-cap subsample contains 107,546 company-month observations for 1,057 companies; the mid-cap subsample comprises 719 companies, with 110,518 company-month observations; the large-cap subsample consists of 211 companies, with 40,169 company-month observations.

The results presented in **Tables 4, 5, 6 and 7** indicate that there is a lead-lag effect of returns between customer and supplier companies in all portfolios, regardless of their size.

Starting by Table 4, which presents the results for the micro-cap subsample, it is possible to observe that the monthly alphas monotonically increase as the first quintile has an intercept of -0.31, statistically significant at the 1 percent level (t-statistic is -25.18), and the fifth quintile generates a monthly premium of 0.41 percent, also statistically significant at the 1 percent level (t-statistic is 24.46). Therefore, the L-S strategy yields a statistically significant (t-statistic is (38.17) monthly abnormal return of 0.71 percent, which converts into an annual premium of 8.52 percent.

Regarding Table 5, that reports the results for the small-cap subsample, we can see that the L-S portfolio yielded the same statistically significant monthly alpha (0.71 percent) as the micro-cap sample. This return results from selling stocks in quintile 1, which have a

Table 4. Supplier Portfolio's Abnormal Returns: Micro-cap Sample January 1996-December 2018

	Q1 (low)	Q2	Q3	Q4	Q5 (high)	L-S
A. Equally-weighted monthly returns						
Intercept (%)	-0.31***	-0.05***	0.00	0.06***	0.41***	0.71***
	(-25.18)	(-16.88)	(1.48)	(20.72)	(24.46)	(38.17)
Market	0.02510***	0.00836***	0.00540***	0.00690***	0.02416***	-0.00095
	(13.01)	(19.07)	(18.90)	(14.95)	(9.18)	(-0.32)
SMB	0.02715***	0.00792***	0.00518***	0.00687***	0.02444***	-0.00271
	(4.76)	(6.11)	(6.13)	(5.04)	(3.14)	(-0.31)
HML	-0.00296	0.00157	0.00151*	0.00128	-0.01554*	-0.01258
	(-0.58)	(1.35)	(1.99)	(1.04)	(-2.22)	(-1.60)
MOM	0.00569	0.00177*	-0.00036	-0.00251***	-0.01130*	-0.01700***
	(1.42)	(1.94)	(-0.61)	(-2.61)	(-2.06)	(-2.76)
Adjusted R^2	38.08%	57.47%	58.74%	49.19%	27.13%	1.93%

Note: The table shows supplier portfolios' abnormal returns of the micro-cap subsample of the trimmed supplier sample, resulting in 56,304 company-month observations for 399 companies.

t-statistics in parentheses.

*Significant at the 10 percent level.

***Significant at the 1 percent level.

statistically significant intercept of -0.29 percent, and buying the stocks in quintile 5, that have a statistically significant intercept of 0.42 percent. Additionally, we can also note that the intercepts monotonically increase as we approach the quintile with the highest performance.

Subsequently, Table 6 presents the results for the mid-cap subsample. In fact, this L-S portfolio had the worst performance among the subsamples derived from the trimmed supplier sample. The strategy yielded a statistically significant monthly premium of 0.63 percent, which translates into an annual abnormal return of 7.56 percent. Similarly to the other results, the monthly alphas increase monotonically with Q1 reporting a statistically significant intercept of -0.25 percent and Q5 presenting a statistically significant intercept of 0.38 percent.

Table 5. Supplier Portfolio's Abnormal Returns: Small-cap Sample January 1996-December 2018

	Q1 (low)	Q2	Q3	Q4	Q5 (high)	L-S
A. Equally-weighted monthly returns						
Intercept (%)	-0.29***	-0.05***	0.00***	0.08***	0.42***	0.71***
	(-27.36)	(-17.41)	(3.30)	(22.88)	(22.91)	(31.54)
Market	0.03094***	0.01180***	0.00930***	0.01104***	0.02479***	-0.00615*
	(18.45)	(24.75)	(25.15)	(19.54)	(8.51)	(-1.72)
SMB	0.01376***	0.00616***	0.00580***	0.00851***	0.01843*	0.00467
	(2.77)	(4.36)	(5.30)	(5.09)	(2.14)	(0.44)
HML	-0.00755*	-0.00030	0.00048	-0.00039	-0.00586	0.00170
	(-1.70)	(-0.24)	(0.49)	(-0.26)	(-0.76)	(0.18)
MOM	0.00582*	0.00186*	-0.00068	-0.00508***	-0.02114***	-0.02696***
	(1.67)	(1.88)	(-0.89)	(-4.32)	(-3.48)	(-3.62)
Adjusted R^2	56.53%	70.06%	71.70%	63.19%	27.17%	3.78%

Note: The table shows supplier portfolios' abnormal returns of the small-cap subsample of the trimmed supplier sample, resulting in 107,546 company-month observations for 1,057 companies.

t-statistics in parentheses.

*Significant at the 10 percent level.

***Significant at the 1 percent level.

Furthermore, Table 7 demonstrates the results for the large-cap subsample. This L-S portfolio was the best performer not only among the subsamples derived from the trimmed supplier sample but also across all samples considered in this study. The strategy yielded a statistically significant monthly premium of 0.74 percent by selling stocks in the first quintile, which presented a statistically significant intercept of -0.29 percent, and buying stocks in the fifth quintile, that reported a statistically significant intercept of 0.46 percent. Conversely, the L-S portfolio generated an annual abnormal return of 8.88 percent.

The reported results demonstrate that the lead-lag effect is not induced by micro-cap stocks, considering the largest monthly abnormal return (0.74 percent) was obtained from the subsample containing only large-cap stocks. It is worth emphasizing that this was the sample that provided the largest return in the overall study. Therefore, removing from our sample the smallest and most illiquid stocks does not have a meaningful impact on our results.

Table 6. Supplier Portfolio's Abnormal Returns: Mid-cap Sample January 1996-December 2018

	Q1 (low)	Q2	Q3	Q4	Q5 (high)	L-S
A. Equally-weighted monthly returns						
Intercept (%)	-0.25***	-0.04***	0.00***	0.07***	0.38***	0.63***
	(-26.10)	(-16.03)	(4.47)	(23.79)	(23.32)	(31.87)
Market	0.02994***	0.00984***	0.00746***	0.00903***	0.02459***	-0.00535*
	(19.76)	(25.48)	(26.41)	(20.60)	(9.40)	(-1.70)
SMB	0.01209***	0.00445***	0.00333***	0.00348***	0.00144	-0.01065
	(2.70)	(3.90)	(3.98)	(2.69)	(0.19)	(-1.14)
HML	-0.00045	0.00170*	0.00202***	0.00343***	0.00481	0.00527
	(-0.11)	(1.66)	(2.70)	(2.95)	(0.69)	(0.63)
MOM	0.00691*	0.00164*	-0.00098*	-0.00369***	-0.02034***	-0.02725***
	(2.19)	(2.05)	(-1.66)	(-4.05)	(-3.73)	(-4.15)
Adjusted R^2	59.85%	71.62%	74.70%	66.84%	33.47%	5.52%

Note: The table shows supplier portfolios' abnormal returns of the mid-cap subsample of the trimmed supplier sample, resulting in 110,518 company-month observations for 719 companies.

t-statistics in parentheses.

*Significant at the 10 percent level.

***Significant at the 1 percent level.

Conversely, on the study of Shahrur et al. (2010), only the large-cap subsample did not provide a positive abnormal return. Moreover, the results also demonstrated that the strategy provides monotonically increasing returns according to the company's size, i.e., the largest return was provided by the smallest cap subsample, while the lowest return was retrieved from the mid-cap subsample (excluding the large-cap subsample). This was not the case in our study, as the largest-cap sample yielded the highest return and the two lowest-cap subsamples generated the second highest return (0.71 percent), leaving the mid-cap subsample with the worst return of 0.63 percent. Nevertheless, both studies point out that the lead-lag effect is not driven by small stocks.

Moreover, since about 55 percent of our supplier sample is listed in China, we performed an individual analysis for this market. The results presented in **Table 8** demonstrate a similar outcome to the overall analysis we have done, with the L-S portfolio yielding a monthly alpha

Table 7. Supplier Portfolio's Abnormal Returns: Large-cap Sample January 1996-December 2018

	Q1 (low)	Q2	Q3	Q4	Q5 (high)	L-S
A. Equally-weighted monthly returns						
Intercept (%)	-0.29***	-0.04***	0.01***	0.08***	0.46***	0.74***
	(-24.54)	(-14.45)	(6.12)	(22.82)	(23.09)	(30.30)
Market	0.03099***	0.01041***	0.00752***	0.00950***	0.02438***	-0.00661*
	(16.72)	(22.51)	(26.58)	(17.11)	(7.75)	(-1.70)
SMB	-0.00232	-0.00096	-0.00130	-0.00211	-0.00736	-0.00504
	(-0.42)	(-0.70)	(-1.56)	(-1.29)	(-0.79)	(-0.44)
HML	0.00520	-0.00010	0.00017	0.00087	-0.00451	-0.00971
	(1.06)	(-0.08)	(0.23)	(0.59)	(-0.54)	(-0.94)
MOM	0.00838*	0.00191*	-0.00089	-0.00384***	-0.02585***	-0.03423***
	(2.17)	(1.98)	(-1.50)	(-3.32)	(-3.95)	(-4.22)
Adjusted R^2	53.86%	68.20%	76.60%	60.02%	28.21%	4.99%

Note: The table shows supplier portfolios' abnormal returns of the large-cap subsample of the trimmed supplier sample, resulting in 40,169 company-month observations for 211 companies.
t-statistics in parentheses.
*Significant at the 10 percent level.
***Significant at the 1 percent level.

of 0.15 percent (in the case of equally-weighted monthly returns) and 0.20 percent (in the case of value-weighted monthly returns), both statistically significant at the 1 percent level. This accrues into an annual premium of 1.80 percent and 2.40 percent, respectively

Comparing these results with Li et al. (2020), which also found empirical evidence of supply-chain return predictability in China, we retrieved lower returns from our strategy. In fact, the authors' L-S portfolio yielded monthly alphas of 0.68 percent (on an equally-weighted basis) and 0.92 percent (on a value-weighted basis) in an analysis between 2000 and 2017. The possible reasons for this discrepancy are better argued in the conclusions. However, we could point out the different period of analysis and/or different criteria for supplier sample selection as the main explanation.

Table 8. Supplier Portfolio's Abnormal Returns: China Sample, January 1996-December 2018

	Q1 (low)	Q2	Q3	Q4	Q5 (high)	L-S
A. Equally-weighted monthly returns						
Intercept (%)	-0.05***	-0.00	0.02*	0.05***	0.10***	0.15***
	(-5.78)	(-0.34)	(2.03)	(4.22)	(8.26)	(22.28)
Market	0.01015***	0.00963***	0.00942***	0.00912***	0.00863***	-0.00152
	(6.86)	(6.21)	(5.70)	(5.32)	(4.50)	(-1.38)
SMB	0.01986***	0.02295***	0.02497***	0.02572***	0.02815***	0.00829*
	(4.54)	(5.00)	(5.11)	(5.07)	(4.96)	(2.56)
HML	0.00351	0.00201	0.00119	0.00087	-0.00010	-0.00451
	(0.89)	(0.49)	(0.27)	(0.19)	(-0.20)	(-1.55)
MOM	0.00029	-0.00052	-0.00066	-0.00089	-0.00134	-0.00164
	(0.10)	(-0.16)	(-0.19)	(-0.25)	(-0.34)	(-0.72)
Adjusted R^2	16.05%	14.74%	13.47%	12.42%	10.32%	3.77%
B. Value-weighted monthly returns						
Intercept (%)	-0.05***	-0.00	0.03*	0.05***	0.10***	0.20***
	(-6.04)	(-0.04)	(2.57)	(4.88)	(9.06)	(22.69)
Market	0.00983***	0.00924***	0.00908***	0.00884***	0.00864***	-0.00119
	(7.19)	(6.45)	(5.85)	(5.41)	(4.51)	(-1.05)
SMB	0.01502***	0.01745***	0.01913***	0.02026***	0.02327***	0.00824*
	(3.72)	(4.12)	(4.17)	(4.19)	(4.10)	(2.47)
HML	0.00559	0.00497	0.00475	0.00453	0.00389	-0.00170
	(1.54)	(1.31)	(1.15)	(1.04)	(0.76)	(-0.57)
MOM	0.00153	0.00093	0.00095	0.00089	0.00058	-0.00095
	(0.54)	(0.31)	(0.29)	(0.26)	(0.15)	(-0.40)
Adjusted R^2	16.53%	14.31%	12.39%	11.07%	8.51%	2.24%

Note: This table shows supplier portfolios' abnormal returns for a sample including only Chinese companies, resulting in 367,089 company-month observations for 2,869 companies.

t-statistics in parentheses.

*Significant at the 10 percent level.

***Significant at the 1 percent level.

4.2 Fama-MacBeth (1973) regression results

Table 9 presents the results of the supplier sample Fama-MacBeth (1973) regression, divided in three models: model 1 regresses our sample only with the *Customer return*$_{t-1}$ control variable, model 2 uses all control variables except for the size-based industry portfolios, and in model 3, instead of including the *Industry return*$_{t-1}$, we included the size-based industry portfolios.

Considering the aforementioned hypothesis that, if β_1 is positive and statistically significant then we confirm our research question, we can conclude that the results retrieved from the model 1 are in line with our finding that the supplier firm return and the lagged customer return are correlated. Regarding model 2, the results demonstrate that the lead-lag effect still persists after including the main control variables. To what concerns model 3, we also confirm that the results are robust to the inclusion of the size-based industry portfolios.

Table 9. Fama-MacBeth Regression: Supplier's Monthly Stock Return, January 1996-December 2018

	Model 1	Model 2	Model 3
Intercept (%)	0.82*	0.45	0.85
	(2.55)	(1.38)	(1.43)
Customer return$_{t-1}$	4.16520***	4.87760***	5.83000*
	(2.60)	(2.87)	(1.81)
Return$_{t-1}$		-0.02360***	-0.02360*
		(-3.12)	(-2.22)
Return$_{t-12,t-2}$		0.00440	0.00190
		(1.36)	(0.73)
Industry return$_{t-1}$		0.02120	
		(0.86)	
Large-size industry return$_{t-1}$			0.27210
			(1.07)
Medium-size industry return$_{t-1}$			0.08630
			(0.10)
Small-size industry return$_{t-1}$			0.07950
			(0.64)
Industry return$_{t-12,t-2}$		0.00420	-0.03930
		(0.95)	(-0.34)
MVE$_{t-1}$		-0.00000*	-0.00000***
		(-2.50)	(-2.80)
PTB$_{t-1}$		-0.00005*	-0.00009
		(-1.71)	(-1.58)
Adjusted R^2	0.41%	-2.04%	-2.92%
Nº of months	276	276	276

Note: The table presents the results from the Fama-MacBeth regression of supplier monthly stock returns on the customer returns and control variables. The supplier sample contains 5,962 companies, including 844,390 company-month observations. The t-statistics, presented in parentheses, are calculated with the standard deviation of the time series of monthly estimates for each coefficient. Additionally, the adjusted R^2 is also presented as a monthly average. *Significant at the 10 percent level; ***Significant at the 1 percent level.

5. Conclusion

We live in a world of increasing globalisation, where firms are linked to each other through different types of economic relationships. Recently, there has been a growing interest in studying how idiosyncratic shocks spread across economically linked companies, and how that affects asset pricing. Simultaneously, researchers have been arguing against the assumptions of the EMH. Since research has showed a limit to human's attention, authors have been finding empirical evidence that investors are not able to process all public information and, thus, they are not able to efficiently price securities, as the EMH defends (Barber & Odean, 2008; Hou, 2007; Menzly & Ozbas, 2010; Shahrur et al., 2010; Zareei, 2021).

Our research question aimed at finding whether there is a lead-lag effect between supplier and customer companies, between 1995 and 2018, in the 10 largest emerging markets by GDP: China, India, Brazil, Russia, Mexico, Indonesia, Turkey, Thailand, South Africa and Malaysia. The preference for studying emerging markets is, to the extent of our knowledge, due to the existing gap in the literature. We are aware that Li et al. (2020) have already analysed supply-chain return predictability in China. Therefore, we decided to be the first study to extend the analysis to other emerging markets that were not previously investigated.

To conduct the study, we retrieved the customer-supplier relationships data from the 2021 OECD inter-country input-output database and the companies' data from the Refinitiv Eikon's database. Our sample contained 5,962 companies, representing 844,390 company-month observations. According to the majority of the authors (see Appendix I), the best methodologies to analyse the lead-lag effect are panel and Fama-MacBeth (1973) regressions.

The results we retrieved were in line with our hypothesis. The value-weighted portfolio's monthly alpha obtained for the whole supplier sample was 0.40 percent, which converts into an annual abnormal return of 4.80 percent. The results for the equally-weighted portfolio were very similar, generating a monthly premium of 0.39 percent, which represents an annual abnormal return of 4.68 percent. Subsequently, we furthered our analysis to understand if the results were induced by very small and highly illiquid companies, by applying more criteria to the sample. The trimmed supplier sample provided a monthly excess return of 0.5 percent. However, we still decided to regress subsamples based on market capitalisation and the conclusions remained the same, regardless of the sample's size. In fact, the largest-cap subsample provided the highest monthly return of the whole study of 0.74 percent, with the micro and small-cap subsamples yielding a 0.71 percent premium and the mid-cap subsample generating 0.63 monthly alphas. Additionally, since the Chinese market represented about 55 percent of our sample, we decided to perform an individual analysis, where we retrieved a lower monthly alpha, compared to the aforementioned results, of 0.20 percent using value-weighted monthly returns and 0.15 percent using equally-weighted monthly returns. Finally, using a Fama-MacBeth (1973) regression, we also found evidence that these results were not being driven by other control variables which are correlated with contemporaneous stock returns.

Hence, the results challenge the concept of an efficient market. Indeed, this study demonstrates that the supply-chain lead-lag effect is the result of the slow diffusion of relevant information, which defies the idea that prices reflect all available information. For investors, this means that, because they fail to make the necessary connections between customers and suppliers due to limited attention, it opens a window of opportunity to yield annual abnormal returns by buying or selling supplier firms according to the monthly lagged customer returns.

Comparing with previous studies, our strategy yields lower annual abnormal returns. Menzly and Ozbas (2006) focused on the U.S. market between 1963 and 2002 and developed a trading strategy which resulted in an annual premium of 6.50 percent. Subsequently, Cohen and Frazzini (2008) also studied the U.S. market between 1980 and 2004 and built a long-short strategy that generated monthly alphas of over 1.50 percent, which converts into an annual abnormal return of about 18 percent. Moreover, Menzly and Ozbas (2010) demonstrate, between 1963 and 2005, that the U.S. cross-predictability return strategy is able to provide an annual premium of 8.70 percent. Furthermore, Shahrur et al. (2010) studied 22 developed markets between 1995 and 2007 and showed that the lead-lag effect yields an equally-weighted monthly abnormal return of 1.23 percent, which translates into 14.76 percent annually. Additionally, Li et al. (2020) analysed the Chinese market for the period between 2001 and 2017 and found evidence of industry-level supply-chain predictability generating a monthly premium of 0.92 percent, that converted into an annual abnormal return of 11.04 percent. Lastly, Zareei (2021) analysed the U.S. market and retrieved an annualised abnormal return of 34.50 percent, between the period of 1965 and 2015.

Indeed, we believe this lower return retrieved for the emerging economies deserves further investigation. We would expect that the diffusion of information would be slower in emerging markets, thus leading to higher results. Hence, it would be interesting to check whether using a similar study period would improve the returns, and if the 2008 crisis is the main cause for these lower returns, as most comparable studies do not include it. Furthermore, following Shahrur et al. (2010), we believe we were more strict regarding the criteria applied to our supplier companies' sample, which could have influenced the results. Regarding this, we also propose further investigation on relevant filters to include in the companies' sample.

Moreover, the fact that China represents about 55 percent of our supplier sample could mean the results are being driven by this economy and, thus, we propose further analysis by excluding China and also by including other emerging economies. Finally, in our study, we did not include the L-S strategy's expense costs. It would be important to analyse whether, after accounting for transaction costs, the strategy still yields an abnormal return.

Appendixes

Appendix I – Research methodologies

Author(s)	Type of return predictability	Tool to identify economic link	Stock exchange(s)	Years	Number of observations	Methodology
Menzly and Ozbas (2006)	Cross-predictability among industries	Bureau of Economic Analysis survey	NYSE, AMEX, NASDAQ	1963-2002	65 industries	Panel and Fama-MacBeth regressions
Hong et al. (2007)	Industry and market returns lead-lag effect	Ken French, Mark Watson, NAREIT, CRSP, DRI databases	Equities listed in the U.S. stock market	1946-2002	34 value-weighted industry portfolios	Panel regression
Hou (2007)	Lead-lag effect between big and small firms	Ken French database	NYSE, AMEX, NASDAQ	1963-2001	12 industries	Panel regression, cross-autocorrelations and VAR test
Cohen and Frazzini (2008)	Supply-chain lead-lag effect	Compustat	NYSE, AMEX, NASDAQ	1980-2004	11,484 companies	Panel and Fama-MacBeth regressions
Menzly and Ozbas (2010)	Supply-chain cross-predictability	Bureau of Economic Analysis survey	NYSE, AMEX, NASDAQ	1963-2005	6,036 companies	Panel regression

Shahrur et al. (2010)	Supply-chain lead-lag effect	Benchmark IO accounts for the U.S. economy	Stocks listed on developed countries belonging to the MSCI World Index	1995-2007	6,174 companies	Panel and Fama-MacBeth regressions
Albuquerque et al. (2015)	Cross-border predictability among firms with trade credit links	IMF Direction of Trade Statistics	MSCI, S&P/IFC	1993-2009	15,627 companies in 37 producer countries	Panel and pooled regressions
Scherbina and Schlusche (2015a)	Lead-lag effect in news-related firms	Granger causality tests	NYSE, AMEX, NASDAQ	1926-2011	3,305 monthly firm observations	Panel and Fama-MacBeth regressions
Scherbina and Schlusche (2015b)	Cross-predictability among co-mentioned stocks in news	Thomson Reuters News Analytics and Primary News Access Code	NYSE, AMEX, NASDAQ	1996-2013	299,060 news stories	Panel and Fama-MacBeth regressions
Cao et al. (2016)	Cross-predictability among alliance partners	Securities Data Company platinum database	NYSE, AMEX, NASDAQ	1991-2012	232,640 monthly firm observations	Panel and Fama-MacBeth regressions

Qiu et al. (2016)	Lead-lag effect in technology-linked firms	Compustat	NYSE, AMEX, NASDAQ	1968-2011	50,000 monthly firm observations	Panel and Fama-MacBeth regressions
Jin and Li (2020)	Geographically-linked firms lead-lag effect	NETS Publicly Listed Database	NYSE, AMEX, NASDAQ	1990-2013	668,117 monthly firm observations	Panel and Fama-MacBeth regressions
Li et al. (2020)	Supply-chain lead-lag effect	World Input-Output database	Equities listed in the Chinese stock market	2001-2017	44 industries	Panel and Fama-MacBeth regressions
Zhang et al. (2020)	Industry and market returns lead-lag effect	Granger causality tests	Shanghai stock exchange	1993-2015	15 industries	Bivariate VAR model
Bai et al. (2020)	Cross-predictability in firms with overlapping offshore sales networks	HM database	NYSE, AMEX, NASDAQ	1998-2018	565,866 monthly firm observations	Fama-MacBeth regression
Chen et al. (2020)	Lessor-lessee relationship lead-lag effect	CRSP/Ziman database, S&P Global Market Intelligence	Publicly listed REITs in the S&P Global Market Intelligence	2000-2013	96 REITs	Panel and Fama-MacBeth regressions

Appendix II – Supplier portfolio's abnormal returns: Table A.1

Table A.10. Supplier Portfolio's Abnormal Returns: Trimmed Supplier Sample, January 1996-December 2018

	Q1 (low)	Q2	Q3	Q4	Q5 (high)	L-S
A. Equally-weighted monthly returns						
Intercept (%)	-0.19***	-0.03***	0.02***	0.08***	0.31***	0.50***
	(-16.67)	(-6.63)	(4.27)	(15.26)	(22.57)	(34.82)
Market	0.00897***	0.00361***	0.00268***	0.00248***	0.00287	-0.00610***
	(5.05)	(4.65)	(4.10)	(3.06)	(1.31)	(-2.69)
SMB	0.00501	0.00257	0.00196	-0.00020	-0.00747	-0.01248*
	(0.95)	(1.12)	(1.01)	(-0.08)	(-1.15)	(-1.86)
HML	-0.00415	-0.00148	-0.00133	-0.00165	-0.00892	-0.00478
	(-0.88)	(-0.72)	(-0.77)	(-0.77)	(-1.53)	(-0.79)
MOM	-0.00014	-0.00053	-0.00151	-0.00272	-0.01014*	-0.01000*
	(-0.04)	(-0.33)	(-1.11)	(-1.61)	(-2.22)	(-2.12)
Adjusted R^2	8.10%	6.90%	6.10%	4.60%	3.30%	2.60%

Note: The trimmed supplier sample includes 314,537 company-month observations for 2,386 unique companies.

t-statistics in parentheses.

*Significant at the 10 percent level.

***Significant at the 1 percent level.

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