Essays on Uncertainty and Productivity

A thesis presented in partial fulfillment of the requirements for the degree of Doctor of Philosophy in Finance

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Abstract

Uncertainty has become a defining characteristic of the global economy, shaping both macroeconomic performance and firm-level behavior. Recent crises such as the Global Financial Crisis, the COVID-19 pandemic, and the Russo-Ukrainian war have highlighted how shocks transmit across markets through energy and financial linkages, disrupting stability and growth. Understanding the multifaceted dimensions of uncertainty and its interaction with real and financial activities is therefore essential for evaluating global economic resilience. This thesis investigates these dimensions through three interrelated essays combining macro-sectoral, energy, and financial perspectives. Essay One examines the structure and evolution of expected uncertainty spillovers across emerging market sectors using a quantile time-frequency connectedness framework, uncovering heterogeneous interdependencies across time horizons and market conditions. Essay Two assesses how the global geopolitical-energy uncertainty (GEU) influences firm-level productivity, offering new insights into the productivity effects of intertwined geopolitical and energy shocks. Essay Three analyzes how cross-listing in US markets affects the productivity of energy-sector firms during the last two decades characterized by rising uncertainty.

Acknowledgement[1]

I begin this thesis by extending my sincere appreciation to my supervisory team, including Professor Faruk Balli, Professor Hatice Ozer Balli, Dr. Mei Qiu, and Dr. Hannah Nguyen, whose expertise, constructive advice, and steady encouragement have guided me through every step of my doctoral journey. Their complementary strengths and high academic standards have profoundly shaped both my research direction and my personal growth as an emerging scholar. Working under their supervision has been an honor and an invaluable experience.

I owe a deep debt of gratitude to Professor Faruk Balli for his inspiring mentorship and rigorous academic guidance. His attention to detail, insightful comments, and continuous encouragement have set the benchmark for excellence in my research. I remain especially thankful for his genuine care and support from the moment I prepared my PhD application and scholarship documents, through every academic and professional milestone thereafter.

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I am grateful to Professor Hung Do and Associate Professor Harvey Nguyen for their invaluable guidance at the earliest stage of my academic path. Professor Hung Do kindly introduced me to my current supervisors when I applied to Massey University and later shared the ARPM Bootcamp Scholarship opportunity offered by GARP, which I was fortunate to receive. Associate Professor Harvey Nguyen helped me lay the groundwork for a strong research profile and academic CV as early as 2021, two years before I began my PhD. Their advice and encouragement gave me the confidence to pursue this path wholeheartedly.

[1] In this thesis, ChatGPT (OpenAI, 2025) was utilized for general editing or proofreading of content.

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This doctoral project was made possible through the Massey University Doctoral Scholarship, which allowed me to dedicate myself entirely to research. I also acknowledge the School of Accountancy, Economics and Finance for maintaining essential financial databases and research resources that supported my empirical analyses. My appreciation extends to the faculty and staff of the School, whose academic environment has been both stimulating and supportive. In particular, I wish to thank Hiroko Hodge, Mark Woods, Myrah Corrales, and Muharram Azizova for their consistent technical and administrative assistance, which ensured a smooth research process.

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Chapter One - Introduction

Chapter One presents an overview of the thesis. Furthermore, this chapter outlines the research objectives, key findings, and contributions of each essay to the existing literature. Finally, it concludes with a summary of the research outputs and the overall thesis structure.

1.1. Introduction

Uncertainty has become a defining feature of the global economy, shaping both macroeconomic performance and firm-level outcomes. Over the past two decades, the world has witnessed several episodes of heightened and persistent uncertainty, including the Global Financial Crisis of 2007–2008, the European sovereign debt crisis of the early 2010s, the COVID-19 pandemic in 2020, and the 2022 escalation of the Russo-Ukrainian war that generated significant turmoil in global financial markets. Uncertainty shocks lead to sharp declines in investment, resource reallocation, and productivity (Bloom, 2009), followed by slow and incomplete recoveries. Emerging economies in particular suffer deeper and more persistent contractions and take significantly longer to return to pre-crisis levels than developed markets (Carrière-Swallow & Céspedes, 2013). Even before the COVID-19 crisis, IMF Managing Director Kristalina Georgieva remarked that "*If I had to identify a theme at the outset of the new decade it would be increasing uncertainty*" (Ahir et al., 2022). Empirical evidence also indicates that financial, policy, and political uncertainties exert significant impacts on economic activity and investment (Apaitan et al., 2022).

At the meso level, uncertainty is transmitted across industries through sectoral linkages and financial interconnectedness. When a shock arises in one sector, it tends to propagate across markets through sectoral connectedness (Zhang et al., 2020). Empirical studies show that sectors play a critical role in systemic risk as volatility spillovers evolve dynamically across equity industries (Eckernkemper, 2018; Shahzad et al., 2021). Such spillovers shape both policymakers' decisions and investors' portfolio allocations. Within the sectoral network, the energy sector plays a key role due to its importance as a fundamental input across the economy and its price volatility.

Energy is a strategic resource underpinning economic growth (Wen et al., 2019). Because of its scarcity, spatial separation between supply and demand, and low demand elasticity, energy-price uncertainty can disrupt investment decisions, industrial production, and overall economic activity (Elder & Serletis, 2010; Jo, 2014; Peersman & Van Robays, 2012). Hamilton (2003) and Charfeddine et al. (2020) emphasize that oil-price uncertainty exerts significant adverse effects on economic growth at both national and global scales. Geopolitical instability further intensifies the negative effects of energy uncertainty, amplifies precautionary behavior, and restricts the availability of energy (notably oil) for productive use (Liu et al., 2019; Mei et al., 2020; Wang et al., 2021). Such heightened energy uncertainty, in turn, undermines firms' productivity (Liu et al., 2024; Ren, Liu et al., 2023).

Recently, Dang et al. (2024a) develop the Global Geopolitical-Energy Uncertainty (GEU) index, integrating geopolitical, energy, and policy risks into a single composite measure. The GEU index is highly responsive to major geopolitical tensions and energy shocks, with strong explanatory power for global energy-price volatility, sectoral stock-market performance, and key macroeconomic indicators across advanced and emerging economies. While its relevance has been well established at the global, national, and sectoral levels, its implications for firm-level productivity remain unexplored, a gap this thesis seeks to address.

At the firm level, the effects of uncertainty depend crucially on financial integration and corporate flexibility. Uncertainty discourages investment (Bloom, 2009), innovation, and risk-taking, yet firms with greater financial flexibility or international exposure can mitigate these effects. Cross-listing, for instance, enables firms to access larger, more liquid, and efficient capital markets than their home markets (Balli et al., 2022; Lambrecht & Myers, 2012). In turn, financial liberalization facilitates capital access and resource allocation, thereby supporting investment and growth (Heil, 2019).

As Krugman (1997) famously observed, "*Productivity isn't everything, but in the long run it is almost everything*". Syverson (2011) adds that productivity is "*quite literally a matter of survival for businesses*." Firm-level total factor productivity (TFP) measures output beyond the contribution of observed inputs and represents an essential driver of economic growth (Baier et al., 2006; Dowrick & Nguyen, 1989; Thompson & Rushing, 1999; Tian & Twite, 2011). Examining TFP is thus critical for managers seeking to enhance competitiveness and for policymakers designing strategies to foster growth, employment, and resilience.

Overall, uncertainty operates through interconnected macroeconomic, energy, and financial dimensions, influencing the stability of economies and the performance of firms. Understanding these channels is essential for identifying how shocks propagate and how firms and policymakers respond. This thesis contributes to the literature by offering a multidimensional examination of uncertainty and productivity. The first essay provides a macro–sectoral perspective by examining how expected uncertainty spillovers evolve and interact across sectors in emerging markets, revealing the structure of intersectoral transmission within the real economy. The second essay focuses on the energy domain, analyzing how global geopolitical–energy uncertainty (GEU) affects firm-level productivity. The third essay investigates how cross-listing process, which allows firms to access larger and more liquid international capital markets, influences the productivity of energy-sector firms during a period of high uncertainty.

The remainder of this chapter is structured as follows. Sections 1.2 to 1.4 summarize the three essays, highlighting their findings and contributions to the literature. Section 1.5 presents the research outputs derived from this thesis, while Section 1.6 describes the overall organization of the subsequent chapters.

1.2. Essay One

The first essay investigates how uncertainty transmits across sectors in emerging markets using the quantile time-frequency connectedness framework of Chatziantoniou, Abakah, et al. (2022). Motivated by evidence that uncertainty shocks cause deeper and more persistent contractions in emerging economies (Carrière-Swallow & Céspedes, 2013; Apaitan et al., 2022; Abid, 2020), the study aims to uncover the dynamic interdependencies among key sectors. Given that emerging markets account for nearly half of global GDP and two-thirds of global growth (World Economics, 2022), understanding these transmission mechanisms is crucial for stabilizing financial markets and guiding policy responses.

This essay makes several contributions to the literature. It is the first to analyze expected sectoral uncertainty spillovers in emerging markets using aggregated sectoral indices, providing empirical insights into the frequency and quantile-dependent nature of connectedness. By testing the "meteor shower" and "heat wave" hypotheses (Engle et al., 1990), it extends the limited literature on sectoral connectedness in emerging markets. In addition, by constructing bivariate and multivariate portfolio analyses (Kroner & Sultan, 1993; Markowitz, 1952), the study highlights how risk diversification across sectors can reduce exposure to uncertainty shocks.

The results reveal strong and time-varying sectoral interconnectedness, with a total connectedness index of 91.01%. Long-term spillovers dominate, and the Consumer Cyclicals sector emerges as the main net transmitter of uncertainty, while Communications & Networking and Healthcare are major receivers. Spillovers are asymmetric across market conditions, being higher in turbulent periods. A positive relationship between uncertainty indices and sectoral connectedness is also observed during periods of smooth and normal market conditions.

1.3. Essay Two

Energy plays a vital role in sustaining economic growth (Wen et al., 2019), yet its volatility, particularly oil price fluctuations, can disrupt investment, production, and overall economic activity (Elder & Serletis, 2010; Jo, 2014; Peersman & Van Robays, 2012; Hamilton, 2003; Charfeddine et al., 2020). These volatilities are closely tied to geopolitical risks, which further heighten uncertainty in energy markets, constrain productive use, and reduce firm efficiency (Liu et al., 2019; Mei et al., 2020; Wang et al., 2021; Mignon & Saadaoui, 2024). Moreover, geopolitical and energy risks are mutually reinforcing, with bidirectional causality between oil price shocks and geopolitical instability (Abdel-Latif & El-Gamal, 2019; Su et al., 2021). Despite this interdependence, prior studies typically analyze these risks separately, overlooking their joint impact on firm productivity.

To fill this gap, the second essay employs the global geopolitical-energy uncertainty (GEU) index of Dang et al. (2024a), which jointly captures geopolitical and energy uncertainty. While the GEU index has been shown to explain global energy price volatility, sectoral performance, and macroeconomic indicators, its effects on firm productivity remain unexplored. Using firm-level data from 2001-2023, this essay provides the first evidence on how combined geopolitical and energy uncertainty influences total factor productivity (TFP), a key determinant of firm-level economic growth (Tian & Twite, 2011).

Empirical results indicate that higher GEU significantly reduces firm productivity, particularly in the US, UK, France, and Germany. The adverse effects are stronger for smaller and energy-intensive firms. Mechanism analysis shows that profitability mitigates, whereas cost intensity and global energy prices amplify, the negative impact of GEU shocks. Overall, the findings establish GEU as a crucial determinant of firm productivity and highlight how both firm-specific characteristics and energy market conditions shape productivity outcomes under rising geopolitical-energy uncertainty.

1.4. Essay Three

Cross-border capital market liberalization has reduced investment barriers and enabled firms to access global financing more easily (Dodd, 2013). However, differences in investor protection, ownership restrictions, and trading costs persist, encouraging firms to overcome these barriers by cross-listing shares on foreign exchanges (Balli et al., 2022; Reiter, 2021). Cross-listing helps firms gain cheaper foreign capital and improve corporate governance under stricter disclosure requirements (Hail & Leuz, 2009; Coffee, 1999a; Stulz, 1999). Yet, the relationship between cross-listing and firm productivity, especially in the energy sector, remains underexplored, despite its critical role in global economic growth (Stern, 1993, 2000; UNEP, 2023; The World Bank, 2023a).

This essay provides the first empirical evidence on how cross-listing in US markets affects firm productivity in the energy sector over 2002-2022, a period marked by several crises. It examines productivity changes before and after cross-listing, compares energy with non-energy sectors, and distinguishes between developed and emerging economies. The study also identifies the determinants of firm productivity in the energy sector.

Findings show that energy firms experience a significant decline in productivity after cross-listing in the US, while no strong effect is found in other sectors. This decline coincides with sharp increases in capital expenditures and fixed assets, suggesting that firms use new capital for large-scale investments that temporarily lower efficiency. Regarding the determinants of firm productivity, we note that negative impacts of capital expenditures (after cross-listing) and state ownership on firm productivity become much stronger in developed countries than in emerging countries. Overall, while cross-listing expands access to capital, firm productivity benefits depend crucially on how that capital is utilized within the energy sector.

1.5. Research outputs from the thesis

- Essay One, entitled "*Sectoral uncertainty spillovers in emerging markets: A quantile time-frequency connectedness approach*", was published in International Review of Economics & Finance (ABDC: A).

  Dang, T. H. N., Balli, F., Balli, H. O., Gabauer, D., & Nguyen, T. T. H. (2024). Sectoral uncertainty spillovers in emerging markets: A quantile time–frequency connectedness approach. *International Review of Economics & Finance*, *93*, 121-139. https://doi.org/10.1016/j.iref.2024.04.017

- Essay Two, entitled "*The global geopolitical-energy uncertainty index and total factor productivity: New evidence from firm-level analysis*", was published in Energy Economics (ABDC: A*).

  Dang, T. H. N., Balli, F., Balli, H. O., Qiu, M., & Nguyen, H. (2026). The global geopolitical-energy uncertainty index and total factor productivity: New evidence from firm-level analysis. *Energy Economics*, *153*, 109054. https://doi.org/10.1016/j.eneco.2025.109054

In relation to this essay, we constructed the global geopolitical-energy uncertainty (GEU) index. This GEU index has been employed in this essay as one of the variables of interest. The research paper in which the GEU index was developed has been presented at following conferences and seminar.

a. Hoang Nhat Tam Dang, Faruk Balli, Hatice Ozer Balli, and Thi Thu Ha Nguyen "Assessing the economic impact of the global geopolitical-energy uncertainty index" 29th Annual (2025) New Zealand Finance Colloquium, the University of Otago School of Business, Dunedin, New Zealand, 13-14 February 2025.

b. Hoang Nhat Tam Dang, Faruk Balli, Hatice Ozer Balli, and Thi Thu Ha Nguyen "Assessing the economic impact of the global geopolitical-energy uncertainty index" Massey Sustainable Finance Conference, Auckland, New Zealand, 2-3 December 2024.

c. Hoang Nhat Tam Dang, Faruk Balli, Hatice Ozer Balli, and Thi Thu Ha Nguyen "Assessing the economic impact of the global geopolitical-energy uncertainty index" Massey University Economics and Finance Series, Auckland, New Zealand, 23 October 2024.

- Essay Three, entitled "*Firm productivity in the Energy-electricity sector over the last two decades with crisis: The role of cross-listing*" was published in Energy Economics (ABDC: A*).

  Dang, T. H.-N., Balli, F., Balli, H. O., & Nguyen, H. (2024). Firm productivity in the Energy-electricity sector over the last two decades with crisis: The role of cross-listing. *Energy Economics*, *130*, 107309. https://doi.org/10.1016/j.eneco.2024.107309

This essay has also been presented at the 32nd Australia New Zealand Econometric Study Group Meeting (ANZESG) meeting, Wellington, New Zealand, 9 February 2024.

1.6. Structure of the thesis

The remainder of this thesis is organized as follows. Chapter Two presents the first essay, investigating the sectoral expected uncertainty connectedness in emerging markets across different frequencies and quantiles using the novel quantile time-frequency connectedness approach of Chatziantoniou, Abakah, et al. (2022). In Chapter Three, the second essay examines the impact of the global geopolitical-energy uncertainty (GEU) on firm-level total factor productivity, considering variation across countries, industries, and firm sizes. The third essay, presented in Chapter Four, explores how cross-listing impacts firms' productivity in Energy sector using annual data of firm cross-listing over the last two decades with crisis. Last, Chapter

Five concludes this thesis by highlighting key findings, implications and possible future research for each of the three essays.

Chapter Two - Essay One “Sectoral uncertainty spillovers in emerging markets: A quantile time-frequency connectedness approach”

Abstract

This study investigates the sectoral expected uncertainty connectedness in emerging markets across different frequencies and quantiles using the novel quantile time-frequency connectedness approach of Chatziantoniou, Abakah, et al. (2022). The employed dataset spans from January 1st, 2003 to October 4th, 2022, encompassing 10 key sectors. The findings reveal a robust and notable interconnection among these sectors, with a substantial total connectedness index of 91.01%. We also note that the largest proportion of the sectoral total connectedness is associated with long-term spillovers. Consumer Cyclicals emerges as the primary source of net risk transmission. Conversely, the Communications & Networking and Healthcare appear to be the greatest net receivers of shocks at the median level. Furthermore, we find that the degree of interconnectedness substantially varies over time, frequency, and quantile, and by economic events. In addition, we find suggestive evidence of asymmetric sectoral uncertainty connectedness effects as the uncertainty spillovers are higher during turbulent market conditions than normal market conditions. A positive relationship between uncertainty measures and sectoral connectedness is also observed during periods of smooth and normal market conditions. Besides, we also conduct different portfolio analyses illustrating the importance of risk diversification to reduce investment uncertainty. This has important implications for international investors and policymakers in forming optimal investment portfolios reducing adverse risk spillovers.

Keywords: Quantile time-frequency connectedness; emerging markets; sectoral spillover; expected uncertainty transmission; portfolio analysis.

JEL codes: C50; F65; G15

Statement of contribution form - Essay One

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STATEMENT OF CONTRIBUTION
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We, the student and the student's main supervisor, certify that all co-authors have consented to their work being included in the thesis and they have accepted the student's contribution as indicated below in the Statement of Originality.

Student name:	Tam Hoang Nhat Dang
Name and title of main supervisor:	Professor Faruk Balli
In which chapter is the manuscript/published work?	Essay One in Chapter Two

Describe the contribution that the student and members of the supervisory team have made to the manuscript/published work:[1]

Tam discussed the research ideas with his supervisors, and together they agreed on the topic of Essay One in Chapter Two. He then collected and cleaned all datasets, and conducted the full set of empirical analyses. The supervisors reviewed Tam's results, provided suggestions, and addressed his questions during their weekly meetings. Tam drafted the initial version of the paper, and he and his supervisors subsequently refined and revised the manuscript in preparation for journal submission. Additionally, this paper benefited from the involvement of an external co-author, Dr. David Gabauer, who contributed to the methodology and the revision process.

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[1] Refer to the Massey University Publishing and Authorship guidelines (OneMassey for staff, Stream for students) and/ or Contributor Roles Taxonomy (CRediT) guidelines for guidance.

2.1. Introduction

Substantial fluctuations in uncertainty might lead to rapid drops and recoveries in real macroeconomic variables that drive the business cycle. More interestingly, it has been found that emerging economies suffer much more severe falls in investment and private consumption following an exogenous uncertainty shock, take significantly longer to recover, and do not experience a subsequent overshoot in activity compared to developed economies (Carrière-Swallow & Céspedes, 2013). Indeed, there is suggestive evidence that uncertainty shocks generate sudden and large declines in Thai stock prices and foreign portfolio investment before gradually affecting the real economy through investment and trade channels. While financial uncertainty matters most for the Thai economy overall, consumption demand largely responds to macroeconomic uncertainty, while economic policy and political uncertainty generate the most persistent effects on investment (Apaitan et al., 2022). Moreover, the increased levels of uncertainty are reported to adversely affect the exchange rates of emerging economies (Abid, 2020). Interestingly, the larger the US stock market uncertainty, measured by VIX, the lower emerging market returns as well as the higher stock market volatilities in emerging economies (Sarwar & Khan, 2017). In a similar fashion, there is evidence that increased US uncertainty has a larger negative effect on the gross domestic product of emerging economies than on the US economic growth (Gupta et al., 2020).

As shown in Figure 2.1, the world has recently witnessed various periods of high and prolonged uncertainty such as during the Global Financial Crisis of 2007-08, the European Debt Crises of 2015, the outbreak of the COVID-19 pandemic in 2020, as well as the beginning of the Russo-Ukrainian war period which comes with high uncertainty in the energy sector. Even prior to the beginning of the COVID-19 pandemic, IMF Managing Director Kristalina Georgieva said "If I had to identify a theme at the outset of the new decade it would be increasing uncertainty" (Ahir et al., 2022).

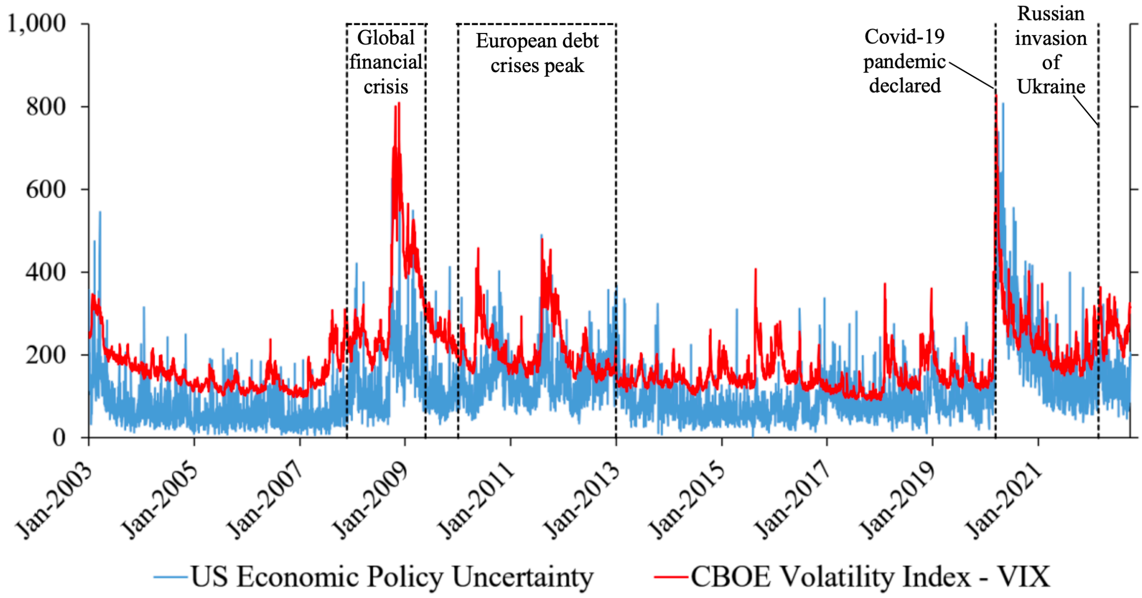


Figure 2.1. US economic policy uncertainty and CBOE Volatility Index (VIX)

Thus, as emerging economies suffer most severely over a prolonged period of time from uncertainty shocks, it is crucial to investigate the expected sectoral uncertainty transmission mechanism of emerging economies. Analyzing these interdependencies supports the identification of the health and growth prospects of specific segments of emerging economies independently, helping governments and policymakers to make informed decisions regarding economic policies and regulations that can impact the individual sectors and thus the overall economy by minimizing the intersectoral uncertainty spillovers in order to foster the stability of the financial market of emerging economies as well as to prosper economic growth. Furthermore, investigating emerging market economies is of great relevance, given that those economies make up 49% of the global GDP and 67% of the world GDP growth over 2011-2021 (World Economics, 2022). Additionally, emerging economies are considered to play a significant role in supporting the world's economic recovery amid the post-crisis period (Wu & Pan, 2021).

Therefore, the aim of this study is to adequately examine the magnitude of uncertainty spillovers across different sectors over time, frequency, and quantile spectrum. To serve that purpose, we employ the recently developed time-frequency quantile connectedness approach of Chatziantoniou, Abakah, et al. (2022).

The main reason why we are utilizing conditional volatility spillovers to measure the expected sectoral uncertainty propagation mechanism of emerging economies is caused by the fact that the current level of sectoral conditional volatility represents the sectoral uncertainty that is expected given all available data (Bollerslev, 1986; Engle, 1982). Furthermore, this study investigates the two hypotheses of Engle et al. (1990). The first one is called the "heat wave" hypothesis and postulates that volatility occurring in a market appears to remain only in this market on the next day but will not transmit to other markets while the second hypothesis is called "meteor shower" and suggests that volatility occurring in a market appears to propagate to another market. Hence, by identifying strong conditional volatility spillovers from one to another sector, we find empirical support for the "meteor shower" hypothesis while the absence of conditional volatility spillovers from one to another sector would support the "heat wave" hypothesis. In addition, we cover two further hypotheses regarding "contagion" and "decoupling" hypotheses. While the former posits that there exists a higher level of volatility spillovers among markets over a crisis, causing the portfolio diversification's benefits to become limited (Hkiri et al., 2017), the latter suggests that investors could still achieve benefits from portfolio diversification (Bekiros, 2014; Yarovaya & Lau, 2016) as emerging markets appear to act rather independently.

Chatziantoniou, Abakah, et al. (2022) combine the quantile connectedness approach with the frequency connectedness of Baruník and Křehlík (2018) to allow the time-domain connectedness measures to be decomposed in different frequencies, which might help identify the heterogeneity of the transmission mechanism across various frequencies and quantiles (Vo & Dang, 2023). Up to now, an increasing number of studies have employed the time-frequency connectedness method thanks to its advantages (see Umar et al. (2022), Jiang and Chen (2022), Suleman et al. (2023) among the others). Indeed, by analyzing the degree of connectedness across time, we will see how different market periods including recent economic and financial crises have changed the strength and magnitude of uncertainty spillovers while the frequency dimension allows us to investigate whether uncertainty spillovers have more pronounced short or long-term effects on emerging markets. Finally, the quantile spectrum allows us to differentiate the sectoral market connectedness during times of low uncertainty (at lower quantiles) and during times of high uncertainty (at higher quantiles), illustrating smooth and turbulent market conditions.

Recent studies show evidence of significant effects of economic policy uncertainty (EPU) on sectoral connectedness in some emerging markets, including China (Su & Liu, 2021) and Vietnam (Dang et al., 2023). As such, in this study, we aim to revisit this relationship, using different uncertainty indices (i.e., the CBOE Volatility Index, the US Economic Policy Uncertainty Index, and the Equity Market-related Economic Uncertainty Index), which are also employed in other empirical studies on uncertainties (Al-Yahyaee et al., 2019; Bouri et al., 2017; Dai et al., 2021).

Finally, we create bivariate hedging portfolios (Kroner & Sultan, 1993) as well as multivariate minimum-risk portfolios (Markowitz, 1952) in order to see whether hedging one sector with another sector or investing in a multitude of sectors significantly reduces investment uncertainty. This analysis shows that governments of emerging economies might be able to induce economic stability by adequately investing in different economic sectors.

Thus, the contribution of our study is threefold. First, to the best of our knowledge, no previous studies have investigated expected sectoral uncertainty spillovers in emerging markets, especially by utilizing aggregated sectoral emerging market indices in order to highlight the degree of expected sectoral emerging market interdependencies and sectoral interconnectedness. Second, we are the first who provide empirical evidence regarding the expected uncertainty spillovers of emerging economies. Third, we expand the scarce literature on sectoral financial market research, especially for emerging economies. As such, this study fills those research gaps by means of the recently-developed quantile time-frequency connectedness approach of Chatziantoniou, Abakah, et al. (2022) examining the expected uncertainty transmission mechanism of emerging markets sectors over the period from January 1st, 2003 until October, 4th 2022.

We find strong evidence that sectoral market interconnectedness is time-varying and heavily impacted by economic and financial crises. Interestingly, the largest fraction of sectoral uncertainty connectedness is caused by more volatile long-term dynamics while short-term dynamics appear to be more persistent. Furthermore, we find that the degree of sectoral market uncertainty is larger at the upper tail of the quantile spectrum which implies that high expected uncertainty is causing substantial market interdependencies and thus co-movements, while we find that sectors of emerging economies behave more independently during periods of lower levels of uncertainty. This indicates suggestive evidence of asymmetric sectoral uncertainty connectedness effects. Additionally, a positive relationship between uncertainty indices and the sectoral total connectedness is identified during times of low uncertainty and normal market conditions. Last, we suggest different portfolio analyses that appear to help international investors reduce their investment risk significantly when developing their investment portfolios.

Our paper is organized as follows. Section 2.2 presents the existing literature review on the topic. Section 2.3 discusses the methodology and Section 2.4 presents the data sampling.

Our empirical results are reported and discussed in Section 2.5. Finally, Section 2.6 presents our concluding remarks.

2.2. Literature review

Already numerous studies have investigated the transmission mechanisms of different financial markets or financial assets. Especially when it comes to developing economies, we find ample evidence that the connectedness among financial markets tends to increase international risk sharing (Chen et al., 2014; Labidi et al., 2018; Mobarek et al., 2016) and that the network interconnectedness is often economic event dependent (Baruník et al., 2016; Bouri et al., 2021; Chatziantoniou et al., 2021). Several researchers examine the implications of stronger connectedness across global financial markets with a focus on market returns, volatility, or cross-country correlations (Badshah et al., 2018; Bekaert et al., 2005; Carrieri et al., 2007; Hedström et al., 2020; Moneta & Rüffer, 2009; Stenfors et al., 2022). Spillovers across markets are found to decrease the probability of mitigating risks via portfolio diversification (Hedström et al., 2020). Other studies extensively concentrate on the transmission mechanisms between stock markets and international assets (among the many, see Jung and Maderitsch (2014), Antonakakis et al. (2017), Shahzad et al. (2018), Fassas and Siriopoulos (2019)).

However, recently there has been increasing interest in investigating the financial transmission mechanism between emerging economies (Eterovic et al., 2022; Gabauer et al., 2022; Huidrom et al., 2020; Urom et al., 2022) or between emerging and developed economies (Ahmed et al., 2017; Diebold & Yilmaz, 2009; Mensi, Shafiullah, et al., 2021). While all aforementioned studies focus on emerging and developed market spillovers, the literature on sectoral stock market spillovers is rather limited. Furthermore, the majority of those studies focus on developed markets, especially on the US (Baruník et al., 2016; Laborda & Olmo, 2021; Lastrapes & Wiesen, 2021; Malik, 2022; Mensi, Al Rababa'a, et al., 2022), EU (Arouri et al., 2011; Balli et al., 2013), Australia (Balli et al., 2020; Balli et al., 2016), and New Zealand (Balli et al., 2020). Investigating the return and volatility spillover effects between the S&P 500 stock sectors and natural gas prices under the spillover framework proposed by Diebold and Yılmaz (2012) and the frequency connectedness approach developed by Baruník and Křehlík (2018), Geng et al. (2020) note that the most return spillovers occur in the short term (up to 12 weeks). Meanwhile, Mensi, Nekhili, et al. (2021) adopt Diebold and Yılmaz (2014)'s approach and (Baruník et al., 2017)'s realized semivariances to investigate the sectoral dynamic asymmetric spillovers in the US. They show evidence that the time-varying connectedness across US stock sectors appears intensified over the periods of geopolitical, energy-related, and economic events and that there exists asymmetry in the spillovers under good versus bad volatility. Balli et al. (2021) find that the crises tend to intensify the spillover effects amongst the markets and that the spillovers reach their peaks over the Global Financial Crisis (2008-2009) and the European sovereign debt crisis (2010-2012). Additionally, shocks from economic events appear to amplify the level of transmission across sectoral markets and hence, negatively affect the benefits of investment diversification. Costa et al. (2022) analyze the volatility spillover effects among 11 sector indices in the US during the COVID-19 pandemic and find that there is an extraordinary increase in total spillovers from the early stages of the coronavirus pandemic until July 2020. However, the authors find little evidence of the structural changes from the perspective of total net connectedness. Pham et al. (2023) examine the relationship between the utility sector and natural gas in the US, using the quantile connectedness approach. The authors find that the return spillover effects appear time-varying and stronger at the extremes (i.e., at the lowest and highest quantiles) than at the middle quantiles.

The scarce literature on sectoral emerging markets spillover covers China (Akhtaruzzaman et al., 2021; Gao et al., 2023; Shahzad et al., 2021; Shen et al., 2021; Su & Liu, 2021; Yin et al., 2020), India (Chatziantoniou, Gabauer, et al., 2022), Vietnam (Mensi, Ziadat, et al., 2022), and African developing countries (Akhtaruzzaman et al., 2022). In the case of China, based on price fluctuations and internet sentiment, Gao et al. (2023) examine the risk connectedness across sectors in the Chinese stock market after the COVID-19 outbreak. Under the time-varying parameter vector autoregressive (TVP-VAR) approach, the authors find that after the pandemic outbreak, the sectoral risk transmission within the Chinese stock market is amplified, implying the increased instability in the system. Additionally, the risk connectedness tends to vary with various market conditions and becomes significantly intensified under extreme market circumstances. Using 1-min data of sector index series in China, Shahzad et al. (2021) study the asymmetric volatility connectedness across Chinese stock sectors over the Covid-19 pandemic period. Their findings show that the sectoral spillover effects are time-varying and significantly asymmetric during the COVID-19 pandemic. The authors also emphasize that the bad volatility connectedness tends to dominate the good volatility spillover. Focusing on the periods of extreme risk events (including the Chinese stock market crash, the trade war between China and the US, and the Chinese liquidity crisis), Shen et al. (2021) investigate the transmission channel among Chinese economic sectors and show that the sectoral spillover effects appear significantly higher during the aforementioned extreme risk periods. They also observe that the financial sectors have a buffer role in the stabilization of the economic system. Focusing on the Covid-19 period, Akhtaruzzaman et al. (2021) investigate the financial contagion between China and G7 countries and find that the dynamic conditional correlations became dramatically higher during the pandemic. Furthermore, they note that financial sectors tend to play a more significant role in the transmission of financial contagion than non-financial sectors. In the context of India, Chatziantoniou, Gabauer, et al. (2022) investigate the interconnectedness of 12 Indian sectorals using the TVP-VAR-based connectedness approach of Antonakakis et al. (2020). They find that the dynamic total connectedness has been heterogeneous over time and economic-event dependent. Moreover, connectedness was strongest during the Great Financial Crisis of 2008, the double-digit inflation and stock market crash of 2011, the national election of 2014, and the demonetization of 2016. Among sectors, consumers' spending, industry, finance, and basic materials are net transmitters of shocks, while information technology, fast-moving consumer goods, health care, and telecommunications are net receivers of shocks. It is argued that their findings are helpful in formulating policies that alleviate sectoral imbalances, promote balanced growth, and are useful for pursuing optimal portfolio diversification strategies. Meanwhile, with respect to Vietnam, Mensi, Ziadat, et al. (2022) adopt the extreme quantile connectedness approach proposed by Chatziantoniou et al. (2021) to investigate the spillover effects between crude oil futures and 10 stock market sectors in Vietnam. The authors find that the connectedness is stronger under bearish circumstances than bullish circumstances and that the risk spillovers significantly increase over turbulent periods such as the Global Financial Crisis, the European debt crisis, Brexit, the oil crisis, and the COVID-19 pandemic. In the context of African developing economies, Akhtaruzzaman et al. (2022) examine the financial risk transmission from the US to developing countries in Africa over the coronavirus period. The authors show that South Africa, Morocco, Nigeria, and Egypt play as net risk receivers whereas the US acts as the net exporter of financial risk. Additionally, the study indicates that the downside risk exposures of banks and financial firms became significantly higher over the period January - April 2020.

Previous studies indicate that the connectedness across sectors varies over time and strongly responds to various political and financial events (Chatziantoniou, Gabauer, et al., 2022; Shen et al., 2021; Yin et al., 2020). Indeed, when a shock occurs in a sector, it tends to propagate to other sectors and even to the whole financial markets due to sectoral connectedness (Zhang et al., 2020). In more detail, Eckernkemper (2018) emphasizes that sectors play a significant role in systemic risk and that the volatility contributions tend to change across different equity sectors. The volatility of a sector tends to spill over to another, which eventually might impact the volatility of the whole network (Shahzad et al., 2021). Such spillovers could affect policymakers' decisions and investors' returns. Mensi, Al Rababa'a, et al. (2021) note that different sectors tend to possess relatively different characteristics. Indeed, Mensi, Al Rababa'a, et al. (2022) claim that neglecting the sectoral cross-section differences might lead to negative outcomes in terms of portfolio diversification. For instance, market participants might have an assumption that one critical event would exert the same impact on different sectors in the system. Accordingly, they would probably encounter more losses as they did not pay more attention to the sectors that received higher negative impacts from the shocks. This assumption appears to hold true during the COVID-19 pandemic when some sectors were more significantly affected by the pandemic outbreak than others (Alomari et al., 2022). As such, Adekoya et al. (2022) argue that sectoral analysis appears much more significant than the analyses at the regional or national level in the age of globalization.

According to Gao et al. (2023), given the simplicity of information sharing and the diversified investment strategies, the sectoral interconnectedness of financial markets appears to have an important role in risk transmission as risk spillovers among sectors and markets might be generated due to stock price fluctuations and investors' sentiment. As such, exploring the source and the magnitude of uncertainty spillovers is crucial as it helps uncover the sectoral uncertainty contributions and the network of spillovers across sectors (Shahzad et al., 2021). From the perspective of volatility transmission, examining the connectedness of various stock markets' sectors appears vital for mitigating financial risks (Gao et al., 2023). Moreover, investigating the sectoral spillover mechanisms appears significant for governments to design appropriate policy measures that can deal with market failures as well as for a majority of investors and asset managers to design their investment strategies which might reduce risk exposure (Costa et al., 2022; Wu et al., 2019). Indeed, Mensi, Yousaf, et al. (2022) suggest that sectoral analysis might be helpful for investors to design more efficient hedging strategies using various equity sectors instead of the aggregate stock market indices. Also, Phylaktis and Xia (2009) claim that sectors might provide additional benefits for portfolio diversification over periods of turbulent market conditions and financial contagion. Sector-based investment portfolios might help investors manage their risks as strategies regarding sector-based investments tend to exhibit independent movements (Elyasiani et al., 2011).

Given that there are no previous studies examining the sectoral uncertainty connectedness utilizing aggregated sectoral emerging market indices, this study aims to fill this research gap by investigating the expected uncertainty spillovers across sectoral emerging markets.

2.3. Methodology

2.3.1. GJR-DCC-GARCH model

In order to obtain expected sectoral uncertainty measures, we estimate a DCC-GARCH model (Engle, 2002) with univariate GJR-GARCH processes. The GJR-GARCH model of Glosten et al. (1993) is chosen as it captures asymmetric conditional volatility effects which are frequently found in the financial literature and which would be omitted by using standard GARCH (Bollerslev, 1986) models.

In the spirit of Engle (2002), we can outline the dynamic conditional correlations generalized autoregressive conditional heteroscedasticity (DCC-GARCH) model for $K \times 1$ dimensional return series, $\mathbf{x}_t$ (see Section 2.4) as follows:

$$\mathbf{x}_t|\mathbf{\Omega}_{t-1} \sim N(\mathbf{0}, \mathbf{H}_t), \quad \mathbf{z}_t|\mathbf{\Omega}_{t-1} \sim N(\mathbf{0}, \mathbf{I}) \tag{2.1}$$

$$\mathbf{x}_t = \mathbf{D}_t\mathbf{z}_t, \quad \mathbf{D}_t = diag\left\{h_{1t}^{\frac{1}{2}}, \dots, h_{Kt}^{\frac{1}{2}}\right\} \tag{2.2}$$

$$\mathbf{H}_t = \mathbf{D}_t\mathbf{R}_t\mathbf{D}_t, \quad \mathbf{R}_t = diag(\mathbf{Q}_t)^{-1}\mathbf{Q}_t diag(\mathbf{Q}_t)^{-1}, \quad \mathbf{Q}_t = (1-a-b)\xi + a\mathbf{z}_t\mathbf{z}_{t-1}' + b\mathbf{Q}_{t-1} \tag{2.3}$$

where $\mathbf{z}_t$, ξ, $\mathbf{H}_t$, and $\mathbf{R}_t$ are standardized residuals, the unconditional correlation matrix of standardized residuals, the conditional covariance matrix and the conditional correlation matrix, respectively.

In a two-step estimation procedure, Engle (2002) demonstrates that estimating the DCC-GARCH model does not result in biased estimates. Initially, K univariate GARCH models are estimated to derive $\mathbf{D}_t$. Then, the parameters (a and b) of the DCC-GARCH model are estimated to obtain $\mathbf{R}_t$ and subsequently $\mathbf{H}_t$. The log-likelihood function can be expressed as the combined sum of the volatility and correlation components:

$$L(\theta, \phi) = L_V(\theta) + L_C(\theta, \phi) \tag{2.4}$$

$$L_V(\theta) = -\frac{1}{2}\sum_t \sum_{i=1}^{k} \left(log(2\pi) + log\left(h_{i,t} + x_{i,t}^2/h_{i,t}\right)\right) \tag{2.5}$$

$$L_C(\theta, \phi) = -\frac{1}{2}\sum_t \left(log|\mathbf{R}_t| + \mathbf{x}_t{}'\mathbf{R}_t^{-1}\mathbf{x}_t - \mathbf{x}_t{}'\mathbf{x}_t\right) \tag{2.6}$$

where $L_V(\theta)$ and $L_C(\theta, \phi)$ stand for the volatility and correlation component of the log-likelihood function, respectively.

In the first step, the parameter θ represents the estimated univariate GJR-GARCH parameters, while the parameter ϕ represents the DCC-GARCH parameter in the second step. The GJR-GARCH(1,1)[2] model of Glosten et al. (1993) can be outlined as follows.

$$h_t = \zeta + \alpha_1 \epsilon_{t-1}^2 + \gamma_1 \epsilon_{t-1}^2 I_{t-1} + \beta_1 h_{t-1} \tag{2.7}$$

where ζ, α_1, and β_1 are the unconditional variance, the shock, and the persistence parameter, respectively, while I_{t-1} is an indicator variable which is equal to unity if $\epsilon_{t-1} < 0$ and zero vice versa.

2.3.2. Quantile time-frequency connectedness approach

In the next step, we estimate the uncertainty transmission mechanism of emerging markets by means of the quantile-frequency connectedness approach of Chatziantoniou, Abakah, et al. (2022). For this purpose, the following quantile vector autoregressive model, QVAR(p), is estimated,

$$\mathbf{h}_t = \boldsymbol{\mu}_t(\tau) + \boldsymbol{\Phi}_1(\tau)\mathbf{h}_{t-1} + \boldsymbol{\Phi}_2(\tau)\mathbf{h}_{t-2} + \cdots + \boldsymbol{\Phi}_p(\tau)\mathbf{h}_{t-p} + \mathbf{v}_t(\tau) \tag{2.8}$$

where $\mathbf{h}_t$ and $\mathbf{h}_{t-i}$, $i = 1, \ldots, p$ represent $K \times 1$ dimensional conditional volatility vectors, τ is between $[0,1]$ and represents the quantile of interest, p stands for the lag length of the QVAR model, $\boldsymbol{\mu}(\tau)$ is an $K \times 1$ dimensional conditional mean vector, $\boldsymbol{\Phi}_j(\tau)$ is an $K \times K$ dimensional QVAR coefficient matrix, and $\mathbf{v}_t(\tau)$ demonstrates the $K \times 1$ dimensional error vector which has an $K \times K$ dimensional error variance-covariance matrix, $\boldsymbol{\Sigma}(\tau)$. To transform the QVAR(p) to its quantile vector moving average representation, QVMA(∞), we use Wold's theorem: $\mathbf{h}_t = \boldsymbol{\mu}(\tau) + \sum_{j=1}^{p} \boldsymbol{\Phi}_j(\tau)\mathbf{h}_{t-j} + \mathbf{v}_t(\tau) = \boldsymbol{\mu}(\tau) + \sum_{i=0}^{\infty} \boldsymbol{\Psi}_i(\tau)\mathbf{v}_{t-i}$.

Subsequently, the M-step ahead generalized forecast error variance decomposition (GFEVD) (see, Koop et al. (1996), Pesaran and Shin (1998)) which lies at the heart of the connectedness approach is calculated.[3] The GFEVD can be interpreted as the impact a shock in series j has on series i in terms of its forecast error variance share and can be written in the following form:

$$\theta_{ij}(M) = \frac{\left(\boldsymbol{\Sigma}(\tau)\right)_{jj}^{-1} \sum_{m=0}^{M} \left(\left(\boldsymbol{\Psi}_m(\tau)\boldsymbol{\Sigma}(\tau)\right)_{ij}\right)^2}{\sum_{m=0}^{M} \left(\boldsymbol{\Psi}_m(\tau)\boldsymbol{\Sigma}(\tau)\boldsymbol{\Psi}'_m(\tau)\right)_{ii}} \tag{2.9}$$

[2] We use a GJR-GARCH(1,1) model as Hansen and Lunde (2005) have shown that estimating GARCH models with one shock and one persistence parameter is sufficient.

[3] The GFEVD is preferred over its orthogonal counterpart as the retrieved results are completely invariant of the variable ordering. Additionally, Wiesen et al. (2018) point out, that the GFEVD should be employed if no theoretical framework - which would allow to identify the error structure - is available.

$$\tilde{\theta}_{ij}(M) = \frac{\theta_{ij}(M)}{\sum_{j=1}^{K} \theta_{ij}(M)} \tag{2.10}$$

where M represents the forecast horizon. As the rows of $\tilde{\theta}_{ij}$ do not sum up to one, we need to normalize them by the row sum which results in $\tilde{\theta}_{ij}$. Through the normalization, we get the following identities: $\sum_{j=1}^{K} \tilde{\theta}_{ij}(M) = 1$ and $\sum_{j=1}^{K} \sum_{i=1}^{K} \tilde{\theta}_{ij}(M) = K$. Hence, each row sum is equal to unity representing how a shock in series i has influenced the series itself and all other series j.

In the next step, all connectedness measures can be computed. We start with the *(overall) net pairwise connectedness (NPDC)* which is computed as follows,

$$NPDC_{ij}(M) = \tilde{\theta}_{ij}(M) - \tilde{\theta}_{ji}(M) \tag{2.11}$$

If $NPDC_{ij}(M) > 0$ ($NPDC_{ij}(M) < 0$), it means that series j influences series i more (less) than vice versa. Hence, if $NPDC_{ij}(M) > 0$, series j dominates series i and vice versa.

The *(overall) total directional connectedness TO others* measures how much of a shock in series i is transmitted to all other series j:

$$TO_i(M) = \sum_{i=1, i \neq j}^{K} \tilde{\theta}_{ji}(M) \tag{2.12}$$

The *(overall) total directional connectedness FROM others* measures how much series i is receiving from shocks in all other series j:

$$FROM_i(M) = \sum_{i=1, i \neq j}^{K} \tilde{\theta}_{ij}(M) \tag{2.13}$$

The *(overall) NET total directional connectedness* represents the difference between the *(overall) total directional connectedness TO others* and the *(overall) total directional connectedness FROM others*, which can be interpreted as the net influence series i has on the predetermined network.

$$NET_i(M) = TO_i(M) - FROM_i(M) \tag{2.14}$$

If $NET_i > 0$ ($NET_i < 0$), series i influences all others j more (less) than being influenced by them. Thus, it is considered a net transmitter (receiver) of shocks.

The *(overall) total connectedness index (TCI)* of Chatziantoniou, Gabauer, and Stenfors (2021a) that measures the degree of network interconnectedness can be calculated by:

$$TCI(M) = \frac{1}{K-1}\sum_{i=1}^{K} TO_i(M) = \frac{1}{K-1}\sum_{i=1}^{K} FROM_i(M) \tag{2.15}$$

The higher the TCI value, the higher the market risk, and vice versa.

So far, we have focused on the connectedness assessment in the time domain. Analogously, we continue with the connectedness assessment in the frequency domain. Following the spectral decomposition method of Stiassny (1996), we can explore the connectedness relationship in the frequency domain. First, we consider the frequency response function, $\mathbf{\Psi}\left(e^{-i\omega}\right) = \sum_{m=0}^{\infty} e^{-i\omega m}\,\mathbf{\Psi}_m$, where $i = \sqrt{-1}$ and ω denotes the frequency to continue with the spectral density of $\mathbf{x}_t$ at frequency ω which can be defined as a Fourier transformation of the QVMA(∞) representation:

$$\mathbf{S}_x(\omega) = \sum_{m=-\infty}^{\infty} E\,(\mathbf{h}_t \mathbf{h'}_{t-m})e^{-i\omega m} = \mathbf{\Psi}\left(e^{-i\omega m}\right)\mathbf{\Sigma}_t \mathbf{\Psi'}^{\left(e^{+i\omega m}\right)} \tag{2.16}$$

Notably, the frequency GFEVD is the combination of spectral density and the GFEVD. As in the time domain, we need to normalize the frequency GFEVD which can be formulated as follows.

$$\theta_{ij}(\omega) = \frac{\left(\mathbf{\Sigma}(\tau)\right)_{jj}^{-1}\left|\sum_{m=0}^{\infty}\left(\mathbf{\Psi}(\tau)\left(e^{-i\omega m}\right)\mathbf{\Sigma}(\tau)\right)_{ij}\right|^2}{\sum_{m=0}^{\infty}\left(\mathbf{\Psi}(e^{-i\omega m})\mathbf{\Sigma}(\tau)\mathbf{\Psi}(\tau)(e^{i\omega m})\right)_{ii}} \tag{2.17}$$

$$\tilde{\theta}_{ij}(\omega) = \frac{\theta_{ij}(\omega)}{\sum_{k=1}^{K}\theta_{ij}\,(\omega)} \tag{2.18}$$

where $\tilde{\theta}_{ij}(\omega)$ represents the portion of the spectrum of the ith series at a given frequency ω that can be attributed to a shock in the jth series. It can be interpreted as a within-frequency indicator.

To assess short-term and long-term connectedness rather than connectedness at a single frequency, we aggregate all frequencies within a specific range, $d = (f, g)$: $f, g \in (-\pi, \pi), f < g$:

$$\tilde{\theta}_{ij}(d) = \int_f^g \tilde{\theta}_{ij}\,(\omega)d\omega \tag{2.19}$$

From here, we can calculate exactly the same connectedness measures as in Diebold and Yılmaz (2012, 2014) which can be interpreted identically, however, in this case, they refer to frequency connectedness measures that provide information about spillovers in certain frequency ranges d:

$$NPDC_{ij}(d) = \tilde{\theta}_{ij}(d) - \tilde{\theta}_{ji}(d) \tag{2.20}$$

$$TO_i(d) = \sum_{i=1, i\neq j}^{K} \tilde{\theta}_{ji}\,(d) \tag{2.21}$$

$$FROM_i(d) = \sum_{i=1, i\neq j}^{K} \tilde{\theta}_{ij}\,(d) \tag{2.22}$$

$$NET_i(d) = TO_i(d) - FROM_i(d) \tag{2.23}$$

$$TCI(d) = \frac{1}{K-1}\sum_{i=1}^{K} T\,O_i(d) = \frac{1}{K-1}\sum_{i=1}^{K} F\,ROM_i(d) \tag{2.24}$$

In our case, we have two frequency bands illustrating short-term and long-term dynamics ranging from 1 to 5 days, $d_1 = (\pi/5, \pi)$ and from 6 to infinite days, $d_2 = (0, \pi/5]$ (see Chatziantoniou, Abakah, et al. (2022). Thus, $NPDC_{ij}(d_1)$, $TO_i(d_1)$, $FROM_i(d_1)$, $NET_i(d_1)$, and $TCI(d_1)$ illustrate the short-term net pairwise connectedness, short-term total directional connectedness TO others, short-term total directional connectedness FROM others, short-term NET total directional connectedness, and short-term total connectedness index, while $NPDC_{ij}(d_2)$, $TO_i(d_2)$, $FROM_i(d_2)$, $NET_i(d_2)$, and $TCI(d_2)$ illustrate the long-term net pairwise connectedness, long-term total directional connectedness TO others, long-term total directional connectedness FROM others, long-term NET total directional connectedness, and long-term total connectedness index, respectively.

Finally, we show the relationship between the frequency-domain measures of Baruník and Křehlík (2018) to the Diebold and Yılmaz (2012, 2014) time-domain measures:

$$NPDC_{ij}(M) = \sum_{d} NPDC_{ij}(d) \tag{2.25}$$

$$TO_i(M) = \sum_{d} TO_i(d) \tag{2.26}$$

$$FROM_i(M) = \sum_{d} FROM_i(d) \tag{2.27}$$

$$NET_i(M) = \sum_{d} NET_i(d) \tag{2.28}$$

$$TCI(M) = \sum_{d} TCI(d) \tag{2.29}$$

Intuitively speaking, the overall connectedness measures are equal to the sum of the corresponding frequency connectedness measures. Keep in mind that all those connectedness measures are based on a specific quantile, τ.

2.3.3. Hedge ratios

In order to examine whether the investment uncertainty can be reduced by employing hedging or minimum-risk portfolios, we implement the bivariate hedge ratio approach proposed by Kroner and Sultan (1993) as well as the minimum variance portfolio of Markowitz (1952).

Kroner and Sultan (1993) have shown that the investment risk of holding a long position in asset i can be reduced by holding a short position of asset j. In this context, the hedge ratio determines the expenses associated with hedging a 1 USD long position in asset i with a $HR_{ij,t}$ USD short position in asset j. This can be mathematically formulated as follows

$$HR_{ij,t} = \frac{\mathbf{H}_{ij,t}}{\mathbf{H}_{jj,t}} \tag{2.30}$$

where $\mathbf{H}_{ij,t}$ and $\mathbf{H}_{jj,t}$ stand for the conditional covariance between asset i and j and the conditional variance of asset j.

2.3.4. Multivariate minimum variance portfolio

In the pursuit of minimizing portfolio risk, we shift our focus towards the multivariate minimum variance portfolio of Markowitz (1952). To provide a comprehensive understanding, we begin by outlining the general framework and subsequently delve into the process of obtaining diverse portfolio weights. The multivariate minimum risk portfolio can be seen as a minimization optimization problem which can be formulated as follows.

$$\underset{\mathbf{w}_t}{\operatorname{argmin}} \quad \mathbf{w}_t^{\prime \mathbf{H}_t \mathbf{w}_t} \qquad \text{s.t.} \quad \mathbf{w}_t'\mathbf{1} = 1, \qquad \mathbf{0} \leq \mathbf{w}_t \leq \mathbf{1} \tag{2.31}$$

where $\mathbf{w}_t$ denotes the $K \times 1$ dimensional portfolio weights vector in time t that results from minimizing the $K \times K$ dimensional covariance matrix, $\mathbf{H}_t$. As $\mathbf{H}_t$ is varying over time, we are extending the standard Markowitz (1952) by means of time-varying portfolio weights.

2.3.5. Portfolio performance

Finally, the portfolio performance is assessed based on the Sharpe ratio (Sharpe, 1994) and the hedging effectiveness (Ederington, 1979) which provides insight into the return-to-risk behavior of the portfolio as well as the degree of variance risk reduction achieved by investing in a portfolio rather than investing solely in a single asset i. The Sharpe ratio (SR) - often referred to as the reward-to-volatility ratio - is computed as follows.

$$SR = \frac{\bar{\mathbf{x}}_{pf}}{\sqrt{var(\mathbf{x}_{pf})}} \tag{2.32}$$

where $\bar{\mathbf{x}}_{pf}$ and $var(\mathbf{x}_{pf})$ stand for the average portfolio return and the portfolio variance, respectively. The higher the SR, the higher the return relative to the portfolio risk.

To determine the significance of the investment risk reduction, we utilize the HE test statistics developed by Antonakakis et al. (2020). The HE can be computed in the following manner.

$$HE_i = 1 - \frac{var(\mathbf{x}_{pf})}{var(\mathbf{x}_i)} \tag{2.33}$$

where $var(\mathbf{x}_i)$ denotes the variance of return of asset i, and HE_i provides information on the percentage-wise variance reduction by investing in a portfolio compared to asset i. Thus, a high (low) HE index indicates a high (low) risk reduction.

2.4. Data

The employed daily sectoral dataset has been obtained from Refinitiv EIKON and ranges from January 1st, 2003 to October 4th, 2022. Refinitiv EIKON develops sectoral indices for the Global Emerging Markets comprising 26 countries around the world, including Argentina, Bahrain, Brazil, Chile, China, Czech Republic, Egypt, Hungary, India, Indonesia, Kuwait, Malaysia, Mexico, Morocco, Oman, Pakistan, Philippines, Poland, Qatar, Russia, South Africa, Taiwan, Thailand, Turkey, UAE, and Vietnam. Those indices provide a detailed view of the performance of the following different sectors: Basic Materials (BM), Communications & Networking (CN), Consumer Cyclicals (CC), Consumer Non-Cyclicals (CNC), Energy (ENE), Financials (FIN), Healthcare (HC), Industrials (IND), Technology (TEC), and Utilities (UTI). Analyzing these indices offers advantages to investors, analysts, and economists as they can assess the health and growth prospects of specific segments of the economy independently, helping them make better investment decisions. The performance of sectoral indices also acts as an indicator of the overall health of specific industries and the broader economy. Governments and policymakers use this data to make informed decisions regarding economic policies and regulations that can impact individual sectors and the overall economy.

As the raw series are non-stationary according to a battery of unit-root tests (Dickey & Fuller, 1979; Elliott et al., 1996; Kwiatkowski et al., 1992; Phillips & Perron, 1988; Zivot & Andrews, 2002), all sectoral indices are transformed into their daily returns using first log-differences, $x_t = log(y_t) - log(y_{t-1})$ where y_t stands for the daily closing price at time *t*. The daily returns and their conditional volatilities are illustrated in Figure 2.2.

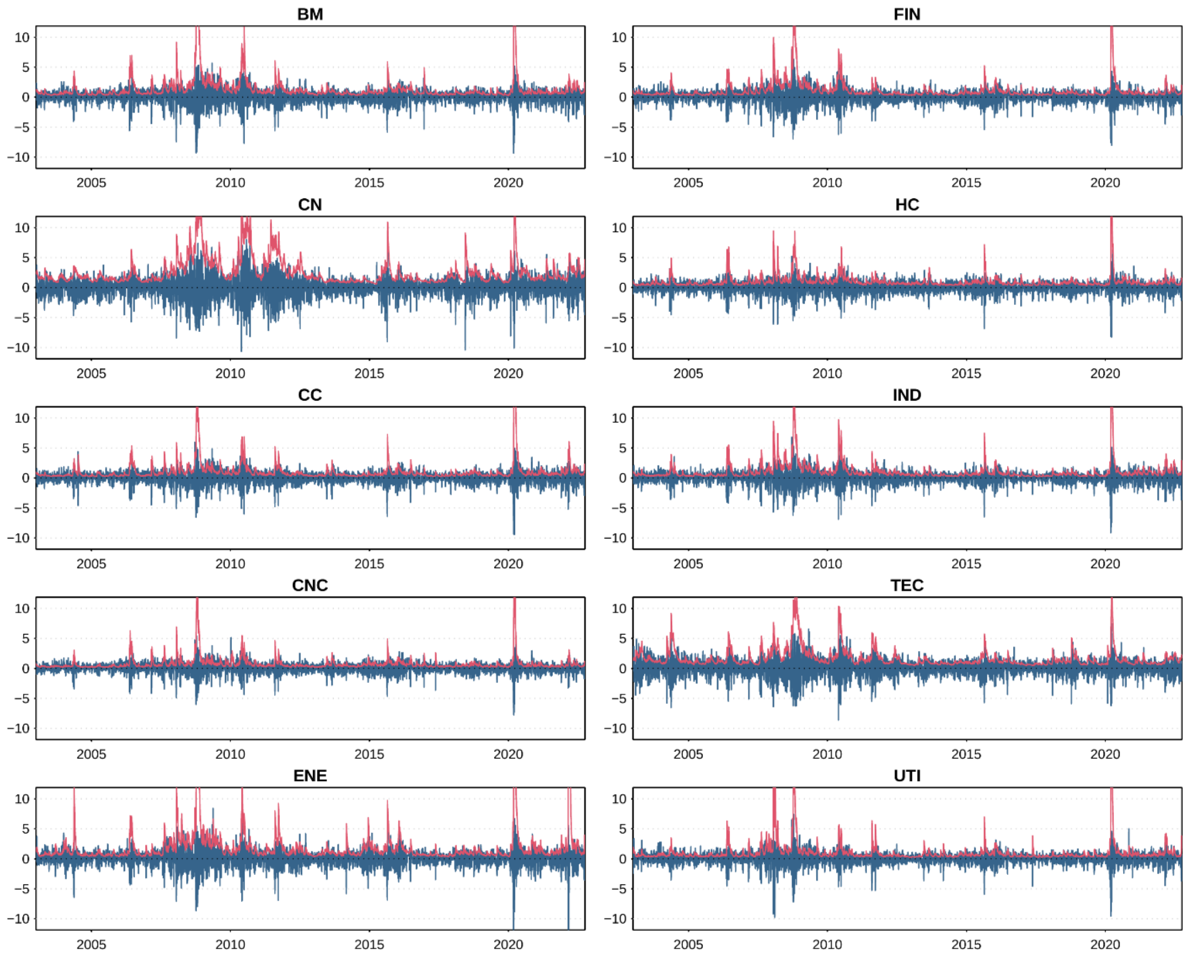


Figure 2.2. Daily returns and conditional volatilities

Notes: Daily returns (blue lines) are computed by the first log-differences and the conditional volatilities (redlines) are estimated using a GJR-DCC-GARCH model (Engle, 2002; Glosten et al., 1993). The sectors are Basic Materials (BM), Communications & Networking (CN), Consumer Cyclicals (CC), Consumer Non-Cyclicals (CNC), Energy (ENE), Financials (FIN), Healthcare (HC), Industrials (IND), Technology (TEC) and Utilities (UTI).

Table 2.1 provides a battery of summary statistics. Interestingly, all sectoral indices are at least at the 1% significance level left-skewed (D'Agostino, 1970), leptokurtic (Anscombe & Glynn, 1983), and non-normally distributed (Jarque & Bera, 1980). In addition, we find suggestive evidence that all sectoral indices are stationary at the 1% significance level. Furthermore, the weighted Portmanteau test of Fisher and Gallagher (2012) reveals that all sectoral indices exhibit ARCH/GARCH errors at least at the 1% significance level. Finally, we find that all sectoral indices are significantly positively correlated with each other using the Kendall rank correlation coefficients.

Table 2.1. Summary statistics

	BM	CN	CC	CNC	ENE	FIN	HC	IND	TEC	UTI
Mean	0.025	0.006	0.024*	0.031**	0.019	0.030**	0.038***	0.024*	0.031*	0.022
	(0.114)	(0.779)	(0.084)	(0.011)	(0.312)	(0.044)	(0.006)	(0.097)	(0.085)	(0.119)
Variance	1.293***	2.595***	1.006***	0.738***	1.810***	1.096***	0.979***	1.052***	1.703***	1.017***
Skewness	-0.864***	-0.469***	-1.035***	-0.889***	-1.447***	-0.762***	-0.794***	-0.935***	-0.311***	-1.196***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Ex.Kurtosis	7.557***	4.168***	8.903***	7.837***	18.700***	6.792***	5.650***	7.336***	3.940***	11.353***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
JB	12806.528***	3891.071***	17804.632***	13761.498***	76309.539***	10327.370***	7341.163***	12215.875***	3390.936***	28686.796***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
ADF	-60.258***	-71.448***	-61.392***	-62.690***	-63.096***	-62.242***	-67.315***	-63.607***	-67.941***	-63.349***
	(0.000)	(0.023)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
PP	-60.934***	-71.455***	-62.027***	-63.310***	-63.889***	-62.740***	-67.702***	-64.520***	-67.920***	-63.851***
	(0.000)	(0.023)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
KPSS	0.242***	0.029***	0.283***	0.389***	0.368***	0.302***	0.314***	0.198***	0.036***	0.308***
	(0.000)	(0.023)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
ERS	-28.418***	-25.957***	-26.473***	-10.627***	-25.164***	-23.859***	-10.477***	-12.394***	-28.191***	-5.399***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
ZA	-60.460***	-71.522***	-61.638***	-25.188***	-63.319***	-62.442***	-67.531***	-24.484***	-68.143***	-63.575***
	(0.000)	(0.023)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
$Q^2(20)$	2678.951***	1231.206***	3053.551***	2829.378***	742.921***	2705.892***	1354.903***	2492.037***	1502.313***	2183.524***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)

Kendall rank correlation coefficients

	BM	CN	CC	CNC	ENE	FIN	HC	IND	TEC	UTI
BM	1.000***	0.319***	0.657***	0.613***	0.567***	0.637***	0.487***	0.626***	0.415***	0.562***
CN	0.319***	1.000***	0.359***	0.290***	0.238***	0.330***	0.301***	0.406***	0.461***	0.283***
CC	0.657***	0.359***	1.000***	0.647***	0.508***	0.665***	0.547***	0.678***	0.456***	0.576***
CNC	0.613***	0.290***	0.647***	1.000***	0.512***	0.606***	0.506***	0.588***	0.384***	0.571***
ENE	0.567***	0.238***	0.508***	0.512***	1.000***	0.549***	0.396***	0.508***	0.333***	0.539***
FIN	0.637***	0.330***	0.665***	0.606***	0.549***	1.000***	0.474***	0.655***	0.449***	0.574***
HC	0.487***	0.301***	0.547***	0.506***	0.396***	0.474***	1.000***	0.546***	0.350***	0.467***
IND	0.626***	0.406***	0.678***	0.588***	0.508***	0.655***	0.546***	1.000***	0.479***	0.586***
TEC	0.415***	0.461***	0.456***	0.384***	0.333***	0.449***	0.350***	0.479***	1.000***	0.347***
UTI	0.562***	0.283***	0.576***	0.571***	0.539***	0.574***	0.467***	0.586***	0.347***	1.000***

Notes: ***, **, * denote significance at 1%, 5%, and 10% significance levels. Values in parentheses represent p-values; Skewness: D'Agostino (1970) test; Kurtosis: Anscombe and Glynn (1983) test; JB: Jarque and Bera (1980) normality test; ADF: Dickey and Fuller (1979) unit-root test; PP: Phillips and Perron (1988) unit-root test; KPSS: Kwiatkowski et al. (1992) unit-root test; ERS: Elliott et al. (1996) unit-root test; ZA: Zivot and Andrews (2002) unit-root test with a structural break; $Q^2(20)$: Fisher and Gallagher (2012) weighted Portmanteau test statistics. The sectors are Basic Materials (BM), Communications & Networking (CN), Consumer Cyclicals (CC), Consumer Non-Cyclicals (CNC), Energy (ENE), Financials (FIN), Healthcare (HC), Industrials (IND), Technology (TEC), and Utilities (UTI).

2.5. Empirical results

2.5.1. Sectoral uncertainty connectedness in emerging markets

2.5.1.1. Median-frequency connectedness measures

We begin the empirical results section by interpreting the averaged median connectedness measures. The diagonal values in Table 2.2 refer to the own-variance shares while the off-diagonal values demonstrate the cross-variance shares. Additionally, each cell represents the impact series *j* has on series *i* (at the average over the total time period, short-term, and long-term periods, respectively). For example, we note that CN has the greatest own-variance share spillover of 24.88%. Out of the 24.88%, the short-term own-variance spillover is 1.88%, whereas the long-term own-variance spillover is 23%. Given that the own-variance spillover of CN stays at 24.88%, the rest of the sectors account for 75.12% (i.e., 100% - 24.88%) of the forecast error variance in CN. We find that TEC and IND have the greatest impacts on CN by 11.48% and 10.43%, respectively. Meanwhile, UTI is the sector that exerts the least effect on CN, by only 6.36%. Decomposing the shock into short-term and long-term spillovers, in the case of the TEC sector that has the largest effect on CN, we document that 0.78% originate from short-term spillovers whereas 10.70% are caused by long-term TEC spillovers. Generally, we note that CN affects the market by 53.93% and is affected by 75.12%, implying that this sector is a net receiver of risks (-21.20%). In particular, this sector is a net receiver of shock in both the short term and long term as its short-term net spillovers are equal to -0.27% and long-term net spillovers stay at -20.93%.

Interestingly, CN and HC are found to be the largest net risk recipients with net spillovers of -21.20% and -10.98%, respectively. As such, those two sectors should be paid serious attention to because they receive the most shocks from other sectors and thus, appear most vulnerable in the system. The emergence of those sectors as net absorbers of shocks in the network is not surprising as Communications and Healthcare are among the sectors that thrive and attract the most capital inflows (Martin, 2018). Additionally, emerging markets are reported to attract significant amounts of capital from the rest of the world, including foreign direct investment (FDI) (Ngowi, 2005) and foreign portfolio investment (FPI) (Berrill, 1990). Therefore, it appears that those emerging markets' sectors might attract substantial inflows of foreign capital from other regions, in the form of both FDI and FPI, causing those sectors to receive more risks and act as the greatest net receivers of risks in the network. Meanwhile, the main net exporter of shocks is CC (17.59%), which also acts as the largest net transmitter of shocks in both the short-term (2.24%) and long-term (15.34%). We also note that IND is the second greatest net exporter of shocks in the entire system with net spillovers of 10.65%. As those sectors are considered the sources of risk transmission, they need to be stabilized first to contain risk spillovers.

Furthermore, we find that investigating the expected uncertainty transmission mechanism is of crucial importance as the sectors are substantially integrated. This can be derived from the average total connectedness index (TCI) which is equal to 91.01%, meaning that on average 91.01% of the shock in one series is transmitted to others while only 8.99% refers to the own-variance share. Thus, a shock in one series has a significant impact on all other series. Finally, it should be noted that the largest proportion of the TCI is associated with long-term dynamics. This highlights the relevance of designing policies that mitigate the effects of adverse spillover shocks.

Table 2.2. Dynamic total connectedness: Total, short-term and long-term

	BM	CN	CC	CNC	ENE	FIN	HC	IND	TEC	UTI	FROM
BM	15.34	5.46	11.90	10.10	10.41	10.82	7.70	10.82	8.03	9.42	84.66
	(1.76,13.58)	(0.38, 5.09)	(1.16,10.74)	(0.92, 9.18)	(0.93, 9.48)	(1.02, 9.80)	(0.63, 7.08)	(1.03, 9.79)	(0.60, 7.43)	(0.87, 8.55)	(7.53,77.13)
CN	7.92	24.88	9.54	6.74	7.56	7.76	7.34	10.43	11.48	6.36	75.12
	(0.38, 7.54)	(1.88,23.00)	(0.53, 9.01)	(0.35, 6.39)	(0.38, 7.18)	(0.44, 7.32)	(0.35, 6.99)	(0.64, 9.79)	(0.78,10.70)	(0.31, 6.05)	(4.14,70.98)
CC	10.46	5.17	16.73	10.64	8.88	10.87	8.25	11.39	8.07	9.53	83.27
	(0.99, 9.48)	(0.38, 4.78)	(1.67,15.05)	(0.95, 9.69)	(0.70, 8.18)	(1.01, 9.87)	(0.64, 7.61)	(1.08,10.31)	(0.61, 7.47)	(0.81, 8.72)	(7.17,76.10)
CNC	10.44	4.97	12.00	16.29	9.89	10.50	8.20	10.36	7.57	9.79	83.71
	(1.18, 9.25)	(0.39, 4.58)	(1.43,10.57)	(2.41,13.88)	(1.01, 8.88)	(1.23, 9.26)	(0.83, 7.37)	(1.19, 9.17)	(0.59, 6.98)	(1.18, 8.61)	(9.04,74.67)
ENE	10.43	5.55	9.99	10.11	18.89	10.47	7.55	9.44	7.91	9.65	81.11
	(0.93, 9.50)	(0.30, 5.26)	(0.85, 9.14)	(0.81, 9.30)	(2.05,16.84)	(0.90, 9.57)	(0.55, 7.00)	(0.79, 8.64)	(0.52, 7.39)	(0.88, 8.77)	(6.54,74.57)
FIN	10.55	5.42	12.07	10.34	10.04	14.87	7.40	11.56	8.31	9.45	85.13
	(0.95, 9.59)	(0.39, 5.02)	(1.14,10.93)	(0.92, 9.42)	(0.83, 9.21)	(1.59,13.28)	(0.58, 6.82)	(1.07,10.49)	(0.66, 7.65)	(0.84, 8.60)	(7.38,77.74)
HC	9.37	5.81	11.42	9.77	8.81	9.05	19.08	10.45	7.21	9.04	80.92
	(0.94, 8.43)	(0.48, 5.33)	(1.17,10.25)	(1.00, 8.77)	(0.83, 7.98)	(0.91, 8.13)	(2.79,16.29)	(1.14, 9.31)	(0.62, 6.58)	(0.94, 8.10)	(8.04,72.88)
IND	9.95	6.85	12.30	9.49	8.82	10.59	8.40	15.30	8.80	9.49	84.70
	(0.97, 8.98)	(0.54, 6.31)	(1.21,11.10)	(0.88, 8.61)	(0.73, 8.08)	(1.07, 9.52)	(0.69, 7.71)	(1.67,13.63)	(0.73, 8.07)	(0.90, 8.59)	(7.72,76.97)
TEC	8.71	8.94	10.13	6.96	8.14	9.31	6.75	10.42	23.74	6.89	76.26
	(0.49, 8.22)	(0.61, 8.33)	(0.62, 9.51)	(0.41, 6.56)	(0.47, 7.68)	(0.59, 8.72)	(0.36, 6.39)	(0.66, 9.76)	(1.91,21.83)	(0.36, 6.53)	(4.57,71.69)
UTI	10.00	5.76	11.50	10.20	10.47	10.03	8.35	10.49	7.41	15.80	84.20
	(1.19, 8.81)	(0.40, 5.36)	(1.30,10.20)	(1.25, 8.94)	(1.12, 9.35)	(1.21, 8.81)	(0.84, 7.51)	(1.26, 9.23)	(0.62, 6.80)	(2.35,13.45)	(9.19,75.01)
TO	87.84	53.93	100.86	84.34	83.02	89.39	69.94	95.35	74.79	79.62	
	(8.02, 79.81)	(3.88, 50.05)	(9.41, 91.44)	(7.49, 76.85)	(7.00, 76.02)	(8.39, 81.00)	(5.46, 64.48)	(8.86, 86.49)	(5.73, 69.06)	(7.10, 72.52)	TCI
NET	3.18	-21.20	17.59	0.62	1.91	4.27	-10.98	10.65	-1.46	-4.58	91.01
	(0.49, 2.69)	(-0.27, -20.93)	(2.24, 15.34)	(-1.55, 2.18)	(0.46, 1.45)	(1.00, 3.26)	(-2.58, -8.40)	(1.13, 9.52)	(1.16, -2.63)	(-2.10, -2.49)	(7.93, 83.08)

Notes: Results are based on a 200-day rolling-window QVAR(τ=0.5) model with a lag length of order 1 (BIC) and a 100-step-ahead forecast. The sectors are Basic Materials (BM), Communications & Networking (CN), Consumer Cyclicals (CC), Consumer Non-Cyclicals (CNC), Energy (ENE), Financials (FIN), Healthcare (HC), Industrials (IND), Technology (TEC) and Utilities (UTI). TCI stands for the total connectedness index. The positive (negative) "NET" value of sector i implies that sector *i* acts as a net transmitter (receiver) of shocks. Values in parentheses represent the short-term and long-term connectedness measures, respectively.

Subsequently, we have visualized the bilateral transmission mechanism in Figure 2.3 to facilitate the understanding of the network dynamics. On the aggregated level, we find that CN and HC are driven by most other series while CC and IND are on the net transmitting end of the shock transmission. When decomposing these network dynamics in their short-term and long-term dynamics, it becomes evident that HC and UTI are the main net receivers of short-term dynamics while CC appears to be the main net transmitter of shocks - illustrated by the thickness of the directional net pairwise directional connectedness. While CN had a relatively insignificant role in the short-term transmission mechanism, it is the major net receiver of long-term uncertainty shocks while CC and IND are the main net transmitters of long-term uncertainty shocks.

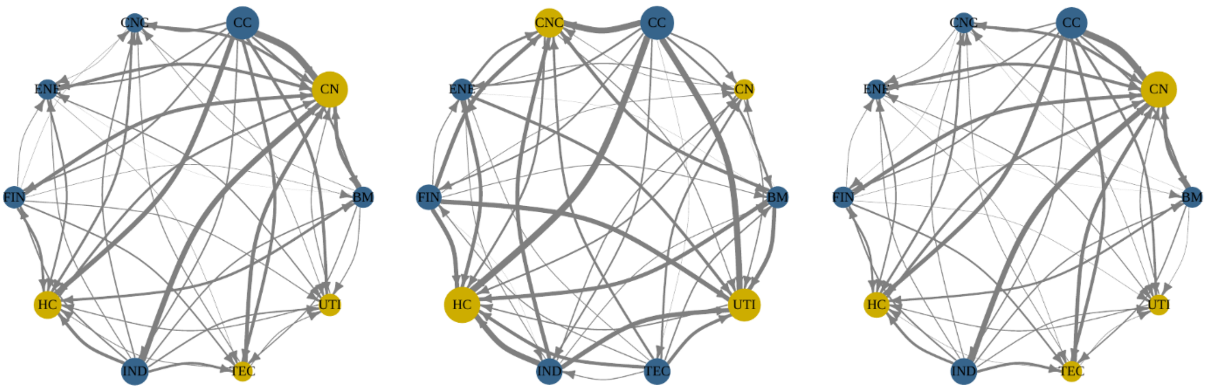


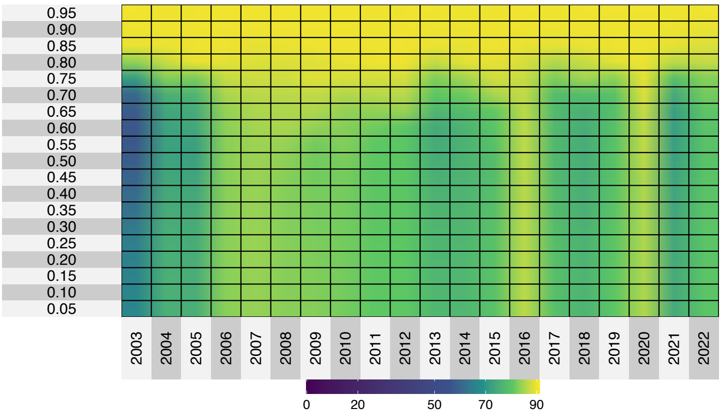
Figure 2.3. Averaged median total, short-term and long-term net pairwise directional connectedness

Notes: The network plots (from left to right) refer to the overall, short-term, and long-term net pairwise connectedness measures, respectively. Blue (yellow) nodes indicate that sector i is a net transmitter (receiver) of shocks while the size of the nodes shows the average net total directional connectedness. The sectors are Basic Materials (BM), Communications & Networking (CN), Consumer Cyclicals (CC), Consumer Non-Cyclicals (CNC), Energy (ENE), Financials (FIN), Healthcare (HC), Industrials (IND), Technology (TEC) and Utilities (UTI).

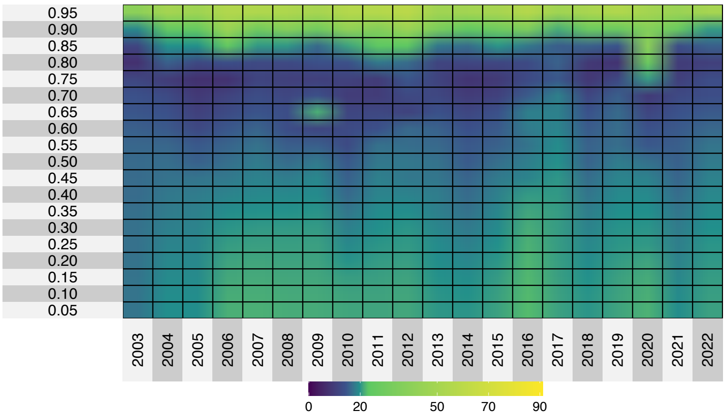
2.5.1.2. Dynamic quantile-frequency total connectedness

In this subsection, we concentrate on the uncertainty connectedness across sectors in emerging markets by quantiles. This is of great relevance as the average median TCI masks potential time-varying effects as well as time-specific events, we continue with interpreting the time, short-term, and long-term dynamic total connectedness measures that are illustrated in Figure 2.4. Those heatmaps provide additional information on the total connectedness across time, frequency, and quantile spectrum encompassing sectoral connectedness during times of low uncertainty (lower quantiles) and during times of high uncertainty (higher quantiles). For illustrative purposes, the median-frequency TCI measure of Table 2.2 is obtained by averaging the dynamic total connectedness over the total time, short-term, and long-term periods. Thus,

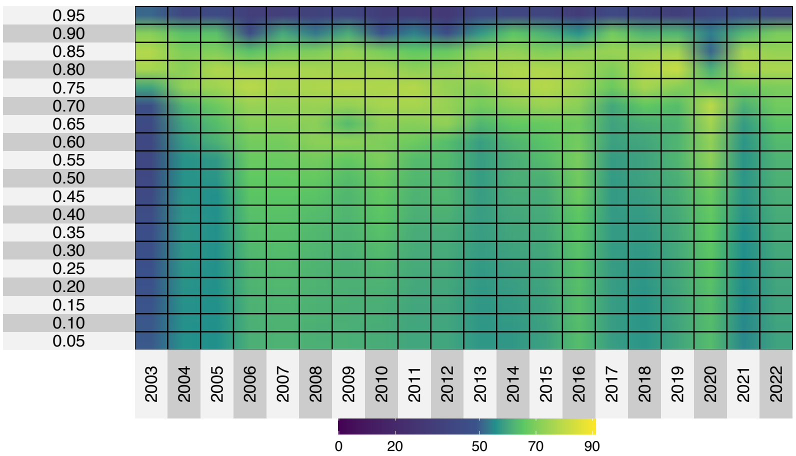
Table 2.2 does not only mask the dynamics over time but it only represents the propagation mechanism at one specific quantile (τ=0.50). As shown in Figure 2.4, the total connectedness varies over time, frequency, and quantiles.



a. Dynamic time total connectedness



b. Dynamic short-term total connectedness



c. Dynamic long-term total connectedness

Figure 2.4. Time, short-term and long-term dynamic total connectedness

When focusing on the time total connectedness (Figure 2.4a), the yellow shades along the vertical axis indicate times of higher uncertainty transmission across quantiles, which can be associated with some major events such as (i) the Global Financial Crisis (2007-2008), (ii)

Chinese stock market turbulence (2016), and (iii) the outbreak of the COVID-19 pandemic (2020). Additionally, we note that the market risk tends to be significantly higher from 2006 until 2012 before the uncertainty spillovers among sectors drop remarkably across quantiles (from 0.05-0.75). Interestingly, Figure 2.4a shows the asymmetry in the sectoral uncertainty connectedness around the median of the vertical axis as the risk spillovers appear much stronger during periods of turbulent market conditions (upper quantiles) than during times of smooth market conditions (lowest quantiles). It implies that spillovers in high uncertainty periods and spillovers in low uncertainty periods behave differently. Such asymmetry in spillovers is also found in Vo and Dang (2023). However, this observation is slightly different from Chatziantoniou et al. (2021) and Chatziantoniou, Abakah, et al. (2022), in which the authors find evidence of higher connectedness at both the highest and lowest quantiles.

Figure 2.4b reflects the dynamic short-term connectedness over time and across quantiles. Remarkably, we identify that there is a significant asymmetry amongst the time-varying quantile spillovers as the short-term connectedness appears higher on the upper end (higher quantiles) than on the lower end (lower quantiles). It implies that market risk in the short term tends to propagate across sectors more strongly during periods of high uncertainty than in times of low uncertainty.

From Figure 2.4c, which illustrates the sectoral long-term spillovers, we see another interesting story. Along the horizontal axis, we find that long-term spillovers appear higher during periods of smooth market conditions (lower quantiles) than in periods of turbulent market conditions (higher quantiles). However, when comparing with the short-term total connectedness, we clearly see a difference at the highest quantiles. Apparently, short-term dynamics are even more integrated in the short term than in the long term. This could be interpreted that stronger dynamics at the highest quantiles occur in the short run rather than the long run which also makes intuitive sense as, for instance, the pronounced degree of shock transmission we observe at the beginning of economic and financial crises has decreased in the long run to return to stable economic condition.

2.5.2. The impact of uncertainty on sectoral total connectedness

In this subsection, we examine how economic and financial uncertainty indices affect the sectoral total connectedness which is commonly interpreted as sectoral market risk. In other words, we are interested in whether and how widely used economic and financial uncertainty indicators are related to the network market risk at different quantiles. For that purpose, we employ the following regression model:

$$TCI_t(\tau) = \delta_0 + \delta_1 Index_t + u_t \tag{2.34}$$

where $TCI_t(\tau)$ is the dynamic total connectedness at the τ-quantile on day t. $Index_t$ stands for each of the following uncertainty indices: the CBOE Volatility Index (VIX), the US Economic Policy Uncertainty Index (EPU US), and the Equity Market-related Economic Uncertainty Index (EPU EM). Those uncertainty indices are obtained from FRED Economic Data, which are also on a daily basis.

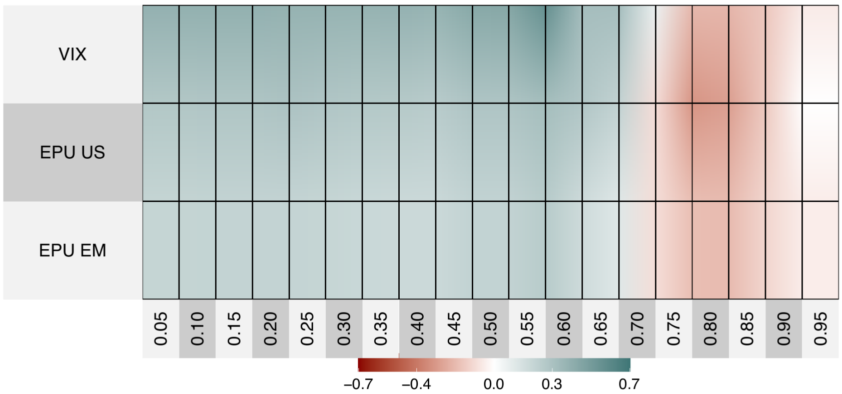


Figure 2.5. Quantile relation between TCI and uncertainty measures

The regression results are illustrated in Figure 2.5 which appears to illustrate more intuitively how the coefficient is gradually changing over quantiles. The blue shades stand for positive coefficients, implying a positive relationship between the uncertainty indices and the sectoral total connectedness while the red shades indicate negative coefficients between the uncertainties and sectoral spillovers. As can be seen in Figure 2.5, we find that uncertainty indices do exert a positive impact on the dynamic total connectedness - up until $\tau = 0.70$. This finding indicates that in times of low uncertainty and normal market conditions, an increase in economic and financial uncertainties is associated with an increase in sectoral interconnectedness across different quantiles. This finding is similar to the results of Dang et al. (2023).

Interestingly, at 75% quantile and above, we note that the uncertainty indices have a negative effect on the dynamic total connectedness. This result is relatively similar to what we have found from Figure 2.4c that the long-term spillovers become lower at the upper quantiles. One possible explanation for this interesting finding is that stock markets are generally regarded to have an adaptive feature (Mauboussin, 2002), and market participants tend to be adaptive to variations in market conditions to secure a stable level of their expected return (Hiremath & Kumari, 2014). Those appear to cause the herd mentality of the markets to become herd immunity to uncertainties during periods of turbulent market conditions.

2.5.3. Robustness check

In order to verify our obtained empirical results, we compare the total connectedness measures retrieved from the quantile-frequency connectedness approach of Chatziantoniou, Abakah, et al. (2022) (QVAR frequency) with closely related alternative connectedness frameworks. As the quantile-frequency connectedness approach is the only approach that combines quantile connectedness measures (Chatziantoniou et al., 2021) with the frequency connectedness approach of Baruník and Křehlík (2018) (VAR frequency), we compare the median total connectedness measures of the quantile-frequency connectedness approach with the frequency connectedness approach of Baruník and Křehlík (2018) and the time total connectedness measures with the quantile extended joint connectedness approach of Cunado et al. (2023) (QVAR extended). Figure 2.6 shows the results of all three connectedness approaches. By comparing the results of the frequency connectedness approach with the quantile-frequency connectedness approach, we find that patterns appear to be qualitatively similar to each other while our employed approach has the advantage of being outlier-insensitive. Even though the decreases and increases in total connectedness are similar, we find that the VAR-based approach prolongs those changes due to the fact that VARs are outlier-sensitive. This phenomenon has also been observed in Chatziantoniou, Abakah, et al. (2022).

As Baruník and Křehlík (2018) pointed out that the time total connectedness measures are equal to the short-term plus long-term total connectedness, we use the quantile extended joint connectedness approach of Cunado et al. (2023) as a second alternative. In this respect, we are using a different connectedness framework that is also based upon quantile vector regressions and thus outlier-insensitive. We find that the total connectedness measures of the quantile extended connectedness approach are qualitatively as well as quantitatively similar to our employed approach. Thus, we can conclude that our provided empirical results appear to be robust compared to alternative connectedness models.

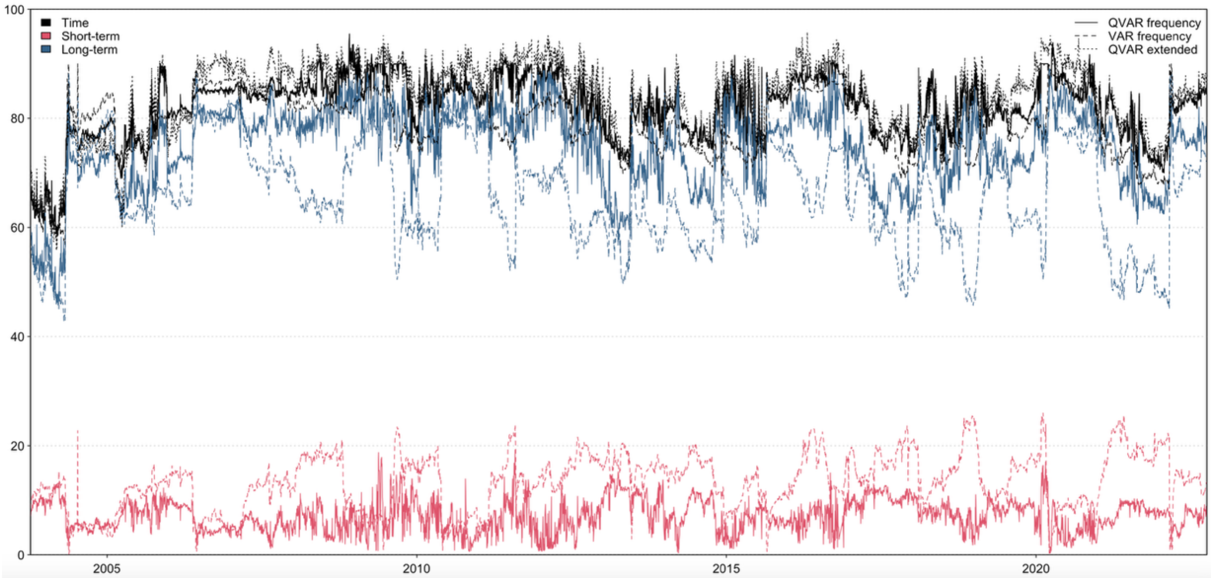


Figure 2.6. Robustness check: Dynamic total connectedness

Notes: Results are based on a 200-day rolling-window model with a lag length of order one (BIC), and a 100-step-ahead generalized forecast error variance decomposition. Solid lines represent the quantile-frequency QVAR approach of Chatziantoniou, Abakah, et al. (2022) (QVAR frequency), dashed lines demonstrate the frequency VAR approach of Baruník and Křehlík (2018) (VAR frequency), and the dotted line represents the QVAR extended connectedness approach of Cunado et al. (2023) (QVAR extended).

2.5.4. Portfolio analysis

So far, our findings confirm strong uncertainty connectedness amongst sectors in emerging markets over time. As such, it is of great importance to perform the investigation of diversification strategies. In this section, we pursue two portfolio strategies, namely, dynamic hedge ratios and dynamic minimum variance portfolios.

Table 2.3 represents the hedge ratios (Kroner & Sultan, 1993), hedging effectiveness (Ederington, 1979), and associated test statistics (Antonakakis et al., 2020). Looking at the mean values of the hedge ratio, we note that the cheapest hedge is when a 1 USD long position in CNC is hedged with CN (0.23 USD), whereas the most costly hedge would be when we hedge 1 USD long position in ENE with 1.09 USD short position in CNC. The HE reveals that all sectoral pairs form portfolios that significantly reduce investment uncertainty. We find that a long position in CC and a short position in IND will lead to the highest HE (0.81) among all the possible combinations, followed by the pair of CC and FIN with the HE of 0.80. These two pairs of sectors obtain the largest risk reduction for investors. Meanwhile, a long position in CN with a short position in ENE (or vice versa) will lead to the least risk reduction as they have the lowest HE of 0.16 and 0.19, respectively.

Table 2.3. Hedge ratios

	Mean	Std.Dev.	5%	95%	HE	p.value		Mean	Std.Dev.	5%	95%	HE	p.value
BM/CN	0.33	0.09	0.22	0.49	0.29	0.00	FIN/BM	0.77	0.12	0.60	0.97	0.74	0.00
BM/CC	0.97	0.14	0.75	1.22	0.78	0.00	FIN/CN	0.32	0.09	0.20	0.48	0.32	0.00
BM/CNC	1.07	0.18	0.80	1.38	0.72	0.00	FIN/CC	0.90	0.13	0.71	1.12	0.79	0.00
BM/ENE	0.67	0.13	0.46	0.88	0.66	0.00	FIN/CNC	0.98	0.16	0.76	1.26	0.71	0.00
BM/FIN	0.91	0.13	0.71	1.15	0.75	0.00	FIN/ENE	0.60	0.12	0.42	0.80	0.63	0.00
BM/HC	0.74	0.15	0.53	1.03	0.56	0.00	FIN/HC	0.67	0.13	0.48	0.91	0.54	0.00
BM/IND	0.92	0.14	0.70	1.15	0.74	0.00	FIN/IND	0.87	0.12	0.66	1.04	0.79	0.00
BM/TEC	0.51	0.12	0.34	0.71	0.42	0.00	FIN/TEC	0.50	0.11	0.34	0.71	0.48	0.00
BM/UTI	0.88	0.17	0.62	1.18	0.67	0.00	FIN/UTI	0.81	0.14	0.60	1.06	0.67	0.00
CN/BM	0.73	0.19	0.46	1.03	0.25	0.00	HC/BM	0.64	0.13	0.44	0.86	0.52	0.00
CN/CC	0.92	0.25	0.57	1.33	0.30	0.00	HC/CN	0.29	0.08	0.18	0.43	0.24	0.00
CN/CNC	0.88	0.27	0.49	1.38	0.21	0.00	HC/CC	0.80	0.15	0.56	1.04	0.60	0.00
CN/ENE	0.48	0.14	0.27	0.73	0.16	0.00	HC/CNC	0.87	0.16	0.62	1.14	0.55	0.00
CN/FIN	0.83	0.23	0.51	1.23	0.28	0.00	HC/ENE	0.47	0.12	0.30	0.67	0.39	0.00
CN/HC	0.74	0.20	0.46	1.11	0.22	0.00	HC/FIN	0.68	0.13	0.48	0.91	0.51	0.00
CN/IND	1.00	0.25	0.64	1.40	0.36	0.00	HC/IND	0.77	0.15	0.54	1.02	0.60	0.00
CN/TEC	0.82	0.18	0.57	1.14	0.49	0.00	HC/TEC	0.40	0.10	0.26	0.58	0.31	0.00
CN/UTI	0.75	0.23	0.43	1.17	0.20	0.00	HC/UTI	0.70	0.14	0.47	0.94	0.50	0.00
CC/BM	0.76	0.13	0.59	0.95	0.77	0.00	IND/BM	0.75	0.12	0.59	0.96	0.73	0.00
CC/CN	0.33	0.09	0.21	0.49	0.35	0.00	IND/CN	0.37	0.09	0.25	0.55	0.40	0.00
CC/CNC	0.98	0.16	0.76	1.25	0.77	0.00	IND/CC	0.90	0.13	0.73	1.13	0.79	0.00
CC/ENE	0.55	0.11	0.36	0.73	0.57	0.00	IND/CNC	0.95	0.19	0.70	1.30	0.69	0.00
CC/FIN	0.83	0.13	0.65	1.03	0.80	0.00	IND/ENE	0.56	0.11	0.38	0.75	0.56	0.00
CC/HC	0.72	0.14	0.53	0.98	0.63	0.00	IND/FIN	0.84	0.13	0.69	1.08	0.78	0.00
CC/IND	0.86	0.11	0.67	1.04	0.81	0.00	IND/HC	0.73	0.14	0.53	1.01	0.64	0.00
CC/TEC	0.49	0.11	0.32	0.69	0.49	0.00	IND/TEC	0.52	0.12	0.36	0.74	0.51	0.00
CC/UTI	0.79	0.14	0.57	1.01	0.68	0.00	IND/UTI	0.82	0.15	0.60	1.10	0.69	0.00
CNC/BM	0.62	0.11	0.47	0.80	0.73	0.00	TEC/BM	0.74	0.18	0.50	1.06	0.40	0.00
CNC/CN	0.23	0.08	0.14	0.38	0.25	0.00	TEC/CN	0.54	0.12	0.37	0.74	0.50	0.00
CNC/CC	0.73	0.12	0.56	0.92	0.77	0.00	TEC/CC	0.91	0.22	0.61	1.30	0.44	0.00
CNC/ENE	0.47	0.11	0.33	0.65	0.59	0.00	TEC/CNC	0.91	0.24	0.57	1.38	0.33	0.00
CNC/FIN	0.67	0.11	0.51	0.85	0.72	0.00	TEC/ENE	0.52	0.15	0.32	0.77	0.27	0.00
CNC/HC	0.58	0.11	0.43	0.79	0.58	0.00	TEC/FIN	0.86	0.19	0.58	1.20	0.46	0.00
CNC/IND	0.68	0.13	0.48	0.89	0.70	0.00	TEC/HC	0.68	0.17	0.44	0.99	0.29	0.00
CNC/TEC	0.36	0.10	0.22	0.53	0.37	0.00	TEC/IND	0.93	0.21	0.61	1.27	0.49	0.00
CNC/UTI	0.67	0.12	0.48	0.86	0.68	0.00	TEC/UTI	0.71	0.18	0.45	1.02	0.29	0.00
ENE/BM	0.90	0.22	0.66	1.26	0.64	0.00	UTI/BM	0.68	0.14	0.48	0.92	0.66	0.00
ENE/CN	0.30	0.11	0.18	0.49	0.19	0.00	UTI/CN	0.26	0.09	0.15	0.41	0.25	0.00
ENE/CC	0.94	0.22	0.67	1.34	0.55	0.00	UTI/CC	0.78	0.16	0.59	1.05	0.67	0.00
ENE/CNC	1.09	0.26	0.76	1.51	0.55	0.00	UTI/CNC	0.90	0.18	0.68	1.22	0.66	0.00
ENE/FIN	0.96	0.22	0.69	1.31	0.60	0.00	UTI/ENE	0.57	0.12	0.40	0.78	0.60	0.00
ENE/HC	0.73	0.22	0.48	1.07	0.41	0.00	UTI/FIN	0.75	0.13	0.55	0.99	0.67	0.00
ENE/IND	0.92	0.22	0.65	1.28	0.53	0.00	UTI/HC	0.63	0.14	0.45	0.90	0.55	0.00
ENE/TEC	0.48	0.16	0.30	0.74	0.30	0.00	UTI/IND	0.78	0.14	0.56	1.02	0.69	0.00
ENE/UTI	0.98	0.21	0.69	1.34	0.58	0.00	UTI/TEC	0.38	0.10	0.25	0.56	0.33	0.00

Notes: Results are based on the hedge ratio of Kroner and Sultan (1993), hedging effectiveness (HE) of Ederington (1979), and the test statistics for the hedging effectiveness of Antonakakis et al. (2020). The sectors are Basic Materials (BM), Communications & Networking (CN), Consumer Cyclicals (CC), Consumer Non-Cyclicals (CNC), Energy (ENE), Financials (FIN), Healthcare (HC), Industrials (IND), Technology (TEC) and Utilities (UTI).

Additionally, by looking at the 5% and 95% percentiles as well as the standard deviation of each pair of sectors, we can see that the hedge ratios are changing over time, indicating that the hedge ratios possess substantial time-varying behavior. It implies that market participants should adopt a dynamic hedging strategy instead of a static one. We observe that the most volatile hedge ratios occur when a long position in CN is hedged with CNC. There is also a high variability in the hedge ratio between ENE and CNC. Meanwhile, the least volatile hedged ratios are found in the pairs of CNC/CN and HC/CN. Hence, investors who use CN to hedge their long position in CNC and HC might not only benefit from cheap hedges (i.e., 0.23 USD in the case of CNC and 0.29 USD in the case of HC) but also have the least volatile ratios which might lead to a less dynamic hedging strategy.

Finally, we have a look at the dynamic minimum variance portfolio shown in Table 2.4. We find that forming a minimum variance portfolio significantly reduces investment risk as indicated by the significant hedging effectiveness measures. Specifically, we identify that by short selling, we reduce the investment risk with respect to all underlying assets while the long restriction (without short selling) does not reduce the investment risk with respect to CNC. Furthermore, the portfolio with short-sellings has a higher Sharpe ratio (SR) than the one without short-sellings (0.58 compared to 0.41), suggesting that allowing for short positions is preferable for investors who want to mitigate their investment risks. Furthermore, we find that the portfolio weights are time-varying as indicated by the 5% and 95% quantiles as well as the standard deviation. Such dynamic feature suggests that investors should follow active portfolio rebalancing instead of employing a static strategy.

Table 2.4. Minimum variance portfolio

	Without short-sellings							With short-sellings						
	Mean	Std.Dev.	5%	95%	HE	p-value	SR	Mean	Std.Dev.	5%	95%	HE	p-value	SR
BM	0.03	0.07	0.00	0.19	0.44	0.00		-0.12	0.22	-0.42	0.31	0.51	0.00	
CN	0.03	0.05	0.00	0.12	0.72	0.00		0.03	0.09	-0.06	0.19	0.75	0.00	
CC	0.08	0.12	0.00	0.34	0.28	0.00		-0.01	0.32	-0.49	0.55	0.37	0.00	
CNC	0.37	0.18	0.02	0.65	0.01	0.61		0.60	0.32	0.03	1.08	0.14	0.00	
ENE	0.02	0.05	0.00	0.13	0.60	0.00	0.41	-0.04	0.14	-0.22	0.21	0.65	0.00	0.58
FIN	0.07	0.10	0.00	0.28	0.34	0.00		0.05	0.25	-0.31	0.49	0.42	0.00	
HC	0.10	0.11	0.00	0.31	0.26	0.00		0.15	0.20	-0.12	0.52	0.35	0.00	
IND	0.10	0.14	0.00	0.39	0.31	0.00		0.06	0.33	-0.40	0.63	0.40	0.00	
TEC	0.05	0.06	0.00	0.17	0.57	0.00		0.06	0.12	-0.11	0.30	0.63	0.00	
UTI	0.15	0.13	0.00	0.39	0.28	0.00		0.22	0.25	-0.18	0.65	0.37	0.00	

Notes: Results represent time-varying weights of the minimum variance portfolio (Markowitz, 1952) including the hedging effectiveness (HE) of Ederington (1979) with the associated test statistics provided by Antonakakis et al. (2020). SR stands for the Sharpe ratio. The sectors are Basic Materials (BM), Communications & Networking (CN), Consumer Cyclicals (CC), Consumer Non-Cyclicals (CNC), Energy (ENE), Financials (FIN), Healthcare (HC), Industrials (IND), Technology (TEC) and Utilities (UTI).

2.6. Conclusions

This paper investigates the uncertainty spillovers across emerging markets' sectors during the 2003-2022 period, employing the quantile time-frequency connectedness method. Moreover, the impacts of various uncertainty indices on the sectoral total connectedness are examined. Key findings from our study could be presented as follows.

First, our findings show that sectoral uncertainty transmission is exceptionally strong as the total connectedness index is 91.01%, implying that the uncertainty transmission across sectors is substantial. The largest proportion of the sectoral total connectedness is found to be associated with long-term dynamics. Consumer Cyclicals (CC) is found to be one of the greatest risk transmitters in the short and long term. Meanwhile, Communications & Networking (CN) and Healthcare (HC) are the largest risk absorbers at the median level. The emergence of those two sectors as net absorbers of shocks in the network is not surprising as Communications and Healthcare are among the sectors that thrive and attract the most capital inflows (Martin 2018).

Second, from the perspective of quantile, the sectoral uncertainty spillovers oscillate considerably over time. We note that the periods of high spillovers appear to coincide with remarkable major events, such as (i) the global financial crisis (2007-2008), (ii) Chinese stock market turbulence (2016), and (iii) the outbreak of the COVID-19 pandemic (2020). In addition, we find suggestive evidence of asymmetric effects in uncertainty connectedness among sectors as the connectedness becomes much stronger during turbulent market conditions (higher quantiles) than smooth market conditions (lower quantiles), showing that spillovers in high uncertainty periods and spillovers in low uncertainty periods behave differently. Such asymmetry in spillovers is also found in Vo and Dang (2023). However, this observation is slightly different from Chatziantoniou et al. (2021) and Chatziantoniou, Abakah, et al. (2022), in which the authors find evidence of higher connectedness at both the highest and lowest quantiles.

Third, we find a positive relationship between uncertainty measures and the sectoral total connectedness during periods of low uncertainty and normal market conditions. However, under turbulent market circumstances (at 75% quantile and above), we find that the uncertainty indices have a negative effect on the dynamic total connectedness. We consider that stock markets are generally regarded to have an adaptive feature (Mauboussin, 2002), and market participants tend to be adaptive to variations in market conditions to secure a stable level of their expected return (Hiremath & Kumari, 2014), causing the herd mentality of the markets to become herd immunity to uncertainties during periods of high uncertainty.

Last but not least, as we have found strong uncertainty connectedness among sectors in emerging markets over time, we consider that it is crucial to pursue portfolio diversification strategies. Two different strategies are employed, including the dynamic hedge ratios (Kroner & Sultan, 1993) and the minimum variance portfolio (Markowitz, 1952). As our proposed portfolios are found to help reduce the investment risk significantly, international investors appear to benefit from our hedging analyses to develop their optimal investment portfolios for risk mitigation.

Chapter Three - Essay Two "The global geopolitical-energy uncertainty index and total factor productivity: New evidence from firm-level analysis"

Abstract

This paper examines the impact of the global geopolitical-energy uncertainty (GEU) on firm-level total factor productivity, considering variation across countries, industries, and firm sizes. Employing the novel GEU index proposed by Dang et al. (2024a) and firm-level annual data from 2001 to 2023, we find strong evidence that the GEU index negatively affects firm productivity. The impact of the GEU index appears heterogeneous across countries and firm characteristics. Firms in developed countries such as the US, UK, France, and Germany are more negatively affected, whereas Canadian firms show a positive response. Energy-intensive firms and smaller firms experience stronger negative impacts. Mechanism analysis further demonstrates that both firm level characteristics and macroeconomic energy conditions shape productivity responses to GEU. Higher profitability reduces the negative impact of GEU shocks, while higher cost intensity and higher global energy prices amplify the adverse effects, increasing productivity losses. Our baseline results remain robust under different robustness checks. The paper's findings offer guidance for firms to develop effective strategies to manage risks during periods of heightened geopolitical-energy uncertainty.

Keywords: Firm productivity; Total factor productivity; Geopolitical energy uncertainty; Geopolitical risks; Energy uncertainty

JEL codes: D24; D80; G30; F51; Q43

Statement of contribution form - Essay Two

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Student name:	Tam Hoang Nhat Dang
Name and title of main supervisor:	Professor Faruk Balli
In which chapter is the manuscript/published work?	Essay Two in Chapter Three

Describe the contribution that the student and members of the supervisory team have made to the manuscript/published work:[1]

Tam discussed the research ideas with his supervisors, and together they agreed on the topic of Essay Two in Chapter Three. He then collected and cleaned all datasets, and conducted the full set of empirical analyses. The supervisors reviewed Tam's results, provided suggestions, and addressed his questions during their weekly meetings. Tam drafted the initial version of the paper, and he and his supervisors subsequently refined and revised the manuscript in preparation for journal submission.

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3.1. Introduction

Energy is a critical strategic resource underpinning economic growth (Wen et al., 2019). Acheampong et al. (2021), for instance, provide empirical evidence showing a strong positive association between economic growth and energy consumption. Within the broader energy context, oil stands out as a particularly important source due to its widespread use in various economic activities, having strategic importance for national and global economies. However, due to its scarcity, the spatial separation between demand and supply, and its low elasticity of demand, oil price uncertainties can disrupt investment decisions, industrial production and dampen overall economic activities (Elder & Serletis, 2010; Jo, 2014; Peersman & Van Robays, 2012). According to Hamilton (2003) and Charfeddine et al. (2020), oil price uncertainties have significant detrimental effects on economic growth on both national and global scales.

It is also important to note that oil price stability is highly susceptible to geopolitical risks. Empirical evidence suggests that geopolitical risks drive up energy price volatilities, amplify precautionary behaviors, and restrict the availability of oil energy for productive use (Liu et al., 2019; Mei et al., 2020; Wang et al., 2021). This heightened volatility, in turn, is detrimental to firms' productivity (Liu et al., 2024; Ren, Liu, et al., 2023). In fact, Mignon and Saadaoui (2024) demonstrate that positive shocks of geopolitical risks can raise concerns over supply chain disruptions and induce expectations for oil supply shortages, thereby constraining business operations and reducing production capacity. Generally, geopolitical risks can reduce firm investment and innovation, inhibiting productivity growth (Caldara & Iacoviello, 2022; Nguyen et al., 2022).

On the other hand, previous studies have also found that oil prices exert a significant negative causal effect on geopolitical risk, whereas oil price volatility has a significant positive effect (Ivanovski & Hailemariam, 2022). Abdel-Latif and El-Gamal (2019) and Su et al. (2021) document significant interactions between oil price and geopolitical risks and demonstrate bidirectional causal linkages between the two risk factors. More recent studies reinforce this interdependence, showing that geopolitical instability drives oil markets through both supply and demand channels, while energy volatility simultaneously feeds back into geopolitical risk dynamics (Jiao et al., 2023).

Taken together, existing literature offers three key insights: (1) both geopolitical and oil price risks have significant impacts on productivity; (2) these two risk factors influence each other in a bidirectional manner; and (3) geopolitical risk exerts influence on productivity both directly and indirectly through its impact on oil prices, while oil price risk may hinder productivity both directly and indirectly via influencing geopolitical risk.

Building on the evidence that geopolitical and oil price risks are closely interrelated and jointly influence firm productivity, it becomes clear that examining these risks in isolation may overlook important interactions. As prior studies have largely analyzed geopolitical and energy risks separately, often neglecting their combined impact, an integrated approach is necessary. To this end, we employ the novel global geopolitical-energy uncertainty (GEU) index developed by Dang et al. (2024a), which jointly captures geopolitical and energy uncertainty. Dang et al. (2024a) show that the GEU index is highly responsive to major geopolitical tensions and energy shocks, and that it has strong explanatory power for global energy price volatility, sectoral stock market performance, and key macroeconomic indicators across both developed and developing economies. While its relevance has been established at the global, national, and sectoral levels, its implications for firm-level productivity remain unexplored. This study seeks to address this gap in the literature by investigating the GEU index's impact on firm productivity, thereby offering new insights into the risk-productivity nexus. In this way, we move beyond prior studies that treat geopolitical and energy risks separately, offering the first firm-level evidence on their joint productivity effects.

By examining the combined effects of geopolitical and energy risks through the GEU index, our study centers on firm productivity as the key outcome of interest. Krugman (1997) asserts that "*Productivity isn't everything, but in the long run it is almost everything*". Similarly, Syverson (2011) argued that "*…another robust finding in the literature—virtually invariant to country, time period, or industry—is that higher productivity producers are more likely to survive than less efficient industry competitors"*. Therefore, our study focuses on the vital importance of geopolitical and energy risks for firm productivity although they have profound economic implications in other areas, such as supply chain stability, product competitiveness, capital costs, investment decisions, and strategic planning. As noted by Syverson (2011), "*productivity is quite literally a matter of survival for businesses*". While geopolitical and energy risks may affect investment and other firm decisions, our analysis is not an investment specification. Compared to investment, which represents one possible short-run adjustment channel (Bloom, 2009), productivity captures the broader and more persistent efficiency implications (Krugman, 1997). Hence, we explicitly focus on firm productivity (TFP) as the primary outcome variable, since it directly reflects firms' efficiency and long-term performance. We argue that understanding the GEU index's impact on firm productivity is essential for firms to assess risk exposure, formulate mitigation strategies, and sustain productivity. This consideration is particularly crucial for firms in energy-intensive industries under the background of escalating geopolitical and energy market uncertainties.

Theoretically, GEU may adversely affect firm productivity through several mechanisms. First, an increase in the GEU index, by construction reflecting both geopolitical and energy uncertainty, represents the type of uncertainty that, as Bloom (2009) argues, raises the option value of waiting and induces firms to postpone their hiring and investments, thereby reducing resource reallocation and causing a significant drop in productivity growth. Accordingly, firms with higher investment intensity appear to be particularly sensitive, as uncertainty tends to trigger delays of capital expenditures, slowing down their productivity growth. Second, firms with heavier cost structures appear more vulnerable (Bernard et al., 2006; Kling et al., 2021), since higher costs undermine competitiveness and magnify exposure to shocks. Third, at the macro level, GEU shocks often operate through energy price shocks, which raises input costs and leads firms to scale down capacity utilization, resulting in short-term productivity losses (André et al., 2023).

Overall, this study employs the comprehensive global geopolitical-energy uncertainty (GEU) index of Dang et al. (2024a) to examine its effects on firm-level productivity across various industries and countries around the world over the period from 2001 to 2023. The study pursues following specific objectives. First, we examine the overall impact of the GEU index on firm productivity (TFP). Second, we investigate cross-country heterogeneity in this relationship. Third, we compare differential responses between energy-intensive versus less energy-intensive firms and between smaller versus larger firms. Finally, we explore potential mechanisms through which GEU affects firm productivity. Unlike previous studies which focus on the individual impacts of either geopolitical risk or energy risk, the present study takes a holistic approach to investigating the combined influence of both risk factors. By utilizing the new GEU index which integrates geopolitical risks alongside energy market uncertainties, we aim to provide new evidence to enhance understanding of their joint effects on productivity.

The study makes two contributions to the literature. *First*, to the best of our knowledge, this is the first study to examine the impact of geopolitical-and-energy risk on firm-level productivity, using the comprehensive GEU index developed by Dang et al. (2024a) and a large sample of firms from different industries worldwide. *Second*, the study contributes to the productivity literature by providing new evidence demonstrating that the GEU index is a significant determinant of firm productivity. We measure productivity using total factor productivity (TFP), which is widely recognized as a key determinant of firm-level economic growth (Tian & Twite, 2011), and a critical indicator of firm's efficiency in converting input factors into outputs (Dang et al., 2024b).

Several key findings are observed from our study. First, an increase in the GEU index has a significant negative impact on firm-level productivity across the entire sample. Second, the productivity response to the GEU index varies across firms depending on their characteristics, the energy intensity of their industries, and their country of origin. Specifically, a rise in the GEU index has a significant negative influence on productivity of the firms in France, Germany, the UK, and the US, while a significant positive impact is observed for Canadian firms[4]. Furthermore, smaller firms and those operating in energy-intensive industries have stronger negative responses than their larger counterparts and those in less energy-intensive industries. Third, both firm-level characteristics and macroeconomic energy conditions determine the extent to which GEU shocks affect productivity. Mechanism analysis shows that more profitable firms are better able to withstand GEU shocks, while firms with higher cost intensity experience larger productivity losses. Capital expenditure generally enhances productivity, but this positive effect is weakened during periods of heightened uncertainty, consistent with the notion that firms delay investment under high GEU periods. At the macro level, higher global energy prices amplify the negative impact of GEU, highlighting the role of energy costs as a key transmission channel.

The remainder of this paper proceeds as follows. A literature review is presented in Section 2, followed by discussions of research methodology and data presented in Section 3. We present and discuss empirical results in Section 4 and report the results for robustness tests in Section 5 shows. Section 6 concludes our study.

3.2. Literature review

This section presents an overview of the relevant literature, focusing on three key areas: energy uncertainty and geopolitical risk, their interactions, and the implications of these risks for productivity.

[4] Of these five nations, Canada is the only net oil exporter. These results are consistent with Peersman and Van Robays (2012) who find that economic activity responses to oil shocks are different for net oil-importing countries and net oil-exporting countries.

3.2.1. Energy uncertainty and geopolitical risk

Foundational studies emphasize the macroeconomic consequences of oil price uncertainty. Elder and Serletis (2010) show that such uncertainty can overshadow investments, depress consumption, and reduce aggregate output measured by real GDP. Similarly, Peersman and Van Robays (2012) extend this by showing that such effects are heterogeneous across countries, with net energy importers experiencing persistent declines in economic activity. Furthermore, Elder (2019) shows that heightened oil price volatility disproportionately affects energy-intensive industries. These findings highlight the broader macroeconomic importance of oil price volatility and have motivated subsequent studies to explore the specific channels through which it transmits to the real economy. For instance, Gao et al. (2022) argue that rising volatility induces precautionary inventory-taking, which reduces oil available for production, hampers investment and consumption, lowers employment opportunities, and dampens overall economic activity. Extending the evidence to a cross-country perspective, Dang et al. (2023) provide systematic cross-country evidence that energy uncertainty hampers economic activity across sectors. Together, this stream of work demonstrates that uncertainty in energy markets transmits to the real economy through multiple channels, from inventories to sectoral production and cross-country dynamics.

Building on these macro-level insights, later contributions extend the focus to financial markets and firm-level outcomes. Kilian and Park (2009) and Xiao et al. (2018) show that oil price uncertainty reduces stock market returns, especially in bearish markets. Whereas earlier studies emphasized aggregate outcomes, Phan et al. (2020) provide micro-level evidence that oil price uncertainty negatively impacts firm performance, thereby bridging the missing firm-level perspective. Firms respond to such uncertainty by increasing their cash holdings (Zhang et al., 2020), delaying or discouraging merger and acquisition activities (Barrows et al., 2023), and reducing innovation (Amin et al., 2023; Yang & Song, 2023). This evidence underscores that energy-related uncertainty does not only suppress aggregate activity but also reshapes firm-level decision-making and performance.

Parallel to this energy-focused literature, geopolitical risk has emerged as another key uncertainty factor. Caldara and Iacoviello (2022) pioneered a textual-based index of geopolitical risk, demonstrating its explanatory power for GDP growth and firm investments. Employing the geopolitical risk index of Caldara and Iacoviello (2022), subsequent studies extend these findings by showing significant effects on firms' idiosyncratic volatility and firm value (Pringpong et al., 2023; Ren, Cao, et al., 2023). Moreover, this line of work extends beyond aggregate indicators, with recent evidence highlighting sectoral and asset-class channels, such as spillovers to defense firms through sentiment and capital flows (Klein, 2024).

3.2.2. Interactions of energy uncertainty and geopolitical risk

A growing body of research has recognized the interdependence of energy markets and geopolitical conditions. Early evidence suggests that geopolitical risk drives oil prices and their volatility (Antonakakis et al., 2017; Bouoiyour et al., 2019; Liu et al., 2019). Consistent with this, Mei et al. (2020) document increased oil price volatility under geopolitical tensions, while Su et al. (2021) find positive oil price responses to geopolitical risk shocks. Beyond this one-directional view, more recent studies emphasize feedback effects, implying a two-way interaction between energy markets and geopolitical conditions. For instance, Ivanovski and Hailemariam (2022) report that oil prices and volatility exert significant causal effects on geopolitical risk. Meanwhile, more recent studies have in turn emphasized the reverse channel, showing that geopolitical instability can also drive oil markets, such as Jiao et al. (2023) who demonstrate that geopolitical shocks affect oil markets through both supply and demand channels. Taken together, these findings underscore the interconnectedness between energy uncertainty and geopolitical risk.

3.2.3. Uncertainties/risks and firm productivity

The productivity literature emphasizes how uncertainty impedes firms' efficiency. Bloom (2009, 2014) and Bloom et al. (2018) argue that heightened uncertainty raises the option value of waiting, causing firms to delay investment and hiring. Such delays slow resource reallocation and reduce productivity growth. Empirical studies corroborate this theoretical channel. For instance, Choi et al. (2018) show that higher aggregate uncertainty reduces productivity growth, particularly in industries dependent on external financing. Related studies document negative effects of climate and policy-related uncertainties on productivity at both the firm (Ren et al., 2022) and regional levels (Dai & Zhu, 2024).

Moving from general uncertainty to energy-specific risks, recent work documents that oil price uncertainty significantly lowers firm productivity. For instance, Ren, Liu, et al. (2023) and Liu et al. (2024) provide evidence that oil price uncertainty negatively impacts firm-level productivity. By contrast, research directly linking geopolitical risk to productivity remains limited. Caldara and Iacoviello (2022) report a negative impact of geopolitical risk on expected total factor productivity across 18 emerging economies. However, the authors do not explore the underlying mechanisms. Nguyen et al. (2022) fill this void by showing that geopolitical risk hampers productivity growth through slower technological progress and reduced per-capita income.

To summarize, prior studies establish strong links between oil price uncertainty and macroeconomic activity, firm-level outcomes, and financial markets, as well as between geopolitical risk and investment, valuation, and sectoral performance. Moreover, recent contributions underscore the mutual interactions between energy uncertainty and geopolitical risk. However, these insights remain fragmented, as most studies treat the two risks separately and only limited evidence connects them to productivity outcomes. In particular, firm-level productivity effects—where uncertainty may be most consequential for long-term competitiveness—have not been systematically analyzed. Thus, unlike earlier studies that consider geopolitical and energy risks separately, we provide novel firm-level evidence on how these risks jointly affect productivity. Motivated by this gap, the present study hypothesizes that heightened global geopolitical–energy uncertainty, as captured by the GEU index of Dang et al. (2024a), exerts a negative effect on firm-level total factor productivity.

3.3. Methodology and data

3.3.1. Methodology

In this study, we investigate how firm-level productivity is affected by the global geopolitical-energy uncertainty index (i.e., the GEU index). This index is developed by Dang et al. (2024a), measuring the risks/uncertainties from both geopolitical tensions and the energy markets at the global scale. The index is constructed using a text-based approach and based on the Economist Intelligence Unit's global reports. There are three components in the GEU index, including the geopolitical risk sub-index, the energy-related sub-index and economic policy uncertainty sub-index. Those three sub-indices are combined together to make up the final GEU index using the principal component analysis (PCA). The details of this approach are presented in Appendix C.

Our model is based on previous empirical studies on the determinants of firm productivity to develop the regression models (Dang et al., 2024b; Ding et al., 2016; Ren, Liu, et al., 2023; Ren et al., 2022; Zhang et al., 2023). Equation (3.1) presents our baseline regression model.

$$TFP_{i,t} = \varphi_e + \omega_t + \beta_1 GEU_t + M_{i,t}\gamma + \varepsilon_{i,t} \qquad (3.1)$$

where i and t represent firm and year, respectively. φ_e controls for firm fixed effects, or industry[5] fixed effects, or country[6] fixed effects. ω_t captures year fixed effects. TFP represents firm productivity (or the total factor productivity). Similar to Dang et al. (2024b), we estimate the total factor productivity employing the method proposed by Wooldridge (2009) for our baseline analyses. GEU stands for the global geopolitical-energy uncertainty index developed by Dang et al. (2024a), which is our primary variable of interest. M is the matrix of control variables that include (i) *Firm_size*, measured by the natural logarithm of total assets; (ii) *Liquidity*, measured by the natural logarithm of (1 + ((current assets – current liabilities) / total assets)); and (iii) *Growth*, the growth opportunities of firms, measured by the natural logarithm of Price-to-Book ratio. The inclusion of those control variables in our regression models is in line with previous empirical studies on productivity at firm level, such as Tian and Twite (2011), Ding et al. (2016), and Li and Su (2022).

In Section 3.4.1, we adopt regression model (3.1) for the full sample as well as for different selected economies to examine the heterogeneity of the GEU index's impact on firm productivity at the country level. We also decompose our full sample into two sub-samples, including (i) energy-intensive industries[7] and (ii) less energy-intensive industries. Accordingly, we examine whether the GEU index exerts a significantly different effect on the productivity of firms from energy-intensive industries compared to firms from less energy-intensive industries. To serve that purpose, we perform the regression model as in Equation (3.2).

$$TFP_{i,t} = \varphi_e + \omega_t + \alpha_1 GEU_t + \alpha_2 Energy\_intensive_i + \alpha_3 GEU_t * Energy\_intensive_i + M_{i,t}\delta + \varepsilon_{i,t} \quad (3.2)$$

where $Energy\_intensive$ is a dummy variable that takes the value of 1 for industries that are considered as energy intensive, including Basic Materials, Energy, Industrials, and Utilities, and 0 otherwise.

Also in Section 3.4.1, we based on the median of *Firm_size* to categorize all firms in our sample into two sub-samples, including (i) smaller firms and (ii) larger firms. We want to check whether the impact of GEU index on firm productivity is different between smaller and larger firms in our sample (see Equation (3.3)).

$$TFP_{i,t} = \varphi_e + \omega_t + \theta_1 GEU_t + \theta_2 Smaller\_firm_i + \theta_3 GEU_t * Smaller\_firm_i + M_{i,t}\vartheta + \varepsilon_{i,t} \quad (3.3)$$

[5] Including: Basic Materials, Consumer Discretionary, Consumer Staples, Energy, Health Care, Industrials, Real Estate, Technology, Telecommunications, and Utilities.
[6] Including: Australia, Austria, Belgium, Brazil, Canada, China, Cyprus, Denmark, Finland, France, Germany, Hong Kong, India, Ireland, Italy, Japan, Malaysia, Netherlands, New Zealand, Norway, Pakistan, Philippines, South Africa, South Korea, Spain, Sweden, Switzerland, United Kingdom, United States, Vietnam.
[7] Industries categorized as energy intensive include Basic Materials, Energy, Industrials, and Utilities.

where $Smaller\_firm$ is a dummy variable, representing smaller firms in our sample. The median of $Firm\_size$ is used as a threshold to divide our full sample into smaller firms and larger firms. Accordingly, $Smaller\_firm$ equals 1 if $Firm\_size$ is smaller than or equal to the median of $Firm\_size$, and 0 otherwise.

To strengthen the credibility of our empirical analysis, we complement the baseline regressions with a range of identification, placebo, and robustness tests. Specifically, we employ two-step system GMM estimations and an event-study difference-in-differences framework as identification tests (Sub-section 3.4.3). We further conduct placebo analyses, including alternative-shock replacements (using GPR and EPU indices), future-shock tests with leads of the GEU index, and circular time-shift exercises that misalign the timing of shocks (Appendix 3.A). For robustness, we re-estimate the results using alternative productivity measures (Levinsohn–Petrin and Olley–Pakes), alternative estimation approaches (linear mixed model and Hausman–Taylor) (Section 3.5), as well as the panel impulse response function and demeaned interaction terms following Balli and Sørensen (2013) (Appendix 3.B). Together, these additional analyses ensure that our findings are not driven by spurious correlations, reverse causality, or model specification choices.

3.3.2. Data

We employ the global geopolitical-energy uncertainty index proposed by Dang et al. (2024a) as our variable of interest. The global economic policy uncertainty index (EPU) of Baker et al. (2016) and the global geopolitical risk index of Caldara and Iacoviello (2022) are obtained from the website www.policyuncertainty.com. Apart from those uncertainty indices, all annual firm-level data are collected from Refinitiv Workspace (formerly Refinitiv Eikon). Due to data availability, our ultimate sample includes 1,042 firms from 30 countries[8] with 6,886 firm-year observations over the period from 2001 to 2023. Our final sample includes 10 industries: Basic Materials, Consumer Discretionary, Consumer Staples, Energy, Health Care, Industrials, Real Estate, Technology, Telecommunications, and Utilities. Financial industry is excluded from our ultimate sample as this industry has substantially different financial reporting practices (Chen et al., 2019).

[8] Including: Australia, Austria, Belgium, Brazil, Canada, China, Cyprus, Denmark, Finland, France, Germany, Hong Kong, India, Ireland, Italy, Japan, Malaysia, Netherlands, New Zealand, Norway, Pakistan, Philippines, South Africa, South Korea, Spain, Sweden, Switzerland, United Kingdom, United States, Vietnam.

The descriptive statistics of variables employed in our study are presented in Table 3.1A. As can be seen from Table 3.1A, we find that the mean of firm productivity measures (i.e., *TFP_Wrdg*, *TFP_LP*, and *TFP_OP*) is not quite different from the mean of estimated firm productivity from previous studies (Dang et al., 2024b; Figal Garone et al., 2020; Fiorini et al., 2021; Nakatani, 2023; Tian & Twite, 2011), implying that our estimations of firm productivity appear reliable. The correlation matrix is presented in Table 3.1B, showing the cross correlations ranging from -0.299 to 0.288. It implies that no significant multicollinearity is found among explanatory variables in our study. Furthermore, we also perform the panel unit root tests (i.e., the augmented Dickey-Fuller and Phillips-Perron) and find that all variables employed in the regression models are stationary.

Table 3.1. Summary statistics

A. Descriptive statistics

Variable	Observation	Mean	Median	Standard deviation	Min	Max
Firm's output	6,886	18.253	18.315	2.515	8.987	25.024
Capital input	6,886	20.01	20.119	2.648	8.987	26.431
Labor input	6,886	7.968	8.013	2.309	0.000	13.175
Intermediate input	6,886	19.962	19.981	2.623	8.006	27.326
TFP_Wrdg	6,886	2.327	2.397	1.010	-5.136	7.120
TFP_LP	6,886	2.030	2.093	1.001	-5.357	7.025
TFP_OP	6,886	4.149	4.196	1.082	-3.154	9.053
GEU	6,886	-0.044	0.154	0.883	-1.979	1.550
Firm_size	6,886	21.028	21.044	2.398	13.472	27.300
Liquidity	6,886	0.131	0.122	0.175	-1.493	0.754
Growth	6,886	0.557	0.545	0.983	-14.117	6.876
Energy_intensive	6,886	0.530	1.000	0.499	0.000	1.000
Smaller_firm	6,886	0.500	0.500	0.500	0.000	1.000
GPR	6,886	4.621	4.592	0.229	4.348	5.172
EPU	6,886	4.942	4.847	0.475	4.140	5.771

B. Correlation matrix

	TFP_Wrdg	*GEU*	*Firm_size*	*Liquidity*	*Growth*
TFP_Wrdg	1.000				
GEU	-0.008	1.000			
Firm_size	0.288	0.092	1.000		
Liquidity	0.180	-0.007	-0.299	1.000	
Growth	0.285	0.110	0.077	-0.080	1.000

Notes: *Firm's output* is the natural logarithm of operating income. *Capital input* is the natural logarithm of net fixed assets. *Labor input* is the natural logarithm of number of employees. *Intermediate input* is the natural logarithm of total costs excluding depreciation and amortization[9]. *TFP_Wrdg* is the estimated firm productivity using Wooldridge (2009)'s method. *TFP_LP* is the estimated firm productivity using Levinsohn and Petrin (2003)'s method. *TFP_OP* is the estimated firm productivity using Olley and Pakes (1996)'s method. *GEU* is the global geopolitical-energy uncertainty index proposed by Dang et al. (2024a). *Firm_size* stands for the natural logarithm of total assets. *Liquidity* is the natural logarithm of (1 + ((current assets – current liabilities) / total assets)). *Growth* stands for growth opportunities of firms, measured by the natural logarithm of

[9] *Firm's output*, *capital input*, *labor input*, and *intermediate input* are employed to estimate the total factor productivity (or firm productivity) based on the Wooldridge (2009)'s method for the baseline analysis, and the methods of Olley and Pakes (1996) and Levinsohn and Petrin (2003) in the robustness tests.

Price-to-Book ratio. *Energy_intensive* is a dummy variable, which is 1 for industries that are energy intensive (i.e., Basic Materials, Energy, Industrials, and Utilities) and 0 otherwise. *Smaller_firm* is a dummy variable, which is 1 for firms with *Firm_size* that is less than or equal to the median of *Firm_size* in the sample, and 0 otherwise. *GPR* stands for the global geopolitical risk index of Caldara and Iacoviello (2022). *EPU* is the global economic policy uncertainty index (EPU) of Baker et al. (2016).

3.4. Empirical results

3.4.1. The GEU index and firm-level productivity

In this section, we employ the panel regression model as in Equation (3.1) to investigate how firm productivity responds to the GEU index. The regression results in case of full sample are presented in Table 3.2. As can be seen, the GEU index has a statistically significant negative impact on firm productivity across different model specifications in which we control for different fixed effects[10], including firm fixed effects, year fixed effects, firm-year fixed effects, industry-year fixed effects, and country-year fixed effects. This result is in line with previous studies such as Bloom (2009), Bloom (2014), and Ren et al. (2022) who argue that higher uncertainty leads to decreases in firm productivity (or productivity growth).

Table 3.2. The impact of GEU index on firm-level productivity (baseline results)

	(1)	(2)	(3)	(4)	(5)
GEU	-0.083***	-0.054***	-0.070***	-0.063***	-0.080***
	(0.011)	(0.015)	(0.014)	(0.015)	(0.014)
Firm_size	0.160***	0.158***	0.192***	0.155***	0.142***
	(0.020)	(0.005)	(0.028)	(0.005)	(0.006)
Liquidity	1.571***	1.783***	1.581***	1.755***	1.662***
	(0.122)	(0.080)	(0.124)	(0.082)	(0.083)
Growth	0.281***	0.295***	0.288***	0.285***	0.373***
	(0.023)	(0.031)	(0.024)	(0.031)	(0.016)
Firm FE	Yes	No	Yes	No	No
Year FE	No	Yes	Yes	Yes	Yes
Industry FE	No	No	No	Yes	No
Country FE	No	No	No	No	Yes
N	6,462	6,886	6,462	6,886	6,881
Adjusted R^2	0.532	0.248	0.534	0.279	0.310

Notes: Robust standard errors are presented within parentheses. ***, ** and * stand for the significance level of 1%, 5% and 10%, respectively. The estimations are based on the model: $TFP_{i,t} = \varphi_e + \omega_t + \beta_1 GEU_t + M_{i,t}\gamma + \varepsilon_{i,t}$ (3.1). The dependent variable is *TFP_Wrdg*, estimated using Wooldridge (2009)'s method.

Next, we perform the same regression (3.1) for some selected countries in our sample to examine the heterogeneity in the GEU index's impact on firm productivity across different countries. Table 3.3 shows our regression results at the country level, which only presents the

[10] The Hausman test confirms that a fixed effects model is more appropriate for our panel data.

results of countries with a sufficient number of observations to perform the regression. As can be seen from Table 3.3, we find that 5/12 economies experience significant negative impacts from the GEU index on firm-level productivity, including Finland, France, Germany, the UK, and the US. Interestingly, we note that Canada is the only economy witnessing a statistically significant positive effect from the GEU index. Canada appears to have relative geopolitical stability, compared to other European countries or the US that tend to be more directly impacted by geopolitical disruptions or conflicts. Indeed, Canada only shares its border with the US that is regarded as a stable and friendly neighbor. Additionally, Canada is far from the Middle East or Eastern Europe and hence, it has a buffer from different geopolitical tensions that might impact those regions. Meanwhile, European countries appear to be more exposed to geopolitical disruptions, especially due to the reliance of those economies on energy supplies from unstable countries (such as Russia). Furthermore, although the US is not geographically near unstable regions, this country tends to get heavily involved in global geopolitical conflicts, given that the US is considered a global superpower, and it also relies on energy supplies from foreign sources. Apart from that, Canada's energy security is considered robust as it is among the countries with the most diverse mixes of energy sources across the globe. That country appears to be more energy self-sufficient due to a significant proportion of its own resources compared to other economies (Best et al., 2010).

Table 3.3. The impact of the GEU index on firm-level productivity (for some selected countries in the sample)

	Austria		Belgium		Canada		Finland		France		Germany	
GEU	-0.095	-0.102	-0.118	0.010	0.105**	0.093*	-0.128*	-0.149	-0.075**	-0.058*	-0.136***	-0.116***
	(0.108)	(0.121)	(0.092)	(0.062)	(0.053)	(0.055)	(0.067)	(0.093)	(0.036)	(0.031)	(0.039)	(0.039)
Firm_size	0.099	-0.032	0.165***	0.224*	0.005	0.081	-0.021	0.143	0.154***	0.350***	0.133***	0.265***
	(0.075)	(0.303)	(0.045)	(0.119)	(0.030)	(0.113)	(0.070)	(0.184)	(0.023)	(0.052)	(0.015)	(0.096)
Liquidity	1.613**	1.597**	1.824***	3.515***	0.887**	1.014*	0.333	1.544*	1.832***	2.210***	1.612***	1.342***
	(0.688)	(0.723)	(0.518)	(0.673)	(0.380)	(0.550)	(0.642)	(0.785)	(0.380)	(0.338)	(0.147)	(0.200)
Growth	0.347**	0.296	0.398***	0.134	0.213**	0.154	0.571***	0.436***	0.371***	0.269***	0.523***	0.455***
	(0.164)	(0.186)	(0.103)	(0.082)	(0.098)	(0.153)	(0.108)	(0.103)	(0.038)	(0.043)	(0.038)	(0.057)
Industry-year FE	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No
Firm-year FE	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes
N	142	141	264	259	299	282	133	117	1,324	1,292	969	937
Adjusted R^2	0.269	0.295	0.313	0.514	0.266	0.418	0.418	0.481	0.275	0.499	0.338	0.504

	Italy		Japan		Spain		Sweden		UK		US	
GEU	-0.103	-0.094	-0.152	-0.123	-0.058	-0.068	-0.080	-0.015	-0.132***	-0.109***	-0.103***	-0.066**
	(0.103)	(0.109)	(0.105)	(0.102)	(0.072)	(0.072)	(0.068)	(0.089)	(0.032)	(0.030)	(0.029)	(0.031)
Firm_size	0.266***	-0.062	0.188*	0.992***	0.105***	0.358***	0.166***	-0.304	0.207***	0.072	0.118***	0.135**
	(0.086)	(0.152)	(0.095)	(0.212)	(0.038)	(0.136)	(0.030)	(0.210)	(0.016)	(0.062)	(0.013)	(0.065)
Liquidity	0.735	0.779	2.628***	4.722***	1.585***	2.112***	2.119***	4.512***	2.017***	1.160***	1.292***	1.668***
	(0.695)	(0.598)	(0.361)	(1.604)	(0.386)	(0.465)	(0.409)	(1.005)	(0.204)	(0.317)	(0.187)	(0.333)
Growth	0.134	0.192	0.525***	0.632***	0.258***	0.197*	0.266*	0.131	0.381***	0.297***	0.361***	0.327***
	(0.102)	(0.165)	(0.099)	(0.147)	(0.077)	(0.111)	(0.135)	(0.137)	(0.031)	(0.039)	(0.035)	(0.043)
Industry-year FE	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No
Firm-year FE	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes
N	241	232	177	110	318	315	146	122	1,095	1,056	1,445	1,367
Adjusted R^2	0.193	0.302	0.422	0.681	0.256	0.278	0.309	0.483	0.309	0.529	0.295	0.535

Notes: Robust standard errors are presented within parentheses. ***, ** and * stand for the significance level of 1%, 5% and 10%, respectively. We present the estimation results only for countries with a sufficient number of observations to perform the regression. The estimations are based on the model: $TFP_{i,t} = \varphi_e + \omega_t + \beta_1 GEU_t + M_{i,t}\gamma + \varepsilon_{i,t}$ (3.1). The dependent variable is *TFP_Wrdg*, estimated using Wooldridge (2009)'s method.

Categorizing our sample into energy-intensive industries[11] versus less energy-intensive industries, we aim to investigate if there is any difference in the impact of the GEU index on firm productivity in industries that are more energy intensive. The results of regression model (3.2) are shown in Table 3.4. As can be seen, the GEU index is found to exert stronger significant negative effects on firm productivity in case of energy-intensive industries, indicated by the statistically significant negative coefficients of the interaction term *GEU*Energy_intensive*. This finding is in line with Elder (2019) who finds that energy-intensive industries experience significant negative effects from the oil price uncertainty. This finding implies that firms from energy-intensive industries need to take the GEU index as a significant determinant of their total factor productivity, and thus they need to have appropriate measures to avoid the negative impacts from the geopolitical-energy uncertainties on their productivity.

Table 3.4. The impact of the GEU index on firm-level productivity (energy-intensive industries versus less energy-intensive industries)

	(1)	(2)	(3)
GEU	-0.033	-0.067^{***}	-0.058^{***}
	(0.021)	(0.018)	(0.019)
Energy_intensive	-0.218^{***}	-0.191^{***}	-0.188^{***}
	(0.022)	(0.021)	(0.021)
*GEU*Energy_intensive*	-0.047^{**}	-0.050^{**}	-0.051^{**}
	(0.024)	(0.023)	(0.023)
Firm_size	0.162^{***}	0.145^{***}	0.147^{***}
	(0.005)	(0.006)	(0.006)
Liquidity	1.810^{***}	1.696^{***}	1.698^{***}
	(0.080)	(0.082)	(0.082)
Growth	0.288^{***}	0.359^{***}	0.360^{***}
	(0.030)	(0.016)	(0.016)
Year FE	Yes	No	Yes
Country FE	No	Yes	Yes
N	6,886	6,881	6,881
Adjusted R^2	0.260	0.317	0.318

Notes: Robust standard errors are presented within parentheses. ***, ** and * stand for the significance level of 1%, 5% and 10%, respectively. The estimations are based on the model: $TFP_{i,t} = \varphi_e + \omega_t + \alpha_1 GEU_t + \alpha_2 Energy\_intensive_i + \alpha_3 GEU_t * Energy\_intensive_i + M_{i,t}\delta + \varepsilon_{i,t}$(3.2). The dependent variable is TFP_Wrdg, estimated using Wooldridge (2009)'s method. $Energy\_intensive$ is a dummy variable that takes the value of 1 for industries that are considered as energy intensive, including Basic Materials, Energy, Industrials, and Utilities, and 0 otherwise. The dummy variable "*Energy_intensive*" gets absorbed when firm fixed effects or industry fixed effects are employed because it is fully collinear with those fixed effects. Hence, we do not present the estimation results of firm fixed effects or industry fixed effects.

[11] Industries categorized as energy intensive include Basic Materials, Energy, Industrials, and Utilities.

Based on the median of *Firm_size*, we categorize all firms in our sample into two sub-samples, including (i) smaller firms and (ii) larger firms. We aim to investigate whether the impact of GEU index on firm productivity is different between smaller and larger firms in our sample. Estimation results are presented in Table 3.5.

Table 3.5. The impact of the GEU index on firm-level productivity (smaller firms versus larger firms)

	Full sample	Less energy-intensive industries	Energy-intensive industries
	(1)	(2)	(3)
GEU	-0.039**	-0.019	-0.060***
	(0.016)	(0.025)	(0.020)
Smaller_firm	-0.016	-0.026	0.009
	(0.046)	(0.088)	(0.049)
GEU Smaller_firm*	-0.059***	-0.046	-0.080***
	(0.021)	(0.032)	(0.028)
Firm_size	0.191***	0.230***	0.137***
	(0.030)	(0.043)	(0.042)
Liquidity	1.589***	1.690***	1.468***
	(0.124)	(0.175)	(0.177)
Growth	0.287***	0.226***	0.368***
	(0.024)	(0.029)	(0.034)
N	6,462	2,989	3,473
Adjusted R^2	0.535	0.551	0.515

Notes: Robust standard errors are presented within parentheses. ***, ** and * stand for the significance level of 1%, 5% and 10%, respectively. Firm-year fixed effects are controlled in all models. The estimations are based on the model: $TFP_{i,t} = \varphi_e + \omega_t + \theta_1 GEU_t + \theta_2 Smaller\_firm_i + \theta_3 GEU_t * Smaller\_firm_i + M_{i,t}\vartheta + \varepsilon_{i,t}$ (3.3). The dependent variable is *TFP_Wrdg*, estimated using Wooldridge (2009)'s method. $Smaller\_firm$ is a dummy variable, which equals to 1 if *Firm_size* is smaller than or equal to the median of *Firm_size*, and 0 otherwise.

Looking at Table 3.5, we note that firms with smaller firm size appear to witness greater adverse impact from the geopolitical-energy uncertainties, indicated by the statistically significant negative coefficient of the interaction term *GEU* Smaller_firm* (-0.059) in column (1) of Table 3.5. When decomposing our full sample into "Less energy-intensive industries" and "Energy-intensive industries", we find that only the firm productivity from "Energy-intensive industries" (column (3)) experiences a statistically significant effect with the coefficient of -0.080, meanwhile no significant impact is found in case of "Less energy-intensive industries" (column (2)). These findings suggest that the GEU index tends to have significantly more negative impacts on the productivity of smaller firms, particularly those in energy-intensive industries.

3.4.2. Mechanism Analysis: Firm characteristics and energy price channels

To investigate the potential channels through which the GEU index affects firm productivity, we estimate interaction models between the GEU index and firm- or energy-related characteristics. Specifically, we standardize a set of firm-level variables, including profitability (EBIT/total assets), cost intensity (total costs/total assets), and capital expenditure ratio (capital expenditure/total assets). Also, measures of energy price changes (log returns of global energy price index[12] and West Texas Intermediate (WTI) spot crude oil price[13]) are included to represent energy price exposure. The general empirical model is as in Equation (3.4).

$$TFP_{i,t} = \mu_i + \omega_t + \gamma_1 GEU_t + \gamma_2 Z_{i,t} + \gamma_3 GEU_t * Z_{i,t} + M_{i,t}\delta + \varepsilon_{i,t} \tag{3.4}$$

where $Z_{i,t}$ stands for the standardized firm characteristic (Panel A-Table 3.6) or energy price exposure (Panel B-Table 3.6). Firm and year fixed effects (μ_i and ω_t) are included to control for unobserved heterogeneity across firms and over time. γ_3 is the coefficient of interest, which captures whether the sensitivity of firm productivity ($TFP_{i,t}$) to GEU shocks varies systematically with firm characteristics or energy price dynamics.

While the regressions in Equation (3.4) identify the average effects of GEU through firm characteristics and energy prices, they do not reveal how these mechanisms vary across different levels of the underlying variables. To address this limitation, we compute and plot the marginal effects of GEU with respect to firm productivity at different values of profitability, cost intensity, capex ratio, and energy price changes. In other words, Figure 3.1 illustrates ∂TFP/∂GEU = $\gamma_1 + \gamma_3 \times$Z, where Z denotes the standardized firm or energy variable, thereby providing a more nuanced picture of the heterogeneous responses along the distribution of firm characteristics and energy price exposures.

Table 3.6 presents the results of mechanism analysis (Equation 3.4). Panel A considers firm characteristics, such as profitability, cost intensity, and investment intensity, as potential mechanisms, while Panel B explores the role of energy prices as a macro-level transmission channel. As shown in Table 3.6A, the positive and significant interaction *GEU*Profitability* indicates that more profitable firms are better able to withstand GEU shocks. Figure 3.1a illustrates this channel: the marginal effects of GEU turn less negative and eventually positive at higher profitability levels, highlighting the buffer role of earnings capacity. Since

[12] Obtained from Federal Reserve Economic Data: https://fred.stlouisfed.org/series/PNRGINDEXM.
[13] Obtained from Federal Reserve Economic Data: https://fred.stlouisfed.org/series/WTISPLC

profitability and productivity tend to be positively linked *(Bottazzi et al., 2008; Foster et al., 2008)*, higher profitability can be viewed as reflecting greater productivity and efficiency, which in turn enhances firms' resilience to GEU shocks. Cost intensity also emerges as a relevant channel, as the negative interaction term (*GEU*Cost_intensity*) indicates that firms with heavier cost structures suffer stronger productivity losses from GEU shocks. Figure 3.1b supports this evidence, as the marginal effect of GEU on firm productivity becomes increasingly negative with rising cost intensity. This evidence is consistent with prior findings that higher costs undermine firm outcomes (Bernard et al., 2006; Kling et al., 2021), suggesting that cost burdens magnify the vulnerability of firms to external shocks. When examining capital expenditure (*Capex_ratio*), the statistically significant positive coefficient indicates that firms with higher capital spending tend to achieve greater productivity. In normal times, industries that invest more in capital assets are better able to leverage innovation, leading to higher total factor productivity (Ma et al., 2022). However, the interaction term between GEU and the capital expenditure ratio (*GEU*Capex_ratio*) is statistically insignificant. Despite this, the negative sign of the coefficient suggests that during periods of heightened uncertainty, the positive effect of capital investment may be weakened or dampened. This finding is consistent with Bloom (2009, 2014) and Bloom et al. (2018)'s argument that, under conditions of high uncertainty, firms tend to delay investment, meaning that capital expenditures no longer translate directly into productivity gains. Figure 3.1c supports this interpretation by showing a downward-sloping and statistically significant marginal effect, indicating that as the capex ratio increases, the adverse impact of GEU on firm productivity becomes stronger.

Turning to energy prices, Table 3.6B indicates that global energy price amplifies the detrimental effect of GEU, as reflected in the negative and significant interaction term (*GEU*Global_energy*). Similarly, although the interaction between GEU and WTI is statistically insignificant, its coefficient is still negative. Figure 3.1d and 3.1e further demonstrate this mechanism, showing that the marginal effect of GEU index on firm productivity becomes more adverse as global energy price return and WTI return rise, underlining the importance of energy price as a macro transmission channel. Consistent with this evidence, André et al. (2023) document that energy price shocks lead firms to scale down capacity utilization, which results in short-term declines in their productivity.

Table 3.6. Mechanism Analysis: Firm Characteristics and Energy Prices

Panel A. Firm level mechanism

	(1)	(2)	(3)
GEU	-0.055***	-0.070***	-0.075***
	(0.013)	(0.014)	(0.014)
Profitability	0.301***		
	(0.034)		
*GEU*Profitability*	0.122***		
	(0.021)		
Cost_intensity		-0.037	
		(0.036)	
*GEU*Cost_intensity*		-0.019*	
		(0.011)	
Capex_ratio			0.046***
			(0.017)
*GEU*Capex_ratio*			-0.017
			(0.011)
Firm_size	0.172***	0.184***	0.173***
	(0.026)	(0.028)	(0.031)
Liquidity	1.323***	1.585***	1.627***
	(0.122)	(0.123)	(0.143)
Growth	0.222***	0.288***	0.294***
	(0.022)	(0.024)	(0.024)
N	6,405	6,462	6,163
Adjusted R^2	0.580	0.535	0.533

Panel B. Energy price mechanism

	(1)	(2)
GEU	-0.072***	-0.072***
	(0.015)	(0.015)
Global_energy	-0.059***	
	(0.012)	
*GEU*Global_energy*	-0.027*	
	(0.015)	
WTI		-0.054***
		(0.012)
*GEU*WTI*		-0.021
		(0.018)
Firm_size	0.207***	0.206***
	(0.031)	(0.031)
Liquidity	1.544***	1.542***
	(0.132)	(0.133)
Growth	0.326***	0.322***
	(0.025)	(0.024)
N	5,739	5,739
Adjusted R^2	0.544	0.542

Notes: Robust standard errors are presented within parentheses. ***, ** and * stand for the significance level of 1%, 5% and 10%, respectively. Firm-year fixed effects are controlled in all models. The estimations are based on the model: $TFP_{i,t} = \mu_i + \omega_t + \gamma_1 GEU_t + \gamma_2 Z_{i,t} + \gamma_3 GEU_t * Z_{i,t} + M_{i,t}\delta + \varepsilon_{i,t}$ (3.4). The dependent variable is *TFP_Wrdg*, estimated using Wooldridge (2009)'s method. *Profitability* is the standardized (EBIT/Total Assets). *Cost_intensity* is the standardized (Total costs/Total assets). *Capex_ratio* is the standardized (Capital expenditure/Total assets). *Global_energy* is the standardized return of Global price of Energy index. WTI is the standardized return of Spot crude oil price: West Texas Intermediate.

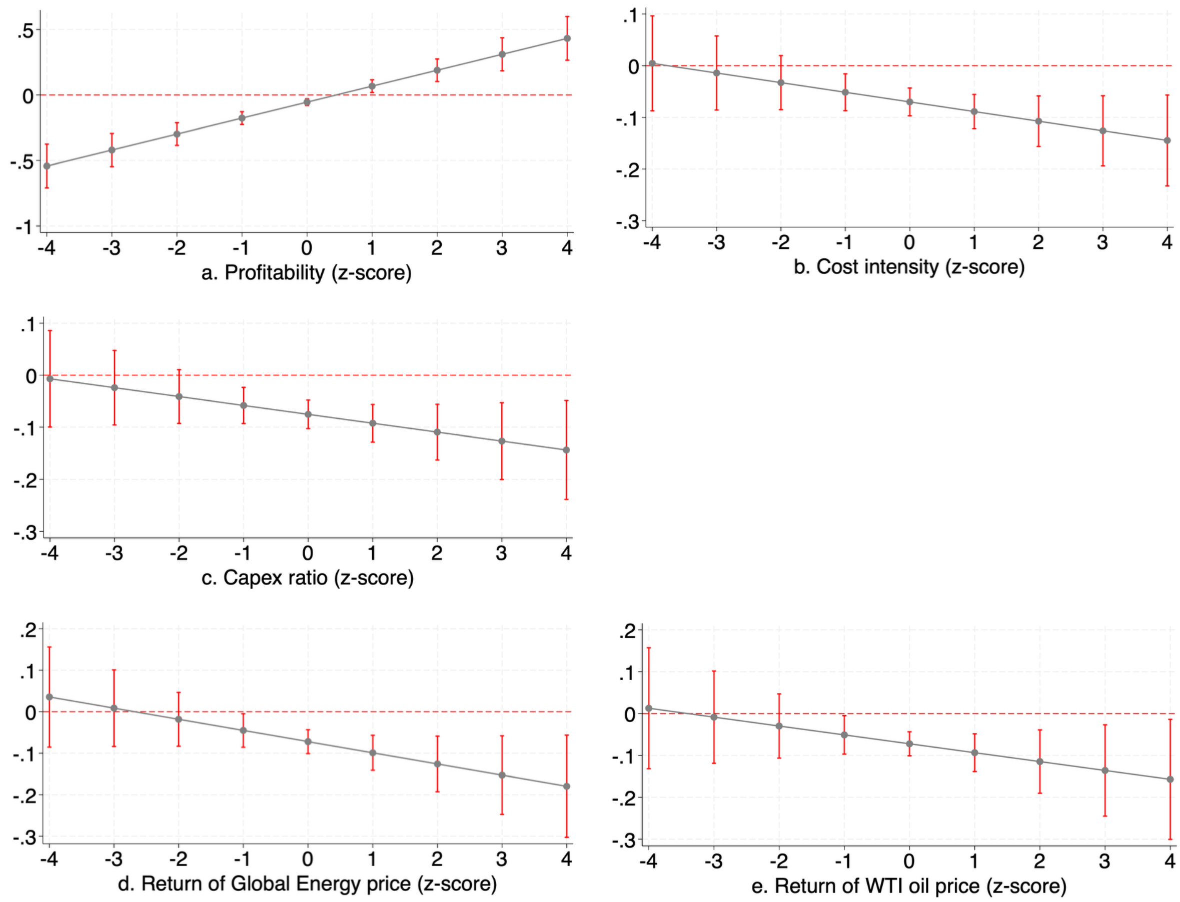


Figure 3.1. Marginal effects of the GEU index on firm productivity, conditional on firm characteristics and energy prices

Notes: Vertical red bars represent the 95% confidence intervals. The y-axis in each panel reports the effect of the GEU index on firm productivity, while the x-axis shows the standardized value of the corresponding channel.

3.4.3. Identification tests

3.4.3.1. Two-step system generalized method of moments (GMM)

In this sub-section, we perform identification tests to validate our baseline findings. First, we re-estimate our baseline regressions using a two-step system generalized method of moments (GMM) estimation. The system GMM is recommended in panel settings where endogeneity may arise (Nickell, 1981). Proposed by Arellano and Bover (1995) and Blundell and Bond (1998), this approach helps address potential biases from fixed effects in short panels while mitigating endogeneity concerns (Canh et al., 2020). Additionally, the Windmeijer (2005) finite-sample corrected standard errors are estimated to ensure more reliable inference.

Table 3.7 reports the two-step system GMM results. The lagged dependent variable is positive and significant, confirming the persistence of firm productivity. The significant and negative effect of the GEU index in column (1) confirms our findings from Table 3.2, while the adverse and significant interaction terms (i.e., *GEU*Energy_intensive* and *GEU**

Smaller_firm) in columns (2) and (3) remain consistent with results from Table 3.4 and 3.5. Especially, the diagnostic tests (including AR(2), Hansen, and Difference-in-Hansen) further confirm the validity of the instruments, supporting the robustness of our baseline findings.

Table 3.7. Identification tests: Two-step system GMM

	(1)	(2)	(3)
TFP_Wrdg$_{(t-1)}$	0.428***	0.529***	0.278***
	(0.106)	(0.178)	(0.048)
GEU	-0.043**	0.520**	0.778
	(0.017)	(0.257)	(0.502)
Energy_intensive		0.644	
		(0.551)	
*GEU*Energy_intensive*		-0.987**	
		(0.446)	
Smaller_firm			0.092
			(0.091)
GEU Smaller_firm*			-1.662*
			(0.997)
Firm_size	0.096***	0.062*	0.130***
	(0.020)	(0.035)	(0.019)
Liquidity	1.019***	0.746**	1.273***
	(0.202)	(0.308)	(0.163)
Growth	0.221***	0.210***	0.222***
	(0.029)	(0.045)	(0.047)
N	5,844	5,844	5,844
Number of groups	618	618	618
Number of instruments	37	47	34
Arellano-Bond test for AR(1)	$z = -5.68$, $p < 0.001$	$z = -4.41$, $p < 0.001$	$z = -10.00$, $p < 0.001$
Arellano-Bond test for AR(2)	$z = 1.60$, $p = 0.110$	$z = 1.47$, $p = 0.142$	$z = -1.50$, $p = 0.133$
Hansen test	$\chi^2(12) = 10.26$, p=0.593	$\chi^2(20)= 21.51$, p=0.368	$\chi^2(7)= 1.67$, p=0.976
Difference-in-Hansen test (levels)	$\chi^2(1) = 0.16$, p=0.687	$\chi^2(4) = 4.29$, p=0.369	$\chi^2(2) = 0.30$, p=0.863

Notes: Robust (Windmeijer-corrected) standard errors are presented within parentheses. ***, ** and * stand for the significance level of 1%, 5% and 10%, respectively. The dependent variable is *TFP_Wrdg*, estimated using Wooldridge (2009)'s method. Year fixed effects are controlled. Diagnostic tests: Arellano–Bond AR(1) and AR(2) tests check for serial correlation in first-differenced residuals; the Hansen test assesses the joint validity of instruments; and the Difference-in-Hansen test evaluates the exogeneity of instrument subsets.

3.4.3.2. Event-study analysis using difference-in-differences

To help address endogeneity concerns by assessing pre-trends and dynamics, we implement an event-study specification within a two-way fixed-effects difference-in-differences (TWFE DiD) framework, following Autor (2003), as an additional identification test of our baseline results. We define 2015 as the event year because the GEU index shows a clear shift around this time. Specifically, the average value of the GEU index before 2015 is negative (mean ≈ -0.55), whereas it rises sharply after 2015 (mean ≈ 0.58), with higher peaks. This pattern indicates a significant increase in geopolitical-energy uncertainty starting from 2015, making it a natural cutoff point for our event-study analysis. This year also corresponds with major real-world developments that heightened geopolitical and energy risk for the period after it. Notably, energy markets became more volatile following the 2014–2015 oil price collapse, driven by OPEC production decisions, U.S. shale growth, and fluctuating global demand. Geopolitical tensions escalated, including ongoing conflicts in the Middle East, the Syrian civil war, and instability in Iraq and Libya, as well as continued Russia-West confrontations related to Ukraine and European energy security. In addition, the 2015 Paris Agreement (COP21) introduced uncertainty regarding carbon pricing, emissions targets, and the timing and stringency of climate and energy policies. In this analysis, energy-intensive firms are the treatment group, and non-energy-intensive firms are the control group. The event-study analysis is based on the regression as in Equation (3.5).

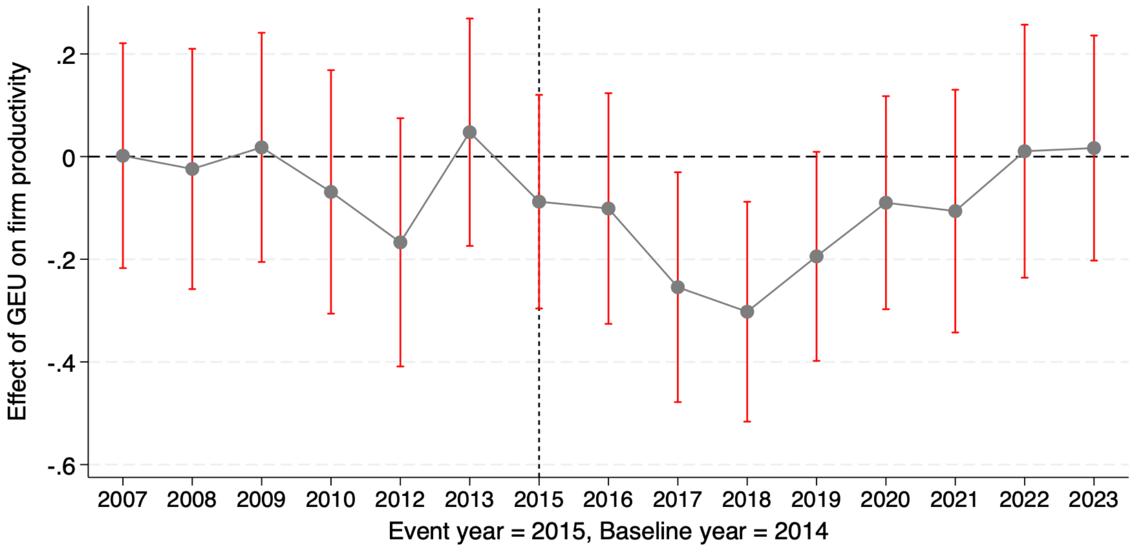
$$TFP_{i,t} = \mu_i + \omega_t + \sum_{k=-8,k\neq-1}^{8} \beta_k(D_i \times 1\{t - t_0 = k\}) + M_{i,t}\delta + \varepsilon_{i,t} \tag{3.5}$$

where t_0 = 2015 is the event year. k is the relative year to the event year, which is ∈ [-8,8] excluding the baseline year 2014 ($k = -1$). D_i is the treatment indicator, which equals 1 for energy-intensive firms and 0 otherwise. β_k is the treatment effect at relative year k. $1\{t - t_0 = k\} = \begin{cases} 1, & t - t_0 = k \\ 0, & t - t_0 \neq k \end{cases}$.

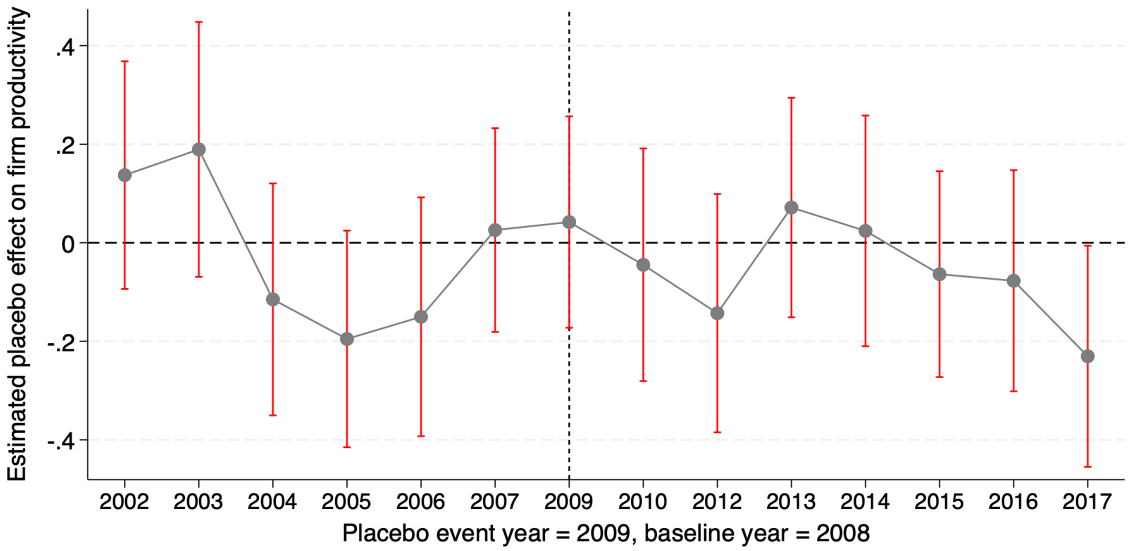
The main event-study analysis is illustrated in Figure 3.2a. Besides, to further validate our findings, we also conduct a placebo event-study using Equation (3.5) but re-centering the event year at 2009 (baseline 2008) (see Figure 3.2b). Insignificant placebo estimates would indicate that the main results (in Figure 3.2a) are not driven by spurious correlations or arbitrary timing.

As illustrated in Figure 3.2a, firm productivity shows no significant differences between treated and control groups prior to 2015, consistent with the parallel trend assumption. After the onset of GEU shocks in 2015, the coefficients turn negative, with the most pronounced significant declines during 2017-2018. Indeed, between 2017 and 2018, energy markets became more volatile due to OPEC production changes, U.S. shale growth, and conflicts in the Middle East, including U.S. sanctions on Iran. At the same time, trade tensions between the U.S. and China and unclear energy policies added further uncertainty. This suggests that heightened geopolitical-energy uncertainty exerted a significant and adverse impact on firm TFP, even though the magnitude of the effect fluctuates in subsequent years.

To further validate this result, Figure 3.2b applies a placebo test with a fake event year of 2009. The absence of statistically significant effects (in Figure 3.2b) around the placebo event (2009) reinforces that the post-2015 decline (in Figure 3.2a) is not driven by spurious correlations or pre-existing trends. Overall, the evidence highlights that GEU shocks represent a genuine source of productivity loss for firms, and the placebo test enhances confidence in the identification strategy.



a. Event-study difference-in-differences (event year = 2015)



b. Placebo event-study difference-in-differences (fake event year = 2009)

Figure 3.2. Event-study analysis using a two-way fixed-effects difference-in-differences framework

Notes: Vertical red bars represent the 95% confidence intervals. Figure 3.2a shows the event-study estimates around the actual event year (2015), while Figure 3.2b reports a placebo test for Figure 3.2a using a fake event year (2009). The baseline year (2014 in Figure 3.2a, 2008 in Figure 3.2b) is normalized to zero and therefore not shown. The GEU index is unavailable for 2011, so estimates for that year are also not displayed.

To formally assess the validity of the event-study specification in Figure 3.2, we conduct joint F-tests on the interaction coefficients from Equation (3.5) (see Table 3.8). Panel A reports a parallel-trends test for the actual event year 2015 by testing whether pre-event coefficients (2007–2013, baseline 2014) are jointly equal to zero. Panel B provides a placebo test by re-centering the model at a fake event year 2009 (baseline 2008) and testing whether post-2009 coefficients (2010–2017) are jointly zero. As shown in Table 3.8, both tests yield insignificant F-statistics, implying that neither the pre-2015 coefficients nor the placebo post-2009 coefficients are statistically different from zero. These results are consistent with the evidence in Figure 3.2, confirming that the parallel-trends assumption holds and that the observed productivity decline after 2015 is unlikely to be explained by spurious correlations. Together, Figure 3.2 and Table 3.8 confirm the validity of our identification strategy.

Table 3.8. Event-study DiD identification tests: parallel trends and placebo

Panel	Test type	Null hypothesis	F-stat	p-value
A. Pre-treatment (2015 event)	Parallel-trends test (2007–2013, baseline 2014)	All pre-event interaction terms = 0	0.70	0.649
B. Post-treatment (fake 2009 event)	Placebo test (2010–2017, baseline 2008)	All placebo interaction terms = 0	1.49	0.166

3.5. Robustness tests

In this section, we use two different measures of firm-level total factor productivity as proposed by Levinsohn and Petrin (2003) and Olley and Pakes (1996) along with alternative regression models (including the linear mixed model and Hausman-Taylor model) to check the robustness of our baseline results in Section 3.4.

The linear mixed model (or linear mixed-effects model), an augmented version of simple linear model, comprises both fixed factors and random factors in the model (Duchateau & Janssen, 1997; Verbeke & Molenberghs, 2000). In other words, this model can control for both fixed effects and random effects. As such, it is regarded as a versatile tool for efficiently addressing research questions (Oberg & Mahoney, 2007). Indeed, Oberg and Mahoney (2007) argue that the linear mixed model could model the within-subject correlation and weigh the estimation process so that it might allow subjects with more information and less variable information to contribute more to the analysis. Meanwhile, proposed by Hausman and Taylor (1981), the Hausman-Taylor model is considered to allow the correlation between some regressors with random individual effects. A major benefit of the Hausman-Taylor estimator is that it enables the estimation of time-invariant variables which are dropped by the fixed effects models (Baltagi, 2023). Especially, previous studies suggest that this model could be employed as a treatment for endogeneity (Fetai, 2018; Gardebroek & Lansink, 2003; Lu et al., 2018).

As can be seen from Table 3.9, the estimation results confirm the significantly adverse effects of the GEU index on firm productivity as indicated by the statistically significant negative coefficients of "GEU" in Table 3.9A. Additionally, the statistically significant negative coefficients of the interaction term "*GEU*Energy_intensive*" in Table 3.9B confirm that energy-intensive firms' productivity witnesses more negative impact from the GEU index, compared to less energy-intensive firms. Similarly, findings from Table 3.9C validate our baseline results regarding the more negative impacts of the GEU index on the productivity of smaller firms.

Beyond above robustness checks, we also implement a set of placebo/falsification and robustness tests reported in Appendix 3.A and 3.B. Specifically, Appendix 3.A examines placebo specifications by replacing GEU with alternative global uncertainty indices (GPR and EPU), using future GEU values (t+1, t+2) to rule out reverse causality, and performing circular time-shift tests that misalign the true timing of shocks. Appendix 3.B provides further robustness checks by re-estimating the effects through the panel impulse response function framework and by employing demeaned interaction terms following Balli and Sørensen (2013). Across all these tests, the placebo specifications yield no significant effects, as expected, whereas the additional robustness checks consistently reproduce the negative impacts of GEU observed in the baseline regressions. This evidence confirms that our main results are not driven by spurious correlations, model specification choices, or alternative estimation strategies. Taken together, these tests reinforce the robustness and credibility of our baseline findings.

Table 3.9. Robustness test: The impact of the GEU index on firm-level productivity (using alternative methods and alternative measures of firm productivity)

Panel A. Full sample

	Wooldridge (2009)			Levinsohn and Petrin (2003)			Olley and Pakes (1996)		
	Firm - Year fixed effects	Linear mixed model	Hausman-Taylor model	Firm - Year fixed effects	Linear mixed model	Hausman-Taylor model	Firm - Year fixed effects	Linear mixed model	Hausman-Taylor model
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
GEU	-0.070***	-0.092***	-0.082***	-0.069***	-0.091***	-0.081***	-0.073***	-0.094***	-0.081***
	(0.014)	(0.012)	(0.014)	(0.014)	(0.012)	(0.014)	(0.014)	(0.012)	(0.014)
Firm_size	0.192***	0.154***	0.161***	0.174***	0.136***	0.146***	0.209***	0.207***	0.191***
	(0.028)	(0.010)	(0.029)	(0.028)	(0.010)	(0.029)	(0.028)	(0.011)	(0.030)
Liquidity	1.581***	1.878***	1.572***	1.580***	1.874***	1.572***	1.650***	2.192***	1.649***
	(0.124)	(0.130)	(0.190)	(0.125)	(0.131)	(0.191)	(0.123)	(0.138)	(0.192)
Growth	0.288***	0.375***	0.282***	0.288***	0.369***	0.282***	0.285***	0.360***	0.280***
	(0.024)	(0.021)	(0.039)	(0.024)	(0.021)	(0.039)	(0.024)	(0.022)	(0.040)
N	6,462	6,886	6,886	6,462	6,886	6,886	6,462	6,886	6,886
Adjusted R^2	0.534	-	-	0.525	-	-	0.581	-	-

Panel B. Energy-intensive industries

	Wooldridge (2009)			Levinsohn and Petrin (2003)			Olley and Pakes (1996)		
	Country - Year fixed effects	Linear mixed model	Hausman-Taylor model	Country - Year fixed effects	Linear mixed model	Hausman-Taylor model	Country - Year fixed effects	Linear mixed model	Hausman-Taylor model
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
GEU	-0.058***	-0.067***	-0.057***	-0.055***	-0.065***	-0.056***	-0.057***	-0.068***	-0.054***
	(0.019)	(0.018)	(0.020)	(0.020)	(0.018)	(0.020)	(0.020)	(0.018)	(0.021)
Energy_intensive	-0.188***	-0.184***	-0.338***	-0.200***	-0.196***	-0.361***	-0.160***	-0.167***	-0.387***
	(0.021)	(0.045)	(0.054)	(0.021)	(0.046)	(0.055)	(0.021)	(0.049)	(0.059)
*GEU*Energy_intensive*	-0.051**	-0.047**	-0.047*	-0.052**	-0.047**	-0.047*	-0.052**	-0.048**	-0.050**
	(0.023)	(0.023)	(0.025)	(0.023)	(0.023)	(0.025)	(0.023)	(0.024)	(0.025)
Firm_size	0.147***	0.156***	0.158***	0.124***	0.138***	0.143***	0.164***	0.208***	0.189***
	(0.006)	(0.010)	(0.029)	(0.006)	(0.010)	(0.029)	(0.006)	(0.011)	(0.030)
Liquidity	1.698***	1.902***	1.567***	1.660***	1.898***	1.567***	1.822***	2.213***	1.644***
	(0.082)	(0.130)	(0.190)	(0.083)	(0.131)	(0.191)	(0.085)	(0.138)	(0.192)
Growth	0.360***	0.370***	0.282***	0.354***	0.364***	0.282***	0.346***	0.356***	0.280***
	(0.016)	(0.021)	(0.039)	(0.016)	(0.021)	(0.039)	(0.016)	(0.022)	(0.039)
N	6,881	6,886	6,886	6,881	6,886	6,886	6,881	6,886	6,886
Adjusted R^2	0.318	-	-	0.295	-	-	0.378	-	-

Notes: Robust standard errors are presented within parentheses. ***, ** and * stand for the significance level of 1%, 5% and 10%, respectively.
The estimations in Panel A are based on the model: $TFP_{i,t} = \varphi_e + \omega_t + \beta_1 GEU_t + M_{i,t}\gamma + \varepsilon_{i,t}$ (3.1).
The estimations in Panel B are based on the model: $TFP_{i,t} = \varphi_e + \omega_t + \alpha_1 GEU_t + \alpha_2 Energy\_intensive_i + \alpha_3 GEU_t * Energy\_intensive_i + M_{i,t}\delta + \varepsilon_{i,t}$ (3.2)

Table 3.9. Robustness test: The impact of the GEU index on firm-level productivity (using alternative methods and alternative measures of firm productivity) (con't)

Panel C. Smaller firms									
	Wooldridge (2009)			Levinsohn and Petrin (2003)			Olley and Pakes (1996)		
	Firm - Year fixed effects	Linear mixed model	Hausman-Taylor model	Firm - Year fixed effects	Linear mixed model	Hausman-Taylor model	Firm - Year fixed effects	Linear mixed model	Hausman-Taylor model
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
GEU	-0.039**	-0.058***	-0.055***	-0.038**	-0.056***	-0.053***	-0.041***	-0.058***	-0.054***
	(0.016)	(0.014)	(0.015)	(0.016)	(0.014)	(0.015)	(0.016)	(0.014)	(0.015)
Smaller_firm	-0.016	-0.018	-0.017	-0.014	-0.015	-0.016	-0.016	-0.007	-0.024
	(0.046)	(0.055)	(0.064)	(0.046)	(0.055)	(0.064)	(0.046)	(0.056)	(0.063)
GEU Smaller_firm*	-0.059***	-0.070***	-0.059**	-0.060***	-0.070***	-0.060**	-0.060***	-0.075***	-0.062**
	(0.021)	(0.023)	(0.025)	(0.021)	(0.023)	(0.025)	(0.021)	(0.024)	(0.025)
Firm_size	0.191***	0.151***	0.167***	0.173***	0.133***	0.152***	0.208***	0.206***	0.206***
	(0.030)	(0.014)	(0.026)	(0.030)	(0.014)	(0.026)	(0.031)	(0.015)	(0.027)
Liquidity	1.589***	1.875***	1.588***	1.588***	1.872***	1.588***	1.658***	2.189***	1.671***
	(0.124)	(0.130)	(0.190)	(0.125)	(0.131)	(0.191)	(0.123)	(0.137)	(0.192)
Growth	0.287***	0.374***	0.282***	0.287***	0.368***	0.282***	0.284***	0.359***	0.282***
	(0.024)	(0.021)	(0.039)	(0.024)	(0.021)	(0.039)	(0.024)	(0.022)	(0.040)
N	6,462	6,886	6,886	6,462	6,886	6,886	6,462	6,886	6,886
Adjusted R^2	0.535	-	-	0.526	-	-	0.581	-	-

Notes: Robust standard errors are presented within parentheses. ***, ** and * stand for the significance level of 1%, 5% and 10%, respectively.
The estimations in Panel C are based on the model: $TFP_{i,t} = \varphi_e + \omega_t + \theta_1 GEU_t + \theta_2 Smaller\_firm_i + \theta_3 GEU_t * Smaller\_firm_i + M_{i,t}\vartheta + \varepsilon_{i,t}$ (3.3).
$Smaller\_firm$ is a dummy variable, which equals to 1 if $Firm\_size$ is smaller than or equal to the median of $Firm\_size$, and 0 otherwise.

3.6. Conclusions

Our study explores the impact of the global geopolitical-energy uncertainty index (i.e., the GEU index) proposed by Dang et al. (2024a) on total factor productivity at the firm level. To the best of our knowledge, the impact of the GEU index at the firm level is currently ignored in the extant literature. As such, we fill this research gap by studying how the GEU index affects the firm-level total factor productivity (i.e., firm productivity) for the period from 2001 to 2023.

Our paper shows that the global geopolitical-energy uncertainty is evident to adversely impact firm productivity, not only for the full sample but also for some developed countries such as the US, UK, France and Germany. We also decompose our full sample into energy-intensive industries and less energy-intensive industries to see whether there is any significant difference in the GEU's impact between two groups of industries. As a result, we observe that the productivity of firms from energy-intensive industries tends to experience stronger negative impacts from the GEU index. Additionally, we find that smaller firms are more negatively impacted by the geopolitical-energy uncertainty, compared to larger firms. Additionally, firms with higher cost intensity experience larger productivity losses under GEU, and rising global energy prices intensify the negative effects.

Chapter Four - Essay Three "Firm productivity in the Energy-electricity sector over the last two decades with crisis: The role of cross-listing"

Abstract

Novel to the literature, this study examines how cross-listing impacts firms' productivity in Energy sector. Annual data of firm cross-listing over the last two decades with crisis (2002-2022) are employed for our analyses. We find evidence of significant drop in productivity after Energy firms (including electricity firms) cross-list in the US market. Meanwhile, we do not find strong evidence of significant decreases in firm productivity from other sectors in our sample. We note one possible explanation for this finding is that after cross-listing, Energy firms appear to utilize their increased capital to heavily invest in infrastructure, equipment, and plants for expansion, which might eventually damage their productivity. To seek more thorough explanations for such decreases in Energy firms' productivity after cross-listing, we identify the determinants of firm productivity in Energy sector. Our results provide strong evidence that the increases in capital expenditures after Energy firms cross-list appear to be associated with the decreases in firm productivity. Notably, we note that negative impacts of capital expenditures (after cross-listing) and state ownership on firm productivity become much stronger and more statistically significant in developed countries than in emerging countries. Last, corporate governance and firm liquidity are found to be two determinants that help improve firm productivity in both electricity firms and other energy firms.

Keywords: Total factor productivity; cross-listing; Energy sector; capital expenditures, Energy, Crisis

JEL codes: E24; E30; G15; G32; G34

Statement of contribution form - Essay Three

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We, the student and the student's main supervisor, certify that all co-authors have consented to their work being included in the thesis and they have accepted the student's contribution as indicated below in the Statement of Originality.

Student name:	Tam Hoang Nhat Dang
Name and title of main supervisor:	Professor Faruk Balli
In which chapter is the manuscript/published work?	Essay Three in Chapter Four

Describe the contribution that the student and members of the supervisory team have made to the manuscript/published work:[1]

Tam discussed the research ideas with his supervisors, and together they agreed on the topic of Essay Three in Chapter Four. He then collected and cleaned all datasets, and conducted the full set of empirical analyses. The supervisors reviewed Tam's results, provided suggestions, and addressed his questions during their weekly meetings. Tam drafted the initial version of the paper, and he and his supervisors subsequently refined and revised the manuscript in preparation for journal submission.

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4.1. Introduction

Investment barriers across financial markets have been dramatically reduced due to cross-border capital market liberalization (Dodd, 2013), which allows investors to gain access to various financial assets worldwide (Balli et al., 2022). However, there still exist some international capital flow obstacles which have been unresolved, including trading costs, different investor protection, and different restrictions relating to foreign ownership amongst different capital markets. From the perspective of several corporate managers, such investment barriers could be overcome by cross-listing shares (Balli et al., 2022; Reiter, 2021).

Cross-listing is considered the situation in which the stock of a firm is listed on one foreign stock exchange (Karolyi, 2006; Shi et al., 2012). A significant body of literature has investigated motivations for cross-listing of firms. The extant literature documents two main focuses on the benefits of cross-listing (Peng & Su, 2014). *First*, firms can gain access to great source of foreign capital with a lower cost of financing as firms' shares become available to a greater group of international investors (Hail & Leuz, 2009). In more detail, as cross-listing allows firm shares to be accessible to global investors, it will enhance stock investibility and improve risk sharing, leading to reduced cost of capital. *Second*, in line with the ''bonding hypothesis'', cross-listing on a foreign stock exchange with more stringent legal and disclosure requirements than those in the home stock exchange appears to lead to improved corporate governance practices (Coffee, 1999a; Stulz, 1999).

Cross-listing decision could be highly strategic regarding the growth of firms (Peng & Su, 2014). According to business strategy theory, a decision of cross-listing appears to be an integrated part of the global business strategies of a firm (King & Mittoo, 2007; Pagano et al., 2002). Firms might choose to cross-list on foreign stock exchanges to access overseas capital markets to fund their global investment projects, to support their mergers and acquisitions (M&A) activities in overseas markets as well as to retain their competitive position against other peers in the industry (Dodd, 2013; Mittoo, 2003; Pagano et al., 2002).

Previous studies indicate that firms cross-listing in the US markets appear to access more extensive, efficient, and liquid market compared to the home market (Balli et al., 2022; Lambrecht & Myers, 2012). Additionally, recent studies show evidence that easy access to capital through financial liberalization helps foster investment and enhance resource allocation (Heil, 2019; Lambrecht & Myers, 2012). Furthermore, as demonstrated by Heil (2019), financial liberalization, encompassing the relaxation of foreign capital controls and equity market opening, is linked to improved productivity. As such, our hypothesis posits that the more affordable capital acquired by companies through cross-listing is likely to enhance their access to foreign capital and potentially boost firms' overall productivity.

Firm productivity is regarded as the improved efficiency in the real economic performance of a firm, which is measured by the residual production output beyond the input costs' contribution. The total factor productivity has been considered an essential component of firm's economic growth (Baier et al., 2006; Dowrick & Nguyen, 1989; Thompson & Rushing, 1999; Tian & Twite, 2011). Existing literature indicates that there are different channels through which foreign ownership might exert significant effects on firm productivity (Xu et al., 2022). One of those channels is financing support. Beck, Demirgüç-kunt, et al. (2005) suggest that financial obstacles appear associated with lower firm performance and productivity. Meanwhile, several empirical studies indicate that foreign ownership is linked to reduced financial obstacles (Dong & Men, 2014; Knack & Xu, 2017). Through the financial support from firm's foreign parents, firms with overseas ownership are likely to relax their financial constraints and achieve greater productivity (Xu et al., 2022). Although the nexus between firm productivity and foreign ownership has been investigated, we note that the relationship between cross-listing and firm productivity appears to be largely ignored.

In recent years, energy sector is reported to drive economies and sustain societies worldwide (UNEP, 2023). According to The World Bank (2023a), energy is considered the heart of development as it enables innovations, investments as well as new industries which might lead to job opportunities, shared prosperity, and inclusive growth for economies across the globe. Previous studies show evidence that energy sector is one of significant determinants of GDP growth for emerging economies mostly (Stern, 1993, 2000). Indeed, private sectors highly prioritize Energy sector since the demand for energy services is increasing in not only developed but also developing economies as well as this sector has significant social and environmental impacts (Biagini & Sagar, 2004). Over the last two decades, the world has experienced several energy-related crises, including the 2000s energy crisis (2003-2008), the great oil crash of 2014, the stunning drop in oil prices in 2016 and the 2021-2023 global energy crisis following the Covid-19 pandemic in 2021 and the Russian invasion of Ukraine in 2022. Such crises appear to cause significant impacts on both macroeconomic and firm levels. Given that energy is a highly capital-intensive sector (Raikar & Adamson, 2020), and is considered as the main growth determinant for some emerging economies, the productivity in this sector is directly related to the economic welfare of the world. This study aims to investigate how cross-listing of energy companies impacts their productivity under the age of energy crises. Additionally, we explore the determinants of Energy sector's productivity at firm level.

In that respect, our study contributes to the literature in the following aspects. *First*, to the best of our knowledge, this is the first paper to investigate how cross-listing into the US markets of Energy firms affects their productivity. Specifically, we consider that after cross-listing, firms might have easy access to foreign capital with lower costs. This is even more meaningful for emerging markets where the capital is relatively scarce (Bruhn & Zia, 2013; Veronica et al., 2020) and cost of capital is relatively higher (IEA & ICL, 2023). Eventually, improved access to foreign capital is expected to enable firms to become more competitive (Dodd, 2013; Mittoo, 2003), and thus firms appear to gain higher productivity in general. As such, our study aims to examine how firm productivity in Energy sector changes after cross-listing and find reasonable explanations for those changes. *Second*, we also provide in-depth analysis on firm productivity, including (*i*) estimating and comparing firm productivity between different stages of cross-listing (before cross-listing; Stage (1) - the first five years after cross-listing; and Stage (2) - the remaining years following Stage (1)); (*ii*) comparing firm productivity between Energy sector and other sectors in the sample; and (iii) separating the whole sample into Developed and Emerging countries to see the differences in firm productivity between those two groups of countries. *Third, more importantly,* to understand which factors significantly explain firm productivity in the presence of cross-listing, we identify the determinants of productivity in Energy sector at firm level. We simply test if the productivity increased after the cross listing, and if it is directly related to capital expenditure. Interestingly, the decrease in productivity for energy firms is directly related to their high volume of capital expenditure, in the early stages. We also perform several robustness tests to ensure the reliability of our baseline results.

Findings from our study show that firms in Energy sector (including electricity firms) experience a significant drop in productivity after they cross-list in the US markets, whereas we do not find strong evidence of significant decreases in firm productivity from other sectors in our sample. We also observe that capital expenditures and fixed assets of both electricity firms and other Energy firms witness significant increases after cross-listing. Accordingly, Energy firms might utilize their increased capital (obtained through cross-listing process) to heavily invest in infrastructure, equipment, and plants for expansion, which might eventually damage their productivity. By identifying the determinants of firm productivity in Energy sector, we find strong evidence that the increases in capital expenditures after Energy firms cross-list appear to be associated with the decreases in firm productivity. Especially, the negative effects of factors (i.e., *capital expenditures after cross-listing* and *state ownership*) on firm productivity are found to be much stronger and more statistically significant in developed economies than in emerging economies. Last, corporate governance and firm liquidity are two factors that help enhance firm productivity in both electricity firms and other firms from Energy sector.

The rest of our study is structured as follows. Section 1.2 presents our literature review while Section 1.3 introduces our methodology and data. In Section 1.4, we present and discuss our empirical results. Last, Section 1.5 shows our conclusions and proposed implications.

4.2. Literature review

The process of globalization in financial markets has resulted in a significant increase in the number of non-U.S. firms opting to cross-list their shares on U.S. exchanges (Eun & Sabherwal, 2003; Karolyi, 2006). These companies not only represented those from developed economies but also included numerous firms from emerging economies that were opening their stock markets to foreign investors for the first time. The growing popularity of cross-listings has sparked considerable academic interest, leading to numerous studies focused on understanding the motivations behind firms pursuing cross-listing. Based on conventional wisdom, scholars have primarily identified three key motivations, including (i) share price reactions; (ii) liquidity, multi market trading, price discovery, and (iii) changing market risk exposures and the cost of capital.

Regarding the first justification for cross-listing, empirical studies have predominantly focused on the share price reactions surrounding a firm's listing decision. Several studies have extensively examined this aspect, such as Pascual et al. (2006)' study for Spanish firms cross listed in NYSE, Frijns et al. (2010)' study for four Australian stocks cross-listed in New Zealand and five New Zealand stocks cross-listed in Australia. In the study conducted by Eun and Sabherwal (2003), the authors specifically investigate the contribution of U.S. stock exchanges to the price discovery process for non-U.S. stocks that have been cross-listed in the United States. The findings reveal that the U.S. exchange significantly contributes to the price discovery mechanism for these stocks.

Furthermore, various studies indicate that cross-listing on overseas exchanges can lead to improved liquidity for firms, which is often considered a primary motivation for corporate managers (Bris et al., 2007; Dodd, 2013). These enhancements are evident in several aspects, including lower bid-ask spreads, increased trading volumes, and higher trading values.

Domowitz et al. (1998), for example, reported a higher trading volume, and a decrease in domestic bid-ask spreads for US cross-listed firms from Mexico. Bris et al. (2007) revealed an economically and statistically significant increase in the liquidity of domestic stock after the listing in the U.S. Another significant benefit of cross-listing is the potential for changing market risk exposures and the cost of capital. Cross-listings are often perceived positively because they allow management to circumvent regulatory restrictions, reduce costs, and overcome information barriers that typically impede cross-border equity investment (Karolyi, 2006). Study by Hail and Leuz (2009) showed that companies with cross-listings on U.S. exchanges observe a reduction in their cost of capital ranging from 70 to 120 basis points.

Several additional studies highlight various benefits that cross-listed firms can enjoy. These include an enhancement in the information environment for non-U.S. stocks (Fernandes & Ferreira, 2008), greater analyst coverage and increased forecast accuracy (Lang et al., 2003), and governance improvements (Karolyi, 2006). According to the findings of Edison and Warnock (2008), emerging equity markets often face higher transaction costs, increased risk of failed trades, and potential challenges related to financial information due to diverse accounting practices, disclosure requirements, and enforcement. By deciding to pursue cross-listing on a U.S. exchange, these costs, both direct and informational, can be eased. This strategic move allows the cross-listed firm to benefit from the robust information environment and investor protection regulations associated with the United States.

Productivity is widely recognized as the most significant characteristic of a firm and serves as a versatile measure of its performance. Extensive research has been conducted to identify the factors that contribute to improvements in productivity at the firm level. In a comprehensive survey conducted by Syverson (2011), it is suggested that the existing literature has identified various internal and external drivers that account for differences in productivity among firms. The internal drivers encompass factors such as managerial talent, the quality of capital and labor inputs, research and development, information technology, learning by doing, firm structure decisions, and product innovation. The external drivers of productivity include productivity spillovers, competition within the market, industry deregulation, the flexibility of input markets, and trade competition.

Emerging literature suggests that foreign ownership can serve as another driver of firm productivity. In a recent study by Xu et al. (2022), which utilized the World Bank Enterprise Survey (WBES) dataset comprising over 120,000 firms from 139 countries, the impact of foreign ownership on firm productivity in private firms was examined. The study found strong evidence of positive relationship between foreign ownership and firm productivity. Previous research has also explored two potential channels through which foreign ownership influences productivity: innovation and finance. Foreign ownership is associated with increased innovation activities and reduced financial constraints within host firms and both innovation and improved access to finance are known to contribute to higher firm performance and productivity (Boubakri et al., 2013; Jin et al., 2019; Luong et al., 2017). For instance, several papers have highlighted the link between foreign ownership and reduced financial constraints (Beck et al., 2006). Financing obstacles, in turn, have been identified as factors that hinder firm performance and productivity (Beck, Demirgüç-Kunt, et al., 2005). Therefore, firms with foreign ownership may benefit from the financial support provided by their foreign parents, leading to higher levels of productivity. In addition, Xu et al. (2022) propose that foreign ownership can enhance productivity through the utilization of telecommunication facilities and the management of labor costs. In fact, firms with foreign ownership often rely more extensively on communication technology compared to their purely domestic counterparts. Given that the adoption of telecommunication applications has been found to have a positive impact on firm productivity (Arnold et al., 2008), it is likely that firms with foreign ownership achieve higher productivity levels through their broader usage of telecommunication resources.

Despite the extensive body of research exploring the impact of cross-listing on various aspects of firm performance and studying the effects of foreign ownership on firm productivity, the relationship between cross-listing and firm productivity has received relatively limited attention. It is important to note that while both cross-listing and foreign ownership enable companies to expand their reach beyond their domestic markets, cross-listing and foreign ownership are distinct concepts with different implications. Cross-listing entails a deliberate strategic decision by a company to expand its market presence by listing its shares on a foreign exchange. This strategic move allows the company to attract a larger pool of investors and enhance its visibility in international markets. In contrast, foreign ownership refers to the composition of a company's ownership structure, indicating the participation of foreign investors who hold shares in the company. It signifies the presence of international investors among the company's shareholders and does not necessarily involve cross-listing.

Generally, empirical studies highlighted that cross-listing presents a significant advantage by potentially reshaping market risk exposures and reducing the cost of capital. Simultaneously, studies have consistently shown that the alleviation of financial constraints, facilitated by the financial support extended by foreign investors, can act as a vehicle for enhancing firm productivity. Considering these findings, our hypothesis suggests that the more cost-effective capital acquired by companies through cross-listing has the potential to stimulate their overall productivity.

This research aims to expand the existing body of scholarly knowledge concerning the nexus of firm productivity and cross-listing, with a specific focus on their interplay within the energy sector cross-listed in the US market. Our emphasis on the energy sector is based on a series of energy-related crises that have unfolded over the past two decades. These crises encompassed the 2000s energy crisis (2003-2008), the oil crash of 2014, the substantial decline in oil prices in 2016, and the global energy crisis spanning from 2021 to 2023. This more recent crisis of the Covid-19 pandemic in 2021 and the Russian invasion of Ukraine in 2022 were also included. These crises have affected not only how the world's economy works but also how individual companies operate. Indeed, Ahir et al. (2022) argue that numerous remarkable events occurring in recent years, including the global financial crisis and the Covid-19 crisis, appear to raise concerns regarding increasing economic uncertainties. Especially, Dang et al. (2023) find that the energy-related uncertainties significantly increased during the recent crises, such as global financial crisis (2008), the debt crisis in Europe (2010-2011), the Covid-19 crisis (2020-2021), and the Russia's invasion of Ukraine (2022). Such remarkable events appear to lead to negative effects on both the global economy and the energy markets (Dang et al., 2023; Farid et al., 2023; Naeem et al., 2023; Naeem et al., 2022). Previous empirical studies also show evidence of substantial contagion effects across energy markets over the periods of crisis (Naeem et al., 2021; Naeem et al., 2020; Rehman et al., 2023; Umar et al., 2022). Furthermore, owing to the inherent capital-intensive nature of the energy sector and its key role as a primary ingredient for growth in economies, its productivity has significant implications for the overall global economy. Consequently, this study seeks to explore the intricate relationship between cross-listing and the productivity of energy companies, within the context of the energy crises.

Through a comprehensive analysis, various aspects of this relationship are explored. Firstly, we investigate how cross-listing influences productivity in different market contexts by comparing firms in emerging markets to those in developed markets. This analysis allows us to gain insights into the varying impact of cross-listing on productivity across different market environments. Furthermore, we extend our analysis beyond the energy sector by comparing the productivity of energy sector firms with firms from other sectors that have also undergone cross-listing. This comparative approach suggests whether the impact of cross-listing on productivity is unique to the energy sector or if similar patterns exist across different industries.

In addition, we examine the effects of cross-listing on firm productivity across different phases after the cross-listing process. Specifically, we analyze the first five years following cross-listing and the subsequent years to identify potential variations in the impact of cross-listing on firm productivity over time. Lastly, our study aims to identify the key factors that significantly contribute to variations in productivity among cross-listed energy sector firms in the presence of cross-listing. By uncovering these factors, we can better understand the underlying mechanisms that drive productivity outcomes in this specific context.

4.3. Methodology and Data

4.3.1. Methodology

4.3.1.1. Estimating firm productivity

In this study, we estimate the total factor productivity (TFP) at firm level, a proxy for firm productivity. We based on an assumption that the output of firm i is identified through a Cobb-Douglas production function as in Equation (4.1) (Fons-Rosen et al., 2021).

$$Y_{it} = TFP_{it} L_{it}^{\beta_l} K_{it}^{\beta_k} \quad (4.1)$$

where Y_{it} is the firm value added or firm output. TFP_{it} is the total factor productivity. L_{it} and K_{it} stand for labor input and capital input, respectively. β_l represents the labor output elasticity while β_k is the capital output elasticity.

The firm-level total factor productivity is estimated as in Equation (4.2).

$$\log(TFP_{it}) = \log(Y_{it}) - \hat{\beta}_l \log(L_{it}) - \hat{\beta}_k \log(K_{it}) \quad (4.2)$$

where $\hat{\beta}_l$ and $\hat{\beta}_k$ are estimated using the generalized method of moments (GMM) estimators suggested by Wooldridge (2009) for the baseline results. The extant literature shows several approaches to estimate production functions for firm productivity (see Ackerberg et al. (2015)). In this study, we follow the method proposed by Wooldridge (2009) with one-step GMM estimator for our baseline findings. Additionally, for robustness checks, we also employ the methods of Levinsohn and Petrin (2003) and Olley and Pakes (1996) with Ackerberg et al. (2015) (ACF) correction.

Referring to related studies (Ackerberg et al., 2015; Li et al., 2021; Ren et al., 2022), we adopt following variables (as presented in Table 4.1A) to estimate firm productivity (TFP) following aforementioned approaches.

Table 4.1. List of variables and their data sources

Variable	Symbol	Proxied by	Unit	Data sources
A. Variables to estimate total factor productivity (TFP)				
Firm's output	*Output*	Operating income	US dollar	Refinitiv Eikon
Labor input	*Labor*	Number of employees	Employee	
Capital input	*Capital*	Net fixed assets	US dollar	
Intermediate input	*Intermediate*	Total costs exclude depreciation and amortization	US dollar	
B. Explanatory variables				
Capital expenditures	*Capex*	Firm's capital expenditures	US dollar	Refinitiv Eikon
Corporate governance	*Governance*	Governance pillar score	Score	
State ownership	*State_own*	Percentage of state ownership of capital	Ratio	
Liquidity	*Liquidity*	(Current assets - Current liabilities) / Total assets	Ratio	

4.3.1.2. Estimating the determinants of firm productivity

To identify the determinants of firm productivity in Energy sector, we propose the regression model as in Equation (4.3).

$$TFP_{i,c,t} = \alpha_c + \alpha_t + \beta_1 Capex_{i,c,t} + \beta_2 Cross\_listing + \beta_3 Capex_{i,c,t} * Cross\_listing + X_{i,c,t}\gamma + \varepsilon_{i,c,t} \quad (4.3)$$

where i, c, t stand for firm, country, and year, respectively. TFP is the total factor productivity, estimated using Wooldridge (2009) with one-step GMM estimator. α_c and α_t captures the country-fixed effects and year-fixed effects, respectively. $Capex$ stands for firm's capital expenditures. $Cross\_listing$ is a dummy variable ($Cross\_listing$ = 1 for the period after cross-listing and = 0 otherwise). X represents the matrix of other firm-level variables, including (i) *Governance*, corporate governance, measured by the governance pillar score; (ii) *State_own*, the state ownership of capital; and (iii) *Liquidity*, the ratio of (current assets - current liabilities) to total assets (see Table 4.1B). We based on previous studies on firm productivity (Ding et al., 2016; Tian & Twite, 2011) to employ those firm-level variables in our regression models.

Various model specifications are employed to estimate the determinants of firm productivity, including (1) random effects model; (2) country-fixed effects; (3) year-fixed effects; and (4) both country-fixed effects and year-fixed effects, which is also the regression model in Equation (4.3). In each model from (1) to (4), we present the regression results for the non-demeaned interaction term (i.e., *Capex*Cross_listing*) and the demeaned interaction term (i.e., *Demeaned_capex*Cross_listing*). The demeaned interaction term is proposed by Balli and Sørensen (2013) to minimize the risk in which the estimated interaction terms might capture the data's other features spuriously. Accordingly, the authors suggest the panel regressions should be estimated as in Equation (4.4[14]).

$$Y_{it} = \mu_i + \tau_1 Z_{1it} + \tau_2 Z_{2it} + \tau_3 (Z_{1it} - \bar{Z}_{1i.})(Z_{2it} - \bar{Z}_{2i.}) + \varepsilon'_{it} \quad (4.4)$$

where Z_{1it} and Z_{2it} stand for the explanatory variables for unit *i* at time *t*. $\bar{Z}_{1i.}$ and $\bar{Z}_{2i.}$ represent the mean of Z_{1it} and Z_{2it} over time for cross-sectional unit i, respectively.

Additionally, robust standard errors are adopted in all of our regression models (see the empirical results in Section 4.4.2). Such robust standard errors are considered to be asymptotically equivalent to the ones proposed in Arellano (1987)'s study, which appear robust to both within-panel (serial) correlation and cross-sectional heteroskedasticity.

4.3.2. Data

Based on the consolidated data from Citibank and Bank of New York Mellon depository receipts websites, we obtain list of firms which cross-list to the US stock markets from 2002 to 2022. Annual data of variables for estimating the total factor productivity (TFP) and regression models are all collected from Refinitiv Eikon. Our final sample consists of 911 firm-year observations on 59 cross-listed firms from Energy sector. Regarding electricity firms, we have a total number of 22 electricity firms with 385 firm-year observations.

Table 4.2 reports the summary statistics of all variables employed in our study. We note that our mean of total factor productivity (TFP) (as shown in Table 4.2A) is nearly equal to the mean TFP from previous studies on firm productivity (Figal Garone et al., 2020; Fiorini et al., 2021; Nakatani, 2023; Tian & Twite, 2011). Such similarity confirms the reliability of our estimations of firm productivity. The correlation matrix in Table 4.2B indicates that all cross correlations are less than 80% (in absolute value), which show that there is little evidence of multicollinearity in our models. Additionally, we also perform the panel unit root tests for our employed variables. The augmented Dickey-Fuller (ADF) and Phillips-Perron (PP) unit root tests confirm the stationarity of all variables employed in our study.

[14] This is done for one interaction variable example, to illustrate the model in a simple manner.

Table 4.2. Summary statistics of variables

A. Descriptive statistics						
Variable name	Observations	Mean	Median	SD	Min	Max
Output	911	21.122	20.374	3.065	12.991	30.795
Capital	911	23.025	22.268	3.143	15.006	32.240
Labor	911	8.611	8.517	1.947	2.197	13.223
Intermediate	911	22.974	22.552	3.097	15.118	31.388
TFP-WRDG	911	2.707	2.762	1.077	-2.276	5.562
TFP-LP (2003)	911	0.846	0.928	1.008	-3.926	3.084
TFP-OP (1996)	911	2.365	2.431	1.058	-2.620	5.230
TFP-Translog	911	2.724	2.666	1.240	-2.080	6.311
Capex	911	14.516	19.886	10.52	0.000	29.053
Governance	911	0.343	0.325	0.315	0.000	0.986
State_own	911	0.188	0.000	0.256	0.000	0.727
Liquidity	911	0.086	0.091	0.142	-1.103	0.525
Cross_listing	911	0.673	1.000	0.469	0.000	1.000
B. Correlation matrix						
	TFP-WRDG	*Capex*	*Governance*	*State_own*	*Liquidity*	
TFP-WRDG	1.000					
Capex	0.141	1.000				
Governance	0.078	0.413	1.000			
State_own	0.077	0.464	0.583	1.000		
Liquidity	0.291	0.012	-0.060	-0.013	1.000	

Note: *Output* - firm's output; *Capital* - capital input; *Labor* - labor input; *Intermediate* - intermediate input; *TFP-WRDG* - firm productivity using Wooldridge (2009) method; *TFP-LP (2003)* - firm productivity using Levinsohn and Petrin (2003) method; *TFP-OP (1996)* - firm productivity using Olley and Pakes (1996) method; *TFP-Translog* - firm productivity using translog method; *Capex* - firm's capital expenditures; *Governance* - corporate governance; *State_own* - state ownership of capital; *Liquidity* - firm's liquidity; *Cross_listing* - a dummy variable (= 1 for the period after cross-listing and = 0 otherwise). Except for *Cross_listing*, all other variables presented in this table have already been transformed.

4.4. Empirical results

4.4.1. Firm productivity in Energy sector and cross-listing

In this section, we first estimate the total factor productivity (TFP) employing Wooldridge (2009)'s approach with one-step GMM estimator for our baseline results.

Table 4.3 presents our estimated firm productivity in Energy sector for the whole sample. For comparison purposes, we also include firm productivity estimated for other selected sectors in our sample. We split the period after cross-listing into two different stages: Stage (1) is the first five years after cross-listing, and Stage (2) is the remaining years following Stage (1). Subsequently, we present different comparisons of firm productivity, including (*i*) After cross-listing versus Before cross-listing; (*ii*) Stage (1) versus Before cross-listing, and (*iii*) Stage (2) versus Before cross-listing.

We use the t-test for difference in mean to identify the difference in firm productivity between the groups (i.e., periods after cross-listing versus before cross-listing). Additionally, we adopt the propensity-score matching (PSM) method which was proposed by Rosenbaum and Rubin (1983). This approach is a quasi-experimental method that helps create a control group through matching each treated unit with each non-treated one which has similar properties. By employing those matches, we could examine the effect of an intervention (such as cross-listing decision) (The World Bank, 2023b). For each table in this sub-section, a statistically significant negative (positive) value indicates a significant decrease (increase) in the latter period compared to the former period (for example, “After cross-listing” compared to “Before cross-listing”).

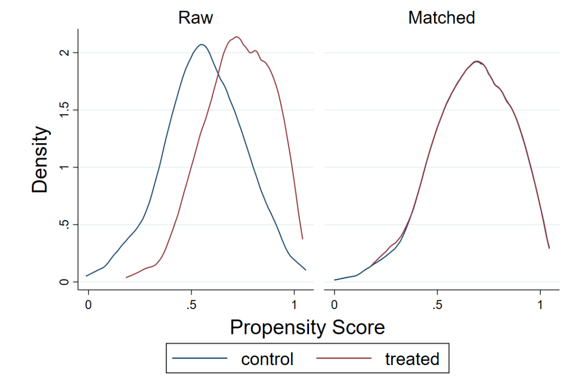
Table 4.3. Firm productivity among sectors: Before and after cross-listing (Full sample)

	Comparison	Difference in mean	Propensity-score matching	Number of observations
Energy	After vs Before	0.011	-0.406***	911
	Stage (1) vs Before	0.098	-0.188**	535
	Stage (2) vs Before	-0.044	-0.543***	674
Electricity firms	After vs Before	-0.182**	-0.253***	385
	Stage (1) vs Before	-0.185**	-0.246**	229
	Stage (2) vs Before	-0.180**	-0.163**	291
Other sectors				
Basic Materials	After vs Before	0.042	0.008	1,515
	Stage (1) vs Before	0.088*	0.060	955
	Stage (2) vs Before	0.011	-0.025	1,133
Consumer Discretionary	After vs Before	0.119***	0.191***	2,774
	Stage (1) vs Before	0.186***	0.246***	1,831
	Stage (2) vs Before	0.064*	0.148**	1,996
Health Care	After vs Before	0.351***	0.229***	1,041
	Stage (1) vs Before	0.305***	0.305***	653
	Stage (2) vs Before	0.382***	0.258***	781
Industrials	After vs Before	0.040	-0.002	3,569
	Stage (1) vs Before	0.097***	0.127***	2,345
	Stage (2) vs Before	-0.003	-0.068	2,647
Real Estate	After vs Before	0.395***	0.256***	663
	Stage (1) vs Before	0.379***	0.278***	448
	Stage (2) vs Before	0.407***	0.223***	492
Technology	After vs Before	0.120*	0.057	827
	Stage (1) vs Before	0.078	0.061	510
	Stage (2) vs Before	0.146*	-0.045	633
Telecommunications	After vs Before	0.027	0.140	384
	Stage (1) vs Before	0.264**	0.154	202
	Stage (2) vs Before	-0.102	-0.055	285
Utilities	After vs Before	-0.061	-0.050	779
	Stage (1) vs Before	-0.0001	0.020	461
	Stage (2) vs Before	-0.098*	-0.143**	589

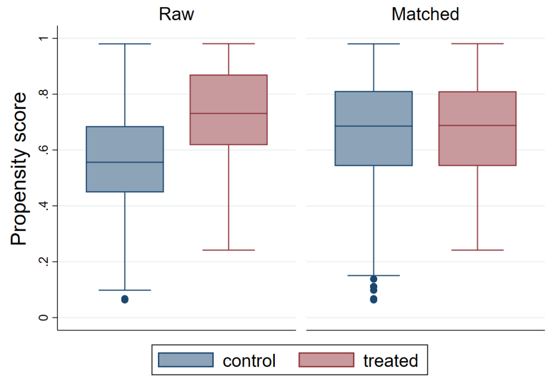
Notes: ***, ** and * indicate significance at the 1%, 5% and 10% level, respectively. Firm productivity is estimated employing the Wooldridge (2009)’s approach. Due to space limit, the standard errors are not presented. “Before” stands for Before cross-listing. “After” is After cross-listing. Stage (1) is the first five years after cross-listing. Stage (2) is the remaining years following Stage (1). A statistically significant negative (positive) value indicates a significant decrease (increase) in the latter period compared to the former period. Column “Difference in mean” is estimated using t-test. See the full table at Appendix Table 4.A1.

Looking at Table 4.3, we find evidence that a majority of sectors witness increases in firm productivity after cross-listing (i.e., Stage (1) and/or Stage (2) compared to Before cross-listing), indicated by the statistically significant positive values from Table 4.3.

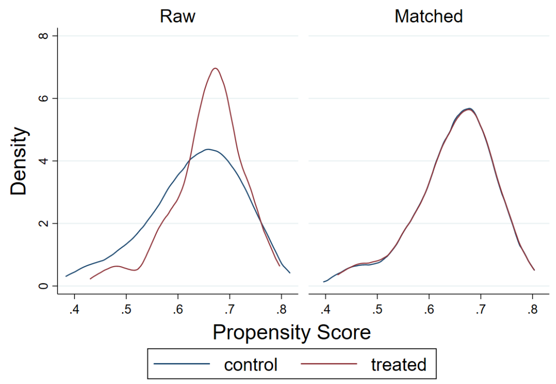
Remarkably, as can be seen in Table 4.3, regarding Energy sector, the propensity-score matching shows statistically significant negative coefficients, which indicate significant decreases in productivity after energy firms cross-list in the US. Similarly, we also find strong evidence (from both the t-test and propensity-score matching) that electricity firms witness decreased productivity after they cross-list. These findings are contrary to our hypothesis that firm productivity will be improved after cross-listing process because we consider that after cross-listing, firms might have easy access to foreign capital with lower costs, which in turn enables firms to become more competitive (Dodd, 2013; Mittoo, 2003), and hence firms might gain higher productivity in general.



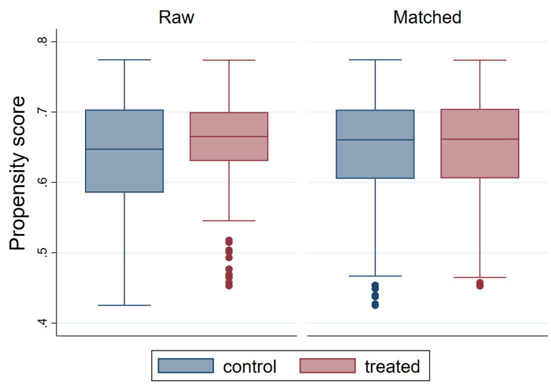
a1. Kernel density plots (Energy sector)



a2. Box plots (Energy sector)



b1. Kernel density plots (Electricity firms)



b2. Box plots (Electricity firms)

Figure 4.1. Plots to check for covariate balance after estimations of propensity-score matching (firm productivity before versus after cross-listing)

We also conduct additional diagnostics to ensure that the propensity-score matching performs properly. Generally, if the matching approach is well specified, the covariates should be balanced. The kernel density plots and box plots in Figure 4.1 might help assess whether the propensity-score matching balances the covariates over treatment levels. As can be seen from Figure 4.1.a1 & 4.1.b1, the kernel density plots for the matched sample appear mostly indistinguishable between the control group (blue line) and the treated group (red line), meaning that the covariates appear to be balanced by matching on the estimated propensity score. With respect to Figure 4.1.a2 & 4.1.b2, we can see that the box plots in case of the matched sample tend to be very similar. We note that the 25th percentiles, the medians, and the 75th percentiles seem to be the same (for the matched sample), even though some differences are found in the lower adjacent values, the tails, and the outliers. As such, the box plots also indicate that the matching method balances the estimated propensity scores. In summary, the diagnostic plots confirm the reliability of the results estimated by the propensity-score matching.

This interesting finding leads us to separate our sectoral sub-samples into developed and emerging countries for further analysis (see Appendix Table 4.A2). Similar to above findings for the full sample, we note that in several sectors from both developed and emerging countries, productivity at firm level appears improved after cross-listing decisions. Again, we document that Energy is the only sector in which firm productivity becomes lower after cross-listing in both emerging and developed countries. As such, we will identify the determinants of firm productivity in Energy sector to see which factors cause the decreases in productivity of energy firms after they cross-list to the US financial markets (see Section 4.4.2).

4.4.2. Determinants of firm productivity in Energy sector

We consider one possible explanation for the declined productivity in Energy sector is that after cross-listing in the US, both electricity firms and other firms from Energy sector tend to use their increased capital to heavily invest in infrastructure, equipment, and plants for expansion. Indeed, the US deregulation and restructuring in Energy sector are found to lead to energy firms' excessive investments (Constellation, 2023; Hill, 2021) in the early years of the deregulation. Such investments might in turn hinder improvements in their productivity. Energy firms cross listed in US markets might have the same amount of investment after they cross list and obtain the funds. In order to check for this assumption, we then perform the tests to see whether firm's capital expenditures and fixed assets increase after firms cross-list.

As can be seen from Table 4.4, our t-test and propensity-score matching show statistically significant positive values in both emerging and developed economies, meaning that capital expenditures and fixed assets of both electricity firms and other Energy firms have significant increases after cross-listing. We also use the kernel density plots to check for the covariate balance after performing the propensity-score matching (see Appendix Figure 4.A1 & 4.A2), which show that the matching method balances the estimated propensity scores. It implies that our results estimated by the propensity-score matching appear reliable. Our findings also confirm the aforementioned assumption that energy companies do have greater ability to raise more external lower-cost funding after they cross-list to the US financial markets and hence, invest more in equipment and infrastructure, which are shown by the increases in their fixed assets after cross-listing process. Besides, our findings are consistent with Lins et al. (2005), Pagano et al. (2002) and Reese and Weisbach (2002) who find that cross-listed firms appear to have a better ability to access external financing at a lower cost. Indeed, extant literature has provided several explanations for why cross-listing might help firms raise lower-cost capital. First, theory suggests that cross-listing could help lower costs regarding market segmentation effectively, which in turn might reduce the cost of external financing (Khurana et al., 2008). Second, according to the investor recognition hypothesis of Merton (1987), if a firm's stock improves its investor base through increasing visibility (i.e., cross-listing), firm's cost of capital should be eventually reduced and firm's market value should increase. Another reason that cross-listed firms might obtain lower-cost external capital lies in the arguments of Coffee (1999b) and Stulz (1999), who suggest that cross-listing will lead to a lower-cost external funding by serving to mitigate the risk arising from wealth expropriation. For instance, if a firm cross-lists in the US market, investors appear to receive better protection from the US institutions than those in the home country of that cross-listed firm (Khurana et al., 2008).

Table 4.4. Firm's capital expenditures and fixed assets in Energy sector: Before and after cross-listing (Emerging versus Developed countries)

		Energy sector						Electricity firms					
		Emerging countries			Developed countries			Emerging countries			Developed countries		
		Difference in mean	Propensity-score matching	N	Difference in mean	Propensity-score matching	N	Difference in mean	Propensity-score matching	N	Difference in mean	Propensity-score matching	N
Capital expenditures	After vs Before	10.224*** (1.167)	10.201*** (1.392)	389	10.767*** (0.772)	10.245*** (0.980)	522	7.970*** (2.383)	5.281** (2.120)	126	14.162*** (0.976)	15.178*** (1.492)	259
	Stage (1) vs Before	8.212*** (1.542)	9.980*** (1.584)	205	9.589*** (1.036)	9.713*** (1.110)	330	12.095*** (2.685)	10.310*** (2.291)	59	13.820*** (1.427)	14.750*** (1.283)	170
	Stage (2) vs Before	11.284*** (1.212)	10.783*** (1.454)	292	11.625*** (0.872)	11.332*** (0.986)	382	6.062*** (2.492)	3.666 (2.469)	95	14.405*** (1.252)	15.177*** (1.536)	196
Fixed assets	After vs Before	1.583*** (0.380)	0.743** (0.330)	389	1.740*** (0.227)	1.559*** (0.290)	522	-0.0084 (0.298)	0.263 (0.198)	126	1.107*** (0.418)	1.491*** (0.406)	259
	Stage (1) vs Before	0.853** (0.487)	-0.316 (0.460)	205	1.224*** (0.276)	1.112*** (0.383)	330	0.585* (0.439)	0.634* (0.325)	59	0.398 (0.555)	0.586 (0.558)	170
	Stage (2) vs Before	1.968*** (0.405)	1.465*** (0.347)	292	2.116*** (0.258)	2.158*** (0.315)	382	-0.283 (0.243)	0.0004 (0.180)	95	1.609*** (0.480)	2.176*** (0.448)	196

Notes: Standard errors are in parentheses. ***, ** and * indicate significance at the 1%, 5% and 10% level, respectively. "Before" stands for Before cross-listing. "After" is After cross-listing. Stage (1) is the first five years after cross-listing. Stage (2) is the remaining years following Stage (1). A statistically significant negative (positive) value indicates a significant decrease (increase) in the latter period compared to the former period. N stands for the number of observations. Column "Difference in mean" is estimated using t-test.

Next, we analyze the determinants of Energy sector's firm productivity to seek more thorough explanations for the decreased firm productivity in Energy sector after cross-listing. For that purpose, we employ the regression model (4.3) as presented in Section 4.3.1.2. The regression models are performed for the full sample (Table 4.5) and for the two sub-samples, including emerging countries and developed countries (Table 4.6). We estimate our regression models using different specifications, including (1) random effects model; (2) country-fixed effects; (3) year-fixed effects; and (4) both country-fixed effects and year-fixed effects, which is also the regression model in Equation (4.3). In each model from (1) to (4), we present the regression results for the non-demeaned interaction term (i.e., *Capex*Cross_listing*) and the demeaned interaction term (i.e., *Demeaned_capex*Cross_listing*) which is proposed by Balli and Sørensen (2013). Furthermore, in all regression models, the robust standard errors are adopted, which are robust to within-panel (serial) correlation and cross-sectional heteroskedasticity, as equivalent to Arellano (1987)'s robust standard errors.

Looking at model specification (1) in Table 4.5, we note that the coefficients of our key variable (*Capex* Cross_listing*) are -0.024 (in case of non-demeaned interaction term) and -0.033 (in case of demeaned interaction term). Those coefficients are statistically significant and negative at 1% level, indicating strong evidence that an increase in firm's capital expenditures after cross-listing appears to reduce firm productivity. This is in line with our above proposition that heavy investments in the infrastructure in the Energy sector (thanks to cross-listing) might lead to the decreases in firm productivity in the short term. We also find similar results across the remaining model specifications (2 to 4) in case of the full sample (Table 4.5) as well as the emerging and developed countries (Table 4.6). This finding mostly explains why productivity of energy firms becomes lower after they cross-list as found in Section 4.4.1. According to the agency theory (Jensen, 1986; Jensen & Meckling, 1976), when there are extra free cashflows, firm managers tend to use such excessive cash to invest in new projects, even though the net present values of those projects are forecast to be negative. Consequently, firm value appears to be deteriorated by the over-investment of free extra cashflows. In addition, it is found that firms that have excessive investments tend to witness lower future stock returns (Fairfield et al., 2003; Titman et al., 2004). Although the cashflow itself appears to exert a positive impact on firm growth, free cashflow might adversely affect firm growth (Brush et al., 2000). Eventually, extra free cashflows tend to damage firm value (Park & Jang, 2013). Given the negative impacts of excessive capital on firm value and growth, although cross-listing might help improve energy firm's ability to raise additional external funding for investments, such extra capital tends to deteriorate firm productivity in short term. This interesting finding is contrary to our hypothesis that the more cost-effective capital acquired by companies through cross-listing has the potential to stimulate their overall productivity.

Additionally, we note that the state ownership of capital (*State_own*) has significant negative effects on firm productivity in Energy sector for the whole sample (Table 4.5). When decomposing the full sample into emerging and developed economies (Table 4.6), we note that the negative impacts of factors (i.e., *Capex*Cross_listing* and *State_own*) are found to be much stronger and more statistically significant in developed economies than in emerging economies. Furthermore, we also find evidence that corporate governance (*Governance*) (in case of the full sample - Table 4.5) and firm's liquidity (*Liquidity*) (in case of the full sample - Table 4.5 as well as emerging countries - Table 4.6A) might help improve firm productivity in Energy sector. These results are consistent with findings from previous studies (Ding et al., 2016; Tian & Twite, 2011).

Regarding electricity firms, as can be seen from Table 4.7, we do not find statistically significant impacts of the capital expenditures after cross-listing (*Capex* Cross_listing*) on firm productivity. However, we note that there are some significant negative effects of cross-listing itself (*Cross_listing*) on electricity firm's productivity in case of the full sample. Similar to the findings from Energy sector (Table 4.5 & 4.6), we also find evidence that corporate governance and firm liquidity are two factors that help enhance firm productivity, which are in line with Tian and Twite (2011) and Ding et al. (2016).

Table 4.5. Determinants of firm productivity in Energy sector (full sample)

	(1)		(2)		(3)		(4)	
	Non-demeaned	Demeaned	Non-demeaned	Demeaned	Non-demeaned	Demeaned	Non-demeaned	Demeaned
Capex	0.013^{**}	0.017^{***}	0.014^{***}	0.012^{**}	0.015^{**}	0.004	0.021^{***}	0.014^{**}
	(0.005)	(0.006)	(0.005)	(0.005)	(0.007)	(0.007)	(0.006)	(0.007)
Cross_listing	0.144	-0.204^{**}	0.076	-0.277^{***}	0.541^{***}	0.306^{***}	0.371^{***}	0.017
	(0.158)	(0.099)	(0.135)	(0.095)	(0.133)	(0.116)	(0.126)	(0.111)
*Capex*Cross_listing*	-0.024^{***}	-0.033^{***}	-0.028^{***}	-0.035^{***}	-0.016^{*}	-0.015^{*}	-0.023^{***}	-0.026^{***}
	(0.008)	(0.008)	(0.007)	(0.008)	(0.008)	(0.009)	(0.008)	(0.008)
Governance	0.294^{*}	0.295^{*}	1.244^{***}	1.255^{***}	0.638^{***}	0.661^{***}	1.287^{***}	1.291^{***}
	(0.175)	(0.174)	(0.154)	(0.152)	(0.142)	(0.142)	(0.149)	(0.150)
State_own	-0.644^{***}	-0.665^{***}	-1.044^{***}	-1.034^{***}	-0.440^{**}	-0.460^{**}	-0.578^{***}	-0.601^{***}
	(0.191)	(0.191)	(0.159)	(0.159)	(0.189)	(0.193)	(0.177)	(0.180)
Liquidity	0.671	0.575	1.003^{***}	0.948^{**}	0.732^{**}	0.716^{**}	0.873^{**}	0.840^{**}
	(0.522)	(0.537)	(0.375)	(0.386)	(0.340)	(0.340)	(0.376)	(0.378)
Random effects	Yes	Yes	No	No	No	No	No	No
Country fixed effects	No	No	Yes	Yes	No	No	Yes	Yes
Year fixed effects	No	No	No	No	Yes	Yes	Yes	Yes
Observations	911	911	911	911	911	911	911	911
Adjusted R^2	0.060	0.067	0.258	0.264	0.086	0.085	0.290	0.289

Notes: Robust standard errors are in parentheses, which are regarded to resolve the concerns of autocorrelation and heteroscedasticity. ***, ** and * indicate significance at the 1%, 5% and 10% level, respectively. Non-demeaned stands for the regression model with non-demeaned interaction term (i.e., *Capex*Cross_listing*). Demeaned stands for the regression model with the demeaned interaction term (i.e., *Demeaned_capex*Cross_listing*) which is proposed by Balli and Sørensen (2013).

Table 4.6. Determinants of firm productivity in Energy sector (Emerging countries versus Developed countries)

	(1)		(2)		(3)		(4)	
	Non-demeaned	Demeaned	Non-demeaned	Demeaned	Non-demeaned	Demeaned	Non-demeaned	Demeaned
A. Emerging countries								
Capex	0.015*	0.018**	0.022***	0.011	0.017*	0.004	0.038***	0.018*
	(0.008)	(0.008)	(0.008)	(0.008)	(0.009)	(0.011)	(0.010)	(0.011)
Cross_listing	0.117	-0.227	-0.053	-0.312**	0.362**	0.452**	0.427**	0.213
	(0.247)	(0.173)	(0.195)	(0.154)	(0.182)	(0.198)	(0.173)	(0.194)
*Capex*Cross_listing*	-0.023**	-0.030***	-0.027**	-0.031***	0.011	0.012	-0.013	-0.013
	(0.011)	(0.010)	(0.011)	(0.011)	(0.011)	(0.014)	(0.011)	(0.013)
Governance	0.085	0.097	1.348***	1.420***	0.852***	1.014***	1.387***	1.502***
	(0.251)	(0.248)	(0.230)	(0.226)	(0.246)	(0.240)	(0.218)	(0.222)
State_own	-0.120	-0.167	-0.881***	-0.903***	0.120	0.136	-0.244	-0.351
	(0.272)	(0.280)	(0.238)	(0.240)	(0.295)	(0.308)	(0.258)	(0.269)
Liquidity	1.968***	1.878***	2.266***	2.304***	1.622***	1.662***	1.830***	1.923***
	(0.594)	(0.604)	(0.395)	(0.400)	(0.437)	(0.441)	(0.402)	(0.404)
B. Developed countries								
Capex	0.010	0.015*	0.009	0.015**	-0.000	0.002	-0.001	0.004
	(0.006)	(0.008)	(0.006)	(0.007)	(0.008)	(0.009)	(0.008)	(0.009)
Cross_listing	0.243	-0.160	0.400**	-0.136	0.593***	0.067	0.344*	-0.099
	(0.189)	(0.126)	(0.175)	(0.118)	(0.173)	(0.148)	(0.200)	(0.148)
*Capex*Cross_listing*	-0.028***	-0.036***	-0.037***	-0.047***	-0.034***	-0.043***	-0.029***	-0.039***
	(0.009)	(0.011)	(0.009)	(0.010)	(0.010)	(0.010)	(0.010)	(0.011)
Governance	0.339	0.330	0.924***	0.912***	0.403**	0.445***	0.893***	0.874***
	(0.227)	(0.229)	(0.198)	(0.195)	(0.160)	(0.159)	(0.205)	(0.203)
State_own	-0.839***	-0.849***	-1.123***	-1.168***	-0.884***	-1.000***	-0.988***	-1.091***
	(0.231)	(0.230)	(0.191)	(0.194)	(0.234)	(0.241)	(0.230)	(0.230)
Liquidity	-0.490	-0.580	-0.469	-0.631*	-0.465	-0.568	-0.477	-0.638*
	(0.568)	(0.603)	(0.350)	(0.378)	(0.323)	(0.356)	(0.351)	(0.385)
Random effects	Yes	Yes	No	No	No	No	No	No
Country fixed effects	No	No	Yes	Yes	No	No	Yes	Yes
Year fixed effects	No	No	No	No	Yes	Yes	Yes	Yes

Notes: Robust standard errors are in parentheses, which are regarded to resolve the concerns of autocorrelation and heteroscedasticity. ***, ** and * indicate significance at the 1%, 5% and 10% level, respectively. Non-demeaned stands for the regression model with non-demeaned interaction term (i.e., *Capex*Cross_listing*). Demeaned stands for the regression model with the demeaned interaction term (i.e., *Demeaned_capex*Cross_listing*) which is proposed by Balli and Sørensen (2013). See the full tables at Appendix Table 4.B1 & 4.B2.

Table 4.7. Determinants of firm productivity of electricity firms

	Full sample		Emerging countries		Developed countries	
	Non-demeaned	Demeaned	Non-demeaned	Demeaned	Non-demeaned	Demeaned
Capex	0.001	-0.002	0.004	0.002	0.004	-0.001
	(0.007)	(0.006)	(0.012)	(0.013)	(0.013)	(0.012)
Cross_listing	-0.497***	-0.391***	-0.279	-0.264	-0.486	-0.303
	(0.190)	(0.148)	(0.175)	(0.229)	(0.652)	(0.249)
*Capex*Cross_listing*	0.008	0.018	0.002	0.009	0.011	0.015
	(0.009)	(0.013)	(0.012)	(0.016)	(0.029)	(0.036)
Governance	0.645***	0.649***	0.834*	0.787*	0.686**	0.669**
	(0.216)	(0.215)	(0.475)	(0.470)	(0.267)	(0.268)
State_own	0.003	0.036	-0.372	-0.296	0.143	0.166
	(0.203)	(0.199)	(0.368)	(0.374)	(0.270)	(0.265)
Liquidity	1.059**	1.046**	0.898	0.903	1.227**	1.251**
	(0.457)	(0.451)	(1.008)	(1.008)	(0.583)	(0.594)
Country fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	385	385	125	125	259	259
Adjusted R^2	0.321	0.325	0.388	0.391	0.289	0.288

Notes: Robust standard errors are in parentheses, which are regarded to resolve the concerns of autocorrelation and heteroscedasticity. ***, ** and * indicate significance at the 1%, 5% and 10% level, respectively. Non-demeaned stands for the regression model with non-demeaned interaction term (i.e., capex*cross_listing). Demeaned stands for the regression model with the demeaned interaction term (i.e., demeaned_capex*cross_listing) which is proposed by Balli and Sørensen (2013).

4.4.3. Robustness tests

4.4.3.1. Robustness tests using different approaches

In this section, we perform different approaches to test for the robustness of our baseline results. First, we employ the two-step system generalized method of moments (GMM) estimation and linear mixed model to re-estimate the determinants of Energy firm productivity. Theoretically, the system GMM estimation will be suggested in case of panel data estimations that encounter endogeneity issues (Nickell, 1981). In this study, we employ the two-step system GMM estimators of Arellano and Bover (1995) and Blundell and Bond (1998) as a robustness check as this estimation appears quite efficient to help mitigate the bias regarding fixed effects in short panels and solve the endogeneity problem (Canh et al., 2020). Furthermore, we use the finite-sample correction for the variance of two-step GMM estimators proposed by Windmeijer (2005) for more accurate inference. Regarding the linear mixed-effects model (or linear mixed model), it is considered an extended version of a simple linear model, allowing not only fixed effects but also random effects. In other words, a linear mixed model includes some factors that are random and other factors that are fixed (Duchateau & Janssen, 1997; Verbeke & Molenberghs, 2000). Oberg and Mahoney (2007) argue that linear mixed models appear to be a versatile tool for addressing research objectives efficiently. Under this framework, within-subject correlation could be modelled and the estimation process could be weighted to allow subjects with more information and information with less variability to give more to our analyses (Oberg & Mahoney, 2007).

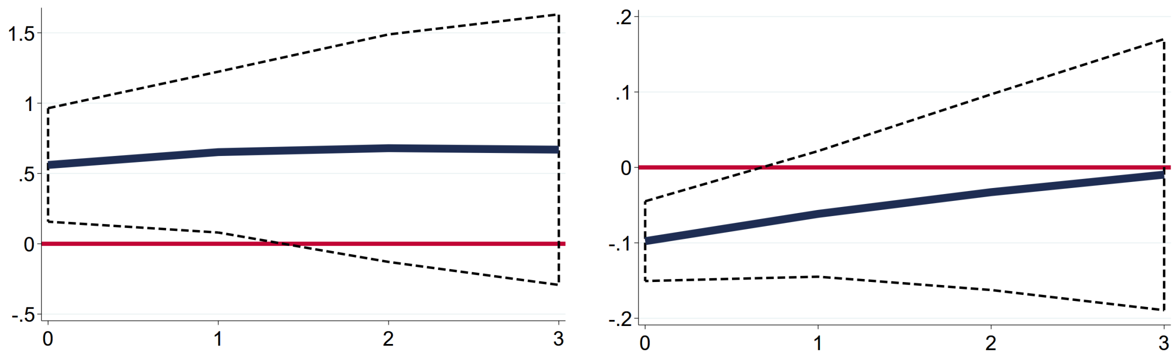
As can be seen from Table 4.8, our robustness tests confirm the significant negative effects of capital expenditures (after cross-listing) (*Capex* Cross_listing*) and state ownership (*State_own*) on firm-level productivity in Energy sector. Also, Table 4.8 confirms the baseline findings (as found in Section 4.4.2) that corporate governance (*Governance*) positively affects firm productivity in both electricity firms and other firms in Energy sector.

Table 4.8. Robustness test: Determinants of firm productivity (using alternative approaches)

	Energy sector				Electricity firms			
	Two-step system GMM estimation		Linear mixed model		Two-step system GMM estimation		Linear mixed model	
	Non-demeaned	Demeaned	Non-demeaned	Demeaned	Non-demeaned	Demeaned	Non-demeaned	Demeaned
Capex	0.029***	0.034***	0.013**	0.017***	-0.006	-0.004	-0.005	-0.006
	(0.010)	(0.010)	(0.005)	(0.006)	(0.006)	(0.006)	(0.005)	(0.005)
Cross_listing	0.702*	-0.302	0.176	-0.192*	-0.798	-0.690***	-0.522*	-0.485***
	(0.382)	(0.193)	(0.156)	(0.099)	(0.501)	(0.239)	(0.305)	(0.174)
Capex Cross_listing*	-0.052***	-0.061***	-0.025***	-0.033***	0.011	0.013	0.003	0.011
	(0.017)	(0.012)	(0.007)	(0.008)	(0.017)	(0.017)	(0.010)	(0.011)
Governance	-0.102	0.064	0.297*	0.298*	0.720***	0.719***	0.591***	0.596***
	(0.319)	(0.331)	(0.173)	(0.172)	(0.241)	(0.251)	(0.219)	(0.221)
State_own	-0.920**	-0.622*	-0.653***	-0.674***	0.262	0.336	0.108	0.118
	(0.426)	(0.366)	(0.190)	(0.191)	(0.324)	(0.302)	(0.253)	(0.256)
Liquidity	0.683	0.802	0.693	0.598	1.430	1.542	1.235***	1.236***
	(1.000)	(0.845)	(0.517)	(0.533)	(0.968)	(1.051)	(0.440)	(0.432)
Observations	852	852	911	911	363	363	385	385
Hansen test of overidentifying restrictions								
Statistic	53.69	52.29	-	-	17.74	17.67	-	-
p-value	1.000	1.000			1.000	1.000		

Notes: Robust standard errors are in parentheses, which are regarded to resolve the concerns of autocorrelation and heteroscedasticity. ***, ** and * indicate significance at the 1%, 5% and 10% level, respectively. Non-demeaned stands for the regression model with non-demeaned interaction term (i.e., *Capex*Cross_listing*). Demeaned stands for the regression model with the demeaned interaction term (i.e., *Demeaned_capex*Cross_listing*) which is proposed by Balli and Sørensen (2013).

Apart from the panel data analysis, we adopt the panel Impulse Response function (IRF) after a panel Vector Autoregression model (PVAR) as another robust test. In term of Energy sector, Figure 4.2 provides the evidence that cross-listing significantly increases firm's capital expenditures (Figure 4.2a) and that a shock from capital expenditures has a significant negative impact on firm productivity (Figure 4.2b).



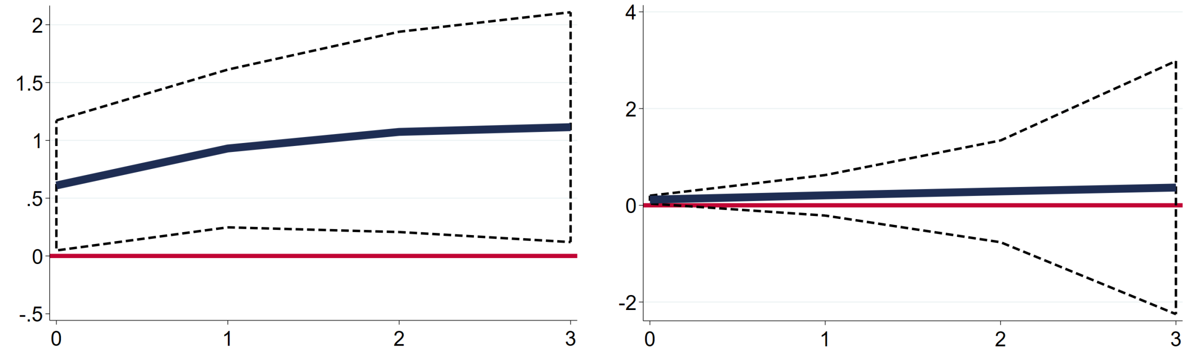
a. Response of Capital Expenditures to a shock from Cross-listing

b. Response of Firm Productivity to a shock from Capital Expenditures

Figure 4.2. Impulse response analysis for Energy sector

Notes: The analysis is based on the 95% confidence interval.

With respect to electricity firms, as can be seen from Figure 4.3a, the impulse response analysis confirms that cross-listing does have positive effects on firm capital expenditures. Additionally, similar to our baseline findings, Figure 4.3b indicates that capital expenditure is not a channel to affect productivity of electricity firms.



a. Response of Capital Expenditures to a shock from Cross-listing

b. Response of Firm Productivity to a shock from Capital Expenditures

Figure 4.3. Impulse response analysis for electricity firms

Notes: The analysis is based on the 95% confidence interval.

4.4.3.2. Robustness tests using alternative measures of firm productivity and capital expenditure

In this section, we employ alternative measures of firm productivity, which are estimated using the methods of (i) Levinsohn and Petrin (2003) with ACF (Ackerberg et al., 2015) correction; (ii) Olley and Pakes (1996) with ACF correction; and (iii) the Translog production function. We conduct the t-test and Propensity-score matching (Table 4.9) as well as the regression models using aforementioned alternative estimations of productivity (Table 4.10). Furthermore, we also use the ratio of capital expenditures/number of employees (*Capex_labor*) as the variable of interest, instead of firm's capital expenditures (*Capex*) to estimate the determinants of firm productivity (Table 4.11). As can be seen, the estimation results from Table 4.9, 4.10 & 4.11 confirm the robustness of our baseline findings in Section 4.4.1 & 4.4.2.

Table 4.9. Robustness test: Firm productivity before and after cross-listing (using alternative productivity measures)

	Levinsohn and Petrin (2003)		Olley and Pakes (1996)		Translog production function	
	Difference in mean	Propensity-score matching	Difference in mean	Propensity-score matching	Difference in mean	Propensity-score matching
A. Energy sector						
After vs Before	-0.103*	-0.422***	-0.117*	-0.414***	0.062	-0.390***
	(0.071)	(0.076)	(0.075)	(0.073)	(0.088)	(0.089)
Stage (1) vs Before	0.030	-0.212**	0.013	-0.239***	0.128	-0.103
	(0.083)	(0.087)	(0.089)	(0.088)	(0.101)	(0.100)
Stage (2) vs Before	-0.186***	-0.568***	-0.199***	-0.592***	0.021	-0.459***
	(0.076)	(0.099)	(0.080)	(0.097)	(0.094)	(0.102)
B. Electricity firms						
After vs Before	-0.238***	-0.272***	-0.160**	-0.249***	-0.238***	-0.250***
	(0.086)	(0.068)	(0.084)	(0.070)	(0.093)	(0.070)
Stage (1) vs Before	-0.223**	-0.257**	-0.189**	-0.208**	-0.184*	-0.271**
	(0.109)	(0.108)	(0.108)	(0.106)	(0.124)	(0.117)
Stage (2) vs Before	-0.247***	-0.181***	-0.142**	-0.187***	-0.271***	-0.142*
	(0.082)	(0.063)	(0.083)	(0.069)	(0.090)	(0.076)

Notes: Standard errors are in parentheses. ***, ** and * indicate significance at the 1%, 5% and 10% level, respectively. "Before" stands for Before cross-listing. "After" is After cross-listing. Stage (1) is the first five years after cross-listing. Stage (2) is the remaining years following Stage (1). A statistically significant negative (positive) value indicates a significant decrease (increase) in the latter period compared to the former period. Column "Difference in mean" is estimated using t-test.

Table 4.10. Robustness test: Determinants of firm productivity (using alternative productivity measures)

A. Energy sector	Baseline model			Two-step system GMM estimation			Linear mixed model		
	LP (2003)	OP (1996)	Translog	LP (2003)	OP (1996)	Translog	LP (2003)	OP (1996)	Translog
Capex	0.014**	0.013*	0.028***	0.027***	0.034***	0.029***	0.011**	0.011*	0.015***
	(0.006)	(0.007)	(0.007)	(0.010)	(0.013)	(0.011)	(0.005)	(0.006)	(0.005)
Cross_listing	0.292**	0.211*	0.527***	0.777**	0.203	0.490	0.138	0.076	0.265*
	(0.121)	(0.121)	(0.148)	(0.379)	(0.303)	(0.423)	(0.161)	(0.163)	(0.161)
*Capex*Cross_listing*	-0.021***	-0.014*	-0.035***	-0.055***	-0.040***	-0.048***	-0.025***	-0.023***	-0.027***
	(0.007)	(0.008)	(0.008)	(0.017)	(0.010)	(0.016)	(0.008)	(0.008)	(0.008)
Governance	1.072***	1.015***	1.457***	-0.182	-0.190	-0.065	0.244	0.303*	0.224
	(0.144)	(0.150)	(0.164)	(0.301)	(0.398)	(0.380)	(0.171)	(0.181)	(0.173)
State_own	-0.484***	-0.282	-0.904***	-1.092**	-0.616	-0.461	-0.672***	-0.607***	-0.664***
	(0.172)	(0.174)	(0.203)	(0.487)	(0.415)	(0.479)	(0.191)	(0.196)	(0.212)
Liquidity	0.853**	1.540***	0.106	0.465	0.681	0.577	0.750	1.060*	0.325
	(0.370)	(0.424)	(0.350)	(0.955)	(1.088)	(0.830)	(0.520)	(0.563)	(0.483)
Observations	911	911	911	852	852	852	911	911	911
B. Electricity firms	Baseline model			Two-step system GMM estimation			Linear mixed model		
	LP (2003)	OP (1996)	Translog	LP (2003)	OP (1996)	Translog	LP (2003)	OP (1996)	Translog
Capex	0.000	-0.001	0.003	-0.005	-0.006	-0.002	-0.005	-0.004	-0.005
	(0.006)	(0.006)	(0.007)	(0.006)	(0.006)	(0.009)	(0.005)	(0.005)	(0.006)
Cross_listing	-0.489***	-0.578***	-0.400**	-1.036**	-0.810	-0.817	-0.487	-0.504*	-0.559*
	(0.189)	(0.194)	(0.196)	(0.496)	(0.494)	(0.529)	(0.297)	(0.294)	(0.334)
*Capex*Cross_listing*	0.009	0.007	0.009	0.017	0.012	0.002	0.001	0.002	0.005
	(0.009)	(0.009)	(0.010)	(0.017)	(0.016)	(0.018)	(0.010)	(0.009)	(0.011)
Governance	0.650***	0.610***	0.638***	0.631***	0.711***	0.705**	0.542**	0.548**	0.643**
	(0.214)	(0.206)	(0.240)	(0.243)	(0.253)	(0.305)	(0.227)	(0.215)	(0.256)
State_own	0.023	0.061	-0.102	0.242	0.198	0.378	0.077	0.207	-0.031
	(0.203)	(0.195)	(0.225)	(0.344)	(0.348)	(0.355)	(0.252)	(0.247)	(0.270)
Liquidity	1.319***	1.444***	0.469	1.593*	1.499*	1.652	1.450***	1.381***	1.061**
	(0.465)	(0.467)	(0.467)	(0.883)	(0.800)	(1.314)	(0.430)	(0.461)	(0.422)
Observations	385	385	385	363	363	363	385	385	385

Notes: Robust standard errors are in parentheses, which are regarded to resolve the concerns of autocorrelation and heteroscedasticity. ***, ** and * indicate significance at the 1%, 5% and 10% level, respectively. LP (2003) stands for Levinsohn and Petrin (2003). OP (1996) stands for Olley and Pakes (1996). Translog stands for Translog production function. Baseline model is the regression model (4.3) presented in Section 4.3.1.2.

Table 4.11. Robustness test: Determinants of firm productivity (using alternative measure of capital expenditure)

	Energy sector			Electricity firms		
	Baseline model	Two-step system GMM	Linear mixed model	Baseline model	Two-step system GMM	Linear mixed model
Capex_labor	0.027***	0.044**	0.019**	-0.001	-0.014	-0.009
	(0.010)	(0.018)	(0.008)	(0.011)	(0.012)	(0.008)
Cross_listing	0.385***	0.350	0.175	-0.462**	-0.464	-0.448
	(0.126)	(0.323)	(0.154)	(0.189)	(0.743)	(0.289)
Capex_labor Cross_listing*	-0.039***	-0.060**	-0.040***	0.010	-0.010	0.001
	(0.012)	(0.026)	(0.012)	(0.015)	(0.047)	(0.015)
Governance	1.296***	0.053	0.308*	0.645***	0.659***	0.594***
	(0.149)	(0.331)	(0.170)	(0.213)	(0.226)	(0.213)
State_own	-0.581***	-0.973**	-0.668***	-0.002	0.555	0.110
	(0.177)	(0.489)	(0.191)	(0.205)	(0.472)	(0.251)
Liquidity	0.891**	0.291	0.709	1.072**	2.958	1.258***
	(0.369)	(1.106)	(0.518)	(0.463)	(2.222)	(0.434)
Observations	911	852	911	385	363	385

Notes: We use *Capex_labor* (capital expenditures/number of employees) as the variable of interest instead of *Capex* (firm's capital expenditures). Robust standard errors are in parentheses, which are regarded to resolve the concerns of autocorrelation and heteroscedasticity. ***, ** and * indicate significance at the 1%, 5% and 10% level, respectively.

4.5. Conclusions

This paper investigates the impact of cross-listing on firm productivity within the energy-electricity sector, focusing on changes that occur before and after cross-listing in the US financial markets. We employ annual data spanning from 2002 to 2022 for our analysis. This extended study period enables us to cover a sequence of energy-related crises that have occurred over the last two decades.

Our findings provide valuable insights into the relationship between cross-listing and firm productivity across different sectors, with particular attention to the energy sector. While most sectors experience increased productivity post-cross-listing, the energy sector (including electricity firms) stands out as an exception. Contrary to our initial expectations, energy firms witness statistically significant decreases in productivity following cross-listing in the US market. We explore the possibility that energy firms, after cross-listing, allocate a significant portion of their resources towards investments in infrastructure, equipment, and expansion, which temporarily hinder improvements in productivity. Indeed, the results are contrary to our initial hypothesis that energy companies gain access to more substantial capital upon US cross-listing, subsequently investing in equipment and infrastructure, leading to improved productivity. Furthermore, looking into additional determinants of firm productivity, the analysis demonstrates that state ownership has a negative impact on energy sector firms' productivity, with this effect being more pronounced in developed economies. Additionally, in line with previous research, we found evidence that corporate governance and liquidity might play a role in enhancing firm productivity within the energy sector (including electricity firms).

Chapter Five - Conclusion

In this chapter, key findings and implications of each essay are highlighted in Section 5.1. Potential avenues for future study are further suggested in Section 5.2.

5.1. Key findings and implications

5.1.1. Essay One (Chapter Two)

The first essay examines uncertainty spillovers across emerging market sectors from 2003 to 2022 using the quantile time-frequency connectedness approach. It also explores how various uncertainty indices affect total sectoral connectedness.

Overall, the results reveal exceptionally strong sectoral uncertainty transmission, with a total connectedness index of 91.01%, largely driven by long-term dynamics. Consumer Cyclicals emerges as a major transmitter of shocks, while Communications & Networking and Healthcare act as primary absorbers. From a quantile perspective, spillovers fluctuate markedly over time and intensify during major crises such as the 2007-2008 Global Financial Crisis, the 2016 Chinese stock market turbulence, and the 2020 COVID-19 pandemic. The connectedness also displays asymmetric behavior, becoming stronger under high-uncertainty conditions. Furthermore, uncertainty indices are positively associated with the sectoral total connectedness during periods of low uncertainty and normal market conditions but negatively related during turbulent periods, suggesting markets' adaptive and "herd immunity" behavior to extreme uncertainty. Finally, given the high and persistent interconnectedness, the paper highlights the importance of portfolio diversification and hedging strategies, showing that both the dynamic hedge ratio and minimum-variance portfolio approaches substantially reduce investment risk for international investors.

Apart from the suggested hedging strategies for investors, our results have the following policy implications. First, given that the sectoral total connectedness is mostly explained by long-term spillovers, policymakers are suggested to shift their focus to the long-term dynamics to design appropriate policies that mitigate the effects of adverse spillover shocks. Second, as Consumer Cyclicals is found to be the largest net transmitter of risk in both the short term and long term, this sector is regarded as the main source of shock transmission and thus. It tends to spread the risks strongly and rapidly to other sectors in emerging markets. As such, governments need to stabilize this sector first to reduce the risk of transmission within the system. Similarly, given that Communications & Networking and Healthcare are noted to be the largest risk receivers at the median level. Those sectors tend to receive the most shocks and hence turn out to be the most fragile and vulnerable sectors in the network. Therefore, those two sectors also need more serious attention and support from the governments. Third, we note that an increase in economic and financial uncertainties is associated with an increase in sectoral interconnectedness across different quantiles. Accordingly, governments are suggested to monitor the uncertainty indices to estimate the variations in the sectoral connectedness. Subsequently, emerging countries might employ timely and appropriate responses to mitigate the risk propagation across sectors.

5.1.2. Essay Two (Chapter Three)

This essay investigates how the global geopolitical-energy uncertainty (GEU) index developed by Dang et al. (2024a) influences firm-level total factor productivity (TFP) over the 2001-2023 period. While the GEU index has been shown to capture the interaction between geopolitical tensions, energy shocks, and policy uncertainty at macro and sectoral levels, its micro-level implications for firms' productivity remain largely unexplored. The second essay addresses this gap by providing the first comprehensive evidence on how global geopolitical-energy uncertainty affects firm productivity across a broad cross-section of countries and industries.

Empirical results confirm that higher geopolitical-energy uncertainty significantly reduces firm productivity, not only in the aggregate level but also among major advanced economies such as the United States, United Kingdom, France, and Germany. To further understand the underlying channels, the essay differentiates between energy-intensive and less energy-intensive industries. The findings indicate that firms operating in energy-intensive sectors experience stronger productivity losses when the GEU index rises, underscoring their heightened vulnerability to global energy disruptions. Besides, firm heterogeneity also matters. Smaller firms appear to experience stronger adverse impacts from geopolitical-energy uncertainty. Similarly, firms with higher cost intensity exhibit greater declines in productivity when faced with heightened GEU levels. Moreover, rising global energy prices further amplify these negative effects, suggesting that energy price dynamics serve as a critical transmission channel through which uncertainty impairs firm productivity.

The findings have several important implications. From a firm perspective, smaller firms and those operating in energy-intensive industries should focus on strengthening operational resilience to mitigate the impact of high geopolitical-energy uncertainty. This could include improving cost management and diversifying energy sources. Also, maintaining profitability and having appropriate investment strategies are essential. Special attention should be given to firms operating in countries or sectors (energy insensitive industries) particularly exposed to GEU. From a policy perspective, governments can help enhance productivity by ensuring stability in energy markets, promoting the development and use of sustainable energy sources, and encouraging firms to adopt energy-efficient technologies and practices. Policies should also consider industry and firm characteristics to ensure they effectively address the impacts of geopolitical-energy uncertainty.

5.1.3. Essay Three (Chapter Four)

Using annual data from 2002 to 2022, a period encompassing multiple global crises, the third essay explores how cross-listing in US financial markets affects the productivity of firms in the energy-electricity sector. Results reveal that, although most sectors tend to experience productivity gains following cross-listing, energy-sector firms display a contrasting pattern, showing a statistically significant decline in productivity after cross-listing in the US markets. A plausible explanation is that these firms channel a substantial share of newly raised capital into large-scale investments in infrastructure, technology, and expansion projects, which may initially depress productivity despite potential long-term benefits. This outcome diverges from the conventional expectation that access to deeper capital markets should immediately enhance efficiency and output.

The results also highlight the importance of ownership structure and institutional factors. State ownership exerts a negative influence on the productivity of energy firms, particularly within developed economies, suggesting inefficiencies associated with government control. In contrast, stronger corporate governance mechanisms and improved market liquidity appear to support productivity improvements in the sector. Overall, the findings underscore the complexity of cross-listing effects in capital-intensive industries and suggest that productivity outcomes depend critically on firm characteristics, investment behavior, and institutional environments rather than on financial market access alone.

These findings provide valuable guidance for policymakers and firm managers seeking to enhance the productivity of energy firms following cross-listing. For energy companies contemplating cross-listing on US financial markets, the observed decrease in productivity, attributed to substantial investments in infrastructure and expansion, underscores the necessity of prudent capital allocation strategies post-cross-listing to effectively mitigate declines in productivity. Additionally, the significance of state ownership as a determinant of firm productivity within the energy sector, particularly in developed economies, implies that government-owned energy companies should devote a higher level of attention and develop strategic plans, as they may encounter challenges in maintaining productivity levels following cross-listing. From a policymaker's perspective, the fact that cross-listing generally enhances productivity in most sectors while the energy sector experiences a decrease implies the importance of taking sector-specific considerations into account. Regulatory bodies should engage in conversation with industry stakeholders to develop frameworks that strike a balance between facilitating capital access and ensuring that firms allocate their resources strategically post-cross-listing. Policymakers should also consider strengthening corporate governance requirements for cross-listed energy and electricity companies and enhancing liquidity in their financial markets, as these measures might support firm productivity.

5.2. Future areas of research

Building upon central theme of uncertainty and productivity, this thesis highlights several directions for future research that stem from the findings of its three essays. Each essay offers distinct methodological and empirical insights, which collectively open new avenues for expanding our understanding of how uncertainty propagates across markets and affects firm outcomes.

The novel quantile time-frequency connectedness approach of Chatziantoniou, Abakah, et al. (2022) employed in the first essay focuses on examining the contemporaneous spillovers only while neglecting the lagged connectedness effects, leading to a shortcoming of this essay. As such, future studies are suggested to adopt the contemporaneous and lagged R^2 decomposed connectedness approach proposed by Balli et al. (2023). This framework appears to be less sensitive to outliers as well as allows us to obtain more insightful information by distinguishing between the contemporaneous and lagged spillover effects. This approach might provide insightful implications for both international investors and policymakers.

Meanwhile, although the second essay provides valuable evidence on the effects of GEU on firm productivity, it relies on annual firm-level data, which may not fully capture firms' short-term adjustments. Furthermore, while TFP is a key measure of efficiency, other dimensions of firm performance could also be examined. Future research could explore higher-frequency data and additional firm-level strategies to mitigate the impact of geopolitical-energy uncertainty.

The third essay examined how cross-listing in US financial markets affects the productivity of energy-sector firms. Future research could broaden this perspective by including cross-listings in other international markets, thereby assessing how institutional and regulatory heterogeneity across host countries influences post-listing productivity outcomes. This is of particular importance as more countries are now seeing significant cross-listing activity, such as Canada, India, and the United Kingdom. Comparative analyses of developed versus emerging market destinations could further clarify whether the productivity effects observed in this study are market-specific or generalizable across different economic and financial environments.

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Appendix for Chapter Three

Appendix 3.A. Placebo/falsification tests

To ensure that our baseline findings are not driven by spurious correlations or reverse causality, we conduct a series of placebo tests. Table 3.A1 examines the GEU-energy intensity interaction, while Table 3.A2 focuses on the GEU-small firm interaction. In each case, we implement three falsification strategies. *First*, we replace the GEU index with alternative global uncertainty measures (i.e., global geopolitical risk - GPR and global economic policy uncertainty - EPU) (see Panel A). *Second*, we use future GEU values (t+1, t+2), which by construction cannot affect current firm productivity; any significance would indicate reverse causality (see Panel B). *Finally*, we perform circular time-shift tests by re-assigning the whole GEU series to future years (k=1–4), which breaks the true timing of shocks (see Panel C). The lead test checks if future shocks predict today's outcomes, while the time-shift test checks if mis-aligned shocks spuriously reproduce the baseline pattern. These placebo specifications follow the same baseline regressions in Equations (3.2) and (3.3), with only minor modifications to the shock variable.

Across all specifications in Panel B and C of Table 3.A1 and 3.A2, the placebo interaction terms are statistically insignificant, supporting the validity of our identification strategy. For Panel A of Table 3.A1, only the GEU–energy intensive interaction (column (1)) has a significant and negative impact on firm productivity, whereas the GPR–energy intensive (column (2)) and EPU–energy intensive (column (3)) interactions are insignificant. This indicates that the GEU index provides a more consistent explanation of energy-intensive firms' productivity responses compared to GPR and EPU. Similarly, in Panel A of Table 3.A2, only the GEU–smaller firm interaction (column (1)) exerts a significant adverse effect on firm TFP, suggesting that the productivity of smaller firms may be more sensitive to GEU, compared to other uncertainty indices. Generally, the more consistent and robust effects of GEU across specifications support the interpretation that GEU is the primary source of the adverse productivity impacts.

Table 3.A1. Placebo/falsification tests for the GEU-energy intensity interaction

Panel A. Alternative-shock placebo test

	(1)	(2)	(3)
Index	-0.058***	-0.381***	0.027
	(0.019)	(0.077)	(0.064)
Energy_intensive	-0.188***	-0.861**	-0.178***
	(0.021)	(0.417)	(0.023)
*Index*Energy_intensive*	-0.051**	0.148	-0.020
	(0.023)	(0.090)	(0.082)
Control variables	Yes	Yes	Yes
N	6,881	6,881	5,844
Adjusted R^2	0.318	0.317	0.322

Panel B. Future-shock placebo test

	(1)	(2)
$GEU_{(t+1)}$	-0.096***	
	(0.023)	
$GEU_{(t+2)}$		-0.070***
		(0.024)
Energy_intensive	-0.196***	-0.196***
	(0.022)	(0.022)
$GEU_{(t+1)}$**Energy_intensive*	-0.012	
	(0.028)	
$GEU_{(t+2)}$**Energy_intensive*		0.020
		(0.028)
Control variables	Yes	Yes
N	5,844	5,225
Adjusted R^2	0.326	0.331

Panel C. Circular time-shift placebo test

	(1)	(2)	(3)	(4)
GEU_k1	0.002			
	(0.020)			
GEU_k2		0.015		
		(0.022)		
GEU_k3			0.044**	
			(0.020)	
GEU_k4				0.034
				(0.023)
Energy_intensive	-0.180***	-0.201***	-0.197***	-0.190***
	(0.021)	(0.023)	(0.023)	(0.024)
*GEU_k1*Energy_intensive*	-0.039			
	(0.025)			
*GEU_k2*Energy_intensive*		-0.003		
		(0.027)		
*GEU_k3*Energy_intensive*			0.033	
			(0.026)	
*GEU_k4*Energy_intensive*				0.041
				(0.029)
Control variables	Yes	Yes	Yes	Yes
N	6,542	6,241	5,974	5,664
Adjusted R^2	0.314	0.313	0.320	0.313

Notes: Robust standard errors are presented within parentheses. ***, ** and * stand for the significance level of 1%, 5% and 10%, respectively. We note that the dummy variable "*Energy_intensive*" gets absorbed when firm fixed effects are employed because it is perfectly collinear with those fixed effects. As such, country-year fixed effects are controlled in models instead of firm-year fixed effects. For Panel A, "*Index*" stands for GEU, GPR or EPU. The estimation in column (1) is based on Equation (3.2), while the variable *GEU* in Equation (3.2) is replaced with *GPR* and *EPU* in the estimations of column (2) and (3), respectively. $GEU_{(t+1)}$ and $GEU_{(t+2)}$ are one- and two-year leads of the GEU index. *GEU_k1 to GEU_k4* denote the index shifted forward by 1-4 years as placebo shocks.

Table 3.A2. Placebo/falsification tests for the GEU-smaller firm interaction

Panel A. Alternative-shock placebo test

	(1)	(2)	(3)
Index	-0.039**	-0.321***	0.061
	(0.016)	(0.060)	(0.046)
Smaller_firm	-0.016	-0.382	-0.040
	(0.046)	(0.390)	(0.051)
*Index*Smaller_firm*	-0.059***	0.079	-0.070
	(0.021)	(0.085)	(0.071)
Control variables	Yes	Yes	Yes
N	6,462	6,462	5,739
Adjusted R^2	0.535	0.535	0.537

Panel B. Future-shock placebo test

	(1)	(2)
$GEU_{(t+1)}$	-0.068***	
	(0.018)	
$GEU_{(t+2)}$		-0.035*
		(0.018)
Smaller_firm	-0.009	-0.010
	(0.048)	(0.050)
$GEU_{(t+1)}$*Smaller_firm*	-0.000	
	(0.026)	
$GEU_{(t+2)}$*Smaller_firm*		0.006
		(0.025)
Control variables	Yes	Yes
N	5,739	5,177
Adjusted R^2	0.528	0.538

Panel C. Circular time-shift placebo test

	(1)	(2)	(3)	(4)
GEU_k1	0.020			
	(0.015)			
GEU_k2		0.030*		
		(0.015)		
GEU_k3			0.070***	
			(0.015)	
GEU_k4				0.045***
				(0.017)
Smaller_firm	-0.018	-0.045	-0.032	-0.015
	(0.048)	(0.050)	(0.049)	(0.052)
*GEU_k1*Smaller_firm*	-0.032			
	(0.022)			
*GEU_k2*Smaller_firm*		-0.005		
		(0.023)		
*GEU_k3*Smaller_firm*			0.011	
			(0.022)	
*GEU_k4*Smaller_firm*				0.027
				(0.025)
Control variables	Yes	Yes	Yes	Yes
N	6,129	5,838	5,561	5,258
Adjusted R^2	0.539	0.535	0.549	0.543

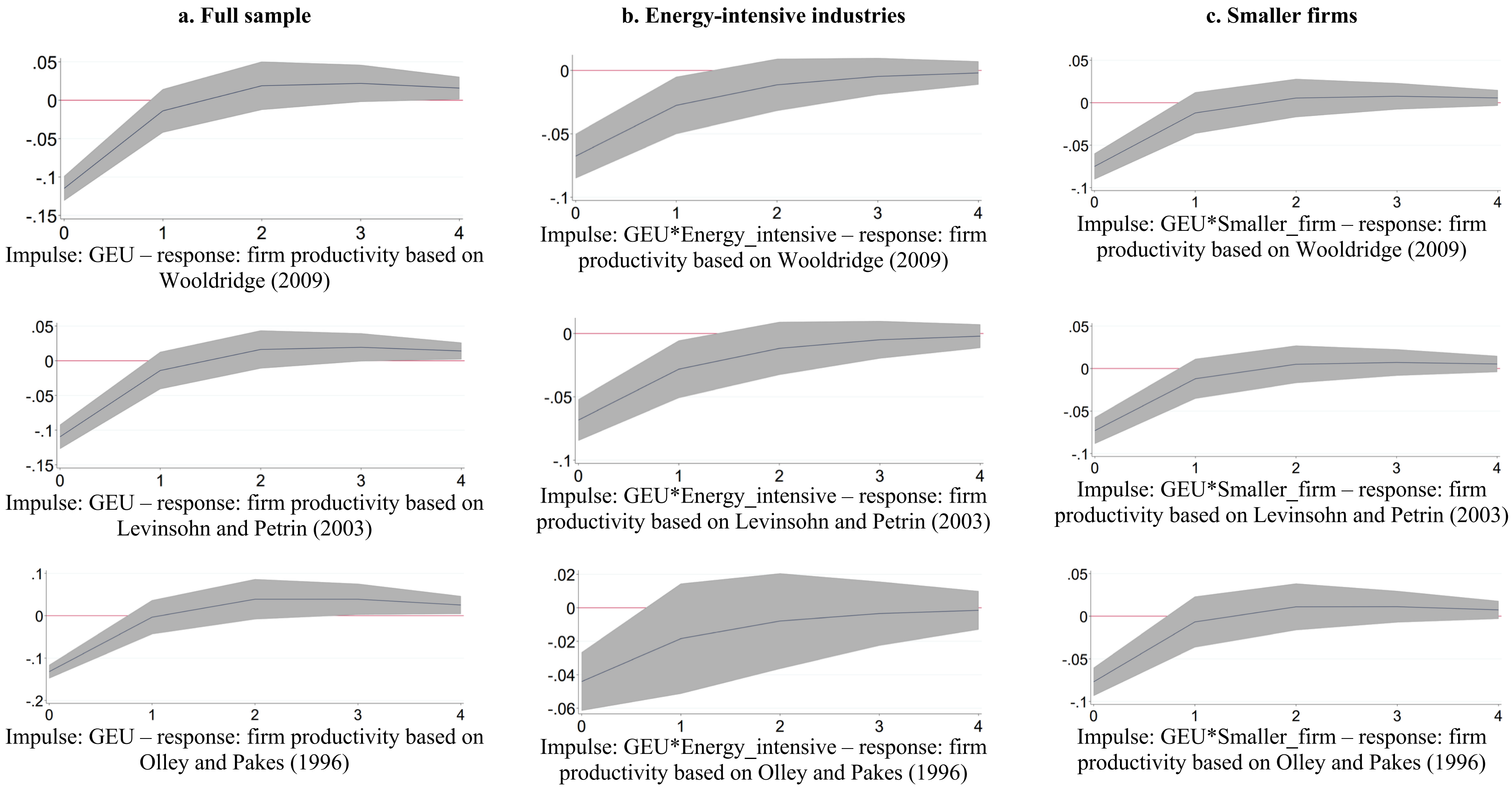
Notes: Robust standard errors are presented within parentheses. ***, ** and * stand for the significance level of 1%, 5% and 10%, respectively. Firm-year fixed effects are controlled in models. For Panel A, "*Index*" stands for GEU, GPR or EPU. The estimation in column (1) is based on Equation (3.3), while the variable *GEU* in Equation (3.3) is replaced with *GPR* and *EPU* in the estimations of column (2) and (3), respectively. $GEU_{(t+1)}$ and $GEU_{(t+2)}$ are one- and two-year leads of the GEU index. *GEU_k1 to GEU_k4* denote the index shifted forward by 1-4 years as placebo shocks.

Appendix 3.B. Additional robustness checks

3.B1. Robustness tests using the panel impulse response function

Apart from the regression models presented in Section 3.5.1, in this section, we employ the panel impulse response function to explore whether one shock from the GEU index might lead to significant decreases in firm productivity or not. Looking at Figure 3.B1 where we use the impulse response analysis with different measures of total factor productivity, we note that one shock from the GEU index leads to a statistically significant decrease in firm productivity (Figure 3.B1a). Moreover, one shock from the interaction term "*GEU*Energy_intensive*" also leads to significant drops in the productivity at firm level (Figure 3.B1b). Those findings confirm our baseline results in Table 3.2 and Table 3.4.

As can be seen from Figure 3.B1c where we perform the impulse response functions with the impulse of "*GEU*Smaller_firm*", it is noted that the interaction term "*GEU*Smaller_firm*" significantly reduces different measures of firm productivity. Such findings confirm our baseline results regarding the GEU index' impact on the productivity of smaller firms presented in Table 3.5.



a. Full sample | **b. Energy-intensive industries** | **c. Smaller firms**

Impulse: GEU – response: firm productivity based on Wooldridge (2009)

Impulse: GEU*Energy_intensive – response: firm productivity based on Wooldridge (2009)

Impulse: GEU*Smaller_firm – response: firm productivity based on Wooldridge (2009)

Impulse: GEU – response: firm productivity based on Levinsohn and Petrin (2003)

Impulse: GEU*Energy_intensive – response: firm productivity based on Levinsohn and Petrin (2003)

Impulse: GEU*Smaller_firm – response: firm productivity based on Levinsohn and Petrin (2003)

Impulse: GEU – response: firm productivity based on Olley and Pakes (1996)

Impulse: GEU*Energy_intensive – response: firm productivity based on Olley and Pakes (1996)

Impulse: GEU*Smaller_firm – response: firm productivity based on Olley and Pakes (1996)

Figure 3.B1. Robustness test: Panel impulse response analysis

Notes: The analysis is based on the 95% confidence interval.

3.B2. Robustness tests using the demeaned interaction term by Balli and Sørensen (2013)

In this section, we employ the demeaned interaction term proposed by Balli and Sørensen (2013). This corrected interaction term is suggested to help reduce the spurious estimations in the model. Following Balli and Sørensen (2013), we re-estimate our regression models with the demeaned interaction terms as in Equation (3.b1) and (3.b2).

$$TFP_{i,t} = \varphi_e + \omega_t + \alpha_1 GEU_t + \alpha_2 Energy\_intensive_i + \alpha_3 Demean\_GEU_t * Energy\_intensive_i + M_{i,t}\delta + \varepsilon_{i,t} \quad (3.b1)$$

$$TFP_{i,t} = \varphi_e + \omega_t + \theta_1 GEU_t + \theta_2 Smaller\_firm_i + \theta_3 Demean\_GEU_t * Smaller\_firm_i + M_{i,t}\vartheta + \varepsilon_{i,t} \quad (3.b2)$$

where $Demean\_GEU = GEU - \overline{GEU}$, and $\overline{GEU}$ stands for the mean of GEU.

As can be seen from Table 3.B1, the coefficients of the demeaned interaction terms in Panel A and B are both statistically significant and negative across different model specifications. Such results confirm our baseline findings that firm productivity from energy-intensive firms and smaller firms are more negatively affected by the GEU index.

Table 3.B1. Robustness test: Using the demeaned interaction term by Balli and Sørensen (2013)

Panel A. Energy-intensive industries			
	Country - Year fixed effects	Linear mixed model	Hausman-Taylor model
	(1)	(2)	(3)
GEU	-0.048**	-0.067***	-0.057***
	(0.020)	(0.017)	(0.020)
Energy_intensive	-0.186***	-0.184***	-0.326***
	(0.045)	(0.045)	(0.054)
*Demean_GEU*Energy_intensive*	-0.044*	-0.050**	-0.046*
	(0.024)	(0.023)	(0.025)
Control variables	Yes	Yes	Yes
N	6,886	6,886	6,886
Adjusted R^2	0.096	-	-

Panel B. Smaller firms			
	Firm - Year fixed effects	Linear mixed model	Hausman-Taylor model
	(1)	(2)	(3)
GEU	-0.038**	-0.062***	-0.058***
	(0.019)	(0.013)	(0.015)
Smaller_firm	-0.013	-0.017	-0.012
	(0.064)	(0.055)	(0.064)
Demean_GEU Smaller_firm*	-0.061**	-0.066***	-0.055**
	(0.026)	(0.024)	(0.025)
Control variables	Yes	Yes	Yes
N	6,886	6,886	6,886
Adjusted R^2	0.095	-	-

Notes: Robust standard errors are presented within parentheses. ***, ** and * stand for the significance level of 1%, 5% and 10%, respectively.
The estimations in Panel A are based on the model: $TFP_{i,t} = \varphi_e + \omega_t + \alpha_1 GEU_t + \alpha_2 Energy\_intensive_i + \alpha_3 Demean\_GEU_t * Energy\_intensive_i + M_{i,t}\delta + \varepsilon_{i,t}$ (3.4).
The estimations in Panel B are based on the model: $TFP_{i,t} = \varphi_e + \omega_t + \theta_1 GEU_t + \theta_2 Smaller\_firm_i + \theta_3 Demean\_GEU_t * Smaller\_firm_i + M_{i,t}\vartheta + \varepsilon_{i,t}$ (3.5).

Appendix 3.C. Principal Component Analysis (PCA) approach

The principal component analysis (PCA) approach, first introduced by Hotelling (1933), is a technique that reduces the dimensionality of data while retaining the maximum possible variance. The method transforms a set of correlated variables into a smaller number of uncorrelated principal components, which capture the essential structure of the data (Fu et al., 2021; Luo et al., 2022). Each component is assigned weights based on the intrinsic characteristics of the indicators, ensuring that the resulting components are free from subjective influence (Zou et al., 2023).

The procedure follows three main steps. First, each sub-index is standardized using Z-score normalization to remove biases from scale differences:

$$z_{ij} = \frac{x_{ij} - \bar{\mu}_j}{\sigma_j} \tag{3.c1}$$

where x_{ij} is the raw value i of sub-index j (where j = 1, 2, 3), $\bar{\mu}_j$ and σ_j are its mean and standard deviation.

Second, the correlation matrix is calculated and decomposed into eigenvalues and eigenvectors.

Finally, principal components are ranked by their explained variance, and those with eigenvalues greater than one are retained (Amuakwa-Mensah et al., 2018; Zou et al., 2023). The selected eigenvectors then serve as weights for constructing the composite GEU index.

Appendix for Chapter Four

Table 4.A1. Firm productivity among sectors: Before versus after cross-listing (Full sample)

		Difference in mean	Propensity-score matching
Energy	After vs Before	0.011	-0.406***
		(0.076)	(0.076)
	Stage (1) vs Before	0.098	-0.188**
		(0.088)	(0.088)
	Stage (2) vs Before	-0.044	-0.543***
		(0.082)	(0.095)
Electricity firms	After vs Before	-0.182**	-0.253***
		(0.084)	(0.068)
	Stage (1) vs Before	-0.185**	-0.246**
		(0.111)	(0.106)
	Stage (2) vs Before	-0.180**	-0.163**
		(0.083)	(0.068)
Basic Materials	After vs Before	0.042	0.008
		(0.050)	(0.063)
	Stage (1) vs Before	0.088*	0.060
		(0.060)	(0.072)
	Stage (2) vs Before	0.011	-0.025
		(0.057)	(0.068)
Consumer Discretionary	After vs Before	0.119***	0.191***
		(0.038)	(0.042)
	Stage (1) vs Before	0.186***	0.246***
		(0.045)	(0.047)
	Stage (2) vs Before	0.064273*	0.148**
		(0.044)	(0.064)
Health Care	After vs Before	0.351***	0.229***
		(0.055)	(0.075)
	Stage (1) vs Before	0.305***	0.305***
		(0.072)	(0.073)
	Stage (2) vs Before	0.382***	0.258***
		(0.062)	(0.078)
Industrials	After vs Before	0.040	-0.0019353
		(0.032)	(0.0363255)
	Stage (1) vs Before	0.097***	0.1267377***
		(0.037)	(0.0435315)
	Stage (2) vs Before	-0.003	-0.0675415
		(0.036)	(0.0445813)
Real Estate	After vs Before	0.395***	0.256***
		(0.064)	(0.084)
	Stage (1) vs Before	0.379***	0.278***
		(0.081)	(0.085)
	Stage (2) vs Before	0.407***	0.223***
		(0.072)	(0.079)
Technology	After vs Before	0.120*	0.057
		(0.084)	(0.143)
	Stage (1) vs Before	0.078	0.061
		(0.110)	(0.175)
	Stage (2) vs Before	0.146*	-0.045
		(0.094)	(0.205)
Telecommunications	After vs Before	0.027	0.1400766
		(0.130)	(0.1169964)
	Stage (1) vs Before	0.264**	0.1539351
		(0.118)	(0.1805214)
	Stage (2) vs Before	-0.102	-0.05525
		(0.153)	(0.174572)
Utilities	After vs Before	-0.061	-0.050
		(0.057)	(0.057)
	Stage (1) vs Before	-0.0001	0.020
		(0.073)	(0.097)
	Stage (2) vs Before	-0.098*	-0.143**
		(0.060)	(0.059)

Notes: Standard errors are in parentheses. ***, ** and * indicate significance at the 1%, 5% and 10% level, respectively. "Before" stands for Before cross-listing. "After" is After cross-listing. Stage (1) is the first five years after cross-listing. Stage (2) is the remaining years following Stage (1). A statistically significant negative (positive) value indicates a significant decrease (increase) in the latter period compared to the former period. Column "Difference in mean" is estimated using t-test.

Table 4.A2. Firm productivity among sectors: Before versus after cross-listing (Emerging and Developed countries)

		Emerging countries		Developed countries	
		Difference in mean (1)	Propensity-score matching (2)	Difference in mean (3)	Propensity-score matching (4)
Energy	After vs Before	0.046	-0.235*	-0.087	-0.388***
		(0.130)	(0.124)	(0.089)	(0.109)
	Stage (1) vs Before	0.154	0.066	0.029	-0.157
		(0.152)	(0.165)	(0.104)	(0.113)
	Stage (2) vs Before	-0.011	-0.475***	-0.171**	-0.429**
		(0.135)	(0.128)	(0.098)	(0.207)
Basic Materials	After vs Before	-0.191*	-0.496***	0.122***	0.176***
		(0.122)	(0.126)	(0.052)	(0.063)
	Stage (1) vs Before	-0.167	-0.127	0.170***	0.242***
		(0.158)	(0.155)	(0.062)	(0.071)
	Stage (2) vs Before	-0.205*	-0.919***	0.086*	0.054
		(0.128)	(0.116)	(0.062)	(0.071)
Consumer Discretionary	After vs Before	0.266***	0.207	0.057*	0.121***
		(0.098)	(0.161)	(0.040)	(0.043)
	Stage (1) vs Before	0.381***	0.269**	0.105**	0.189***
		(0.117)	(0.131)	(0.047)	(0.050)
	Stage (2) vs Before	0.168*	0.286*	0.018	0.077
		(0.115)	(0.161)	(0.047)	(0.069)
Health Care	After vs Before	0.466***	0.605***	0.320***	0.238***
		(0.130)	(0.114)	(0.061)	(0.086)
	Stage (1) vs Before	0.476***	0.475***	0.257***	0.388***
		(0.179)	(0.150)	(0.077)	(0.090)
	Stage (2) vs Before	0.458***	0.682***	0.362***	0.246***
		(0.153)	(0.109)	(0.067)	(0.091)
Industrials	After vs Before	0.133*	0.091	0.002	-0.054
		(0.082)	(0.115)	(0.033)	(0.040)
	Stage (1) vs Before	0.192**	0.224**	0.059*	0.054
		(0.097)	(0.108)	(0.039)	(0.043)
	Stage (2) vs Before	0.089	-0.096	-0.042	-0.050
		(0.093)	(0.098)	(0.038)	(0.047)
Real Estate	After vs Before	0.4625***	0.207*	0.278***	0.175**
		(0.099)	(0.108)	(0.078)	(0.089)
	Stage (1) vs Before	0.608***	0.287**	0.168**	0.339**
		(0.114)	(0.137)	(0.101)	(0.133)
	Stage (2) vs Before	0.356***	-0.052	0.371***	0.349**
		(0.115)	(0.143)	(0.091)	(0.163)
Technology	After vs Before	0.634***	0.388**	-0.065	0.138
		(0.186)	(0.156)	(0.096)	(0.123)
	Stage (1) vs Before	0.426**	0.321	-0.009	0.250**
		(0.251)	(0.252)	(0.124)	(0.124)
	Stage (2) vs Before	0.725***	0.670***	-0.105	-0.232
		(0.182)	(0.188)	(0.111)	(0.279)
Telecommunications	After vs Before	0.399**	0.415***	-0.240*	0.103
		(0.202)	(0.127)	(0.167)	(0.124)
	Stage (1) vs Before	0.344 *	0.378**	0.224**	0.405***
		(0.222)	(0.162)	(0.133)	(0.143)
	Stage (2) vs Before	0.432**	0.444***	-0.468***	0.069
		(0.232)	(0.144)	(0.194)	(0.160)
Utilities	After vs Before	0.195**	0.293***	-0.206***	-0.198**
		(0.096)	(0.096)	(0.070)	(0.087)
	Stage (1) vs Before	0.278**	0.159	-0.135*	-0.007
		(0.121)	(0.111)	(0.090)	(0.094)
	Stage (2) vs Before	0.153*	0.198	-0.2518***	-0.283***
		(0.103)	(0.137)	(0.073)	(0.080)

Notes: Standard errors are in parentheses. ***, ** and * indicate significance at the 1%, 5% and 10% level, respectively. "Before" stands for Before cross-listing. "After" is After cross-listing. Stage (1) is the first five years after cross-listing. Stage (2) is the remaining years following Stage (1). A statistically significant negative (positive) value indicates a significant decrease (increase) in the latter period compared to the former period. Column "Difference in mean" is estimated using t-test.

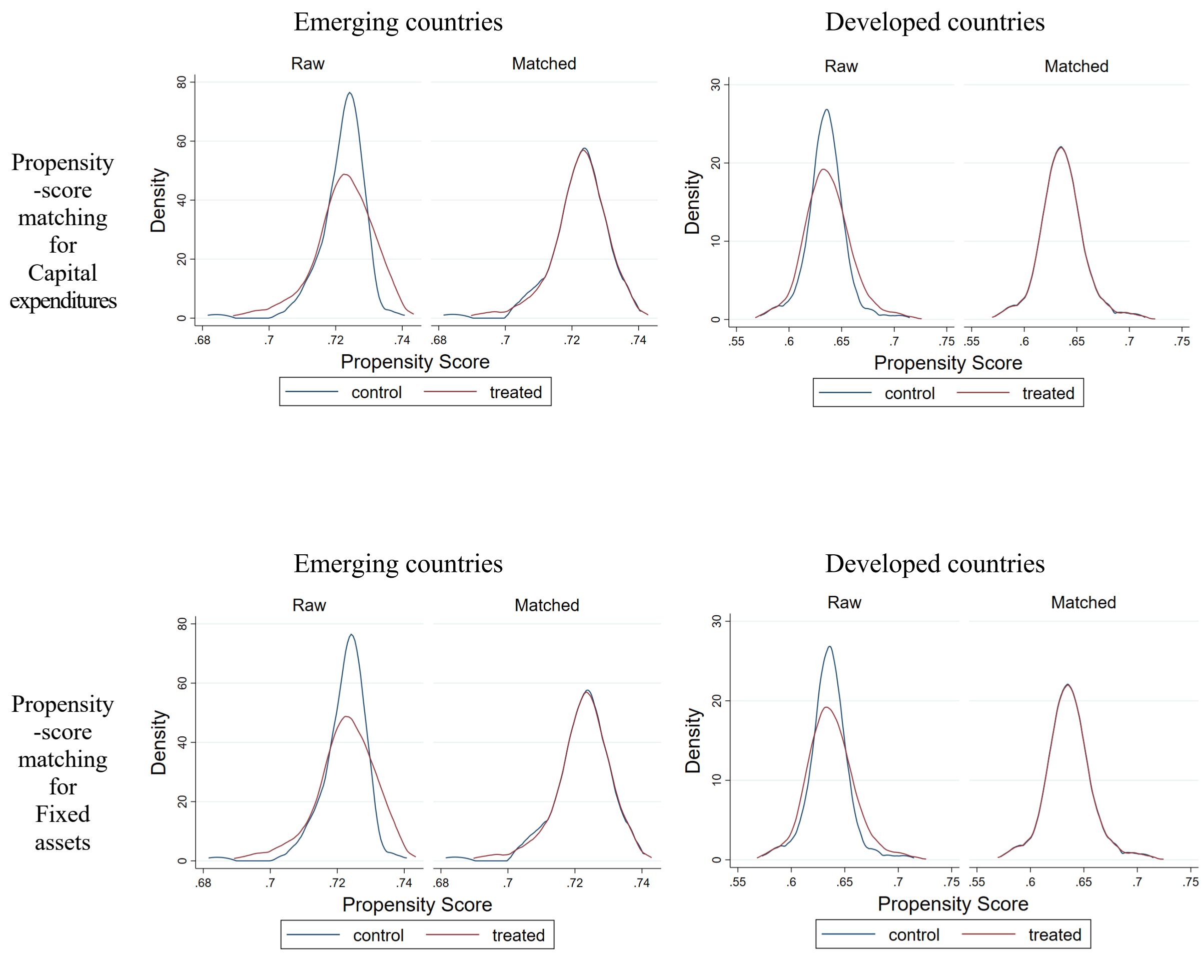


Figure 4.A1. Kernel density plots to check for covariate balance after estimations of propensity-score matching (Energy sector)

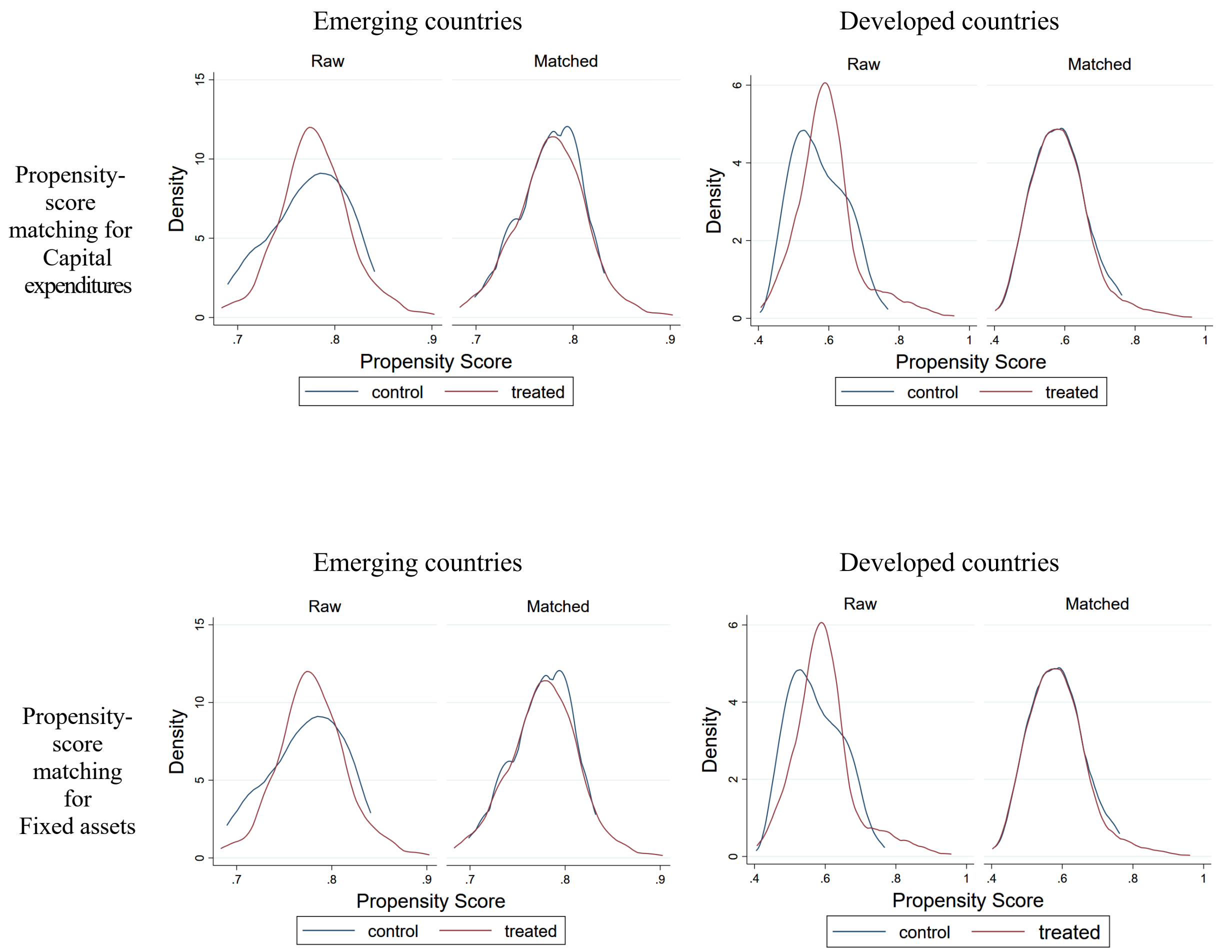


Figure 4.A2. Kernel density plots to check for covariate balance after estimations of propensity-score matching (Electricity firms)

Table 4.B1. Determinants of firm productivity in Energy sector (Emerging countries)

	(1)		(2)		(3)		(4)	
	Non-demeaned	Demeaned	Non-demeaned	Demeaned	Non-demeaned	Demeaned	Non-demeaned	Demeaned
Capex	0.015*	0.018**	0.022***	0.011	0.017*	0.004	0.038***	0.018*
	(0.008)	(0.008)	(0.008)	(0.008)	(0.009)	(0.011)	(0.010)	(0.011)
Cross_listing	0.117	-0.227	-0.053	-0.312**	0.362**	0.452**	0.427**	0.213
	(0.247)	(0.173)	(0.195)	(0.154)	(0.182)	(0.198)	(0.173)	(0.194)
*Capex*Cross_listing*	-0.023**	-0.030***	-0.027**	-0.031***	0.011	0.012	-0.013	-0.013
	(0.011)	(0.010)	(0.011)	(0.011)	(0.011)	(0.014)	(0.011)	(0.013)
Governance	0.085	0.097	1.348***	1.420***	0.852***	1.014***	1.387***	1.502***
	(0.251)	(0.248)	(0.230)	(0.226)	(0.246)	(0.240)	(0.218)	(0.222)
State_own	-0.120	-0.167	-0.881***	-0.903***	0.120	0.136	-0.244	-0.351
	(0.272)	(0.280)	(0.238)	(0.240)	(0.295)	(0.308)	(0.258)	(0.269)
Liquidity	1.968***	1.878***	2.266***	2.304***	1.622***	1.662***	1.830***	1.923***
	(0.594)	(0.604)	(0.395)	(0.400)	(0.437)	(0.441)	(0.402)	(0.404)
Random effects	Yes	Yes	No	No	No	No	No	No
Country fixed effects	No	No	Yes	Yes	No	No	Yes	Yes
Year fixed effects	No	No	No	No	Yes	Yes	Yes	Yes
Observations	389	389	389	389	389	389	389	389
Adjusted R^2	0.123	0.128	0.348	0.353	0.216	0.191	0.442	0.411

Notes: Robust standard errors are in parentheses, which are regarded to resolve the concerns of autocorrelation and heteroscedasticity. ***, ** and * indicate significance at the 1%, 5% and 10% level, respectively. Non-demeaned stands for the regression model with non-demeaned interaction term (i.e., capex*cross_listing). Demeaned stands for the regression model with the demeaned interaction term (i.e., demeaned_capex*cross_listing) which is proposed by Balli and Sørensen (2013).

Table 4.B2. Determinants of firm productivity in Energy sector (Developed countries)

	(1)		(2)		(3)		(4)	
	Non-demeaned	Demeaned	Non-demeaned	Demeaned	Non-demeaned	Demeaned	Non-demeaned	Demeaned
Capex	0.010	0.015*	0.009	0.015**	-0.000	0.002	-0.001	0.004
	(0.006)	(0.008)	(0.006)	(0.007)	(0.008)	(0.009)	(0.008)	(0.009)
Cross_listing	0.243	-0.160	0.400**	-0.136	0.593***	0.067	0.344*	-0.099
	(0.189)	(0.126)	(0.175)	(0.118)	(0.173)	(0.148)	(0.200)	(0.148)
*Capex*Cross_listing*	-0.028***	-0.036***	-0.037***	-0.047***	-0.034***	-0.043***	-0.029***	-0.039***
	(0.009)	(0.011)	(0.009)	(0.010)	(0.010)	(0.010)	(0.010)	(0.011)
Governance	0.339	0.330	0.924***	0.912***	0.403**	0.445***	0.893***	0.874***
	(0.227)	(0.229)	(0.198)	(0.195)	(0.160)	(0.159)	(0.205)	(0.203)
State_own	-0.839***	-0.849***	-1.123***	-1.168***	-0.884***	-1.000***	-0.988***	-1.091***
	(0.231)	(0.230)	(0.191)	(0.194)	(0.234)	(0.241)	(0.230)	(0.230)
Liquidity	-0.490	-0.580	-0.469	-0.631*	-0.465	-0.568	-0.477	-0.638*
	(0.568)	(0.603)	(0.350)	(0.378)	(0.323)	(0.356)	(0.351)	(0.385)
Random effects	Yes	Yes	No	No	No	No	No	No
Country fixed effects	No	No	Yes	Yes	No	No	Yes	Yes
Year fixed effects	No	No	No	No	Yes	Yes	Yes	Yes
Observations	522	522	522	522	522	522	522	522
Adjusted R^2	0.107	0.108	0.170	0.174	0.101	0.102	0.163	0.164

Notes: Robust standard errors are in parentheses, which are regarded to resolve the concerns of autocorrelation and heteroscedasticity. ***, ** and * indicate significance at the 1%, 5% and 10% level, respectively. Non-demeaned stands for the regression model with non-demeaned interaction term (i.e., capex*cross_listing). Demeaned stands for the regression model with the demeaned interaction term (i.e., demeaned_capex*cross_listing) which is proposed by Balli and Sørensen (2013).