

The Heterogeneous Impacts of Firm Upgrading on Energy Intensity*

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Abstract

This paper examines the influence of export activity on a firm's energy intensity, with a particular focus on the role of the upgrading process. We introduce a firm-level complexity index incorporating two dimensions: the complexity of the goods traded, and the complexity of the destination markets served. By employing a quasi-experimental shift-share research design (Borusyak et al., 2022), we show that growth in external demand incentivizes firms to undertake upgrading activities, resulting in lower energy intensity. Furthermore, financial constraints diminish the energy efficiency gains from upgrading, especially for small firms. In addition, we explore whether upgraded firms can leverage higher markups, and show that this strategy is effective only for large firms. These findings indicate the need for targeted support policies for small firms and highlight the critical importance of maintaining open trade in an increasingly fragmented world.

JEL Codes: F14, D22, O33, Q56

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1 Introduction

Firms' energy intensity is central to the green transition, as lower energy intensity helps reduce greenhouse gas (GHG) emissions (Marra et al., 2024). This relationship is interconnected with international trade, where energy efficiency and trade competitiveness may influence one another. The reversal of past globalization trends and ongoing regulatory adaptations call for evidence about their impact on the green goals and structural transformation more generally. Although policymakers are already implementing various industrial policies to navigate the turbulent economic environment (Juhász et al., 2023; Ilyina et al., 2024), the implications for international trade and energy usage remain complex, as countries and firms recalibrate supply chains and trade policies in response to disruptions like COVID-19 and geopolitical conflicts (Antràs, 2020). Such changes could fundamentally reshape energy efficiency patterns, e.g., due to challenges of balancing globalization with domestic economic priorities (Rodrik, 2017), as firms adapt to a new demand environment and trade barriers, making the policy context for export-related energy efficiency all the more critical.

The international trade literature has found ambiguous effects of exports on firm-level energy intensity. Trade can induce exporters to upgrade their technology and thereby reduce their energy intensity (Forslid et al., 2018). However, trade can also induce exporters to adjust their product mix, making them more energy intensive (Barrows and Ollivier, 2018). Nor is the causality easy to sort out. Articles that consider the effects of export on firm-level energy efficiency often conflate causal effects with selection effects (Batrakova and Davies, 2012; Holladay, 2016; Forslid et al., 2018; Barrows and Ollivier, 2018).

In this paper, we provide causal evidence of trade-induced upgrading and its associated impact on firm-level energy intensity. To do so, we employ a unique dataset that covers the universe of firms in Lithuania from 2000–2015. We then augment this dataset with matched customs data that contains the import and export volume of firms' product basket and their relevant trading partners. This period includes Lithuania's major economic transitions, including EU accession in 2004, which accelerated shifts in firm behavior regarding trade and energy intensity through tighter regulatory standards and expanded market access.

This granular information enables us to further leverage external datasets that are crucial for measuring firms' upgrading processes and the external demand shocks they are facing. We begin by constructing a firm-level complexity index that captures the essence of firms'

upgrading process according to [Verhoogen \(2023\)](#). This index captures not only the complexity of the goods traded, but also the complexity of the destination markets served. Hence, a firm can upgrade by trading more complex goods, trading with more complex countries, or both. In our sample, both of these dimensions contribute to the steady upgrading of firms in Lithuania.

We then examine how exogenous shocks to trade affect firm-level complexity. To separate the causal effects of external demand growth from unobservables that affect the energy efficiency of individual Lithuanian exporters, we construct firm-specific external demand shocks by combining aggregate (Lithuania-wide) product-specific foreign demand growth with firm-specific product sales shares, similar to [Hummels et al. \(2014\)](#); [Mayer et al. \(2021\)](#); [Barrows and Ollivier \(2021\)](#). Following the recent work on shift-share instruments, our identification is based on the exogeneity of the external demand growth shocks, that is, the "shocks view" as in [Borusyak et al. \(2022\)](#).¹ While these shocks are exogenous to Lithuanian firms, their impact varies markedly across firms precisely because firms have different export baskets, hence the heterogeneous exposures to the exogenous shocks. In addition, the granularity of our product classification, as well as the observed variation in external demand, ensures the consistency of shift-share instrumental variable (SSIV) estimations in our context.

We find an increased external demand leads to a rise in the growth of firm-level complexity. This finding is robust across different specifications and identification methods. Building on this result, we then explore how the instrumented firm-level complexity growth affects firm's energy intensity. The results present a quite heterogeneous picture: small firms experience a substantial decrease in energy intensity with increasing complexity, whereas large firms' energy efficiency improvement is not significant. These results also suggest that Lithuanias EU accession may have prompted improvements in energy efficiency by lowering barriers to adopting cleaner technologies, enforcing more stringent environmental standards, and promoting competitive upgrading among firms. This finding aligns with prior studies showing how trade exposure can drive productivity gains, especially for firms integrating into supply chains of advanced inputs, which can also affect energy efficiency ([Halpern et al., 2015](#)).

After establishing these findings on upgrading and energy intensity, we turn to a more policy-relevant analysis. Specifically, we explore whether market forces are sufficient to incentivize firms to improve their complexity and thus enhance energy efficiency. For large firms,

¹As a robustness check, we also report results based on the traditional panel instrumental variable approach. Both approaches deliver similar results.

we find that financial constraints generally increase energy intensity, though this negative impact can be mitigated by increasing complexity. For small firms, financial constraints do not directly impact energy intensity but do hinder improvements in energy efficiency during the upgrading process. Employing firm-level markups, we then explore if firms can finance their upgrading by charging a higher markup. We find small firms temporarily charge a lower markup after upgrading, suggesting a tougher competition environment, whereas large firms can capitalize on their resources and thrive after upgrading.

Related Literature

Our paper contributes to several strands of the literature. There is a large literature on the applications of economic complexity indices following the pioneering work of [Hidalgo et al. \(2009\)](#), ranging over various fields and topics ([Hidalgo, 2021](#)). For instance, [Stojkoski et al. \(2023\)](#) integrated economic complexity metrics, traditionally derived from trade geography, with data on patent applications and research publications to improve predictions of inclusive green growth. The authors document robust improvements in explaining international variations in inclusive green growth, showcasing the combined influence of trade, technology, and research on economic growth, income inequality, and emission intensities. We contribute to this literature by constructing a firm-level complexity index that utilizes both the product-level complexity and the country-level complexity, which are the two most important aspects of a firm's upgrading process ([Verhoogen, 2023](#)).

A large body of research has investigated the climate implications of trade on firm-level outcomes. The evidence in this literature is quite mixed. On the one hand, some papers find that trade can reduce firm-level emissions through trade-induced technical change ([Shapiro and Walker, 2018](#); [Forslid et al., 2018](#); [Akerman et al., 2021](#); [Moench and Soofi Siavash, 2023](#)), except [Levinson \(2009\)](#), which finds that technological development is the main driver of emission reduction, with trade only playing a minimal role. On the other hand, some papers suggest that trade can increase firm-level emissions due to firms' adjustment of their product bundle ([Barrows and Ollivier, 2021](#); [Iqbal et al., 2021](#)). We contribute to this literature by causally identifying a channel where trade induces firms to upgrade and reduces firm-level energy intensity.

As a consequence, our study also sheds light on the literature that explores how trade policies and regulations impact climate. For example, [Li et al. \(2023\)](#) uses the 2018 US-China trade

war as a natural experiment and finds that greater exposure to Trump tariffs leads to lower regulation targets in China, inducing an increase in air pollution and carbon emissions. [Brunel and Levinson \(2021\)](#) investigate whether the relatively lax emission regulations in the US have turned the country into a pollution haven. They found increased emissions embodied in trade only through the scale effect, but no pollution haven was created. [Shapiro and Walker \(2018\)](#) found that more stringent environmental regulations encouraged the adoption of environmental technology, which was responsible for the majority of reduced emissions through lowered emission intensity. We contribute by focusing on the firm-level climate implications regarding Lithuania's EU accession.

Our paper is also related to studies that explore the implications of structural transformation for participation in global value chains (GVC). Quite a few earlier studies focus on the technological upgrading effects via GVC participation and their implications for energy efficiency and intensity have been quite mixed ([Wang et al., 2022](#); [De Melo and Solleder, 2023](#)). More recently, [Atkin et al. \(2024\)](#) find that the emergence of China in the GVC era has held back capability growth for a number of African countries which are pushed away from their most complex sectors, which China exports, and into their least complex sectors, which China imports. Our paper offers a joint treatment of firm-level upgrading through participation in GVC and its implications for climate. While most of these studies focus on developing countries and cross-country comparisons with a sectoral view, our paper provides a more granular analysis of a Central and Eastern European (CEE) country that underwent a massive transformation since its EU accession.

The rest of the paper is organized as follows. Section 2 provides a detailed description of our data and how we utilize them to create our preferred measures. It also documents a summary of our raw data and our constructed measures. Section 3 discusses our empirical strategy for our causal analysis. Section 4 presents our benchmark empirical results, while Section 5 provides extensions and additional channels in reference to our benchmark analysis. Section 6 offers a discussion and policy implications in light of our findings. Section 7 concludes.

2 Data and Measurements

2.1 Data Sources

There are three primary datasets for our exercise: (i) the annual firm-level survey carried out by *Valstybės Duomenų Agentūra*, which is the official statistics department of Lithuania; (ii) product-level data from Lithuanian customs *Lietuvos Respublikos Muitinė*; and (iii) the global product-level trade data from CEPII’s BACI database.

Annual Survey of Enterprises

Our main data source comes from the annual survey of all the Lithuanian firms carried out by Statistics Lithuania from 1995-2019. During this time, the Lithuanian economy exhibited an average GDP growth rate of over 4.5%, which is much higher than the Euro area average and the US economy. EU membership not only enabled access to new trading partners but also induced the country to go through a substantial structural transformation, with a rapid decline in the agriculture sector and a sharp increase in the service, wholesale, and retail sectors ([Garcia-Louzao and Tarasonis, 2023](#)).

The survey is mandatory for all types of firms² in Lithuania, except for sole proprietors or associations and public administrative entities. The dataset contains detailed firm-level information combining both balance sheets and income statements, including information about firms’ birth and liquidation dates, employment, sectorial activity, ownership structure, assets, liabilities, equities, value-added, revenues and profits, etc. Unfortunately, there are two shortcomings of this data: (i) from 1995-1999, the reporting criteria were not compatible with international accounting standards; and (ii) from 2016-2019, a significant portion of the above variables are missing.³ Therefore, we provide summary statistics and our main analysis based on the period from 2000 to 2015.

We impose the following restrictions on the original dataset to obtain our sample of analysis. Firstly, we exclude enterprises with no continuous entries. Secondly, firms in financial and insurance activities are excluded, as well as those from agriculture, healthcare, and education, since these firms are either poorly represented in the data or mostly sole proprietor firms and public entities. Thirdly, we winsorize firms that have revenue below or above the 2nd and

²For a more detailed description of the data, see [Constantinescu and Proškutė \(2019\)](#).

³In addition, a reform implemented in 2019 altered the structure of labor costs by shifting the responsibility of social security contributions from companies to employees, the effects of which are not represented in our data.

98th percentile in our sample period. This winsorization produce a final sample of 96,299 firms observed over 569,540 firm-year observations from 2000-2015.

Lithuania Customs Data

We then merge the sample with customs data, which includes firm identifier, product code (Harmonized System (HS) 8-digit, except 2010, which is HS 6-digit), import source, export destination, and their respective volume⁴. The values are in litas before 2012, so we convert it to euros with the conversion ratio 3.4528 litas to 1 euro. To keep the product code consistent through the period of analysis, we aggregate the HS 8-digit to HS 6-digit, while maintaining the same firm-product-source/destination pairs. This allows us to maintain a consistent database with firm-year-HS 6-digit destination/origin information through the entire period of analysis.

BACI data

To compute external demand for Lithuanian firms, we take international trade flow data from CEPII's BACI database, which contains values of bilateral trade flows in the HS 6-digit product classification. To make the product codes comparable across time, we convert all the HS6 codes to the 1992 version.

2.2 A Firm-level Complexity Index

During the period of our analysis, Lithuania was mostly in transition to a market-based economy.⁵ Following the insight from [Verhoogen \(2023\)](#), firms' upgrading process not only benefits from their interactions with buyers or suppliers but also depends on the country they are trading with.⁶ Factors such as demand patterns, availability (and prices) of inputs, and know-how of the entrepreneurs themselves often differ by country. Therefore, to account for the roles of these two dimensions, we utilize both the product-level and country-level data of complexity from the Atlas of Economic Complexity developed by the Harvard Growth Lab.⁷

⁴The customs data is available from 1995-2019, but to keep it consistent with our main analysis, we focus on the period 2000-2015.

⁵According to the IMF, Lithuania became an advanced economy in 2015 but completed its transition to a market-based economy in 2019.

⁶For more evidence on spillovers between firms, see [Bloom et al. \(2013\)](#) and [Lucking et al. \(2019\)](#). For more evidence on spillovers between countries, see [Peri \(2005\)](#) and [Eugster et al. \(2022\)](#).

⁷For a more detailed description of these two indices, see Appendix B.

According to the Atlas webpage, the product complexity index captures the amount and sophistication of know-how required to produce a product,⁸ while a country's complexity index is based on how diversified and complex the country's export basket is. In the context of our analysis, we start with the firm complexity index for each import and export market as follows:

$$\text{FCI}_{ic,t}^{EX} = \sum_j s_{ijc,t}^{EX} \text{Complexity}_{j,t}, \quad (1)$$

$$\text{FCI}_{ic,t}^{IM} = \sum_j s_{ijc,t}^{IM} \text{Complexity}_{j,t}. \quad (2)$$

where $s_{ijc,t}^{EX(IM)}$ stands for the export (import) share of product j within firm i 's total export (import) to (from) country c in a given year t . Therefore, each index captures the average complexity score for all exported and imported varieties j , differentiated by destination and source countries, respectively. The higher the score, the more complexity is associated with the export and import baskets. However, this index ignores cross-country heterogeneity in complexity. That is, certain productive know-how, including sophisticated, unique know-how, is country-specific, hence the same variety can be produced differently in different countries.

Therefore, to account for those particular specialized know-hows from import and export partners, we augment the previous index in the following way:

$$\text{UFCI}_{i,t}^{EX} = \sum_c w_{c,t}^{EX} \text{FCI}_{ic,t}^{EX}, \quad (3)$$

$$\text{UFCI}_{i,t}^{IM} = \sum_c w_{c,t}^{IM} \text{FCI}_{ic,t}^{IM}, \quad (4)$$

where $w_{c,t} = \frac{\text{Complexity}_{c,t}}{\frac{1}{C} \sum_c \text{Complexity}_{c,t}}$ denotes the relative complexity of the country c compared to the average country-level complexity at time t . A country that sources from or exports to an average country receives the same updated index as the original one, whereas a country whose trade partners are more complex than the average "improves" the score (i.e., lowers it) and the opposite occurs if trade happens with less complex trade partners.

Finally, the two indices could have been combined into a single index since the country-

⁸According to the Atlas website, "The most complex products (that only a few, highly complex countries can produce) include sophisticated machinery, electronics and chemicals, as compared to the least complex products (that nearly all countries including the least complex can produce) including raw materials and simple agricultural products."

level complexity index weight only varies by country and time:

$$\text{UFCI}_{i,t}^{EX} = \sum_c w_{c,t}^{EX} \sum_j s_{ijc,t}^{EX} \text{Complexity}_{j,t} = \sum_c \sum_j s_{ijc,t}^{EX} w_{c,t}^{EX} \text{Complexity}_{j,t}, \quad (5)$$

$$\text{UFCI}_{i,t}^{IM} = \sum_c w_{c,t}^{IM} \sum_j s_{ijc,t}^{IM} \text{Complexity}_{j,t} = \sum_c \sum_j s_{ijc,t}^{IM} w_{c,t}^{IM} \text{Complexity}_{j,t}. \quad (6)$$

We take the absolute value of the minimum of the complexity index, $\min \text{Complexity}_{j,t}$, and add it up to the whole series of the complexity index. The new minimum measure is zero.

2.3 A First Look at the Data

The summary statistics in Table 1 offers valuable insights into the characteristics and performance metrics of firms observed between 2000 and 2015. These statistics provide a first glimpse of the dynamics within the business landscape, and shed light on various aspects of firm behaviour, economic performance, and market conditions. For instance, the mean revenue of 1,170,496 reflects the average sales of firms during the observed period. However, the wide standard deviation indicates significant variability in revenue across firms, suggesting diverse business models and market positions as well as firm size. Similarly, while the average employment of around 19 employees per firm provides an indication of workforce size, the considerable standard deviation of 132.42 highlights the heterogeneity in labour demand and firm size within the dataset.

Furthermore, among exporters, the mean export value is 1.3 million. The standard deviation of 8.5 million highlights the substantial variation in export performance, reflecting differences in market access, product competitiveness, and global economic conditions. Additionally, the average export of approximately 10 products per firm suggests a degree of diversification in export portfolios, with firms engaging in multiple product categories to access international markets.

The average expenditure on energy (47 thousand) and cost of sales (930 thousand) provide insights into firms' operating expenses and cost structures. The wide standard deviations indicate considerable dispersion in expenditure patterns and cost drivers, which may reflect differences in production processes, energy efficiency measures, and input prices between firms. Similarly, the mean total debt of 477,290 indicates the average level of financial leverage among firms. Variability in debt levels, as indicated by the standard deviation, suggests differences in

financing strategies, risk profiles, and capital structure decisions between firms.

On the other hand, total factor productivity (TFP) and markup provide insights into firms' efficiency levels and pricing behaviour. The mean TFP of 2.55 suggests an average level of productivity between firms, while the average markup of 1.11 indicates firms' pricing power and market competitiveness. The distributional properties of these variables, including skewness and variability, offer further insight into the underlying drivers of firm performance and market dynamics.

Finally, in terms of firm complexity, the indices measured by UFCI and Δ UFCI (in levels and growth) highlight firms' export complexity as crucial determinants of international trade decisions and market outcomes. The mean values of these variables provide indications of the levels and variability of export-related complexity within the dataset, highlighting the importance of strategic decision-making in global trade operations.

Table 1. Summary statistics

	Mean	Median	Std. Dev.	Small (mean)	Large (mean)
Revenue	1170496.03	103921.50	11243539.42	470017.12	11115233.09
Employment	19.1125	5	132.42	8.08962	175.606
Export	1302561.63	66948	8568029.59	474027.42	5002895.98
Exporter products	10.28	3	25.53	1	24
Expenditure on Energy	47177.41	1660	1205280.38	14943.58	504778.47
Cost of Sales	929668.44	55812	9563562	367302.19	8913612.00
Total Debt	477288.7	39881.5	4528501	223423	4081241
log(TFP)	2.55	2.58	0.71	2.60	2.20
Markup	1.11	1.07	0.18	1.11	1.12
UFCI ^{EX}	57.79	16.71	113.30	43.65	116.89
Δ UFCI ^{EX}	0.03	0.01	0.71	0.02	0.05

Note: Descriptive statistics are computed over the 569,540 firm-year observations corresponding to 96,299 firms observed between 2000 and 2015. Revenue corresponds to total sales revenue. Employment is the average number of employees within a year. Total debt is the sum of current liabilities and long-term debt. Export refers to the total export value at the firm level. Expenditure energy is the sum of expenditure on fuel, electricity, and energy. Cost of sales refers to the total costs of goods sold. Log(TFP) and markup are estimated based on the translog production function specification following the description in Appendix A.

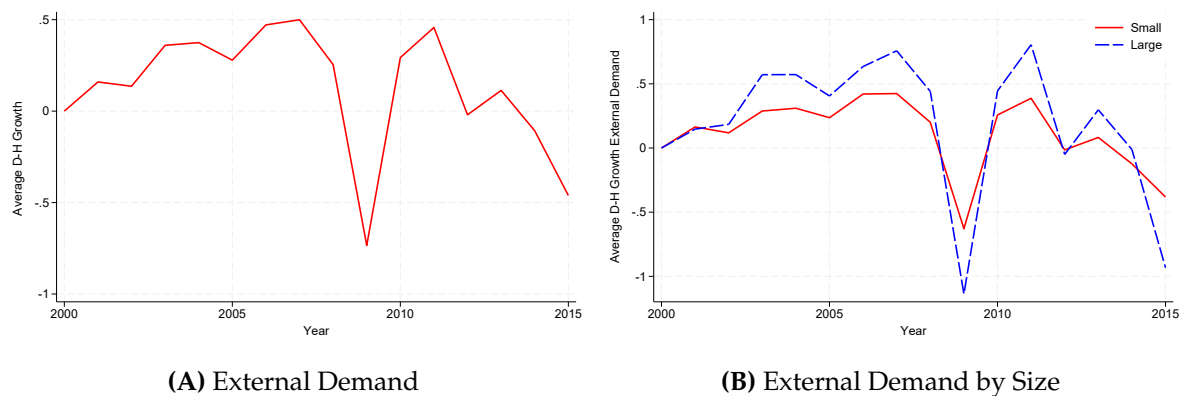
External Demand

To measure the exogenous changes of the demand condition faced by Lithuanian firms, we leverage both the BACI database and the Lithuanian customs data to construct firm-level external demand in Section 3. Here, we present the temporal evolution of this variable. Initially, we observed a discernible upward trajectory, indicative of a favorable trend, that led to the onset of the financial crisis. Subsequently, in line with expectations, external demand underwent a period of negative growth, particularly pronounced in 2009, a consequence of the crisis's profound impact. However, following the gradual recovery commencing in 2011, there was

a notable resurgence in economic activity. Despite this initial rebound, our analysis reveals a subsequent downward trajectory in external demand towards the end of our sample period in 2015. This nuanced pattern highlights the complex interplay of economic factors that influence the dynamics of external demand.

Moreover, in Figure 1, panel (B), we delineate the external demand encountered by various categories of firms, distinguishing between small and large enterprises. A discernible pattern emerges, indicating that large firms generally exhibit more robust growth compared to their smaller counterparts. However, it is noteworthy that large firms also manifest a more pronounced deceleration during the financial crisis, reflecting their heightened exposure to macroeconomic fluctuations.

Figure 1. Growth of External Demand over time, Small vs Large Firms



Description: : Panel (A) plots the average Davis-Haltiwanger (D-H) growth rate of firm-level external demand. Panel (B) plots the average Davis-Haltiwanger growth rate of firm-level external demand by firm size. Small firms are defined as having less than or equal to 50 employees, whereas large firms have more than 50 employees.

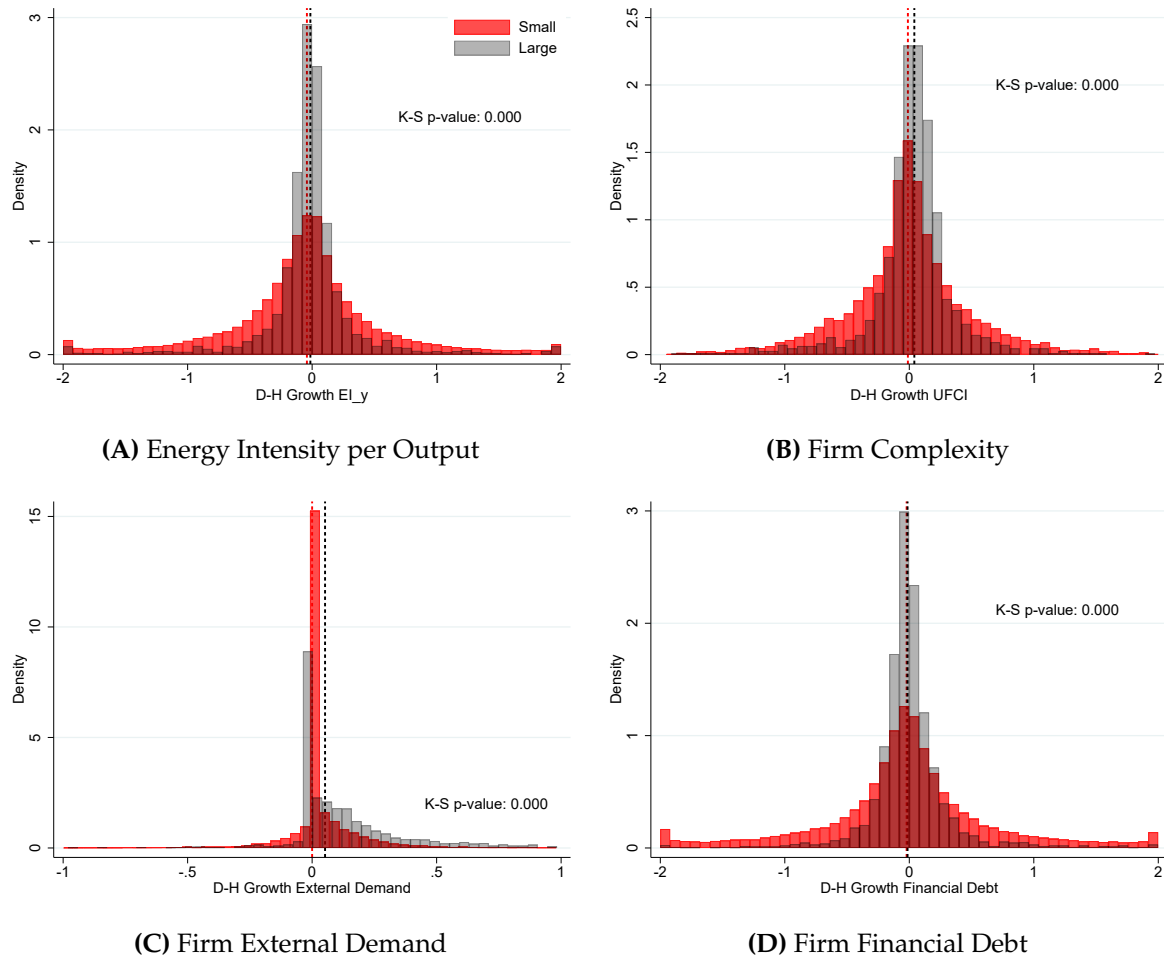
Firm Characteristics

Delving deeper into the distributional characteristics of key variables of interest—namely energy intensity per output, firm complexity index, and firm debt, across small (50 employees or less) and large enterprises (> 50 employees), Figure 2 sheds light on noteworthy patterns.

In panel (A), where we examine the distribution of energy intensity, this shows that large corporations tend to cluster around zero, with narrower tails. In contrast, small firms, while exhibiting a normal distribution, display a broader spread away from zero, indicating a greater variability in energy intensity. This disparity may reflect differing capacities for energy efficiency investments, with larger firms potentially having greater resources to optimize energy usage.

Similarly, panel (B) reveals a similar distribution pattern as in panel (A) for firm complexity among small and large firms. This suggests that firm size matters and complexity tends to follow a similar distribution, implying that factors influencing complexity are relatively different across different scales of operation.

Figure 2. Distribution of Firm Characteristics



Description: Panel (A) plots the Davis-Haltiwanger growth rate of the sum of expenditure on fuel, electricity, and energy over the firms sales. Panel (B) plots the Davis-Haltiwanger growth rate of the firm-level complexity index. Panel (C) plots the Davis-Haltiwanger growth rate of firm-level external demand. Panel (D) plots the Davis-Haltiwanger growth rate of firm-level debt over sales. The K-S p-value indicates the Kolmogorov-Smirnov statistic that tests the statistical distinction between small and large firms.

In contrast, in panel (C), large firms exhibit a pronounced right tail, suggesting higher demand variability compared to their smaller counterparts. This asymmetry may stem from larger firms' exposure to diverse markets and their capacity to accommodate fluctuating demand through scale and flexibility.

Moving to panel (D), which focuses on firm financial debt, the majority of firms' debt growth is concentrated around zero, indicative of moderate changes in debt levels. However,

small firms exhibit elongated tails in the distribution, signifying heightened variability and potentially greater susceptibility to financial risks. This divergence highlights the importance of financial management practices tailored to the unique characteristics of small businesses.

The Kolmogorov-Smirnov statistic reported in each panel tests the statistical distinction in distribution between small and large firms. The results suggest a significant divergence between these two groups across all dimensions considered, underscoring the impact of firm heterogeneity on economic dynamics. This insight highlights the importance of tailored strategies and policies to address the unique challenges and opportunities faced by businesses of varying sizes.

3 Empirical Strategy

In this section, we lay out the identification strategy of our analysis. Broadly speaking, the idea is to employ techniques from the trade literature that suggest plausibly exogenous measures of foreign demand changes from year to year. The strategy is to construct weighted average foreign import demand in countries that Lithuania (henceforth, LT) tends to sell to, product by product, leaving LT's own export to the destinations out of the measure of import demand, and then instrumenting these measures with base-year weighted average shocks. Our primary identification uses the state-of-the-art shift-share design following [Borusyak et al. \(2022\)](#). In addition, we check the robustness of our setting using the traditional panel IV strategy, as in [Barrows and Ollivier \(2021\)](#).

3.1 Change in Product-level Export Demand

Focusing on an LT exporter producing product j at time t , we can construct X_{djt} as the aggregate import of product j into destination d from all countries except LT at time t based on the BACI data. X_{djt} therefore reflects the size of the export market of product j in the country d in t . The intuition is that subsequent changes in destination d 's imports of product j from the world (except from LT) serve as a good proxy for the change in export demand faced by LT firms operating in market (j, d) . By leaving LT's own exports out of X_{djt} , we can almost eliminate the supply-side effects that jointly affect LT's exports and production.

Following the seminal work of [Davis and Haltiwanger \(1990\)](#), we compute the change in product-level export demand (i.e., the Davis-Haltiwanger growth rate) and the sum across

destinations d weighted by the relative importance of destination d in the current year for LT firms:

$$\Delta ED_{jt,t-1} = \sum_{d \in \Omega_d} s_{dj,t-1} \frac{X_{djt} - X_{djt-1}}{\frac{1}{2}(X_{djt} + X_{djt-1})}, \quad (7)$$

where $s_{dj,t-1} \equiv \frac{1}{2} \left(\frac{X_{djt-1}^{\text{from LT}}}{\sum_l X_{lj,t-1}^{\text{from LT}}} + \frac{X_{djt}^{\text{from LT}}}{\sum_l X_{lj,t}^{\text{from LT}}} \right)$ stands for the share of exports that flow to destination d in the total exports of j from LT in the combined years t and $t-1$, with $\sum_d s_{dj,t-1} = 1$. This growth rate operates similarly to a first difference but preserves observations when the shock switches from 0 to a positive number or vice versa (a common feature with trade data), and takes an extremum value of -2 and 2.⁹ Note that X_{djt} is based on CEPII's BACI data, while $X_{djt}^{\text{from LT}}$ is based on LT's trade data only.

One potential endogeneity issue comes from the fact that $\Delta ED_{jt,t-1}$ reflects the current-year shock (between $t-1$ and t) to foreign demand faced by LT producers of j . Although the change in X_{djt} can arguably be taken as exogenous for an LT firm, the export shares $s_{dj,t-1}$ are likely to be determined in part by unobserved shocks to production in LT. To address this endogeneity concern, we can compute an IV for $\Delta ED_{jt,t-1}$ using base-period (t_0) LT export weights:

$$\Delta Z_{jt,t-1} = \sum_{d \in \Omega_d} s_{dj,t_0} \frac{X_{djt} - X_{djt-1}}{\frac{1}{2}(X_{djt} + X_{djt-1})}, \quad (8)$$

where $s_{dj,t_0} \equiv X_{djt_0}^{\text{from LT}} / \sum_l X_{lj,t_0}^{\text{from LT}}$. To capture the most relevant but also pre-determined trade structure, we use the export weights of 2003 (Lithuania entered the EU in May 2004) as the base period.

3.2 Change in Firm-level Export Demand

We can then aggregate the product space of each firm to construct firm-level external demand shocks:

$$\Delta ED_{it,t-1} = \sum_{j \in \Omega_{it,t-1}} r_{ijt,t-1} \Delta ED_{jt,t-1}, \quad (9)$$

where $r_{ijt,t-1} \equiv \frac{1}{2} \left(\frac{V_{ijt-1}}{\sum_{h \in \Omega_{it-1}} V_{iht-1}} + \frac{V_{ijt}}{\sum_{h \in \Omega_{it}} V_{iht}} \right)$ stands for the export sales share of product j in firm i 's total export sales in the combined years t and $t-1$, and $\Omega_{it,t-1}$ is the set of products

⁹The Davis-Haltiwanger (D-H) growth rate, very much similar to the log first difference, is a symmetric growth rate measure but has the added advantage that it accommodates entry and exit. It is a second-order approximation of the log difference for growth rates around zero. Note that the use of a symmetric growth rate does not obviate the need to be concerned about regression to the mean effects. Also, note that the D-H growth rate is not only symmetric but bounded between -2 (exit) and 2 (entry). This has become standard in analyses of firm dynamics. For more details, please refer to [Davis et al. \(1996\)](#); [Törnqvist et al. \(1985\)](#).

offered by firm i in years t and $t - 1$.

Following the same argument in the product-level demand, we can compute the base-year weighted foreign demand instruments as follows:

$$\Delta Z_{it,t-1} = \sum_{j \in \Omega_{it_0}} r_{ijt_0} \Delta Z_{jt,t-1}, \quad (10)$$

where $\Delta Z_{jt,t-1}$ is computed in (10) and $r_{ijt_0} \equiv V_{ijt_0} / \sum_{h \in \Omega_{it_0}} V_{iht_0}$ is the export sales share of product j in firm i 's total export sales in base year t_0 , and Ω_{it_0} is the set of products produced in base year t_0 . Note that V_{ijt} is calculated using the trade data of LT only.

3.3 Identification based on Panel IV

Our instruments $\Delta Z_{jt,t-1}$ and $\Delta Z_{it,t-1}$ have been constructed in a similar way to standard shift-share/Bartik instruments. The time variation in our shocks only stems from the variation in the world export flows X_{djt} and not in the product destination weights s_{djt_0} or in the firm-product weights r_{ijt_0} , which are fixed at their value in the base period.

To identify the impact of foreign demand on firm and firm-product level outcomes, we estimate a standard difference-in-difference model in growth rates, instrumenting current-year weighted trade shocks with base-year weighted trade shocks. The identifying assumption is that once we control for arbitrary industry-by-year trends, variations in instrumented firm-specific demand shocks are uncorrelated with firm-specific technological shocks.

We can estimate the following equation at the firm level with the multi-way error structure:

$$\Delta \text{UFCEI}_{ikt,t-1}^{EX} = \gamma \Delta \text{ED}_{it,t-1} + x'_{ikt} \beta + \alpha_i + \chi_t + \chi_{kt} + \epsilon_{ikt}, \quad (11)$$

where $\Delta \text{UFCEI}_{ikt,t-1}^{EX} = (\text{UFCEI}_{ikt}^{EX} - \text{UFCEI}_{ikt-1}^{EX}) / 0.5(\text{UFCEI}_{ikt}^{EX} + \text{UFCEI}_{ikt-1}^{EX})$ denotes the Davis – Haltiwanger growth rate between t and $t - 1$ for the export complexity index of firm i in industry k , and, as defined in equation (9), $\Delta \text{ED}_{it,t-1}$ stands for the firm-level demand shocks. Note that we base our model in differences to focus on growth, which we allow to have a firm-specific component, as captured by the firm fixed effect α_i . The dynamics are controlled for by χ_t (common time fixed effects) and χ_{kt} , the industry-year fixed effect (constructed as sectoral dummy interacted with time fixed effects), meant to capture industry-specific trends (each firm is a part of the sector, $k(i)$, though for notational simplicity we suppress that dependence).

We also control for additional observables, as will be made clear when we cover the empirical results, in a vector x_{ikt} , which may vary across firms, industries and time. In our baseline specification, we include a lagged share of firm-specific imports and exports with the core EU15 countries as well as a time dummy of EU entry to explore potential heterogeneities before and after belonging to the common market.¹⁰ In the extension, we will also consider time-varying and firm-specific financial constraints. Further note that, at the firm-level regression, we can associate each firm to a single industry based on the product code responsible for the largest share of exports for the firm over the whole period. Due to the reasons discussed above, $\Delta ED_{it,t-1}$ is instrumented by $\Delta Z_{it,t-1}$.

The first-difference specification in (11) eliminates a bias that would arise from a correlation between non-time-varying firm characteristics and the level of demand shocks. We allow for various trends in the growth rate to capture potential joint dynamics with the external demand. The advantage of this specification lies in the fact that changes in demand shock $\Delta ED_{it,t-1}$ are substantially less likely to be correlated with firms observable and unobservable characteristics than *levels* of export demand.

3.4 Identification based on the Shift-Share IV

The identification of the model in (11) rests on the validity of the instrument to capture a (conditional) exogenous variation of external demand from changes in the firm's complexity. Since firms choose product bundles and destination countries endogenously, we have to tackle these sources of endogeneity. That is why, as described above, our construction of foreign demand instruments includes product demand variation in foreign markets for the fixed (base-year) export shares at the firm level.¹¹ However, instead of relying on the linear panel IV regression and shares' exogeneity, we can also recast a firm-level regression to the shock (product) level based on the descriptions in the previous subsection. This identification strategy is based on the equivalence result, as recently covered by [Borusyak et al. \(2022\)](#).

Our model at the firm level exploits the shift-share structure: each firm can choose which products it produces, and which foreign markets it exports to. Each product receives an ex-

¹⁰The EU15 countries are the 15 countries in the European Union before the 2004 EU enlargement, which includes Belgium, Denmark, Germany, Finland, France, Greece, Ireland, Italy, Luxembourg, Netherlands, Austria, Portugal, Spain, the United Kingdom and Sweden.

¹¹Our instrument $\Delta Z_{it,t-1} = \sum_{j \in \Omega_{it_0}} r_{ijt_0} \Delta Z_{jt,t-1}$ is essentially a Bartik instrument, with r_{ijt_0} being the pre-EU product shares of each firm and $\Delta Z_{jt,t-1}$ being the product-level external demand growth.

ternal demand shock based on global trade flows. Hence, each firm gets impacted differently, depending on its export bundle. In other words, the demand shocks are at the "product level", whereas the heterogeneous exposure shares are at the "firm-level". Since we observe multi-product exporters, we can construct firm-level instruments to uncover a causal effect of trade on upgrading (as captured by our complexity index).¹² For this strategy to work, the requirement $\mathbb{E}[\frac{1}{N} \sum_i [\Delta Z_{it,t-1} \times \epsilon_{it}]] = 0$ must hold, where the total number of all firms is N . Notice that, unlike the traditional requirement of $\mathbb{E}[\Delta Z_{it,t-1} \times \epsilon_{it}] = 0$, this may not be satisfied in the absence of an independent and identically distributed (IID) assumption, i.e., when $\mathbb{E}[\frac{1}{N} \sum_i [\Delta Z_{it,t-1} \times \epsilon_{it}]] \neq \mathbb{E}[\Delta Z_{it,t-1} \times \epsilon_{it}]$. If product demand shocks are assumed to be stochastic, then the IID sampling fails.

Lithuanian firms' complexity reacts to demand changes as well as changes in their supply choices. We controlled for demand shocks by looking at foreign trade partners' import demand for each product. That is arguably exogenous from the Lithuanian firm's perspective. To avoid endogeneity due to deliberate choice of product and trade partner choice, we picked base-year export shares. However, IID also requires no spillovers from one firm to another (general equilibrium effects might generate one firm's choices being dependent on another, i.e. when a firm's complexity changes due to product bundle and/or destination countries' changes, other firms might get incentivized to engage in similar reshuffling). Luckily, to explore whether these concerns matter, we can resort to the equivalence result due to [Borusyak et al. \(2022\)](#).

They argue that a natural experiment within the shocks can still make the instrument valid, even if the shares are endogenous, based on a design-based approach. The aforementioned shift-share IV estimator's equivalence result supports this claim. The idea is based on the *Frisch-Waugh-Lovell theorem*, which allows us to separate all exogenous variables and fixed effects in the first stage, resulting in residualized firm complexity growth and firm demand shock. These residuals can be averaged across all firms, leveraging their heterogeneous product shares in the export bundles. The IV estimate obtained from the original firm-level IV procedure can then be equivalent to a "product-level" IV regression, with the model instrumented by product demand shocks with product weights. This procedure does not require IID sampling.

¹²[Goldsmith-Pinkham et al. \(2020\)](#) argue from a model-based approach (i.e., diff-in-diff) that if the shares are exogenous, then it's sufficient to make the Bartik instrument valid. In the case of our analysis, we argue that the firm-product dichotomy in our setting is more suited to the design-based approach, as in [Borusyak et al. \(2022\)](#); that is, a change in external demand between products in global markets can help identify the impact of a change in demand-induced complexity (either upgrading or downgrading).

The residual of this shock-level procedure is defined as the average firm's residual, with more weight being placed on products that Lithuanian firms are exporting more. Hence, firm-level independent sampling is no longer required. What is needed instead is that the conditional product-level demand shocks are quasi-randomly assigned, meaning the expected value, conditional on product-level complexity growth error, exposure shares and observables, is constant. Additionally, there should be enough products to ensure that not all firms specialize in just a few and that there is weak correlation between shock errors. In our context, Lithuanian data provide sufficient opportunities for exogeneity and variation, making shift-share setting our preferred method.

The main reasons are as follows. First, the shocks in our setting are at the product level. That is, the demand for product j is computed by aggregating all possible destinations of product j while excluding LT. This part is essentially independent of any LT data. Second, for each product j , there are multiple firms within LT that export such products. Thus, the shock to such a product can be treated as randomly assigned across all firms that export such a product. That is, conditioning on any relevant firm-level unobservables and average exposure shares, the product-level growth rate based on world import demand is uncorrelated with firm-level supply shocks within LT. Third, there are close to 4000 products that LT exports, and for given unobservables and product shares, these two together produce many weakly dependent shocks.¹³

Brief Discussion

One might argue that even though our shares are already set at the pre-EU level, there still might be some unobservables that are forecastable based on these shares. That is, there still might be some unobserved product-level shocks that affect the residuals ε_i , even though they are uncorrelated with the product-level growth rate based on world import demand. Such a shock, for example, could come from a change in LT consumers' preferences, which is uncorrelated with the product growth rate outside of LT, but might influence the shares and, hence, create a bias in the estimation.

We use a rich set of unobservables to control for firm's time-invariant, aggregate time, and sector-time variations. Hence, if such preference shocks are correlated to these dynamics, they

¹³We perform a falsification test according to the discussions in [Borusyak et al. \(2022\)](#) and report the test results in Appendix C.

would be controlled for. Our studied economy is small and very open (its openness ratio, defined as imports and exports over GDP, is around 150%, see [Lastauskas and Stakenas, 2018](#)). Hence, the domestic market constitutes just a tiny share of total sales for the largest exporters ([Bernard et al., 2007](#); [Melitz, 2003](#)). Our methodology helps us capture those unobserved and observed changes in international demand that actually drive firms' complexity index, but are unimpacted by the LT firms' choices.

We take a random variation in the demand for firm-produced goods from all countries in the world across all goods. Simply put, our measure of international demand shocks capture changes in global economic conditions, consumer preferences, and market dynamics that are clearly outside what the LT firms' upgrading choices can impact. Our setting provides a quasi-experimental setting by exploiting a large number of products and their demand changes on global markets, the idiosyncratic nature of such shocks across firms and products, and weak dependence among shocks. We also ensure that industry-time trends are not driving our results.

Finally, our regression analysis also includes a set of observable controls like lagged trade shares with the core EU (both imports and exports) and a potential break in the impact after the EU accession.¹⁴ The experimental shift-share research design allows us to identify the causal effect of international demand shocks on firm complexity, providing causal insights into how firms respond to changes in global demand conditions.

4 Baseline Results

4.1 External Demand and Firm-level Complexity

We first utilize SSIV regression to explore the causal relationship between the growth of firms' external demand (ΔED), the growth of firms' complexity ($\Delta UFCI$), and EU accession (EU), under various specifications.¹⁵

¹⁴One might question whether other policy actions, such as the EU Emission Trading System (ETS) introduced in 2005, might impact firm behavior. On the one hand, since they happened after the accession, if they affect our results, it is due to the general EU policy, and that is what this period should capture. On the other hand, the number of firms that participated in the ETS is only a subset of firms within the sector. According to [Jaraitė and Maria \(2016\)](#), it's typically around 200 to 300 firms each year in total, which is under 1% of the average number of firms per year in our sample period. In addition, the authors established causal evidence that firms that participated in the ETS actually experienced an improvement in their CO₂ emission intensity.

¹⁵In the Appendix [D](#), we report two alternative versions of Table [2](#), with two different $\Delta UFCI$ as dependent variable: in the first version (Table [A.2](#)), we fixed the relative complexity of country and allow product complexity to vary over time; in the second version (Table [A.3](#)), we fixed the relative complexity of the product and allow country complexity to vary over time. The results are consistent with our benchmark result in Table [2](#), which

Table 2. First Stage: Impacts of External Demand on Complexity based on SSIV

Columns Dependent variable	(1) ΔUFCI	(2) ΔUFCI	(3) ΔUFCI	(4) ΔUFCI	(5) ΔUFCI	(6) ΔUFCI	(7) ΔUFCI
ΔED	0.0914** (0.0444)	0.0968** (0.0431)			0.101*** (0.0375)		
$\text{EU} \times \Delta\text{ED}$			0.0647 (0.0424)	0.0649 (0.0424)		0.0733* (0.0376)	0.0731* (0.0375)
$\text{IMP share}_{t-1}^{\text{EU15}}$		✓	✓				
$\text{EXP share}_{t-1}^{\text{EU15}}$		✓	✓				
$\text{EU} \times \text{IMP share}_{t-1}^{\text{EU15}}$				✓			
$\text{EU} \times \text{EXP share}_{t-1}^{\text{EU15}}$				✓			
$\Delta\text{IMP share}_{t-1}^{\text{EU15}}$					✓	✓	
$\Delta\text{EXP share}_{t-1}^{\text{EU15}}$					✓	✓	
$\text{EU} \times \Delta\text{IMP share}_{t-1}^{\text{EU15}}$							✓
$\text{EU} \times \Delta\text{EXP share}_{t-1}^{\text{EU15}}$							✓
Year FE	✓	✓	✓	✓	✓	✓	✓
Year \times Industry FE	✓	✓	✓	✓	✓	✓	✓
Observations	43,574	43,359	43,359	43,359	40,275	40,275	40,275
Product IV	Z_product	Z_product	Z_prod \times EU	Z_prod \times EU	Z_product	Z_prod \times EU	Z_prod \times EU
LM statistic	119.382	80.648	75.533	75.552	65.779	61.754	61.751
Wald F statistic	155.693	124.584	119.412	119.493	103.916	99.633	99.629
Hansen J statistic	0	0	0	0	0	0	0

Note: Clustered robust standard errors in parentheses, *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. ΔED is the external demand defined in Equation (4.3), ΔUFCI is the Davis-Haltiwanger growth rate defined in Equation (4.5). $\Delta\text{EXP share}_{t-1}^{\text{EU15}}$ stands for the lagged change in firm-level export share to EU15 countries. Similarly for the import share. EU is a dummy variable that takes value one after 2004.

In column 1 of Table 2, the positive coefficient on ΔED suggests that an increase in external demand growth causes a significant increase in firm-level complexity, controlling for year and year-industry fixed effects. When controlling for the level (column 2) or the change (column 5) of firms' lagged import and export share to EU15, the positive coefficient on ΔED increases both economically and statistically. This aligns with the existing literature that emphasizes the positive impact of foreign demand on firm-level outcomes (Barrows and Ollivier, 2021; Forslid et al., 2018).

The positive relationship suggests that firms experiencing higher foreign import demand tend to exhibit greater complexity in their operations. This phenomenon could be attributed to several factors. Firstly, increasing foreign demand can require companies to diversify their product offerings or adapt existing products to meet the specific needs of international markets (Forslid et al., 2018). This diversification can lead to a more intricate organizational structure as firms navigate varied product lines and customer requirements.

Secondly, responding to heightened foreign demand often involves engaging in global value chains, where firms collaborate with suppliers and partners across borders. Such cross-border collaborations can contribute to the increased complexity in managing the logistics, coordination, and quality control aspects of the supply chain (Shapiro, 2016). This aligns with highlights that both channels are important for a firm's upgrading process.

the notion that participation in global value chains is associated with a higher level of organizational complexity (Zhong et al., 2021).

In addition, the positive relationship could also be indicative of the need for firms to invest in advanced technologies and innovative processes to meet the demands of a globalized market. These investments, while enhancing a firm's competitiveness, can concurrently lead to a more intricate operational landscape (Constantinescu and Proškutė, 2019). Furthermore, the positive relationship between foreign demand and firm complexity aligns with the findings of Akerman et al. (2021), who argue that exposure to international markets prompts firms to adopt more sophisticated and complex strategies to remain competitive.

Indeed, the results highlight that external demand plays a crucial role in shaping the growth trajectory of firm complexity. The implications extend beyond mere market expansion, encompassing strategic diversification, supply chain intricacies, and technological advancements. Thus, they provide valuable insights into the dynamics of international trade and its impact on firms' organizational structures.

In column 3, we explore whether the EU accession affects the growth of firm-level complexity, controlling for year and year-industry fixed effects. The results are insignificant whether we control the level of firms' lagged import and export share to EU15 (column 3) or their interactions with the EU dummy (column 4). However, if we control for the change of firms' lagged import and export share to EU15 (column 6) or their interaction with the EU dummy (column 7), we obtain some mild positive and significant results, suggesting that EU accession brings in a mild increase in the growth of firm-level complexity among those firms that exhibit an increasing dependence on the EU15. This may indicate adjustments in firms' structures and strategies following changes in EU membership, reflecting the adaptability of businesses to evolving economic landscapes (Constantinescu and Proškutė, 2019). This could also be linked to market access benefits, regulatory harmonization, or other advantages conferred by EU integration Bai and Ru (2022); Wang et al. (2022).

As a robustness check for our finding, we repeat the same exercise using the traditional Panel IV approach (Table 3). The difference is that SSIV partials out controls effects (it treats them as nuisance), so we do not obtain any coefficients as compared to the Panel IV approach, but merely control for their variations. As can be seen below, the results are in line with those obtained via the SSIV approach. The additional insight here is that a higher export share to EU15 is associated with higher growth of firm-level complexity (columns 2 and 3), but after

Table 3. First Stage: Impacts of External Demand on Complexity based on Panel IV

Columns	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Dependent variable	ΔUFCI	ΔUFCI	ΔUFCI	ΔUFCI	ΔUFCI	ΔUFCI	ΔUFCI
ΔED	0.0156** (0.0073)	0.0179** (0.0076)			0.0232*** (0.0077)		
$\text{EU} \times \Delta\text{ED}$			0.00828 (0.0077)	0.00813 (0.0077)		0.0144* (0.0078)	0.0145* (0.0078)
$\text{IMP share}_{t-1}^{\text{EU15}}$		-0.0098 (0.0108)	-0.0087 (0.0108)				
$\text{EXP share}_{t-1}^{\text{EU15}}$		0.0294* (0.0151)	0.0323** (0.0152)				
$\text{EU} \times \text{IMP share}_{t-1}^{\text{EU15}}$				-0.0106 (0.0113)			
$\text{EU} \times \text{EXP share}_{t-1}^{\text{EU15}}$				0.0020 (0.0159)			
$\Delta\text{IMP share}_{t-1}^{\text{EU15}}$					-0.0019 (0.0089)	-0.0017 (0.0088)	
$\Delta\text{EXP share}_{t-1}^{\text{EU15}}$					0.0095 (0.0121)	0.0093 (0.0121)	
$\text{EU} \times \Delta\text{IMP share}_{t-1}^{\text{EU15}}$							-0.0029 (0.0094)
$\text{EU} \times \Delta\text{EXP share}_{t-1}^{\text{EU15}}$							0.0019 (0.0123)
Firm FE	✓	✓	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓	✓
Year \times Industry FE	✓	✓	✓	✓	✓	✓	✓
Observations	52,500	41,585	41,585	41,585	33,267	33,267	33,267
Method	2SLS	2SLS	2SLS	2SLS	2SLS	2SLS	2SLS
IV	Z_firm	Z_firm	Both	Both	Z_firm	Both	Both

Note: Clustered robust standard errors in parentheses, *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. ΔED is the external demand defined in Equation (4.3), ΔUFCI is the Davis-Haltiwanger growth rate defined in Equation (4.5). $\Delta\text{EXP share}_{t-1}^{\text{EU15}}$ stands for the lagged change in firm-level export share to EU15 countries. Similarly for the import share. EU is a dummy variable that takes value one after 2004.

removing the potential trend for firms' import and export share, this association disappears (columns 5-6).

4.2 Firm-level Complexity and Energy Intensity

In this subsection, we explore the relationship between the growth of firm-level complexity (ΔUFCI_{SSIV}) and energy intensity through the lens of how EU membership may have played a role in shaping this relationship. In our benchmark analysis, we use the growth rate of energy expenditure over sales as the dependent variable (ΔEI_y).¹⁶ In Appendix D, we repeat the same exercise here with the growth rate of energy expenditure over the cost of sales as the dependent variable (ΔEI_{cogs}). The main results are consistent across these two measures.¹⁷

In Table 4, the consistently negative coefficients associated with ΔUFCI_{SSIV} (column 1-2,

¹⁶Our energy expenditure includes the firm's expenditures on gas, fuel and electricity.

¹⁷The robustness checks based on panel IV method are available upon request.

5) and its interaction with the EU dummy (columns 3-4, 6-7) across all specifications align with the economic intuition that more complex and technologically advanced firms tend to adopt energy-efficient practices (Constantinescu and Proškutė, 2019). In addition, after joining the EU in 2004, the relationship between firm complexity and energy intensity is more pronounced. This resonates with the literature emphasizing the role of EU regulations in promoting environmental sustainability (Levinson, 2009; Shapiro, 2016). This is because EU membership may act as a catalyst for firms to adopt cleaner production processes, aligning with the broader regulatory framework.¹⁸

Table 4. Second Stage: Complexity and Energy Intensity

Columns Dependent variable	(1) ΔEI_y	(2) ΔEI_y	(3) ΔEI_y	(4) ΔEI_y	(5) ΔEI_y	(6) ΔEI_y	(7) ΔEI_y
$\Delta UFCI_{SSIV}$	-0.00519*** (0.00161)	-0.00609*** (0.00186)			-0.00478** (0.00205)		
$EU \times \Delta UFCI_{SSIV}$			-0.00635*** (0.00185)	-0.00637*** (0.00185)		-0.00504** (0.00205)	-0.00503** (0.00205)
$IMP \text{ share}_{t-1}^{EU15}$		0.00677 (0.0185)	0.00682 (0.0185)				
$EXP \text{ share}_{t-1}^{EU15}$		-0.00363 (0.0243)	-0.00350 (0.0243)				
$EU \times IMP \text{ share}_{t-1}^{EU15}$				0.0225 (0.0197)			
$EU \times EXP \text{ share}_{t-1}^{EU15}$				-0.0134 (0.0252)			
$\Delta IMP \text{ share}_{t-1}^{EU15}$					0.0158 (0.0172)	0.0158 (0.0172)	
$\Delta EXP \text{ share}_{t-1}^{EU15}$					0.0515** (0.0220)	0.0514** (0.0220)	
$EU \times \Delta IMP \text{ share}_{t-1}^{EU15}$							0.00655 (0.0186)
$EU \times \Delta EXP \text{ share}_{t-1}^{EU15}$							0.0617*** (0.0233)
Firm FE	✓	✓	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓	✓
Year \times Industry FE	✓	✓	✓	✓	✓	✓	✓
Observations	68,728	42,055	42,055	42,055	33,462	33,462	33,462
R-squared	0.153	0.134	0.134	0.134	0.131	0.131	0.131

Note: Clustered robust standard errors in parentheses, *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. ΔEI_y stands for the Davis-Haltiwanger growth rate of firm-level expenditure on energy over sales. $\Delta UFCI_{SSIV}$ is the predicted value of $\Delta UFCI$ based on SSIV in the first stage. $\Delta EXP \text{ share}_{t-1}^{EU15}$ ($\Delta IMP \text{ share}_{t-1}^{EU15}$) stands for the change in firm-level lagged export (import) share to EU15 countries. EU is a dummy variable that takes value one after 2004.

The level of lagged firms' import or export share to EU15 does not affect firms' energy intensity (columns 2-4), but the change of lagged firms' export share to EU15 ($\Delta EXP \text{ share}_{t-1}^{EU15}$)

¹⁸EU adopted its Climate Change Program in 2003, outlining measures to achieve the Kyoto targets. The Kyoto Protocol entered into force in 2005 after Lithuania's accession to the EU. Our split captures climate policy changes well since the EU agenda intensified in later years: the EU Emissions Trading System was launched in 2005 (recall Footnote 14), the EU adopted the Climate and Energy Package in 2009, the EU approved the 2030 Climate and Energy Framework in 2014, the Paris Agreement entered into force in 2016, and the EU, to achieve, inter alia, Paris Agreement goals, adopted the European Green Deal, aiming to make Europe the first climate-neutral continent by 2050.

is positively associated with firms' energy intensity (columns 5-6), and its magnitude and significance rises after the EU accession (column 7). This suggests that after taking care of the potential trends within firms' import and export patterns, having an export product mix dominated by the EU markets, which are relatively closer, may be associated with lower productivity, and thus higher energy intensity.

Heterogeneity across firms

We examine the heterogeneous effects of firm-level complexity on energy intensity for both small (Table 5) and large (Table 6) firms. The results portrayed a diverging pattern for firms of different sizes. As can be seen, most of the findings in Table 4 are driven by small firms. This suggests that small firms with higher complexity might have leveraged their upgrading process and transitioned toward a more efficient use of energy resources. This is consistent with studies highlighting the positive relationship between technological advancement and environmental performance (Porter and Linde, 1995). That is, well-designed environmental regulations can stimulate upgrading and increase efficiency, particularly for small companies.

Contrary to small firms, the coefficients for the complexity of large firms are smaller in magnitude and not consistently statistically significant. This suggests that, for large firms, the relationship between complexity and energy intensity is less pronounced. Large firms may possess different organizational structures and resource optimization strategies that mitigate the impact of complexity on energy intensity. For instance, large firms often engage in diverse activities, and their energy consumption patterns might be influenced by a variety of factors beyond complexity, such as the scale of operations, diversification, and the global nature of their activities. Additionally, the required change for large companies might be more extensive and thus longer to implement.

Focusing on the import and export perspective, small and large firms also deliver different messages. For small firms, having an export product mix dominated by the EU markets associates with higher energy intensity, and this association is even stronger after the EU accession. This indicates, among small firms, easier trade with EU correlates with higher energy intensity. However, for the large firms, importing more from the EU15 is associated with higher energy intensity. Interestingly, after the EU accession, this positive association seems to vanish, indicating a potential shift towards more sustainable practices after joining the EU. This suggests that EU membership might enhance the positive environmental impact of firm complexity for

Table 5. Second Stage: Complexity and Energy Intensity for Small Firms

Columns Dependent variable	(1) ΔEI_y	(2) ΔEI_y	(3) ΔEI_y	(4) ΔEI_y	(5) ΔEI_y	(6) ΔEI_y	(7) ΔEI_y
$\Delta UFCI_{SSIV}$	-0.00553*** (0.00224)	-0.00849*** (0.00276)			-0.00726** (0.00321)		
$EU \times \Delta UFCI_{SSIV}$			-0.00895*** (0.00279)	-0.00895*** (0.00279)		-0.00795** (0.00324)	-0.00795** (0.00324)
$IMP \text{ share}_{t-1}^{EU15}$		-0.00883 (0.0246)	-0.00906 (0.0246)				
$EXP \text{ share}_{t-1}^{EU15}$		0.0368 (0.0372)	0.0362 (0.0371)				
$EU \times IMP \text{ share}_{t-1}^{EU15}$				0.0111 (0.0260)			
$EU \times EXP \text{ share}_{t-1}^{EU15}$				0.0248 (0.0386)			
$\Delta IMP \text{ share}_{t-1}^{EU15}$					0.00700 (0.0232)	0.00681 (0.0233)	
$\Delta EXP \text{ share}_{t-1}^{EU15}$					0.0668* (0.0356)	0.0668* (0.0356)	
$EU \times \Delta IMP \text{ share}_{t-1}^{EU15}$							-0.00308 (0.0251)
$EU \times \Delta EXP \text{ share}_{t-1}^{EU15}$							0.0740** (0.0374)
Firm FE	✓	✓	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓	✓
Year \times Industry FE	✓	✓	✓	✓	✓	✓	✓
Observations	53,715	29,691	29,691	29,691	22,624	22,624	22,624
R-squared	0.175	0.154	0.154	0.154	0.149	0.149	0.149
Firm Size	Small	Small	Small	Small	Small	Small	Small

Note: Clustered robust standard errors in parentheses, *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. ΔEI_y stands for the Davis-Haltiwanger growth rate of firm-level expenditure on energy over sales. $\Delta UFCI_{SSIV}$ is the predicted value of $\Delta UFCI$ based on SSIV in the first stage. $\Delta EXP \text{ share}_{t-1}^{EU15}$ ($\Delta IMP \text{ share}_{t-1}^{EU15}$) stands for the change in firm-level lagged export (import) share to EU15 countries. EU is a dummy variable that takes value one after 2004. Small represents firms that have less than 50 employees.

large firms, possibly through access to cleaner inputs, technologies or regulatory pressures (Shapiro and Walker, 2018).

Size vs Age. Another layer of heterogeneity about firms concerns their age. Though firm size often captures firm age quite well, a few papers (e.g., Haltiwanger et al., 2013; Dyrda, 2022) suggest that firm age and firm size are different, and it is firm age that matters. Therefore, it is worth exploring how our results on heterogeneity would vary over a firm's age distribution.¹⁹ In Appendix Table A.7-A.9, we explored young firms (age under 5), young and small firms (age under 5 and number of employees under 50), young and large firms (age under 5 and number of employees over 50). We show results of a similar investigation of old firms in Appendix Table A.10-A.12. Overall, we find that young firms are experiencing stronger improvement in energy efficiency compared to older firms, both in terms of level and statistical significance. In particular, within young firms, it's mainly the small firms that are consistently experiencing a

¹⁹Our benchmark results related to complexity and energy intensity (Table 4) and its implication related to heterogeneity (Table 5 and 6) all include year fixed effects, so including age in these regressions will not change our results since the impact of age will be absorbed.

Table 6. Second Stage: Complexity and Energy Intensity for Large Firms

Columns Dependent variable	(1) ΔEI_y	(2) ΔEI_y	(3) ΔEI_y	(4) ΔEI_y	(5) ΔEI_y	(6) ΔEI_y	(7) ΔEI_y
$\Delta UFCI_{SSIV}$	-0.00307 (0.00237)	-0.00222 (0.00256)			-0.00122 (0.00265)		
$EU \times \Delta UFCI_{SSIV}$			-0.00240 (0.00255)	-0.00240 (0.00255)		-0.00132 (0.00264)	-0.00133 (0.00264)
$IMP \text{ Share}_{t-1}^{EU15}$		0.0429 (0.0275)	0.0432 (0.0275)				
$EXP \text{ Share}_{t-1}^{EU15}$		-0.0338 (0.0307)	-0.0338 (0.0307)				
$EU \times IMP \text{ share}_{t-1}^{EU15}$				0.0423 (0.0300)			
$EU \times EXP \text{ share}_{t-1}^{EU15}$				-0.0417 (0.0325)			
$\Delta IMP \text{ Share}_{t-1}^{EU15}$					0.0430* (0.0243)	0.0431* (0.0243)	
$\Delta EXP \text{ Share}_{t-1}^{EU15}$					0.0391 (0.0258)	0.0391 (0.0258)	
$EU \times \Delta IMP \text{ share}_{t-1}^{EU15}$							0.0385 (0.0265)
$EU \times \Delta EXP \text{ share}_{t-1}^{EU15}$							0.0513* (0.0278)
Firm FE	✓	✓	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓	✓
Year \times Industry FE	✓	✓	✓	✓	✓	✓	✓
Observations	14,345	11,928	11,928	11,928	10,472	10,472	10,472
R-squared	0.181	0.179	0.180	0.180	0.184	0.184	0.184
Firm Size	Large	Large	Large	Large	Large	Large	Large

Note: Clustered robust standard errors in parentheses, *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. ΔEI_y stands for the Davis-Haltiwanger growth rate of firm-level expenditure on energy over sales. $\Delta UFCI_{SSIV}$ is the predicted value of $\Delta UFCI$ based on SSIV in the first stage. $\Delta EXP \text{ share}_{t-1}^{EU15}$ ($\Delta IMP \text{ share}_{t-1}^{EU15}$) stands for the change in firm-level lagged export (import) share to EU15 countries. EU is a dummy variable that takes value one after 2004. Large represents firms that have more than 50 employees.

reduction in energy intensity. The same conclusion holds when we look at old firms. These findings suggest that size is more important than age in the context of our analysis.

5 Extensions

After demonstrating that external demand provides the impetus for upgrading and leads to lower energy intensity, we shift our focus to analyzing a few *channels* through which complexity impacts firms. We first begin by exploring whether a firm's financial constraints impact that firm's energy intensity during its upgrading process. We then move on to examine how markups respond to changes in instrumented complexity; it is an important channel as it sheds light on firm's ability to finance upgrading by charging a higher markup. In all these extensions, we will explore the role of the firm's size.

5.1 Firm Heterogeneity and Financial Constraints

Table 7 presents new insights into the relationship between firm-level financial constraints, firm-level complexity, and energy intensity. We measure firm-level financial constraint using 'Fin Ratio', which is constructed as the sum of amortization and interest payments of debt over firm sales. By capturing the firm's debt servicing burden, it is informative about its liquidity, operational capacity, and investment ability. Therefore, we conjecture that upgrading is less effective at reducing energy efficiency if the firm is financially constrained.

Table 7. Financial Constraints, Complexity and Energy Intensity

Columns Dependent variable	(1) ΔEI_y	(2) ΔEI_y	(3) ΔEI_y	(4) ΔEI_y	(5) ΔEI_y	(6) ΔEI_y	(7) ΔEI_y
$\Delta UFCI_{SSIV}$	-0.0049*** (0.0017)	-0.0059*** (0.0019)			-0.0045** (0.0021)		
Fin Ratio	0.0152 (0.0112)	0.0483 (0.0236)	0.0482 (0.0236)	0.0486 (0.0235)	0.0648** (0.0298)	0.0647** (0.0297)	0.0642** (0.0297)
$\Delta UFCI_{SSIV} \times \text{Fin Ratio}$	0.0015 (0.0062)	0.0002 (0.0049)	0.0003 (0.0049)	0.0003 (0.0049)	-0.0022 (0.0051)	-0.0021 (0.0051)	-0.0021 (0.0051)
$EU \times \Delta UFCI_{SSIV}$			-0.0062*** (0.0019)	-0.0062*** (0.0019)		-0.0047** (0.0021)	-0.0047** (0.0021)
IMP share $_{t-1}^{EU15}$		0.0064 (0.0184)	0.0065 (0.0184)				
EXP share $_{t-1}^{EU15}$		-0.0024 (0.0243)	-0.0023 (0.0243)				
$EU \times \text{IMP share}_{t-1}^{EU15}$				0.0225 (0.0197)			
$EU \times \text{EXP share}_{t-1}^{EU15}$				-0.0120 (0.0251)			
$\Delta \text{IMP share}_{t-1}^{EU15}$					0.0154 (0.0172)	0.0154 (0.0172)	
$\Delta \text{EXP share}_{t-1}^{EU15}$					0.0517** (0.0220)	0.0516** (0.0220)	
$EU \times \Delta \text{IMP share}_{t-1}^{EU15}$							0.0054 (0.0186)
$EU \times \Delta \text{EXP share}_{t-1}^{EU15}$							0.0620*** (0.0233)
Controls	✓	✓	✓	✓	✓	✓	✓
Firm FE	✓	✓	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓	✓
Year \times Industry FE	✓	✓	✓	✓	✓	✓	✓
Observations	68,070	41,955	41,955	41,955	33,400	33,400	33,400
R-squared	0.153	0.136	0.136	0.136	0.134	0.134	0.134

Note: Clustered robust standard errors in parentheses, *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. ΔEI_y stands for the Davis-Haltiwanger growth rate of firm-level expenditure on energy over sales. $\Delta UFCI_{SSIV}$ is the predicted value of $\Delta UFCI$ based on SSIV in the first stage. Fin Ratio stands for the sum of amortization and interest payment of debt over firm sales. $\Delta \text{EXP share}_{t-1}^{EU15}$ ($\Delta \text{IMP share}_{t-1}^{EU15}$) stands for the change in firm-level lagged export (import) share to EU15 countries. EU is a dummy variable that takes value one after 2004. Firm-level controls include value added over total assets, labor productivity, age, and gross profit margin.

The first insight is that financial constraints, on average, are positively associated with firm-level energy intensity, with a substantial increase in impact and significance when we control for changes in the firms lagged export/import share to EU15 countries. This finding suggests that financially constrained firms tend to be less energy efficient after accounting for potential

trends in firms' import and export patterns. Unfortunately, this impact cannot be mitigated by increasing firm-level complexity (refer to the interaction term between upgrading and financial constraint, which is statistically insignificant).

To understand the mechanisms, we examine firm heterogeneity in more detail in Appendix D. Table A.13 presents data for small companies, while Table A.14 reports results for large firms. As in the baseline results, we observe consistently negative coefficients for firm complexity, highlighting the energy efficiency gains associated with greater complexity, even when controlling for financial constraints. In contrast to Table 7, where we control for firms import and export patterns, financial constraints no longer directly impact energy intensity. However, financial constraints exhibit a positive and significant effect when interacting with upgrading, suggesting that, for small firms, financial constraints significantly reduce energy efficiency during the upgrading process.

For large companies (see Table A.14), financial constraints significantly impact energy efficiency, with financially constrained firms tending to be less energy efficient. However, this negative effect can be mitigated by increasing firm complexity. Unlike small companies, there is no independent effect of upgrading on energy efficiency for large firms (consistent with the evidence without controlling for financial constraints, see Table 6). This finding suggests that energy savings for large companies cannot be achieved solely by accessing more complex products or markets. Instead, they need to improve their financial position while simultaneously advancing in complexity.

Economic theory suggests that firms with higher debt levels may engage in riskier behavior, potentially prioritizing short-term financial obligations over long-term sustainability goals. Our findings complement the advice to address financial constraints in order to encourage firms to invest in energy-efficient technologies (Cagno et al., 2015), emphasizing the importance of having access to foreign markets and improving the traded goods basket. Interestingly, Freitas et al. (2023) argue that factors such as the complexity of exported products, environmental regulations, and production technologies may lead to a positive correlation between energy intensity and export intensity in emerging economies. We find that in a more mature economy, complexity leads to lower energy intensity compared to that of an emerging market, and that other factors, such as access to finance, may influence the expected energy-saving outcomes.

5.2 Firm-level Complexity and Markups

Lastly, we explore the role of markets enabling firms to charge higher markups due to a change in their complexity. Since pricing entails forward-looking behavior, we have divided the sample into small and large firms and calculated local projections for six periods ahead (considering the possibility that it may take time for firm profits to be affected). In other words, we are analyzing the dynamic response of h -periods ahead markups to exogenous changes in firm-level complexity.

The local projection specification for the cumulative effect of the predicted change in ΔUFCl on the Davis-Haltiwanger growth rate of firm-level markup is given by:

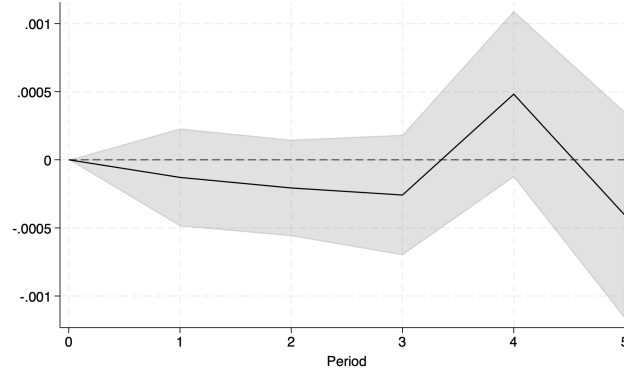
$$\Delta\text{Markup}_{ikt,t+h} = \alpha_i + \chi_t + \chi_{kt} + \beta_h \Delta\widehat{\text{UFCl}}_{ikt,t-1}^{\text{EX}} + \epsilon_{ikt,t+h}, \quad (12)$$

where $\Delta\text{Markup}_{ikt,t+h}$ is the Davis-Haltiwanger growth rate of firm-level markup for firm i in industry k at horizon h , $\Delta\widehat{\text{UFCl}}_{ikt,t-1}^{\text{EX}}$ is the predicted change in the export complexity index based on SSIV, α_i represents firm fixed effects, capturing time-invariant characteristics of each firm, χ_t denotes year fixed effects, capturing common shocks to all firms in a given year, χ_{kt} represents year-industry fixed effects, capturing industry-specific trends over time, and $\epsilon_{ikt,t+h}$ is the error term. The model is estimated for different horizons h to capture the dynamic effects of changes in the export complexity index on firm-level markup growth.

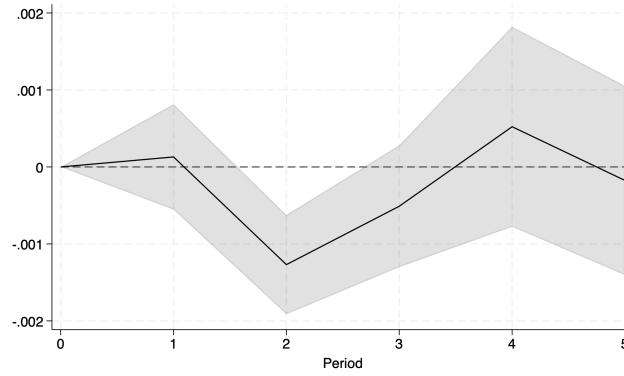
The visualization in Figure 3 illustrates the impulse responses. Initially, markups indicate a slight increase in competition, which is reflected in lower markups. However, over time, there is an increase in markups. It's important to note that these dynamics are not statistically significant across the overall sample. In other words, an average firm cannot expect to gain greater market power as its complexity increases. However, these results obscure the important underlying heterogeneities. When we divide the sample into small and large firms, a different story emerges.

Small firms appear to face tougher competition after upgrading, as can be seen from the temporary reduction in their markups. This evidence echoes that of [Atkin et al. \(2024\)](#), who demonstrate, at a more aggregate level, that the dynamic gains or losses depend on whether more complex goods entail more or less competition. They empirically show the former, resulting in dynamic losses for less developed economies. In our case, smaller firms differ from larger firms (as seen in Figure 2), and they might face tougher competition after climbing up

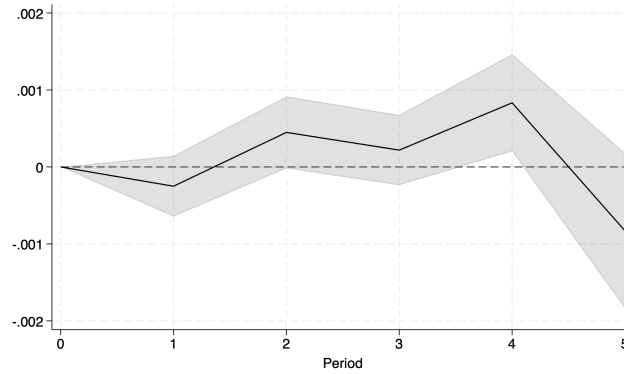
Figure 3. Local projections of markup growth & the predicted value of UFCI



(A) All Firms



(B) Small Firms



(C) Large Firms

Description: The figure plots cumulative impulse response functions identified by local projections (Jordà, 2005) with a 90% confidence interval. The vertical axis depicts the reaction of Davis-Haltiwanger growth rate of firm-level markup obtained via estimation of translog production function (see Appendix A) in response to a change in the predicted value of ΔUFCI based on SSIV in the first stage. Small firms are defined as having less than or equal to 50 employees, whereas large firms have more than 50 employees. Firm, year, and year-industry fixed effects are included. Standard errors are clustered at the firm level.

the complexity ladder in their product bundle. This is because larger and more productive firms are often the incumbents for these more complex goods. However, this fiercer competition effect is transitory, as markups eventually return to baseline levels (as shown in the

cumulative response in the figure).

The situation is different for large firms, which typically find it easier to compete, albeit after a significant delay (see panel (C) of Figure 3). The growing disparity between firms offers a foundational understanding of how market power dynamics evolve, highlighting that larger firms increasingly dominate markets, affecting overall macroeconomic parameters. These firms can often engage in technological advancements and skill enhancements to improve their production processes and product quality, improving their efficiencies and expanding into new markets more effectively than their smaller counterparts (Van Reenen, 2018). The policy and infrastructure support toward large firms might also be instrumental in helping them maintain their market dominance (Brandt and Thun, 2016).

Several important policy recommendations emerge from our analysis. Small firms must be supported or incentivized in their upgrading process via targeted policies, as trade alone can instead lead to tougher competition when they start serving more capable countries and/or producing more complex goods. Before they establish proper market shares, easier access to finance could increase the chance of survival after upgrading. For large firms, we recommend policies that facilitate entry into and trade with more advanced trade partners, which act as catalysts for upgrading. In an environment where trade wars and fragmentation loom, the objective of a more energy-efficient and climate-neutral economy is even more challenging to achieve.

6 Discussion and Policy Implications

Our paper delves into the dynamics that govern the relationship between export activities, firm-level upgrading, and energy efficiency. The granular level analysis provides policy insights on how to navigate the transition towards a greener economy. The observed trends suggest unique challenges and opportunities faced by small and large firms. While smaller enterprises may have utilized increased profits pre-EU integration to invest in energy-efficient measures, the post-integration period shows a stagnation in such efforts. This highlights the need for sustained support mechanisms and tailored policies to support upgrading and energy efficiency initiatives among small companies (Trianni et al., 2013; Cagno et al., 2015).

Based on our findings, we structure our policy recommendations around three major points: support for small firms in their upgrading efforts, mitigation of financial frictions that hinder

energy efficiency gains, and promotion of well-functioning inputs market and free trade.

6.1 Small Firms

Our findings show that small firms are key contributors to energy savings from upgrading. However, due to their small scale and intense competition, these firms see limited profitability gains from such efforts and do not benefit from higher profits (markups), meaning that the market mechanism alone offers limited incentives for these firms to pursue upgrades. Policies such as export promotions, particularly those fostering partnerships with advanced economies, and improving access to complex intermediate inputs are therefore critical. Ensuring well-functioning input markets including capital, labor, and R&D investments is essential for supporting small firms upgrading efforts and preventing costly losses of resource access due to fragmentation or trade barriers.

These differentiated needs are consistent with the recent evidence in [Liu \(2019\)](#) and [IMF policy brief](#), which emphasize that enabling factors behind successful industrial policy include firm size, export orientation and network linkages. Even though our proposed tailored policies for small firms are based on granular empirical evidence and address market failures related to missing market rewards for upgrading, struggle with access to capital and networking in advanced markets, they should be time-bound and transparent, consistent with domestic macroeconomic stability, avoiding negative cross-border spillovers, WTO policy-consistent, and preserve as much as possible competitive neutrality.

6.2 Financial Constraints

As described earlier and summarized in Table 7 and accompanying Tables A.13 and A.14 in the Appendix, our recommendations go beyond simply addressing access to green technologies and energy-efficient practices in the context of financial constraints ([Cecere et al., 2020](#); [Yu et al., 2021](#); [De Haas et al., 2024](#)). For small firms, our study emphasizes their significant role in reducing energy intensity and highlights the challenge of enhancing energy efficiency in the upgrading process when financially constrained. This is because the cost of capital disproportionately affects smaller businesses, hence targeted financial mechanisms can play a significant role in enabling their upgrading efforts.²⁰ Since small businesses make up a large portion of

²⁰This targeted approach is consistent with IP findings, which promote well-structured financing to reduce the gaps among firms and allow smaller firms to pursue energy-efficient upgrades effectively ([Liu, 2019](#)).

the economy in many countries, improving their access to finance is essential for achieving a successful green transition.

For larger firms, financial constraints considerably reduce energy efficiency. Remedies such as well-functioning capital markets, access to external finance, a strong regulatory environment, and a competitive banking sector can alleviate these constraints. Additionally, promoting trade in more complex products or with more complex markets can effectively counteract the negative effects of financial constraints.

6.3 Free Trade

Open and free trade facilitates firm upgrading and energy efficiency by ensuring access to necessary inputs, advanced technology, and innovative practices. Our results indicate that increased external demand encourages firms to enhance product complexity and engage with more sophisticated trade partners. Removing trade barriers and preventing regional fragmentation are essential steps to further these efforts.

Our study builds on earlier advocacy for open trade policies (e.g., [Amsden, 1994](#)) by underscoring the importance of integration along the Global Value Chains (GVC) ([Antràs and Chor, 2013](#)). As suggested by [Chor et al. \(2021\)](#), GVC participation fosters the accumulation of productivity-enhancing inputs, which are especially crucial for achieving energy-efficient production. During our study period, Lithuania's structural changes benefited significantly from the reorganization of European supply chains ([Hagemejer and Mućk, 2019](#)), highlighting that GVC participation is instrumental for firm upgrading and energy transition. This aligns with the recent recommendation in the [IMF policy brief](#), which supports liberalizing measures, such as export promotion, while advising against distortive policies like subsidies.

Our study also emphasizes the need for international policy coordination. Aligning green financing mechanisms with industrial policies across borders is especially important amid ongoing economic fragmentation. Such coordination can help stabilize capital flows, ensuring that small firms have reliable access to essential inputs and financing. Moreover, integrating environmental standards into financing mechanisms that support energy-efficient investments could be particularly beneficial for firms at the early stages of their green transition ([Bertoldi et al., 2021](#)).

7 Conclusions

Our paper emphasizes the pivotal role of firm complexity in determining energy intensity and efficiency. Utilizing a database with the universe of firms that matches balance-sheet information with customs data, we introduce a novel firm complexity index that incorporates such factors as destination and source countries, product mix, and trade relationships. By applying instrumental variables, including the state-of-the-art quasi-experimental shift-share method (Borusyak et al., 2022), we document causal connections between firm complexity (indicative of firm-level upgrading) and how intensely energy is used.

Our study exploits shocks in foreign import demand, revealing a positive association with firm complexity particularly among small firms. These firms experience significant reductions in energy intensity through enhanced complexity, reinforcing existing literature on trade-induced efficiency gains. Our findings confirm previous insights on the energy efficiency potential of trade, adding new dimensions by demonstrating that size-related heterogeneity plays a substantial role.

We also explored the role of markups as market-based rewards for upgrading, as well as the role of financial constraints. We found that markups increase after upgrading for large firms, but there is no evidence that small firms could enjoy higher market power after increased complexity. Furthermore, we found that financial constraints reduce energy efficiency during their upgrading. For large firms, however, this negative effect can be mitigated by increasing firm complexity, whereas for small firms, upgrading does not attenuate the adverse effects of financial constraints.

To summarize, we call for policies that support small firms in their upgrading efforts by facilitating access to finance and promoting export opportunities for all firms, particularly through partnerships with advanced economies, while ensuring that input markets function effectively. Additionally, mitigating financial constraints is crucial to enhance the energy efficiency gains from upgrading. Lastly, promoting free trade and maintaining a competitive environment are vital to leverage global integration for energy efficiency improvements.

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APPENDIX

A Production Function Estimation and Markups

We follow closely the procedure in [Ding et al. \(2024\)](#) to estimate the markups of individual firms using the production function approach (e.g., [de Loecker and Warzynski, 2012](#); [Yeh et al., 2022](#)). Firm-level markup can be obtained through the following equation:

$$\mu_{it} \equiv \frac{e_{it}^c}{\alpha_{it}^c}, \quad (\text{A.1})$$

where the variable input cost shares of output, α_{it}^c , can be calculated directly from the data by taking the ratio of the cost of variable inputs costs over sales. To estimate the output elasticity e_{it}^c , we assume that the productivity component is Hicks neutral and consider a vector of technology parameters, θ , that are constant across time but vary across industries. Thus, we can write the production function as $Q_{it} = \Omega_{it} \tilde{F}(X_{it}; \theta)$. In the data, we measure output Q_{it} using firms' total sales revenue, Y_{it} , deflated by their industry-specific gross output deflator.

Let y_{it} stand for the (log) real sales revenue and assume that the data contain potential measurement errors, ϵ_{it} ; the model to estimate is as follows

$$y_{it} = \omega_{it} + \tilde{f}(x_{it}; \theta) + \epsilon_{it},$$

where $x_{it} = (c_{it}, l_{it}, k_{it})$ refers to the vector of the real value of each input, expressed in logs.²¹ To estimate θ , a simple approach would be to regress the (log) of sales revenue on inputs. However, as productivity levels, ω_{it} , are unobserved, this approach would yield biased estimates ([García-Perea et al., 2021](#); [de Ridder et al., 2022](#)). To tackle this issue, we follow the two-step method proposed by [Olley and Pakes \(1996\)](#), relying on the identification strategy outlined in [Akerberg et al. \(2015\)](#).

In the first stage, we assume that the unobserved productivity is a third-order expansion of the inputs denoted by the function $h(\cdot)$. We then run an OLS on the following specification

$$y_{it} = g_t(x_{it}; \theta) + \epsilon_{it}, \quad (\text{A.2})$$

²¹In the data, the variables refer to the real value of the variable input cost, c_{it} , wage bill, l_{it} , and the value of fixed tangible assets, k_{it} . Please refer to [Ding et al. \(2024\)](#) for the full description of the variables utilized in the estimation process.

where $g_t(\mathbf{x}_{it}; \boldsymbol{\theta}) = h_t(\mathbf{x}_{it}) + \tilde{f}(\mathbf{x}_{it}; \boldsymbol{\theta})$. Productivity is then computed as $\omega_{it} = \hat{g}_t - \tilde{f}(\mathbf{x}_{it}; \boldsymbol{\theta})$. Note that we eliminate measurement error at this initial stage, but we cannot separate the production function component from productivity, since they both depend on inputs. Therefore, under the assumption that ω_{it} follows an AR(1) Markov process, we construct productivity innovations as $\xi_{it} = \omega_{it} - m(\omega_{it-1})$ and rely on moment conditions for identification.²² Since productivity innovation should be unaffected by inputs selected before time t , the estimation of θ can be achieved using the following moment conditions

$$\mathbb{E} \left(\xi_{it}(\theta) \begin{bmatrix} \mathbf{z}_{it-1} \\ \mathbf{k}_{it} \end{bmatrix} \right) = \mathbf{0},$$

where \mathbf{z}_{it-1} represents an instrument vector including all one-period lagged values of every polynomial term containing c_{it} and l_{it} in the production function $\tilde{f}(\mathbf{x}_{it}; \boldsymbol{\theta})$. The value of capital is fixed at its current value as it is assumed to be predetermined and, hence, should be orthogonal to the innovation $\xi_{it}(\theta)$.

To obtain the empirical markups, we assume the following translog functional form for the production function

$$\tilde{f}(\mathbf{x}_{it}; \boldsymbol{\theta}) = \theta_c c_{it} + \theta_l l_{it} + \theta_k k_{it} + \theta_{cc} c_{it}^2 + \theta_{ll} l_{it}^2 + \theta_{kk} k_{it}^2 + \theta_{cl} c_{it} l_{it} + \theta_{ck} c_{it} k_{it} + \theta_{lk} l_{it} k_{it}. \quad (\text{A.3})$$

Following the procedure described above, we estimate θ by GMM separately for each of the 2-digit industries in the data. Using the GMM estimates of equation (A.3), the firm-level markups are

$$\hat{\mu}_{it} = (\hat{\theta}_c + 2\hat{\theta}_{cc}c_{it} + \hat{\theta}_{cl}l_{it} + \hat{\theta}_{ck}k_{it}) \cdot \frac{\tilde{Y}_{it}}{C_{it}} = \frac{\hat{e}_{it}^c}{\tilde{\alpha}_{it}^c}, \quad (\text{A.4})$$

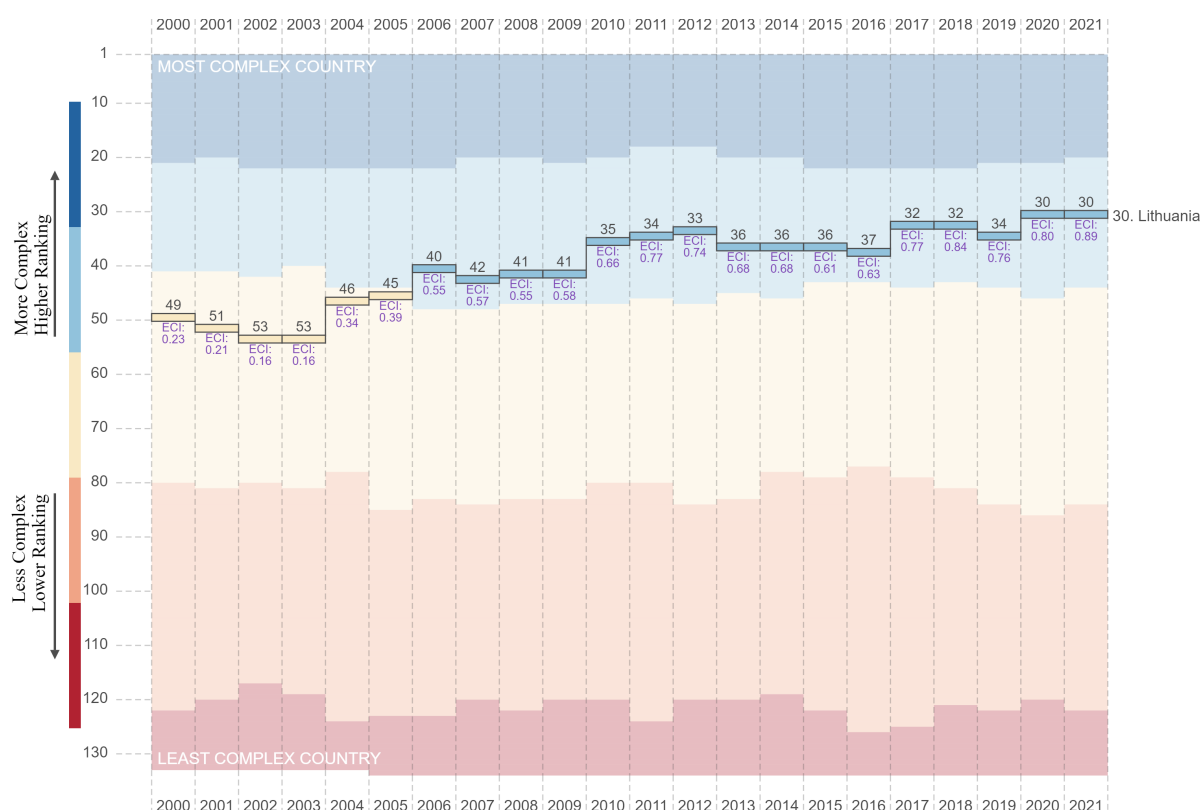
where $\tilde{Y}_{it} = \exp(y_{it} - \hat{e}_{it})$ is the measurement-corrected sales and $\tilde{\alpha}_{it}^c = \frac{C_{it}}{\tilde{Y}_{it}}$ is the variable input costs over corrected sales revenue. Note that this approach to estimate markups also allows us to recover firm-level TFP, ω_{it} , from the estimation of the production function.

²²We assume that $m(\cdot)$ is a third-order expansion of the productivity measure (de Loecker and Warzynski, 2012).

B Complexity Indices

We take two datasets from the [Harvard Growth Lab](#): the Economic Complexity Index (ECI) and the Product Complexity Index (PCI). The former is at the country level, whereas the latter is at the product level. A technical breakout on how these indices are computed can be found in [Hidalgo et al. \(2009\)](#). The following description is taken directly from the website of Harvard Growth Lab.

ECI ranks countries' complexity based on how diversified and complex their export basket is. Countries that are home to a great diversity of productive know-how, particularly complex specialized know-how, are able to produce a great diversity of sophisticated products. The complexity of a country's exports is found to highly predict current income levels, or where complexity exceeds expectations for a country's income level, the country is predicted to experience more rapid growth in the future. ECI therefore provides a useful measure of economic development. For example, Lithuania's complexity exhibits the following pattern:



PCI ranks the diversity and sophistication of the productive know-how required to produce a product. PCI is calculated based on how many other countries can produce the product and the economic complexity of those countries. In effect, PCI captures the amount and sophistication of know-how required to produce a product. The most complex products (that only a

few, highly complex countries can produce) include sophisticated machinery, electronics and chemicals, as compared to the least complex products (that nearly all countries including the least complex can produce) including raw materials and simple agricultural products. Specialized machinery is said to be complex as it requires a range of know-how in manufacturing, including the coordination of a range of highly skilled individuals know-how. For instance, in 2021, the most complex product is "Photographic plates and film, exposed and developed, other than motion-picture film" (PCI = 2.31, HS 1992 code 3705), whereas the least complex product is "Tin ores and concentrates" (PCI = -3.37, HS 1992 code 1221).

Since ECI involves more than 100 countries, whereas PCI involves more than 1000 products, and both of them span over 25 years, we will not provide the summary statistics of them in the interest of space.²³ In Section 2, we provide the summary statistics of our constructed dependent variable ΔUFCI , which utilizes both ECI and PCI.

²³Interested readers can easily find their description and visualization on the Atlas website.

C Falsification Test

To assess the plausibility of the conditional quasi-random shock assignment in [Borusyak et al. \(2022\)](#), we implement the following falsification test of shock orthogonality in our SSIV setting. Table A.1 reports coefficients from regressions of firm-level covariates on our shift-share instruments (normalized to have a unit variance), controlling for year and year-industry fixed effects. HS4 digit-clustered exposure-robust standard errors are reported and obtained from equivalent firm-level IV regressions.

Table A.1. Summary statistics

Balance variables	Coefficient	SE
Labor productivity	-37.1950	30.5795
Labor share	-0.0009	0.0037
Capital intensity	-0.0818	0.0537
Fraction of part-time workers	-0.0137	0.0084
Profit margin	0.0008	0.0117
Leverage ratio	-0.0006	0.0059
Number of observations		35,376

Note: Labor productivity is defined as a firm's sales over its number of hours reported in a given year, labor share is defined as a firm's wage bill over its sales, capital intensity is defined as a firm's fixed tangible assets over its sales, the fraction of part-time workers is a firm's average number of part-time workers over its average number of employees, profit margin is defined as EBITDA over sales, and leverage ratio is firm's long-term debt over its total assets.

The six controls are labor productivity, labor share, capital intensity, fraction of part-time workers, profit margin, and leverage ratio. Broadly speaking, these measures reflect a firm's production characteristics. We find no statistically significant relationship between these variables and our shift-share instruments.

Notice that unlike the case in [Borusyak et al. \(2022\)](#), where the authors can do the balance check both at the industry level (similar to our product level) and the location level (similar to our firm level), here in our case, we can only perform the balance check at the firm level, not at the product level. This is because our product-level information comes from the global 6-digit trade flow data from CEPII, which is exogenous to Lithuania. *In addition, our firm-level data does not contain additional information at the product level.* This means we cannot check whether product-level shocks predict any predetermined product-level variables.

D Additional Tables

Table A.2. First Stage: Fixing Country Complexity

Columns	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Dependent variable	ΔUFCI2	ΔUFCI2	ΔUFCI2	ΔUFCI2	ΔUFCI2	ΔUFCI2	ΔUFCI2
ΔED	0.0948** (0.0454)	0.0990** (0.0442)			0.0997*** (0.0378)		
$\text{EU} \times \Delta\text{ED}$			0.0680 (0.0434)	0.0681 (0.0435)		0.0720* (0.0378)	0.0719* (0.0377)
$\text{IMP share}_{t-1}^{\text{EU15}}$		✓	✓				
$\text{EXP share}_{t-1}^{\text{EU15}}$		✓	✓				
$\text{EU} \times \text{IMP share}_{t-1}^{\text{EU15}}$				✓			
$\text{EU} \times \text{EXP share}_{t-1}^{\text{EU15}}$				✓			
$\Delta\text{IMP share}_{t-1}^{\text{EU15}}$					✓	✓	
$\Delta\text{EXP share}_{t-1}^{\text{EU15}}$					✓	✓	
$\text{EU} \times \Delta\text{IMP share}_{t-1}^{\text{EU15}}$							✓
$\text{EU} \times \Delta\text{EXP share}_{t-1}^{\text{EU15}}$							✓
Year FE	✓	✓	✓	✓	✓	✓	✓
Year \times Industry FE	✓	✓	✓	✓	✓	✓	✓
Observations	43,574	43,359	43,359	43,359	40,275	40,275	40,275
Product IV	Z_product	Z_product	Z_prod \times EU	Z_prod \times EU	Z_product	Z_prod \times EU	Z_prod \times EU
LM statistic	119.382	80.648	75.533	75.552	65.779	61.754	61.751
Wald F statistic	155.693	124.584	119.412	119.493	103.916	99.633	99.629
Hansen J statistic	0	0	0	0	0	0	0

Note: Clustered robust standard errors in parentheses, *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. ΔED is the external demand defined in Equation (4.3), ΔUFCI2 is the Davis-Haltiwanger growth rate defined in Equation (4.5), but with country complexity fixed at initial period. $\Delta\text{EXP share}_{t-1}^{\text{EU15}}$ stands for the lagged change in firm-level export share to EU15 countries. Similarly for the import share. EU is a dummy variable that takes value one after 2004.

Table A.3. First Stage: Fixing Product Complexity

Columns	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Dependent variable	ΔUFCI3	ΔUFCI3	ΔUFCI3	ΔUFCI3	ΔUFCI3	ΔUFCI3	ΔUFCI3
ΔED	0.0880** (0.0438)	0.0924** (0.0428)			0.102*** (0.0377)		
$\text{EU} \times \Delta\text{ED}$			0.0612 (0.0418)	0.0613 (0.0418)		0.0723* (0.0375)	0.0722* (0.0374)
$\text{IMP share}_{t-1}^{\text{EU15}}$		✓	✓				
$\text{EXP share}_{t-1}^{\text{EU15}}$		✓	✓				
$\text{EU} \times \text{IMP share}_{t-1}^{\text{EU15}}$				✓			
$\text{EU} \times \text{EXP share}_{t-1}^{\text{EU15}}$				✓			
$\Delta\text{IMP share}_{t-1}^{\text{EU15}}$					✓	✓	
$\Delta\text{EXP share}_{t-1}^{\text{EU15}}$					✓	✓	
$\text{EU} \times \Delta\text{IMP share}_{t-1}^{\text{EU15}}$							✓
$\text{EU} \times \Delta\text{EXP share}_{t-1}^{\text{EU15}}$							✓
Year FE	✓	✓	✓	✓	✓	✓	✓
Year \times Industry FE	✓	✓	✓	✓	✓	✓	✓
Observations	43,574	43,359	43,359	43,359	40,275	40,275	40,275
Product IV	Z_product	Z_product	Z_prod \times EU	Z_prod \times EU	Z_product	Z_prod \times EU	Z_prod \times EU
LM statistic	119.382	80.648	75.533	75.552	65.779	61.754	61.751
Wald F statistic	155.693	124.584	119.412	119.493	103.916	99.633	99.629
Hansen J statistic	0	0	0	0	0	0	0

Note: Clustered robust standard errors in parentheses, *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. ΔED is the external demand defined in Equation (4.3), ΔUFCI3 is the Davis-Haltiwanger growth rate defined in Equation (4.5), but with product complexity fixed at initial period. $\Delta\text{EXP share}_{t-1}^{\text{EU15}}$ stands for the lagged change in firm-level export share to EU15 countries. Similarly for the import share. EU is a dummy variable that takes value one after 2004.

Table A.4. Second Stage: Complexity and Energy Intensity

Columns	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Dependent variable	ΔEI_{cogs}	ΔEI_{cogs}	ΔEI_{cogs}	ΔEI_{cogs}	ΔEI_{cogs}	ΔEI_{cogs}	ΔEI_{cogs}
$\Delta UFCI_{SSIV}$	-0.00589*** (0.00164)	-0.00718*** (0.00187)			-0.00569*** (0.00207)		
$EU \times \Delta UFCI_{SSIV}$			-0.00744*** (0.00187)	-0.00745*** (0.00187)		-0.00596*** (0.00207)	-0.00595*** (0.00207)
$IMP \text{ share}_{t-1}^{EU15}$		0.00687 (0.0187)	0.00692 (0.0187)				
$EXP \text{ share}_{t-1}^{EU15}$		-0.00104 (0.0247)	-0.000914 (0.0247)				
$EU \times IMP \text{ share}_{t-1}^{EU15}$				0.0217 (0.0199)			
$EU \times EXP \text{ share}_{t-1}^{EU15}$				-0.0122 (0.0257)			
$\Delta IMP \text{ share}_{t-1}^{EU15}$					0.0167 (0.0174)	0.0167 (0.0174)	
$\Delta EXP \text{ share}_{t-1}^{EU15}$					0.0503** (0.0224)	0.0502** (0.0224)	
$EU \times \Delta IMP \text{ share}_{t-1}^{EU15}$							0.00644 (0.0187)
$EU \times \Delta EXP \text{ share}_{t-1}^{EU15}$							0.0608** (0.0238)
Firm FE	✓	✓	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓	✓
Year \times Industry FE	✓	✓	✓	✓	✓	✓	✓
Observations	67,587	41,895	41,895	41,895	33,376	33,376	33,376
R-squared	0.152	0.134	0.134	0.134	0.132	0.132	0.132

Note: Clustered robust standard errors in parentheses, *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. ΔEI_{cogs} stands for the Davis-Haltiwanger growth rate of firm-level expenditure on energy over cost of sales. $\Delta UFCI_{SSIV}$ is the predicted value of $\Delta UFCI$ based on SSIV in the first stage. $\Delta EXP \text{ share}_{t-1}^{EU15}$ ($\Delta IMP \text{ share}_{t-1}^{EU15}$) stands for the change in firm-level lagged export (import) share to EU15 countries. EU is a dummy variable that takes value one after 2004.

Table A.5. Second Stage: Complexity and Energy Intensity for Small Firms

Columns Dependent variable	(1) ΔEI_{cogs}	(2) ΔEI_{cogs}	(3) ΔEI_{cogs}	(4) ΔEI_{cogs}	(5) ΔEI_{cogs}	(6) ΔEI_{cogs}	(7) ΔEI_{cogs}
$\Delta UFCI_{SSIV}$	-0.00653*** (0.00228)	-0.0102*** (0.00279)			-0.00861*** (0.00326)		
$EU \times \Delta UFCI_{SSIV}$			-0.0106*** (0.00281)	-0.0106*** (0.00282)		-0.00934*** (0.00329)	-0.00934*** (0.00329)
$IMP \text{ share}_{t-1}^{EU15}$		-0.00793 (0.0249)	-0.00814 (0.0249)				
$EXP \text{ share}_{t-1}^{EU15}$		0.0420 (0.0374)	0.0414 (0.0374)				
$EU \times IMP \text{ share}_{t-1}^{EU15}$				0.0114 (0.0263)			
$EU \times EXP \text{ share}_{t-1}^{EU15}$				0.0306 (0.0391)			
$\Delta IMP \text{ share}_{t-1}^{EU15}$					0.00831 (0.0235)	0.00813 (0.0235)	
$\Delta EXP \text{ share}_{t-1}^{EU15}$					0.0696* (0.0361)	0.0696* (0.0361)	
$EU \times \Delta IMP \text{ share}_{t-1}^{EU15}$							-0.00364 (0.0253)
$EU \times \Delta EXP \text{ share}_{t-1}^{EU15}$							0.0782** (0.0379)
Firm FE	✓	✓	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓	✓
Year \times Industry FE	✓	✓	✓	✓	✓	✓	✓
Observations	52,660	29,573	29,573	29,573	22,570	22,570	22,570
R-squared	0.173	0.153	0.153	0.153	0.150	0.150	0.150
Firm Size	Small	Small	Small	Small	Small	Small	Small

Note: Clustered robust standard errors in parentheses, *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. ΔEI_{cogs} stands for the Davis-Haltiwanger growth rate of firm-level expenditure on energy over cost of sales $\Delta UFCI_{SSIV}$ is the predicted value of $\Delta UFCI$ based on SSIV in the first stage. $\Delta EXP \text{ share}_{t-1}^{EU15}$ ($\Delta IMP \text{ share}_{t-1}^{EU15}$) stands for the change in firm-level lagged export (import) share to EU15 countries. EU is a dummy variable that takes value one after 2004. Small represents firms that have less than 50 employees.

Table A.6. Second Stage: Complexity and Energy Intensity for Large Firms

Columns	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Dependent variable	ΔEI_{cogs}	ΔEI_{cogs}	ΔEI_{cogs}	ΔEI_{cogs}	ΔEI_{cogs}	ΔEI_{cogs}	ΔEI_{cogs}
$\Delta UFCI_{SSIV}$	-0.00345 (0.00239)	-0.00242 (0.00257)			-0.00160 (0.00265)		
$EU \times \Delta UFCI_{SSIV}$			-0.00262 (0.00256)	-0.00263 (0.00256)		-0.00170 (0.00264)	-0.00172 (0.00265)
$IMP \text{ share}_{t-1}^{EU15}$		0.0415 (0.0278)	0.0418 (0.0278)				
$EXP \text{ share}_{t-1}^{EU15}$		-0.0384 (0.0312)	-0.0383 (0.0311)				
$EU \times IMP \text{ share}_{t-1}^{EU15}$				0.0390 (0.0303)			
$EU \times EXP \text{ share}_{t-1}^{EU15}$				-0.0420 (0.0329)			
$\Delta IMP \text{ share}_{t-1}^{EU15}$					0.0432* (0.0244)	0.0433* (0.0244)	
$\Delta EXP \text{ share}_{t-1}^{EU15}$					0.0351 (0.0262)	0.0350 (0.0262)	
$EU \times \Delta IMP \text{ share}_{t-1}^{EU15}$							0.0398 (0.0266)
$EU \times \Delta EXP \text{ share}_{t-1}^{EU15}$							0.0487* (0.0283)
Firm FE	✓	✓	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓	✓
Year \times Industry FE	✓	✓	✓	✓	✓	✓	✓
Observations	14,271	11,888	11,888	11,888	10,439	10,439	10,439
R-squared	0.181	0.179	0.179	0.179	0.183	0.183	0.183
Firm Size	Large	Large	Large	Large	Large	Large	Large

Note: Clustered robust standard errors in parentheses, *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. ΔEI_{cogs} stands for the Davis-Haltiwanger growth rate of firm-level expenditure on energy over cost of sales. $\Delta UFCI_{SSIV}$ is the predicted value of $\Delta UFCI$ based on SSIV in the first stage. $\Delta EXP \text{ share}_{t-1}^{EU15}$ ($\Delta IMP \text{ share}_{t-1}^{EU15}$) stands for the change in firm-level lagged export (import) share to EU15 countries. EU is a dummy variable that takes value one after 2004. Large represents firms that have more than 50 employees.

Table A.7. Second Stage: Complexity and Energy Intensity for Young Firms

Columns Dependent variable	(1) ΔEI_y	(2) ΔEI_y	(3) ΔEI_y	(4) ΔEI_y	(5) ΔEI_y	(6) ΔEI_y	(7) ΔEI_y
$\Delta UFCI_{SSIV}$	-0.0135*** (0.0052)	-0.0234*** (0.0086)			-0.0229* (0.0138)		
$EU \times \Delta UFCI_{SSIV}$			-0.0226*** (0.0088)	-0.0227*** (0.0088)		-0.0223 (0.0140)	-0.0225 (0.0140)
$IMP \text{ share}_{t-1}^{EU15}$		-0.0364 (0.0788)	-0.00361 (0.0787)				
$EXP \text{ share}_{t-1}^{EU15}$		0.0057 (0.1113)	0.0065 (0.1112)				
$EU \times IMP \text{ share}_{t-1}^{EU15}$				-0.0169 (0.0084)			
$EU \times EXP \text{ share}_{t-1}^{EU15}$				0.0183 (0.1210)			
$\Delta IMP \text{ share}_{t-1}^{EU15}$					-0.0235 (0.0762)	-0.0230 (0.0764)	
$\Delta EXP \text{ share}_{t-1}^{EU15}$					0.0232 (0.1194)	0.0233 (0.1194)	
$EU \times \Delta IMP \text{ share}_{t-1}^{EU15}$							-0.0410 (0.0847)
$EU \times \Delta EXP \text{ share}_{t-1}^{EU15}$							0.0814 (0.1316)
Firm FE	✓	✓	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓	✓
Year \times Industry FE	✓	✓	✓	✓	✓	✓	✓
Observations	13,840	6,273	6,273	6,273	3,136	3,136	3,136
R-squared	0.297	0.306	0.306	0.306	0.371	0.371	0.372
Firm Age	Young	Young	Young	Young	Young	Young	Young

Note: Clustered robust standard errors in parentheses, *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. ΔEI_y stands for the Davis-Haltiwanger growth rate of firm-level sales over cost of sales $\Delta UFCI_{SSIV}$ is the predicted value of $\Delta UFCI$ based on SSIV in the first stage. $\Delta EXP \text{ share}_{t-1}^{EU15}$ ($\Delta IMP \text{ share}_{t-1}^{EU15}$) stands for the change in firm-level lagged export (import) share to EU15 countries. EU is a dummy variable that takes value one after 2004. Young represents firms that are less or equal to 5 years old.

Table A.8. Second Stage: Complexity and Energy Intensity for Young and Small Firms

Columns Dependent variable	(1) ΔEI_y	(2) ΔEI_y	(3) ΔEI_y	(4) ΔEI_y	(5) ΔEI_y	(6) ΔEI_y	(7) ΔEI_y
$\Delta UFCI_{SSIV}$	-0.0143*** (0.0056)	-0.0254*** (0.0094)			-0.0314** (0.0152)		
$EU \times \Delta UFCI_{SSIV}$			-0.0241** (0.0088)	-0.0242** (0.0097)		-0.0306** (0.0153)	-0.0309** (0.0154)
$IMP \text{ share}_{t-1}^{EU15}$		-0.0581 (0.0888)	-0.0570 (0.0887)				
$EXP \text{ share}_{t-1}^{EU15}$		0.0133 (0.1428)	0.0159 (0.1425)				
$EU \times IMP \text{ share}_{t-1}^{EU15}$				-0.0648 (0.0935)			
$EU \times EXP \text{ share}_{t-1}^{EU15}$				0.0686 (0.1534)			
$\Delta IMP \text{ share}_{t-1}^{EU15}$					-0.0370 (0.0863)	-0.0370 (0.0862)	
$\Delta EXP \text{ share}_{t-1}^{EU15}$					-0.0811 (0.1587)	-0.0797 (0.1586)	
$EU \times \Delta IMP \text{ share}_{t-1}^{EU15}$							-0.0538 (0.0943)
$EU \times \Delta EXP \text{ share}_{t-1}^{EU15}$							-0.0006 (0.1698)
Firm FE	✓	✓	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓	✓
Year \times Industry FE	✓	✓	✓	✓	✓	✓	✓
Observations	12,747	5,468	5,468	5,468	2,660	2,660	2,660
R-squared	0.299	0.302	0.302	0.302	0.362	0.362	0.364
Firm Age	Young	Young	Young	Young	Young	Young	Young
Firm Size	Small	Small	Small	Small	Small	Small	Small

Note: Clustered robust standard errors in parentheses, *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. ΔEI_y stands for the Davis-Haltiwanger growth rate of firm-level sales over cost of sales $\Delta UFCI_{SSIV}$ is the predicted value of $\Delta UFCI$ based on SSIV in the first stage. $\Delta EXP \text{ share}_{t-1}^{EU15}$ ($\Delta IMP \text{ share}_{t-1}^{EU15}$) stands for the change in firm-level lagged export (import) share to EU15 countries. EU is a dummy variable that takes value one after 2004. Young represents firms that are less or equal to 5 years old. Small represents firms that have less than 50 employees.

Table A.9. Second Stage: Complexity and Energy Intensity for Young and Large Firms

Columns Dependent variable	(1) ΔEI_y	(2) ΔEI_y	(3) ΔEI_y	(4) ΔEI_y	(5) ΔEI_y	(6) ΔEI_y	(7) ΔEI_y
$\Delta UFCI_{SSIV}$	-0.0289 (0.0192)	-0.0363 (0.0243)			-0.0220 (0.0475)		
$EU \times \Delta UFCI_{SSIV}$			-0.0358 (0.0243)	-0.0369 (0.0245)		-0.0241 (0.0494)	-0.0279 (0.0510)
$IMP \text{ share}_{t-1}^{EU15}$		-0.2009 (0.2495)	-0.1994 (0.2504)				
$EXP \text{ share}_{t-1}^{EU15}$		-0.1718 (0.1884)	-0.1732 (0.1906)				
$EU \times IMP \text{ share}_{t-1}^{EU15}$				-0.1063 (0.2742)			
$EU \times EXP \text{ share}_{t-1}^{EU15}$				-0.1758 (0.2147)			
$\Delta IMP \text{ share}_{t-1}^{EU15}$					0.0287 (0.2183)	0.0266 (0.2201)	
$\Delta EXP \text{ share}_{t-1}^{EU15}$					0.1663 (0.2575)	0.1633 (0.2599)	
$EU \times \Delta IMP \text{ share}_{t-1}^{EU15}$							0.0274 (0.2518)
$EU \times \Delta EXP \text{ share}_{t-1}^{EU15}$							0.2617 (0.2944)
Firm FE	✓	✓	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓	✓
Year \times Industry FE	✓	✓	✓	✓	✓	✓	✓
Observations	694	511	511	511	275	275	275
R-squared	0.524	0.557	0.557	0.559	0.616	0.616	0.619
Firm Age	Young	Young	Young	Young	Young	Young	Young
Firm Size	Large	Large	Large	Large	Large	Large	Large

Note: Clustered robust standard errors in parentheses, *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. ΔEI_y stands for the Davis-Haltiwanger growth rate of firm-level sales over cost of sales $\Delta UFCI_{SSIV}$ is the predicted value of $\Delta UFCI$ based on SSIV in the first stage. $\Delta EXP \text{ share}_{t-1}^{EU15}$ ($\Delta IMP \text{ share}_{t-1}^{EU15}$) stands for the change in firm-level lagged export (import) share to EU15 countries. EU is a dummy variable that takes value one after 2004. Young represents firms that are less or equal to 5 years old. Large represents firms that have more than 50 employees.

Table A.10. Second Stage: Complexity and Energy Intensity for Old Firms

Columns Dependent variable	(1) ΔEI_y	(2) ΔEI_y	(3) ΔEI_y	(4) ΔEI_y	(5) ΔEI_y	(6) ΔEI_y	(7) ΔEI_y
$\Delta UFCI_{SSIV}$	-0.0098** (0.0049)	-0.0085 (0.0054)			-0.0071 (0.0055)		
$EU \times \Delta UFCI_{SSIV}$			-0.0087 (0.0054)	-0.0088 (0.0054)		-0.0070 (0.0056)	-0.0068 (0.0056)
$IMP \text{ share}_{t-1}^{EU15}$		-0.0589 (0.0742)	-0.0586 (0.0741)				
$EXP \text{ share}_{t-1}^{EU15}$		-0.0347 (0.0872)	-0.0358 (0.0869)				
$EU \times IMP \text{ share}_{t-1}^{EU15}$				-0.0571 (0.0748)			
$EU \times EXP \text{ share}_{t-1}^{EU15}$				-0.0566 (0.0818)			
$\Delta IMP \text{ share}_{t-1}^{EU15}$					-0.0388 (0.0514)	-0.0390 (0.0514)	
$\Delta EXP \text{ share}_{t-1}^{EU15}$					-0.0561 (0.0637)	-0.0549 (0.0636)	
$EU \times \Delta IMP \text{ share}_{t-1}^{EU15}$							-0.0463 (0.0515)
$EU \times \Delta EXP \text{ share}_{t-1}^{EU15}$							-0.0801 (0.0637)
Firm FE	✓	✓	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓	✓
Year \times Industry FE	✓	✓	✓	✓	✓	✓	✓
Observations	5,301	3,617	3,617	3,617	3,269	3,269	3,269
R-squared	0.229	0.201	0.201	0.201	0.209	0.201	0.212
Firm Age	Old	Old	Old	Old	Old	Old	Old

Note: Clustered robust standard errors in parentheses, *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. ΔEI_y stands for the Davis-Haltiwanger growth rate of firm-level sales over cost of sales $\Delta UFCI_{SSIV}$ is the predicted value of $\Delta UFCI$ based on SSIV in the first stage. $\Delta EXP \text{ share}_{t-1}^{EU15}$ ($\Delta IMP \text{ share}_{t-1}^{EU15}$) stands for the change in firm-level lagged export (import) share to EU15 countries. EU is a dummy variable that takes value one after 2004. Old represents firms that are older than 20 years old.

Table A.11. Second Stage: Complexity and Energy Intensity for Old and Small Firms

Columns Dependent variable	(1) ΔEI_y	(2) ΔEI_y	(3) ΔEI_y	(4) ΔEI_y	(5) ΔEI_y	(6) ΔEI_y	(7) ΔEI_y
$\Delta UFCI_{SSIV}$	-0.0210** (0.0088)	-0.0258** (0.0109)			-0.0211* (0.0114)		
$EU \times \Delta UFCI_{SSIV}$			-0.0277** (0.0109)	-0.0277** (0.0109)		-0.0216* (0.0114)	-0.0215* (0.0114)
$IMP \text{ share}_{t-1}^{EU15}$		-0.1360 (0.1335)	-0.1367 (0.1332)				
$EXP \text{ share}_{t-1}^{EU15}$		0.0045 (0.2353)	0.0089 (0.2340)				
$EU \times IMP \text{ share}_{t-1}^{EU15}$				-0.1205 (0.0133)			
$EU \times EXP \text{ share}_{t-1}^{EU15}$				-0.0512 (0.2050)			
$\Delta IMP \text{ share}_{t-1}^{EU15}$					-0.1366 (0.0923)	-0.1352 (0.0925)	
$\Delta EXP \text{ share}_{t-1}^{EU15}$					-0.1252 (0.1675)	-0.1285 (0.1664)	
$EU \times \Delta IMP \text{ share}_{t-1}^{EU15}$							-0.1403 (0.0930)
$EU \times \Delta EXP \text{ share}_{t-1}^{EU15}$							-0.2129 (0.1666)
Firm FE	✓	✓	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓	✓
Year \times Industry FE	✓	✓	✓	✓	✓	✓	✓
Observations	3,093	1,744	1,744	1,744	1,505	1,505	1,505
R-squared	0.274	0.225	0.226	0.227	0.234	0.234	0.240
Firm Age	Old	Old	Old	Old	Old	Old	Old
Firm Size	Small	Small	Small	Small	Small	Small	Small

Note: Clustered robust standard errors in parentheses, *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. ΔEI_y stands for the Davis-Haltiwanger growth rate of firm-level sales over cost of sales $\Delta UFCI_{SSIV}$ is the predicted value of $\Delta UFCI$ based on SSIV in the first stage. $\Delta EXP \text{ share}_{t-1}^{EU15}$ ($\Delta IMP \text{ share}_{t-1}^{EU15}$) stands for the change in firm-level lagged export (import) share to EU15 countries. EU is a dummy variable that takes value one after 2004. Old represents firms that are older than 20 years old. Small represents firms that have less than 50 employees.

Table A.12. Second Stage: Complexity and Energy Intensity for Old and Large Firms

Columns Dependent variable	(1) ΔEI_y	(2) ΔEI_y	(3) ΔEI_y	(4) ΔEI_y	(5) ΔEI_y	(6) ΔEI_y	(7) ΔEI_y
$\Delta UFCI_{SSIV}$	0.0026 (0.0059)	0.0013 (0.0064)			0.0033 (0.0067)		
$EU \times \Delta UFCI_{SSIV}$			0.0014 (0.0064)	0.0014 (0.0065)		0.0033 (0.0067)	0.035 (0.0067)
$IMP \text{ share}_{t-1}^{EU15}$		0.0895 (0.0844)	0.0890 (0.0886)				
$EXP \text{ share}_{t-1}^{EU15}$		-0.0975 (0.0881)	-0.0962 (0.0881)				
$EU \times IMP \text{ share}_{t-1}^{EU15}$				0.0816 (0.0902)			
$EU \times EXP \text{ share}_{t-1}^{EU15}$				-0.0968 (0.0883)			
$\Delta IMP \text{ share}_{t-1}^{EU15}$					0.0548 (0.0566)	0.0528 (0.0565)	
$\Delta EXP \text{ share}_{t-1}^{EU15}$					-0.0836 (0.0618)	-0.0840 (0.0618)	
$EU \times \Delta IMP \text{ share}_{t-1}^{EU15}$							0.0446 (0.0565)
$EU \times \Delta EXP \text{ share}_{t-1}^{EU15}$							-0.0845 (0.0624)
Firm FE	✓	✓	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓	✓
Year \times Industry FE	✓	✓	✓	✓	✓	✓	✓
Observations	1,973	1,677	1,677	1,677	1,574	1,574	1,574
R-squared	0.262	0.263	0.263	0.264	0.251	0.252	0.254
Firm Age	Old	Old	Old	Old	Old	Old	Old
Firm Size	Large	Large	Large	Large	Large	Large	Large

Note: Clustered robust standard errors in parentheses, *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. ΔEI_y stands for the Davis-Haltiwanger growth rate of firm-level sales over cost of sales $\Delta UFCI_{SSIV}$ is the predicted value of $\Delta UFCI$ based on SSIV in the first stage. $\Delta EXP \text{ share}_{t-1}^{EU15}$ ($\Delta IMP \text{ share}_{t-1}^{EU15}$) stands for the change in firm-level lagged export (import) share to EU15 countries. EU is a dummy variable that takes value one after 2004. Old represents firms that are older than 20 years old. Large represents firms that have more than 50 employees.

Table A.13. Financial Constraints, Complexity and Energy Intensity: Small Firms

Columns Dependent variable	(1) ΔEI_y	(2) ΔEI_y	(3) ΔEI_y	(4) ΔEI_y	(5) ΔEI_y	(6) ΔEI_y	(7) ΔEI_y
$\Delta UFCI_{SSIV}$	-0.0060*** (0.0023)	-0.0092*** (0.0029)			-0.0089** (0.0034)		
Fin Ratio	0.0086 (0.0125)	0.0138 (0.0359)	0.0135 (0.0359)	0.0135 (0.0358)	-0.0092 (0.0399)	-0.0102 (0.0397)	-0.0100 (0.0397)
$\Delta UFCI_{SSIV} \times \text{Fin Ratio}$	0.0200** (0.0097)	0.0228 (0.0173)	0.0230 (0.0173)	0.0231 (0.0173)	0.0478** (0.0208)	0.0484** (0.0397)	0.0483** (0.0207)
$EU \times \Delta UFCI_{SSIV}$			-0.0097*** (0.0029)	-0.0097*** (0.0029)		-0.0097*** (0.0034)	-0.0097*** (0.0034)
IMP share $^{EU15}_{t-1}$		-0.0111 (0.0245)	-0.0113 (0.0246)				
EXP share $^{EU15}_{t-1}$		0.0380 (0.0371)	0.00374 (0.0370)				
$EU \times \text{IMP share}^{EU15}_{t-1}$				0.0087 (0.0259)			
$EU \times \text{EXP share}^{EU15}_{t-1}$				0.0250 (0.0387)			
$\Delta \text{IMP share}^{EU15}_{t-1}$					0.0061 (0.0232)	0.0060 (0.0232)	
$\Delta \text{EXP share}^{EU15}_{t-1}$					0.0688* (0.0354)	0.0688* (0.0354)	
$EU \times \Delta \text{IMP share}^{EU15}_{t-1}$							-0.0051 (0.0251)
$EU \times \Delta \text{EXP share}^{EU15}_{t-1}$							0.0766** (0.0373)
Controls	✓	✓	✓	✓	✓	✓	✓
Firm FE	✓	✓	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓	✓
Year \times Industry FE	✓	✓	✓	✓	✓	✓	✓
Observations	53,114	29,615	29,615	29,615	22,584	22,584	22,584
R-squared	0.175	0.156	0.156	0.156	0.152	0.153	0.153
Firm Size	Small	Small	Small	Small	Small	Small	Small

Note: Clustered robust standard errors in parentheses, *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. ΔEI_y stands for the Davis-Haltiwanger growth rate of firm-level expenditure on energy over sales. $\Delta UFCI_{SSIV}$ is the predicted value of $\Delta UFCI$ based on SSIV in the first stage. Fin Ratio stands for the sum of amortization and interest payment of debt over firm sales. $\Delta \text{EXP share}^{EU15}_{t-1}$ ($\Delta \text{IMP share}^{EU15}_{t-1}$) stands for the change in firm-level lagged export (import) share to EU15 countries. EU is a dummy variable that takes value one after 2004. Small represents firms that have less than 50 employees. Firm-level controls include value added over total assets, labor productivity, age, and gross profit margin.

Table A.14. Financial Constraints, Complexity and Energy Intensity: Large Firms

Columns Dependent variable	(1) ΔEI_y	(2) ΔEI_y	(3) ΔEI_y	(4) ΔEI_y	(5) ΔEI_y	(6) ΔEI_y	(7) ΔEI_y
$\Delta UFCI_{SSIV}$	-0.0016 (0.0025)	-0.0012 (0.0026)			-0.0003 (0.0027)		
Fin Ratio	0.0885*** (0.0255)	0.0904** (0.0403)	0.0901** (0.0403)	0.0900** (0.0404)	0.1071** (0.0546)	0.1065* (0.0546)	0.1057* (0.0544)
$\Delta UFCI_{SSIV} \times \text{Fin Ratio}$	-0.0137** (0.0063)	-0.0105** (0.0042)	-0.0106** (0.0042)	-0.0106** (0.0042)	-0.0122** (0.0253)	-0.0123** (0.0053)	-0.0122** (0.0053)
$EU \times \Delta UFCI_{SSIV}$			-0.0014 (0.0026)	-0.0014 (0.0026)		-0.0004 (0.0027)	-0.0004 (0.0027)
IMP share $_{t-1}^{EU15}$		0.0451 (0.0274)	0.0454* (0.0274)				
EXP share $_{t-1}^{EU15}$		-0.0373 (0.0306)	-0.0372 (0.0306)				
$EU \times \text{IMP share}_{t-1}^{EU15}$				0.0462 (0.0298)			
$EU \times \text{EXP share}_{t-1}^{EU15}$				-0.0403 (0.0323)			
$\Delta \text{IMP share}_{t-1}^{EU15}$					0.0445* (0.0257)	0.0446* (0.0243)	
$\Delta \text{EXP share}_{t-1}^{EU15}$					0.0358 (0.0257)	0.0357 (0.0257)	
$EU \times \Delta \text{IMP share}_{t-1}^{EU15}$							0.0403 (0.0264)
$EU \times \Delta \text{EXP share}_{t-1}^{EU15}$							0.0483* (0.0277)
Controls	✓	✓	✓	✓	✓	✓	✓
Firm FE	✓	✓	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓	✓
Year \times Industry FE	✓	✓	✓	✓	✓	✓	✓
Observations	14,303	11,904	11,904	10,449	10,449	10,449	10,449
R-squared	0.182	0.182	0.182	0.182	0.186	0.186	0.187
Firm Size	Large	Large	Large	Large	Large	Large	Large

Note: Clustered robust standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. ΔEI_y stands for the Davis-Haltiwanger growth rate of firm-level expenditure on energy over sales. $\Delta UFCI_{SSIV}$ is the predicted value of $\Delta UFCI$ based on SSIV in the first stage. Fin Ratio stands for the sum of amortization and interest payment of debt over firm sales. $\Delta \text{EXP share}_{t-1}^{EU15}$ ($\Delta \text{IMP share}_{t-1}^{EU15}$) stands for the change in firm-level lagged export (import) share to EU15 countries. EU is a dummy variable that takes value one after 2004. Large represents firms that have more than 50 employees. Firm-level controls include value added over total assets, labor productivity, age, and gross profit margin.