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* Views expressed are those of the author and do not necessarily reflect official positions of De Nederlandsche Bank.

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Abstract

This paper estimates the macroeconomic effects of green and brown government spending using public procurement data, focusing on how spending composition reshapes the energy sector. Classifying around 171,000 contracts by product codes, we construct a quarterly panel of green and brown procurement for ten Eurozone economies (2011–2023). We identify spending shocks using the institutional timing of contract award announcements, which is plausibly orthogonal to the business cycle, and estimate impulse responses with panel local projections. Green and brown procurement have near mirror-image effects on the energy sector: green procurement lowers energy prices, reduces energy-sector output, and cuts oil import dependence, while brown procurement raises energy prices and depresses innovation, especially green patenting. These differences extend to aggregate output: the cumulative GDP multiplier of green procurement is about 0.7 on impact and exceeds 1 within one and two years, whereas the brown multiplier remains statistically indistinguishable from zero over the first two years.

Keywords: Green public procurement, Energy transition, Fiscal multipliers

JEL: E62, Q43, Q48

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1 Introduction

The European Union's dependence on imported fossil fuels leaves it exposed to geopolitical energy shocks, as illustrated by the 2022 Russian gas crisis and the 2026 Middle East conflict. Shifting the composition of public spending toward green investment has been advocated as a way to reduce this dependence while supporting output, provided its fiscal multiplier is sufficiently large.[1] Both claims are hard to evaluate: direct evidence on how public spending affects the energy market is scarce, and estimates of the green multiplier vary widely (Afonso et al., 2025; Batini et al., 2021; Bordenave & Ciaffi, 2025; Ficarra, 2024; Hasna, 2021; Shah & Wu, 2025). Assessing either claim also requires understanding whether the composition of public spending matters—that is, whether green and fossil-fuel-intensive ("brown") procurement generate different macroeconomic outcomes.

This paper provides that comparison by examining how the composition of public procurement shapes both the macroeconomy and the energy sector. We find that green and brown procurement generate markedly different responses, nowhere more clearly than in energy markets. Green procurement lowers energy prices, energy-sector output, and oil import dependence, whereas brown procurement raises energy prices and reinforces reliance on fossil fuels. These differences reflect fundamentally different adjustments in the energy sector and propagate to the broader economy. Green procurement generates an immediate increase in output, with a cumulative fiscal multiplier of around €0.7 on impact that exceeds one within the first year, whereas the brown multiplier remains statistically indistinguishable from zero over the first two years. The results therefore suggest that procurement composition is an important determinant of both macroeconomic performance and energy-market outcomes.

Obtaining these results requires overcoming two longstanding empirical challenges. First, existing measures of green public spending are typically based on Environmental Protection Expenditure accounts, which classify spending by the mandate of the spending authority rather than its content, exclude renewable energy, rarely provide a comparable measure of brown spending, and are available only annually. Second, identifying unexpected changes in government spending is difficult because fiscal policy is anticipated and responds to macroeconomic conditions. We address both challenges by con-

[1] The EU's annual green-investment gap alone is estimated at €477 billion (European Commission, 2019).

structing a new quarterly panel of green and brown public procurement for ten Eurozone economies. Using Common Procurement Vocabulary (CPV) product codes, we classify roughly 171,000 contracts according to their environmental content and identify procurement shocks using the institutional timing of contract award announcements, the earliest point at which committed public spending becomes public information. The resulting announcement-based series provides a high-frequency measure of procurement composition that is well suited for identifying spending shocks and estimating their dynamic effects.

The results reveal that the macroeconomic consequences of procurement composition are transmitted primarily through energy markets. Green and brown procurement have near mirror-image effects on energy prices and production, with green procurement also producing a persistent reduction in oil import dependence. These differences propagate to the broader economy. Green procurement generates an immediate expansion in government consumption, private consumption and investment, whereas brown procurement operates mainly through a delayed increase in private consumption. As a result, green procurement produces substantially larger fiscal multipliers, particularly during recessions and periods of elevated uncertainty. Finally, we find evidence that procurement composition also affects the direction of technological change: brown procurement reduces innovation, particularly green patenting.

This paper contributes to three strands of the literature. First, we contribute to the literature estimating green and brown fiscal multipliers (Afonso et al., 2025; Batini et al., 2021; Bordenave & Ciaffi, 2025; Ficarra, 2024; Hasna, 2021; Shah & Wu, 2025). Existing empirical estimates span an order of magnitude, in part because green spending is typically measured using national-accounts Environmental Protection Expenditure, which is annual, classifies spending by the mandate of the spending authority rather than its content, excludes renewable energy, and rarely provides a comparable measure of brown spending. A parallel literature based on calibrated macroeconomic models (Benkhodja et al., 2023; Kalientzidis et al., 2025) and input–output frameworks (Garrett-Peltier, 2017; Marinos et al., 2025; Markaki et al., 2013; Pollin et al., 2009) likewise concludes that green spending is more expansionary than brown, but either imposes transmission mechanisms that are not identified in the data or lacks a causal empirical design. We address these limitations by constructing a new quarterly panel of green and brown public procurement based on product-level Common Procurement Vocabulary (CPV) codes, providing, to our knowledge, the first symmetric measure of green and brown government spending at quarterly frequency across ten Eurozone economies.

Second, we contribute to the literature exploiting granular public procurement data to identify fiscal shocks (Barattieri et al., 2023; Briganti, 2023; Furceri et al., 2026; Gabriel, 2024; Nakamura & Steinsson, 2014). While this literature has focused almost exclusively on defence procurement or aggregate public spending, we extend it to the environmental composition of government spending. Procurement shocks are identified using the institutional timing of contract award announcements, allowing us to exploit high-frequency variation in procurement commitments while avoiding many of the fiscal foresight and timing problems associated with conventional expenditure measures.

Third, we contribute to the literature on the macroeconomic consequences of the green transition by showing that the composition of public spending matters beyond aggregate output. We provide, to our knowledge, the first causal evidence that procurement composition systematically reshapes energy markets, reducing energy prices and fossil-fuel import dependence while generating larger short-run fiscal multipliers than equivalent brown procurement. We further show that these differences are strongest during recessions and periods of elevated uncertainty, and extend to longer-run innovation outcomes, with brown procurement reducing green patenting in particular, consistent with directed technical change (Acemoglu et al., 2023).

The remainder of the paper is organised as follows. Section 2 describes the institutional setting of EU public procurement. Section 3 presents the construction of the procurement dataset, Section 4 outlines the identification strategy and empirical framework, Section 5 presents the empirical results, and the final section concludes.

2 Institutional Setting

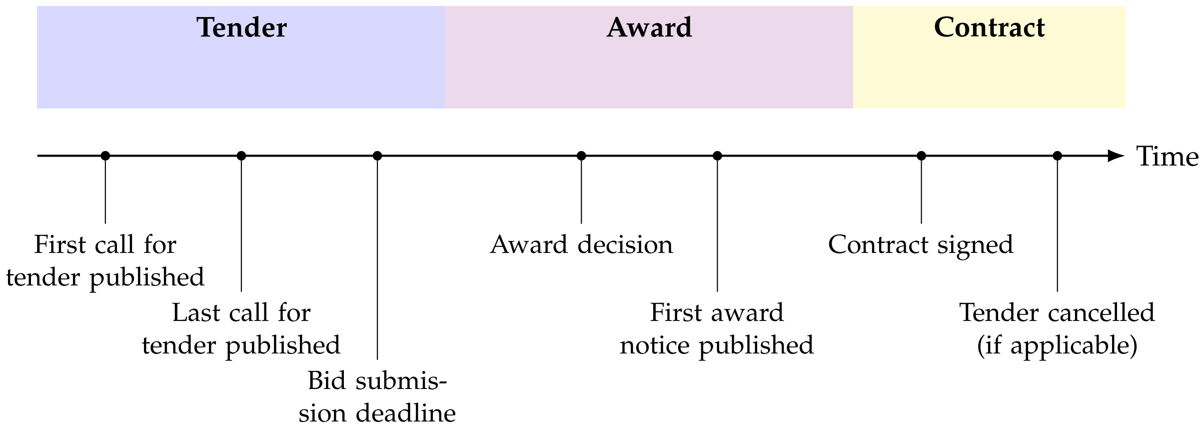
Public procurement, the purchase of goods, services, and works by general government and public bodies, accounts for a large share of economic activity in the European Union, on the order of one-seventh of GDP. Because governments choose what they buy, the environmental composition of this spending is itself a policy lever: the European Commission has actively promoted Green Public Procurement, encouraging contracting authorities to buy goods and services with a lower environmental impact, even as a large volume of public spending continues to flow to fossil-fuel-intensive goods, infrastructure, and services. This makes public procurement a natural setting in which to compare the macroeconomic effects of green and brown government spending.

Procurement above defined value thresholds is governed by a common legal framework, principally Directive 2014/24/EU (European Parliament & Council of the European Union, 2014), which standardises how contracts are advertised and what information is published. Above a certain threshold, contracting authorities must advertise such tenders on Tenders Electronic Daily (TED), the EU's central procurement portal, and publish a standardised notice at each stage of the process. The Opentender database we use compiles these TED notices together with national procurement records (Section 3). Two elements of this standardisation are central to our analysis: the product codes attached to every contract, which we use to classify spending as green or brown, and the dates attached to each stage of a tender, which we use for identification.

The European tendering process unfolds in three distinct phases. The process begins with the publication of the first call for tender by the contracting public authority, which formally opens the tender and provides initial procurement information to the market. Additional clarifications or corrections may follow, captured by the last call for tender publication date. The competitive phase culminates in the bid submission deadline, after which no new bids can be accepted. During this initial tendering phase, the identity of the participating bidders and the values of their bids remain unknown to the public and other participants. The actual decision itself is recorded as the award decision date, which is internal and not known to the public or market participants. Once the award decision is made, it is first communicated publicly with the publication of the first award notice. It is only from this date when the identities of the bidders and the final value of the awarded contract become public. The transition from procurement procedure to contractual relationship is marked by the contract signature date. Exceptional outcomes such as discontinued procedures are captured by the tender cancellation date.

Contracts are awarded through one of several procedures defined by the Directive. The most common is the open procedure, in which any economic operator may submit a tender; the negotiated and restricted procedures instead involve a prior selection of bidders. The large majority of both green and brown contracts in our sample are awarded through competitive procedures that attract multiple bidders, a composition we document in Section 3. Competition matters for identification: when bidding is open and anonymous, the eventual winner is not known in advance, which limits the scope for firms to adjust

Figure 1: Timeline of the European tendering process



behaviour before a contract is awarded.

The timing of this process underpins our identification strategy in two ways. First, the first award notice is the earliest point at which a committed public expenditure becomes public information, so it is the natural date at which a procurement news shock reaches the economy. Second, the interval between the call for tenders and the award notice is governed by administrative and procedural factors rather than chosen in response to the business cycle. We exploit both features, and provide the supporting evidence, in Section 4.

3 Data and Measurement

To address the data limitations identified above, we build a panel dataset of green and brown public procurement spending in 10 large Eurozone economies. The source used is Opentender, a publicly available dataset which publishes contracts from 35 European countries, aggregating data from Tenders Electronic Daily (TED, an EU-wide procurement portal where a contract has to be published if its value exceeds a certain threshold) and national procurement sources. Due to the nature of contract-level data, the final panel dataset can be constructed at quarterly frequency.

3.1 Classifying Procurement Composition

We classify procurement contracts according to their Common Procurement Vocabulary (CPV) codes, which identify the product category of the goods and services purchased. This approach classifies contracts according to their content rather than the mandate of the contracting authority, allowing us to distinguish directly between environmentally beneficial (”green”) and fossil-fuel-intensive (”brown”) procurement.

We identify green procurement using a list of 138 CPV codes covering three broad categories: renewable energy and energy efficiency, pollution and environmental protection, and climate adaptation. The classification builds on Poltoratskaia et al. (2024) and is extended through a manual review of the complete CPV hierarchy. The complete list of green CPVs is reported in Appendix A.

Brown procurement is identified using 220 CPV codes whose primary object is fossil-fuel extraction, production, infrastructure, distribution, or related products and services. Unlike approaches based on emission-intensive production sectors, this classification focuses directly on the environmental content of the procured good or service rather than the industry producing it. The complete brown classification is reported in Appendix A.

Contracts occasionally contain both green and brown CPV codes. These mixed cases account for only a negligible share of procurement and are resolved using a hierarchical decision rule based on the number and specificity of assigned CPV codes. Details of the classification procedure are provided in Appendix B.

Procurement contracts are recorded at the lot level and aggregated to the tender level before constructing quarterly country-level procurement series. We assign each tender to the quarter in which its first award notice is published, corresponding to the earliest point at which committed public spending becomes public information. This aggregation procedure is consistent with our identification strategy, which exploits the institutional timing of award announcements. Further details of the aggregation procedure are provided in Appendix B.

3.2 Procurement Dataset

We characterise below the key features of the green and brown public procurement dataset constructed for the empirical analysis. The sample covers ten Eurozone member states–

Austria, Belgium, France, Germany, Greece, Ireland, Italy, the Netherlands, Portugal, and Spain– from the first quarter of 2011 to the fourth quarter of 2023.

Table 1 reports distributional characteristics green and brown procurement data aggregated at the tender-level. The value and distribution statistics are computed on the final price variable of tenders, before any imputation procedure. Panel A covers green procurement. Across the ten countries, 83,016 green tenders were identified, of which 54,236 carry an awarded status, that is tenders which were either awarded, preawarded, prepared, or finished. Total cumulative green procurement value in nominal terms over 2011–2023 amounted to €61.42 billion. This value is concentrated in France (€18,29bn) and Germany (€17,56bn), which together make up 58% of green procurement value. The distribution of contract values is highly right-skewed in every country, as summarised by a large positive skewness. The overall sample median value of green contracts (€174,000) is much lower than the mean of €2.03 million, confirming that the distribution is dominated by a large mass of small contracts alongside a thin but economically significant right tail of large contracts. The coefficients of variation (the ratio of the standard deviation to the mean) exceed 400% in every country. The very large excess kurtosis shows that the distribution of contract values is leptokurtic, with large outliers.

Panel B shows the corresponding statistics for brown procurement. The CPV classification identifies 88,748 tenders (62,200 active), a similar number to the identified green tenders, confirming that although the classification definitions for green and brown are not fully symmetric, neither category is overrepresented in the identified data, ensuring fair comparability between green and brown spending. Brown procurement reaches €96.03bn in total value, approximately 56% larger than green in aggregate spending terms. The largest sites of brown procurement are France (€26.26bn), Italy (€20.06bn), and Spain (€17.96bn), although for Italy this is concentrated in very few contracts (1,861 compared to 22,320 for Spain and 29,949 for France), which has an average contract value of €15 million. Again, Spain shows the smallest median brown contract value of just €33,000. Looking at the skewness and kurtosis, the distribution of brown procurement contracts values are also heavily right-tailed and leptokurtic, but much less than green contract values.

A feature of administrative procurement data is intermittent reporting. In many cases, an awarded contract is recorded in the dataset but the final award value is missing. The European Union (2020) has observed this problem in the source TED data. We attempt to mitigate this by imputing the missing final value of each tender with its recorded bid value. Out of all monetary values available in the raw Opentender data, after the final value this is the variable which comes closest temporally to the award announcement date. Since bid values are recorded at lot-level in the Opentender data, we first aggregate the sum of bid values belonging to each tender before applying the imputation. As reported in Table 1, this procedure reduces the share of active tenders with missing award values from 44.2% to 22.8% for green procurement and from 51.5% to 25.9% for brown procurement at the tender level. This procedure is especially important for countries such as Austria, France and Portugal, whose missing shares are heavily reduced through the imputation. It is also important to note that since contracts which were only announced but not awarded do not have observations for the final and bid monetary values, the procurement spending series we construct only accounts for contracts which were announced and later implemented.

Quarterly procurement displays substantial variation over both time and countries, providing the identifying variation exploited in the empirical analysis. Green and brown procurement both exhibit considerable quarter-to-quarter volatility together with a gradual upward trend over the sample period. The corresponding aggregate and country-level time series are reported in Appendix B.

Figure 2 reports the composition of procurement tenders by supply type. Green procurement is predominantly service-oriented across almost all countries, whereas brown procurement consists primarily of physical supplies. This difference partly reflects the CPV classification itself, as many green codes correspond to environmental services while brown codes largely identify fossil-fuel products. The contrasting composition of procurement provides useful context for interpreting the macroeconomic responses reported below, particularly the different sectoral and manufacturing effects of green and brown procurement. Austria and Germany are notable exceptions, relying more heavily on works contracts in both categories than the rest of the sample.

The majority of both green and brown procurement is awarded through competitive procedures attracting multiple bidders. Appendix B provides additional evidence on tender procedures and bidder participation.

The macroeconomic variables are drawn primarily from the Euro Area Mixed-Frequency Database (EA-MD-QD) (Barigozzi et al., 2024), which provides harmonised quarterly and monthly series for all ten sample economies. We use national accounts aggregates, labour-

Table 1: Descriptive Statistics - Green and Brown Tenders

Variable	AT	BE	DE	EL	ES	FR	IE	IT	NL	PT	Total
Panel A: Green Procurement											
N tenders (all statuses)	2,041	1,731	16,240	1,016	17,088	29,142	5,634	1,196	1,774	7,154	83,016
N tenders (awarded/active)	1,244	941	11,695	495	13,680	14,604	2,625	1,111	1,284	6,557	54,236
Total value (€bn)	1.14	1.43	17.56	1.16	9.39	18.29	2.54	6.07	2.11	1.73	61.42
Missing final price (%)	62.14	29.54	31.47	13.94	7.70	59.22	83.62	14.04	63.01	96.02	44.18
Missing imputed price (%)	14.39	21.15	27.66	11.52	1.33	37.98	83.09	8.01	52.73	0.53	22.83
Central tendency											
Mean (€M)	2.429	2.157	2.191	2.717	0.743	3.071	5.916	6.353	4.444	6.620	2.028
Median (€M)	0.444	0.400	0.278	0.483	0.042	0.300	0.494	0.810	0.597	0.490	0.174
Dispersion											
Std. dev. (€M)	10.849	11.332	21.802	7.328	38.894	24.454	48.415	41.987	23.533	29.023	31.405
Coeff. of variation (%)	446.68	525.25	994.90	269.69	5,232.71	796.28	818.31	660.91	529.54	438.42	1,548.23
IQR (€M)	0.946	0.940	0.519	1.357	0.118	0.950	1.055	2.655	2.339	2.253	0.488
Tail statistics											
P5 (€M)	0.083	0.087	0.022	0.077	0.001	0.021	0.065	0.139	0.051	0.078	0.003
P25 (€M)	0.220	0.228	0.133	0.248	0.015	0.117	0.215	0.342	0.261	0.268	0.042
P75 (€M)	1.166	1.168	0.652	1.605	0.132	1.066	1.270	2.997	2.600	2.521	0.530
P95 (€M)	9.452	7.500	4.997	10.545	1.000	9.154	12.626	16.748	14.737	19.516	5.441
Max (€M)	166.680	29.329	1,761.539	78.370	486.879	1,000.000	1400.740	954.428	454.000	344.100	1761.539
Higher moments											
Skewness	12.10	17.46	22.96	5.72	108.53	29.15	13.81	16.54	15.65	8.81	92.84
Excess kurtosis	166.00	358.92	595.83	43.23	12,025.03	1,058.25	197.51	325.00	286.40	90.45	11,947.17
Panel B: Brown Procurement											
N tenders (all statuses)	1,916	2,144	9,404	3,984	22,320	29,949	1,684	1,861	1,696	13,790	88,748
N tenders (awarded/active)	1,548	1,224	6,150	1,379	18,733	17,080	832	1,800	1,187	12,267	62,200
Total value (€bn)	1.78	4.50	15.15	5.29	17.96	26.26	1.79	20.06	1.37	1.86	96.03
Missing final price (%)	84.11	46.65	39.56	17.11	12.69	67.52	85.82	25.78	73.63	94.15	51.53
Missing imputed price (%)	45.61	42.08	37.35	13.34	3.19	56.62	84.62	19.94	69.33	2.04	25.89
Central tendency											
Mean (€M)	7.216	6.893	4.077	4.632	1.098	4.733	15.209	15.018	4.390	2.591	3.185
Median (€M)	0.960	0.826	0.487	0.454	0.033	0.540	1.822	2.244	0.606	0.574	0.195
Dispersion											
Std. dev. (€M)	21.483	22.702	33.630	26.833	12.167	30.057	39.201	67.851	13.363	9.509	25.537
Coeff. of variation (%)	297.72	329.34	824.87	579.24	1,108.30	635.11	257.75	451.81	304.38	366.99	801.73
IQR (€M)	3.219	3.049	1.291	0.725	0.185	1.600	6.435	8.179	2.086	1.193	0.852
Tail statistics											
P5 (€M)	0.117	0.081	0.000	0.035	0.000	0.036	0.079	0.249	0.007	0.132	0.000
P25 (€M)	0.365	0.316	0.195	0.255	0.002	0.200	0.360	0.821	0.214	0.300	0.017
P75 (€M)	3.584	3.365	1.486	0.980	0.187	1.800	6.795	9.000	2.300	1.493	0.870
P95 (€M)	28.723	33.773	10.236	14.450	2.684	12.435	80.000	40.430	24.400	9.375	9.102
Max (€M)	198.715	293.317	965.290	579.700	813.125	1,000.000	300.000	1,369.190	155.000	158.744	1,369.190
Higher moments											
Skewness	5.35	7.38	21.85	13.42	37.24	18.94	4.64	12.30	6.73	10.19	25.55
Excess kurtosis	37.02	72.48	535.33	234.93	1,882.29	469.33	29.05	197.80	62.74	135.44	886.83

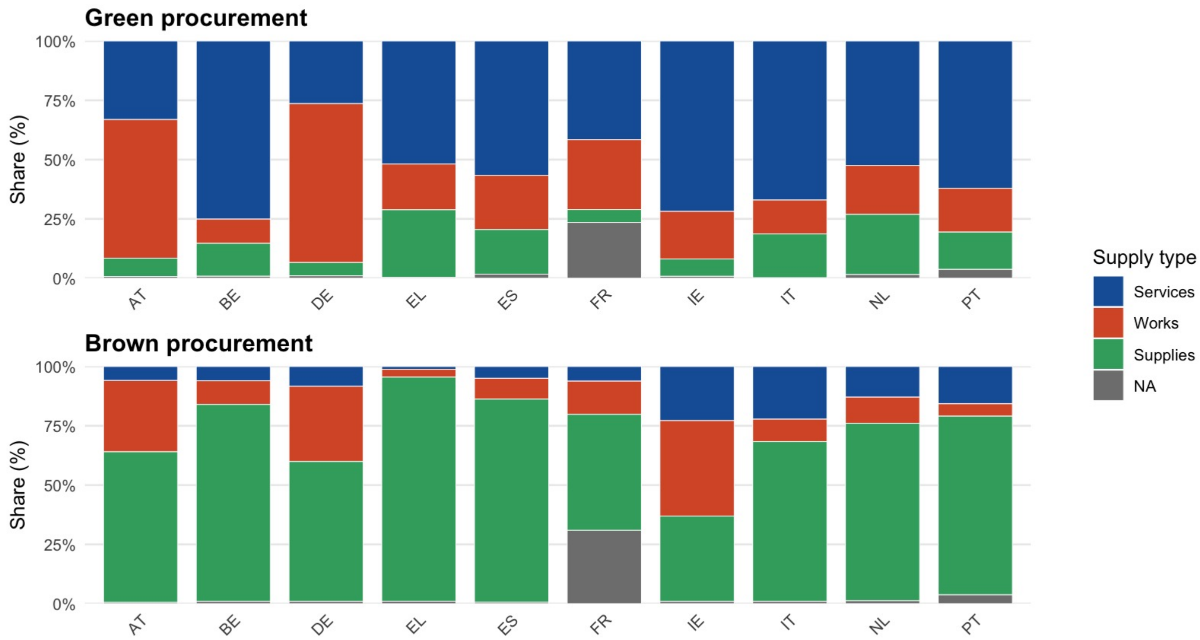
Notes: Value, missing share, and distributional statistics are computed on tenders with status AWARDED, PREAWARDED, PREPARED, or FINISHED only. Calculation of distributional statistics are restricted to tenders with non-missing final price values. N tenders (all statuses) covers all observations, including tenders whose status is ANNOUNCED and CANCELLED.

market indicators, industrial production, prices, interest rates, stock market indices, and measures of economic sentiment. Monthly series are aggregated to quarterly frequency by averaging stocks and summing flows. The complete list of variables is reported in Table B.1.

To examine the energy-market transmission of procurement shocks, we combine Eurostat data on imports, exports and consumption of electricity, gas and oil products. These data allow us to construct energy import-dependence measures and to distinguish the responses of different energy markets.

Finally, innovation outcomes are measured using OECD Triadic Patent Families, distinguishing between total patenting and green patenting. Details of the construction of the

Figure 2: Composition of Procurement Tenders by Supply Type



Notes: This figure shows the percentage shares of tenders from 2011 to 2023 for different supply types in the ten countries considered.

energy and innovation variables are provided in Appendix B.

4 Identification and Empirical Framework

Identifying the causal effects of government spending is challenging because fiscal policy is anticipated, responds to macroeconomic conditions, and is typically observed only in low-frequency aggregate data. These features make it difficult to isolate unexpected changes in public spending and to distinguish them from the business cycle.

Recent work has shown that granular public procurement data provide a promising alternative by exploiting institutional features of procurement procedures and contract timing to identify fiscal shocks (Barattieri et al., 2023; Briganti, 2023; Furceri et al., 2026; Gabriel, 2024; Nakamura & Steinsson, 2014). We build on this literature but focus on the environmental composition of procurement rather than aggregate or defence spending. Our identification strategy exploits the institutional timing of public procurement award notices set out in Section 2 and summarised in Figure 1.

We measure the procurement shock in any given quarter as the total final value of contracts whose award notice was published in that quarter. This is just the raw procurement series grouped by quarter of publication as seen in the data description section. This follows a similar identification logic of Furceri et al. (2026), who group defence contract values by the award date in Opentender. This timing choice has two identification advantages. First, the first award notice is the earliest moment at which committed public spending enters the information set of households and firms, so it most closely corresponds to an empirical measurement of a procurement 'news' shock, as private agents cannot anticipate the exact contract value or award date prior to publication. Second, the timing of award publication is likely determined by bureaucratic processes and the typology of contracts in question, rather than being chosen by contracting authorities in response to macroeconomic conditions. This institutional rigidity severs the link between announcement timing and the business cycle, reducing the risk of endogeneity through reverse causality.

We verify the latter identifying assumption with the following exercise on implementation lags, defined as the number of days between a tender's notice date and its award publication date. Figure C.1 shows the heterogeneity in implementation lags. Green contracts exhibit longer lags than brown contracts, and the median lag can range widely across countries, such as the median green lag in Spain being less than 100 days compared to $\sim$275 in Greece. If implementation lags were systematically predicted by macroeconomic conditions, then the timing of award announcement would be endogenous to the business cycle, invalidating the identifying assumption. To test this hypothesis, we estimate a panel regression of the log implementation lag on a vector of monthly macroeconomic variables measured at the month of the tendering date, controlling for country and year-month fixed effects, with standard errors clustered at the country level. The sample is restricted to tenders which have no missing values for both the tender notice date and the award publication date, yielding 32,794 green and brown tenders. Two specifications are estimated: one with macro variables only, and one with contract-level controls including log contract value, and dummies for supply type, procedure type, and green contracts. Results are reported in Table 2.

Macroeconomic variables have no systematic relationship with the implementation lag. In both specifications, the macro variable block is largely insignificant, and the within R^2 of the macro-only model is negligible at 0.009. The unemployment rate and industrial production in manufacturing are significant in column (1) but lose significance once

Table 2: Are contract announcement lags predicted by macroeconomic conditions?
Two-way fixed effects regression. Dependent variable: Log Announcement Lag

	(1) Macro only		(2) + Controls	
	Coef.	SE	Coef.	SE
Macro variables				
Unemployment Rate	0.011*	(0.006)	0.009	(0.007)
Long-term Interest Rate	0.011	(0.011)	0.014	(0.009)
Log IP Manufacturing	0.761**	(0.267)	0.529	(0.309)
Log IP Energy	−0.411	(0.290)	−0.432	(0.282)
Log PPI Energy	−0.335	(0.461)	−0.254	(0.451)
Log HICP	−2.878	(2.281)	−2.741	(2.058)
Log Economic sentiment	0.634	(0.519)	0.737	(0.508)
Log Stock Index	−0.128	(0.298)	−0.203	(0.288)
Contract controls				
Green contract			0.116***	(0.005)
Log contract value			0.020	(0.017)
Supply: Services			0.321***	(0.028)
Supply: Supplies			0.207***	(0.028)
Supply: Works			0.507***	(0.076)
Procedure: Competitive dialog			1.108***	(0.086)
Procedure: Design contest			1.114***	(0.069)
Procedure: Innovation partner.			1.207***	(0.142)
Procedure: Mini-tender			−1.104***	(0.011)
Procedure: Negotiated			0.579***	(0.081)
Procedure: Negotiated w/ pub.			0.765***	(0.177)
Procedure: Negotiated w/o pub.			−0.424***	(0.065)
Procedure: Open			0.368***	(0.053)
Procedure: Other			−0.042	(0.209)
Procedure: Restricted			0.695***	(0.103)
Country FE	Yes		Yes	
Year-Month FE	Yes		Yes	
Contract controls	No		Yes	
SE clustering	Country		Country	
Observations	32,794		32,794	
Adj. R^2	0.244		0.344	
Within R^2	0.009		0.141	

Notes: Outcome is log implementation lag (days between tender notice date and tender award publication date). Sample restricted to AWARDED, PREAWARDED, PREPARED, and FINISHED contracts, announced in 2011–2023. Standard errors clustered at the country level. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

contract controls are added in column (2). This pattern indicates that the variation in announcement timing is driven by contract-level and procedural characteristics rather than by strategic timing on the part of contracting authorities. The result supports the identifying assumption that the timing of award notices is not endogenous to the business cycle, and that variation in announced procurement value can be treated as an exogenous shift in public spending commitments.

Furthermore, as argued by Barattieri et al. (2023), since competitive bidding procedures are anonymous and firms are unaware of competitors' bids, there is no ex-ante predictable winner. Individual firms therefore face genuine uncertainty about whether they will be awarded the contract and are unlikely to adjust production or hiring before the outcome is known. This limits anticipation effects at the tender notice stage: even if the publication of a call for tender conveys information about future public spending, the uncertainty over which firm will receive the contract, and therefore which firm should respond, prevents private sector adjustment that would invalidate the award announcement as the relevant shock date. Since the majority of both green and brown tenders are competitive procedures with multiple bidders (Figure B.3 and B.4), the identification strategy is strengthened.

One limitation is that agents could anticipate contract values through the contracting authority's estimated value of tenders, which is published at the initial first call for tender notice. However there are several problems in matching the estimated value to the initial notice date as the shock. First, although European Parliament Directive 2014/24/EU Annex V Part C legally mandates contracting authorities to publish the estimated value upon tender notice, in practice there is a high share of missing data in Opentender, likely driven by intermittent reporting standards within TED. Second, a tender notice does not not necessarily signify strong committment to spending. Of the ∼171,000 green and brown tenders identified, ∼30% were inconclusive, most of these being only announced but not later awarded. Third, through this information agents could anticipate the value of contracts, but not the timing of announcement - even if agents know a contract is coming, they cannot precisely predict which quarter the award falls in.

4.1 Are Procurement Announcements Predictable?

The previous subsection established that the timing of procurement announcements is plausibly unrelated to contemporaneous macroeconomic conditions. A separate concern, however, is whether the magnitude of announced procurement systematically responds to the business cycle. Governments may adjust procurement budgets in response to expected economic conditions, so that larger or smaller procurement announcements coincide with changes in the macroeconomic outlook. If so, the announced value of procurement would partly reflect endogenous fiscal policy rather than unexpected procurement shocks. We therefore examine whether announced green and brown procurement can be systematically predicted by contemporaneous macroeconomic variables.

Throughout the paper, nominal procurement values and macroeconomic aggregates are deflated by the GDP deflator, expressed in per-capita terms, and log-transformed. We first perform several complementary predictability tests, reported in Appendix C. These include within-country scatter plots, pooled correlations, lead–lag analyses following Briganti (2023), and Granger causality tests. Across all exercises, we find little systematic evidence that macroeconomic conditions anticipate procurement announcements. We therefore turn to our baseline panel regressions, which provide a more comprehensive assessment while controlling for country and time fixed effects.

Table C.3 provides comprehensive panel regressions of quarterly log real procurement per capita $\ln g_{i,t}^{s}$ on an expanding set of contemporaneous macroeconomic predictors $\mathbf{X}_{i,t}$, controlling for country and time fixed effects, where s denotes green or brown:

$$\ln g_{i,t}^{s} = \alpha_i + \gamma_t + \mathbf{X}_{i,t}\boldsymbol{\beta} + \varepsilon_{i,t}^{s} \tag{1}$$

The results provide little evidence that procurement announcements are systematically predicted by macroeconomic conditions. Most macroeconomic variables are statistically insignificant across specifications, and the explanatory power of the regressions is low. In the richest specification, the within-R^2 reaches only 8.2% for green procurement and 2.1% for brown procurement, implying that the overwhelming majority of within-country, within-quarter variation in procurement remains unexplained by contemporaneous macroeconomic conditions.

Two variables consistently predict green procurement: government consumption and the economic sentiment indicator. By contrast, macroeconomic predictors have little explanatory power for brown procurement, with GDP per capita significant only in a small number of specifications. These findings suggest that brown procurement announcements are largely orthogonal to current macroeconomic conditions, whereas green procurement retains a modest predictable component related to the broader fiscal stance and economic expectations.

To ensure that our conclusions do not depend on this residual predictability, we complement our baseline announcement-based identification with several alternative identification schemes. These include a procurement series purged of its macroeconomically predictable component together with Cholesky and Max-Share structural shocks. Details of their construction are provided in Appendix D, which shows that the resulting impulse responses are qualitatively very similar to the baseline estimates. Throughout the paper we therefore report results based on our baseline announcement-timing identification, using the alternative schemes as robustness checks.

4.2 Local Projections

We estimate impulse responses with panel local projections (Jordà, 2005), which we prefer to VARs because they impose fewer assumptions on the data-generating process and accommodate nonlinearities straightforwardly (Jordà & Taylor, 2025; Plagborg-Møller & Wolf, 2021). At each horizon h we estimate

$$\sum_{j=0}^{h} \Delta y_{i,t+j} = \alpha_i^h + \gamma_t^h + \beta_h^s \varepsilon_{i,t}^s + u_{i,t+h} \tag{2}$$

where $\Delta y_{i,t+j}$ is the quarter-on-quarter change in the logged outcome, $\varepsilon_{i,t}^s$ the identified green or brown shock ($s \in \{\text{Green}, \text{Brown}\}$), and α_i, γ_t are country and quarter fixed effects. The differenced terms telescope, so $\hat{\beta}_h^s$ is the cumulative response of the outcome between $t-1$ and $t+h$. We set the horizon to 12 quarters and normalise to a one-standard-deviation shock, so the response times 100 is the percentage change h quarters out. Ireland is excluded for data availability, and Appendix E reports lag-augmented and restricted-sample robustness.

To study nonlinearities we estimate threshold local projections (Ramey & Zubairy, 2018),

$$\sum_{j=0}^{h} y_{i,t+j} = \alpha_i^h + \gamma_t^h + D_{i,t-1} \times \beta_h^s \varepsilon_{i,t}^s + (1 - D_{i,t-1}) \times \beta_h^s \varepsilon_{i,t}^s + u_{i,t+h} \tag{3}$$

where $D_{i,t-1}$ indicates whether a regime variable exceeds a threshold in $t-1$: year-on-year GDP growth (zero threshold, expansion versus recession) and the World Uncertainty Index (sample-mean threshold). We control for the ECB policy rate to account for the effect of the monetary policy stance on the business cycle.

We report the standard cumulative multiplier, the ratio of the cumulative GDP response to the cumulative spending response (Ramey, 2016). Converting log-elasticity coefficients to euro multipliers via the procurement-to-GDP ratio is unstable when spending is a small, volatile share of GDP (Owyang et al., 2013), so we estimate the multiplier directly in one step (Ramey & Zubairy, 2018):

$$\sum_{j=0}^{h} \frac{y_{i,t+j} - y_{i,t-1}}{y_{i,t-1}} = \alpha_i + \gamma_t + \beta_h^s \sum_{j=0}^{h} \frac{g_{i,t+j}^s - g_{i,t-1}^s}{y_{i,t-1}} + u_{i,t+h} \tag{4}$$

where y and g are GDP and procurement per capita in euros, so that β_h^s is the cumulative euro-for-euro multiplier at horizon h.

5 Results

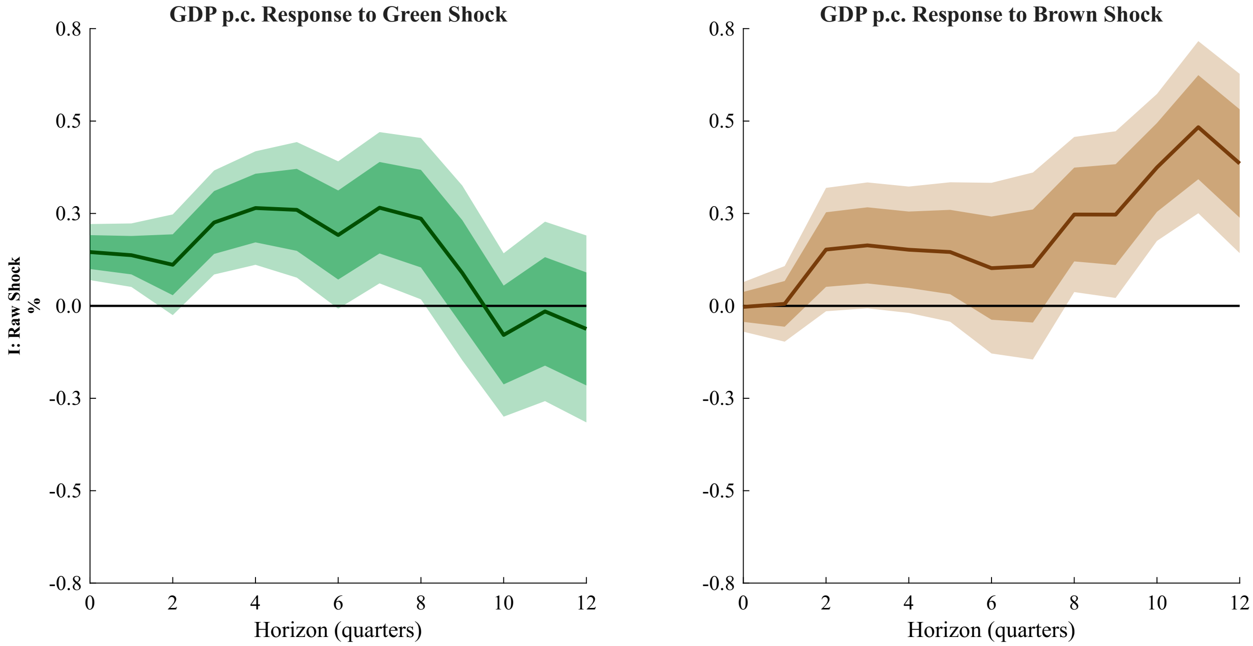
In this section, we examine how the composition of public procurement shapes macroeconomic outcomes. We first establish that green and brown procurement generate markedly different aggregate responses. We then show that these differences are closely linked to contrasting adjustments in energy markets, before quantifying their policy relevance through fiscal multipliers, examining how they vary across macroeconomic states, and finally considering their implications for innovation.

5.1 Composition Matters: Aggregate Macroeconomic Effects

We begin by asking whether the composition of procurement matters for aggregate economic activity. The evidence in Figure 3 suggests that it does. Green procurement raises GDP immediately, whereas the response to brown procurement is substantially delayed. A one-standard-deviation green shock raises GDP per capita by 0.15% on impact, peaking at 0.3% in quarter 7 and remaining statistically significant through the first two years before fading. By contrast, the response to brown procurement is negligible for roughly two years, only reaching 0.5% by quarter 11.

The different GDP responses naturally raise the question of where these differences come from. Although both types of procurement stimulate aggregate demand, they do so in markedly different ways. Figures 4 and 5 trace the responses of the main macroeconomic

Figure 3: GDP Response to Green and Brown Shocks

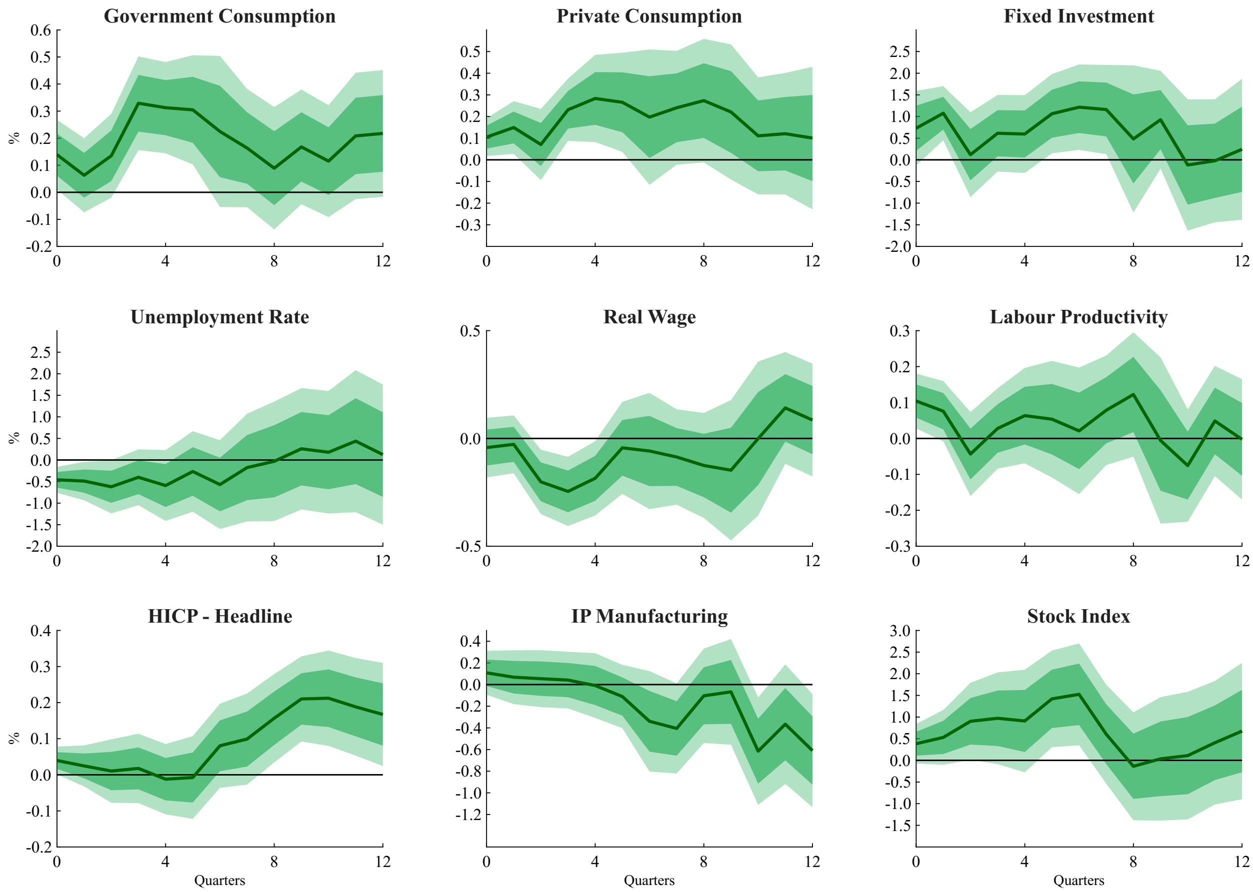


Sample: 2011Q1–2023Q4, IE Excluded. Impulse variables: Logged real procurement p.c. (green = LHS, brown = RHS). Response variable: GDP per capita. Interpretation: Percentage change in GDP p.c to a 1-standard deviation shock to the impulse variable h quarters after the shock.

aggregates to green and brown procurement shocks, respectively. Green procurement generates an immediate expansion in government consumption, private consumption, and fixed investment, accompanied by a decline in unemployment of around 0.5% during the first year. By contrast, brown procurement produces little contemporaneous response in government consumption or investment, with its aggregate effects emerging only gradually through a delayed increase in private consumption, supported by rising real wages and stock prices.

The sectoral composition of these demand responses also differs. Green procurement is associated with a decline in manufacturing output by the end of the horizon, consistent with a reallocation toward the service-intensive activities that dominate green procurement (Figure 2), while manufacturing output and labour productivity increase following brown procurement, reflecting its more goods-intensive composition. Stock prices rise after both shocks although later and more persistently following brown procurement, plausibly supporting demand through a wealth effect (Chodorow-Reich et al., 2021), which could also explain the differential response of private consumption. Overall, the evidence

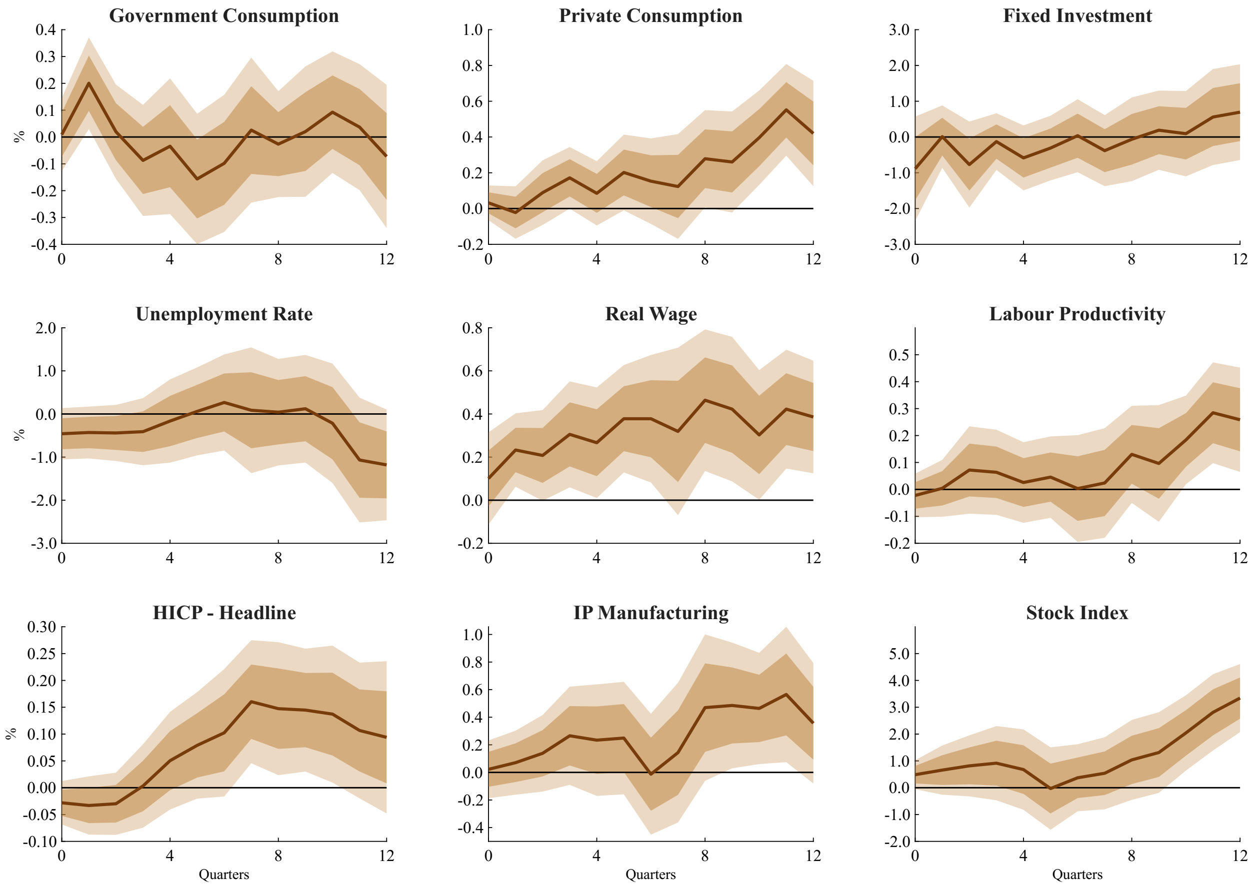
Figure 4: Macroeconomic Propagation – Green Shock



Sample: 2011Q1–2023Q4, IE excluded. Impulse variable: Log Green Procurement p.c.. Interpretation: % change to a 1-standard deviation shock to the impulse variable *h* quarters after the shock.

suggests that both procurement types operate primarily through aggregate demand, but that the timing and composition of that demand differ substantially. To understand these differences better, also in light of the recent energy price shocks, the next subsection focuses on how both procurement shocks impact the energy sector.

Figure 5: Macroeconomic Propagation – Brown Shock



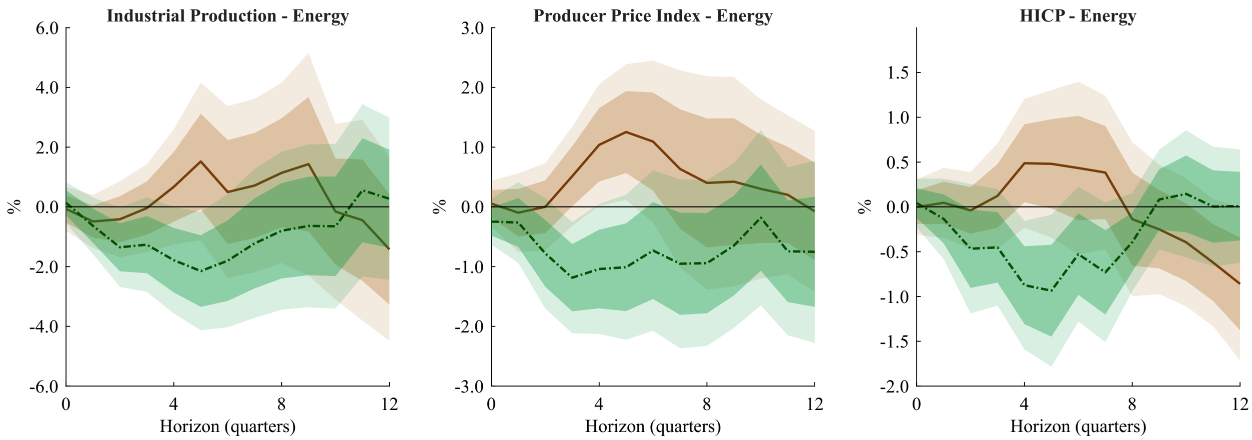
Sample: 2011Q1–2023Q4, IE excluded. Impulse variable: Log Brown Procurement p.c. Interpretation: % change to a 1-standard deviation shock to the impulse variable h quarters after the shock.

5.2 Energy-Market Transmission

The previous subsection showed that procurement composition generates markedly different aggregate responses despite both types of procurement stimulating aggregate demand. We now show that these differences originate largely in the energy sector.

Figure 6 compares the responses of energy production and energy prices to green and brown procurement shocks. The contrast with the aggregate economy is striking. Whereas both procurement types stimulate aggregate demand, they have broadly opposite effects on energy markets. Green procurement reduces energy-sector output together with producer and consumer energy prices, while brown procurement temporarily raises all three.

Figure 6: Energy Effects - Green vs Brown



Sample: 2011Q1–2023Q4, IE excluded. Impulse variables: Log Procurement p.c.

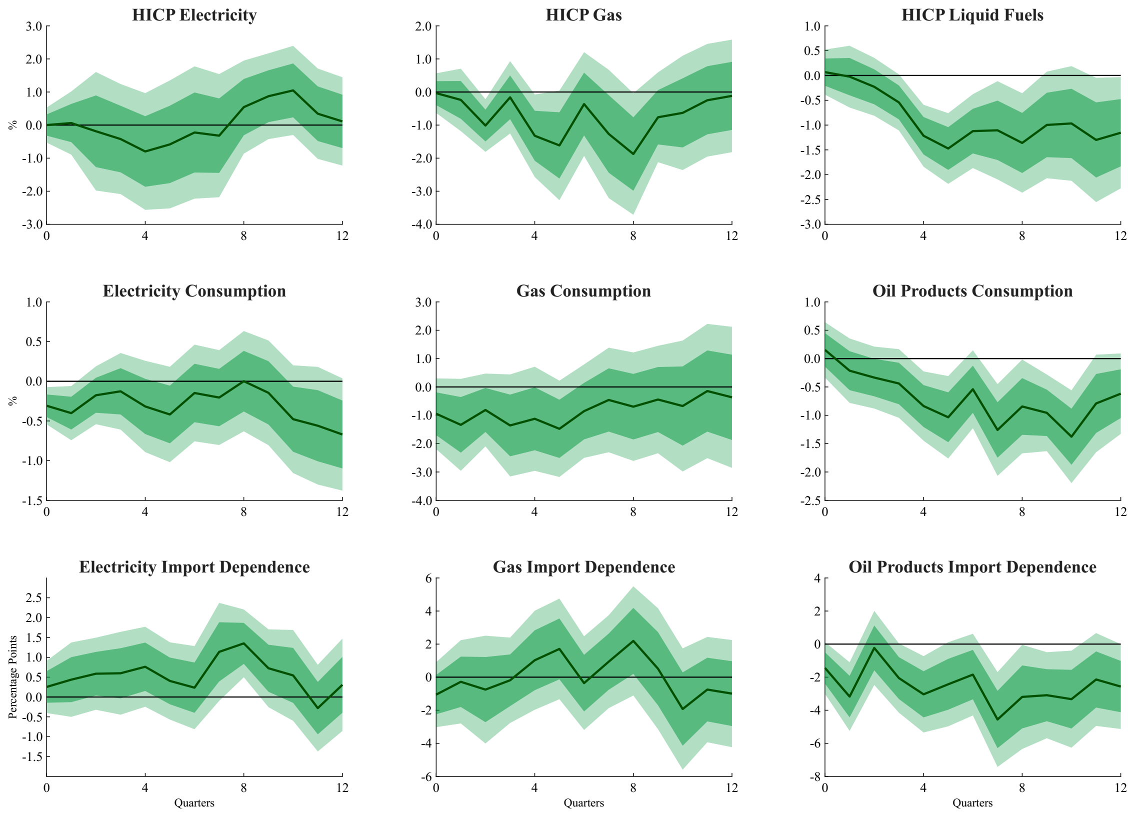
At their peak, green procurement lowers energy industrial production by 2.1%, producer prices by 1.2%, and consumer prices by 0.9%, whereas brown procurement generates responses of similar timing but opposite sign.

These contrasting responses suggest that procurement composition reshapes the energy mix. Green procurement is associated with a reallocation away from fossil-fuel-intensive activities, reducing fossil-fuel production and associated energy prices, whereas brown procurement reinforces demand for fossil-fuel-intensive production. The broad symmetry of the impulse responses suggests substantial substitution within the energy sector.

To understand which energy markets underlie these aggregate responses, Figures 7 and 8 decompose the effects across electricity, gas, and oil products. The decomposition reveals that the aggregate responses differ markedly across energy sources, with the largest and most persistent adjustments occurring in oil markets.

Following a green procurement shock, the decline in aggregate energy prices is largely accounted for by lower liquid fuel prices, which remain around 1.2% below baseline even after three years. This is accompanied by a persistent decline in oil consumption and, most strikingly, in oil import dependence. Oil import dependence falls by 1.4 percentage points on impact, reaches a peak reduction of 4.6 percentage points, and remains 2.6 percentage points below baseline after three years. Given that the European Union imported 96.6% of its oil products in 2024, this represents a sizeable reduction in fossil-fuel dependence. Taken together, these results suggest that green procurement shifts demand away from imported oil products, contributing to both lower energy prices and lower fossil-

Figure 7: Energy Component Effects – Green Shock

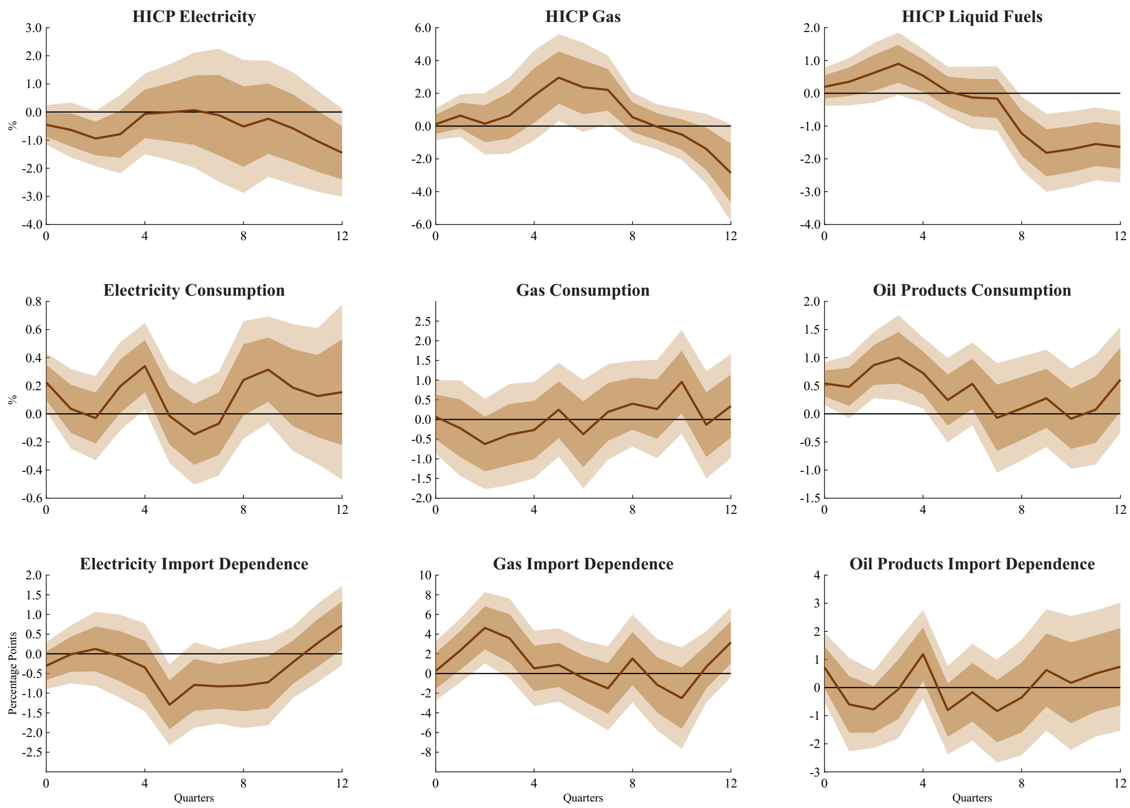


Sample: 2011Q1–2023Q4, IE excluded. Impulse variable: Log Green Procurement.

fuel import dependence. By contrast, gas markets respond little to green procurement, while electricity consumption declines only gradually toward the end of the horizon.

The responses to brown procurement reinforce this interpretation. The temporary increase in aggregate energy prices is driven mainly by higher liquid fuel and gas prices, accompanied by a short-run increase in oil consumption. In contrast to the persistent decline in oil import dependence following green procurement, the effects on electricity imports are small and short-lived, while fossil-fuel dependence remains broadly unchanged. Overall, the decomposition suggests that the contrasting energy responses are driven primarily by changes in oil markets. Green procurement is associated with a persistent reduction in oil import dependence, while brown procurement reinforces reliance on fossil-fuel-intensive energy, highlighting how procurement composition can influence both energy prices and energy security.

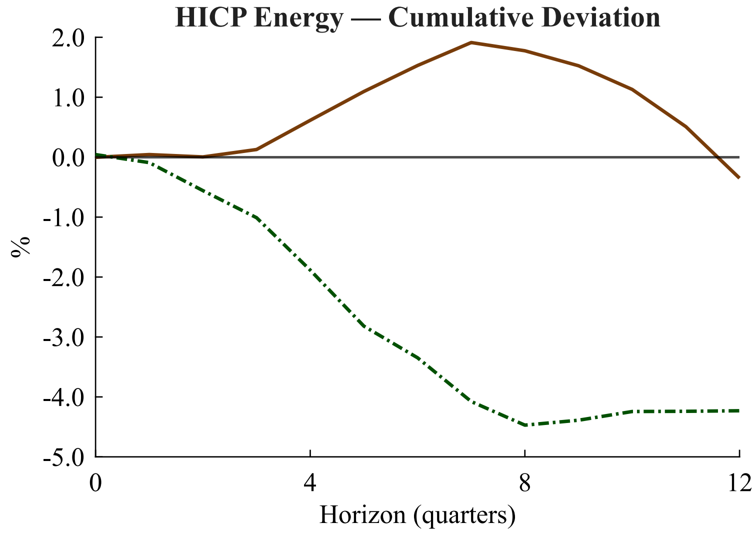
Figure 8: Energy Component Effects - Brown Shock



Sample: 2011Q1–2023Q4, IE excluded. Impulse variable: Log Brown Procurement p.c.

The dominance of oil markets in driving the aggregate energy responses also has important implications for the persistence of energy prices. Figure 9 therefore cumulates the responses of the HICP energy index over time, summarising the cumulative energy price deviation experienced by households, which shows whether households experienced on net more quarters with lower or higher energy prices after a shock. While the increase in energy prices following brown procurement is largely transitory and dissipates over the horizon, the decline following green procurement accumulates into a persistent reduction in household energy prices.

Figure 9: Cumulative HICP Energy Index Deviation from Pre-Shock Level



Notes: Cumulative deviation at horizon h = cumulative sum of Figure 6 impulse response point estimates up to horizon h. Green = dashed, Brown = solid.

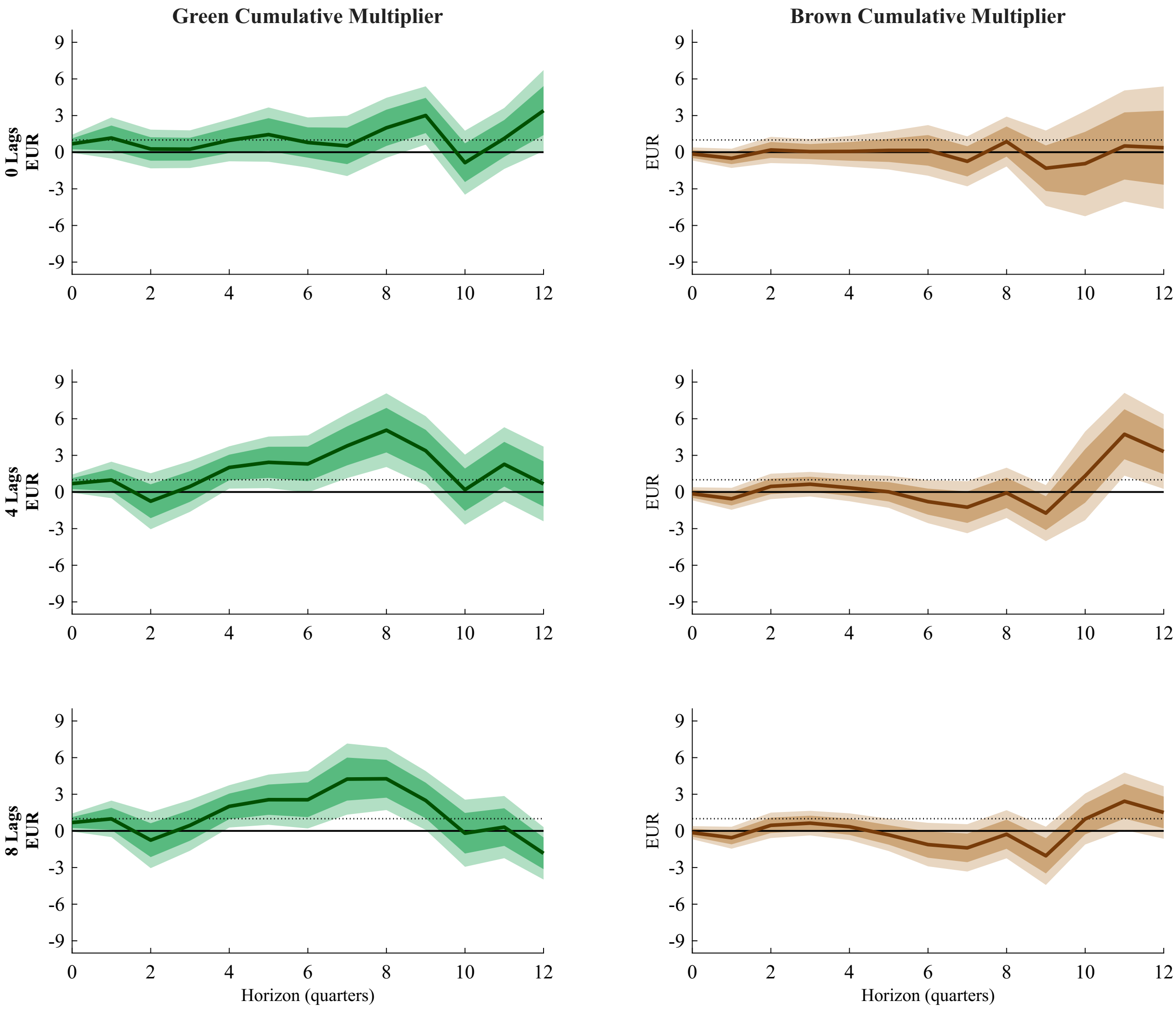
5.3 Fiscal Multipliers

The previous sections established that procurement composition generates markedly different aggregate and energy-market responses. For fiscal policy, however, the relevant question is not only whether output responds, but how much output is generated for each additional euro of procurement. We therefore turn to cumulative fiscal multipliers.

Figure 10 reports cumulative euro-for-euro multipliers estimated using the one-step procedure in equation (4). The contrast between green and brown procurement is striking. In all specifications, green procurement has an impact multiplier of 0.69, and exceeds one within the second year under lag-augmented specifications, whereas the brown multiplier remains statistically indistinguishable from zero over the first two years. The green multiplier peaks around €4–5 after two years before gradually fading, although these estimates become increasingly sensitive to lag length.

This gap mirrors the transmission channels documented above. Green procurement's demand channels, government consumption, private consumption, and investment, all expand on impact (Figure 4), so its multiplier is front-loaded. Brown procurement's aggregate effects, by contrast, build only gradually through a delayed private-consumption response (Figure 5), so any positive multiplier only materialises over a longer horizon.

Figure 10: Cumulative Spending Multipliers



Sample: 2011Q1–2023Q4, IE excluded. Impulse variable: Cumulative change of green/brown procurement per capita normalised by lagged GDP per capita. Controls: 0,4,8 lags of dependent variable and impulse variable. Dashed line: multiplier of 1.

The two multipliers therefore differ as much in timing as in magnitude.

The baseline estimates are sensitive to the number of lags included in the local projections, particularly at longer horizons. To assess whether the main conclusions depend on lag specification, we pool draws from the asymptotic distribution of point estimates across thirteen alternative lag specifications following Briganti (2023) (Figure E.1). The pooled estimates reinforce the baseline findings. The average green multiplier is 0.69 on impact, rises to 1.84 after one year, and reaches 4.21 after two years, whereas the brown multiplier remains close to zero throughout the first two years. The conclusion that green procurement generates substantially larger short-run multipliers than brown procurement is therefore robust to lag specification and remains consistent with previous estimates of green fiscal multipliers (Batini et al., 2021; Bordenave & Ciaffi, 2025; Hasna, 2021).

The longer-horizon estimates should nevertheless be interpreted cautiously. Local projection inference becomes increasingly imprecise as the forecast horizon approaches the sample length (Montiel Olea & Plagborg-Møller, 2021, pp. 1796–99); in our sample, $h/T \approx$ 23%. At the three-year horizon, the estimated multipliers have standard deviations of 2.84 for green procurement and 2.07 for brown procurement, and a panel IPS test does not reject a unit root in cumulative GDP, which may undermine statistical inference when the horizon length is long (Ibid.). We therefore place greater weight on the first two years of the responses. Over this horizon, the evidence consistently indicates that procurement composition matters: green procurement generates multipliers above one, whereas brown procurement produces multipliers that remain statistically indistinguishable from zero.

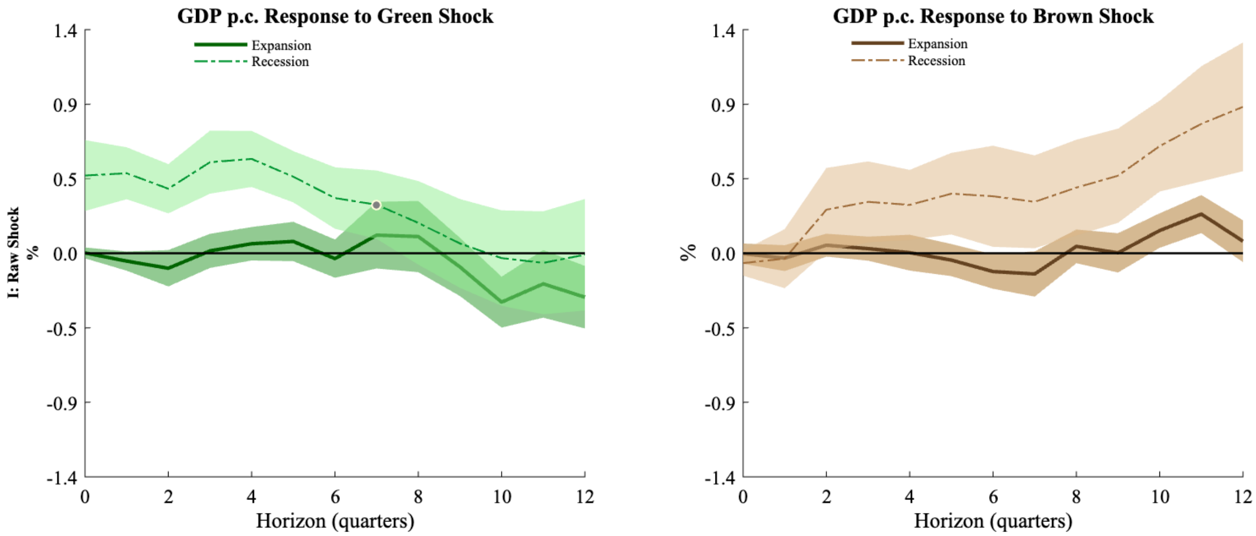
5.4 When Does Composition Matter Most?

The previous results established that procurement composition affects both macroeconomic outcomes and fiscal multipliers. A natural next question is whether these effects depend on the state of the economy. Figure 11 shows that they do.

The aggregate effects of procurement composition are considerably stronger during recessions than during expansions. Green procurement produces an immediate increase in GDP of around 0.5% in recession states, with the effect remaining positive throughout the first two years before gradually fading. Brown procurement also generates larger responses during recessions, although with a markedly different timing: the response is negligible on impact and builds only gradually, peaking at around 0.9% by the end of the horizon. By contrast, during expansions the GDP responses to both procurement types remain close to zero.

These findings suggest that procurement composition matters most when economic slack is greatest. They are consistent with the broader evidence that fiscal multipliers are amplified when productive resources are underutilised (Auerbach & Gorodnichenko, 2012),

Figure 11: GDP Response - Nonlinearity in the Business Cycle



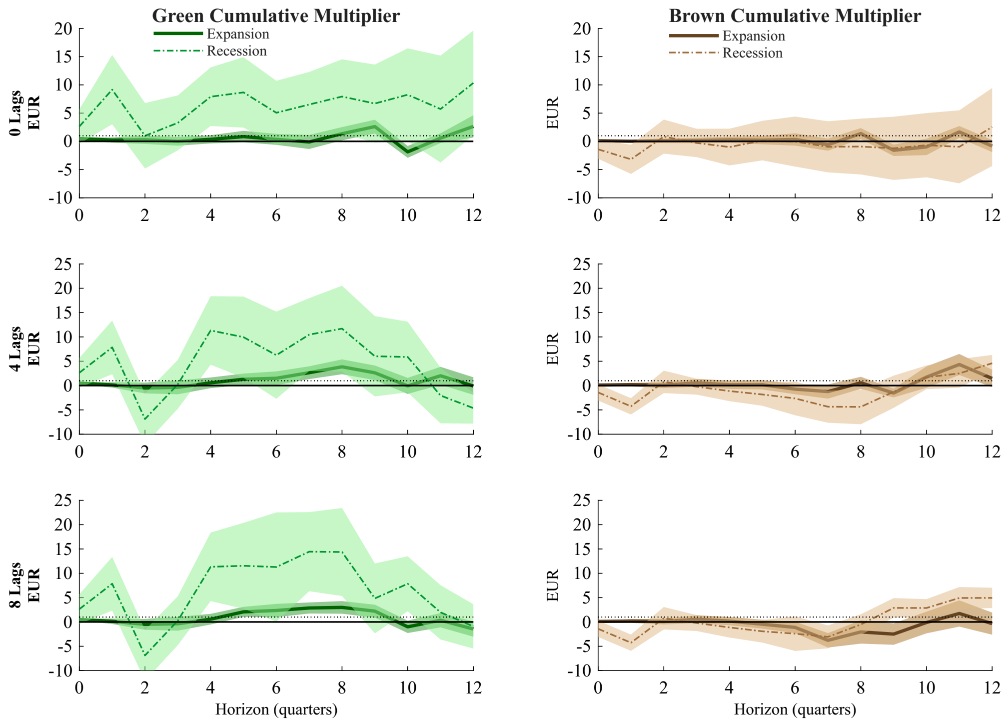
Sample: 2011Q1–2023Q4. Impulse variables: Log procurement p.c. Response variable: GDP per capita. Interpretation: % change in GDP p.c. to a 1-standard deviation shock to the impulse variable h quarters after the shock. Solid line: expansion state (GDP growth positive); Dashed line: recession state (GDP growth negative). Shading: 68% CIs.

implying that both the composition and the timing of procurement programmes shape their macroeconomic effectiveness.

Figure 12 expresses these state-dependent responses in multiplier terms. The contrast between recession and expansion states is particularly pronounced for green procurement. During recessions, the green cumulative multiplier exceeds one at most horizons, typically reaching around €5 and exceeding €10 in some specifications. Moreover, under the 0-lag specification, the multiplier remains elevated after 12 quarters, suggesting persistent output gains following green procurement during downturns.

By contrast, the state dependence of brown procurement is considerably weaker. In recessions, the brown multiplier becomes positive and statistically significant only in some specifications after roughly nine quarters and peaks at around €4.5–4.9, remaining below the corresponding green multiplier. During expansions, brown procurement generates multipliers that are generally indistinguishable from zero, whereas green procurement continues to exceed one in the second year under the 4- and 8-lag specifications.

Figure 12: Cumulative Multiplier - Nonlinearity in the Business Cycle

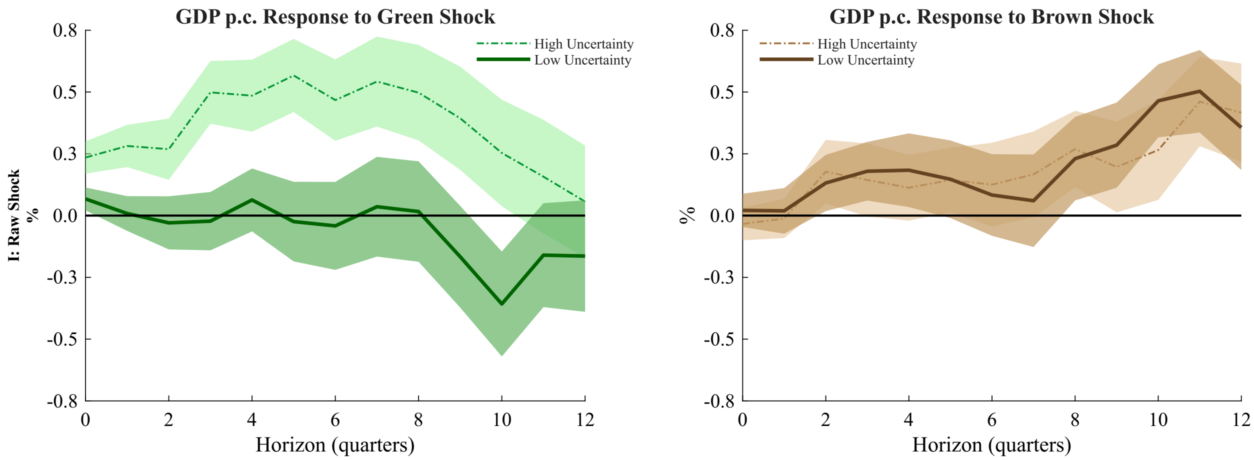


Sample: 2011Q1–2023Q4. Impulse variable: cumulative change of green/brown procurement per capita normalised by lagged GDP per capita. Controls: 0,4 and 8 lags of dependent variable and impulse variable. Solid line: expansion state (GDP growth positive); Dashed line: recession state (GDP growth negative). Shading: 68% CIs.

Taken together, these results indicate that procurement composition matters most when fiscal policy is likely to be most effective. The larger and more persistent recession-state multipliers associated with green procurement suggest that redirecting procurement toward green activities during downturns generates substantially greater output gains than equivalent brown procurement.

At first glance, the recession-state multiplier results may appear inconsistent with the GDP impulse responses in Figure 11, where brown procurement exhibits more persistent output effects. The apparent discrepancy arises because the two statistics answer different questions. The GDP impulse responses measure the effect of a procurement shock on output, whereas the cumulative multiplier additionally accounts for the evolution of procurement spending itself. If brown procurement is followed by a larger or more persistent increase in spending, it may generate a larger GDP response while still producing less output per euro spent. The cumulative multiplier therefore provides the more rel-

Figure 13: GDP Response - Nonlinearity in Uncertainty



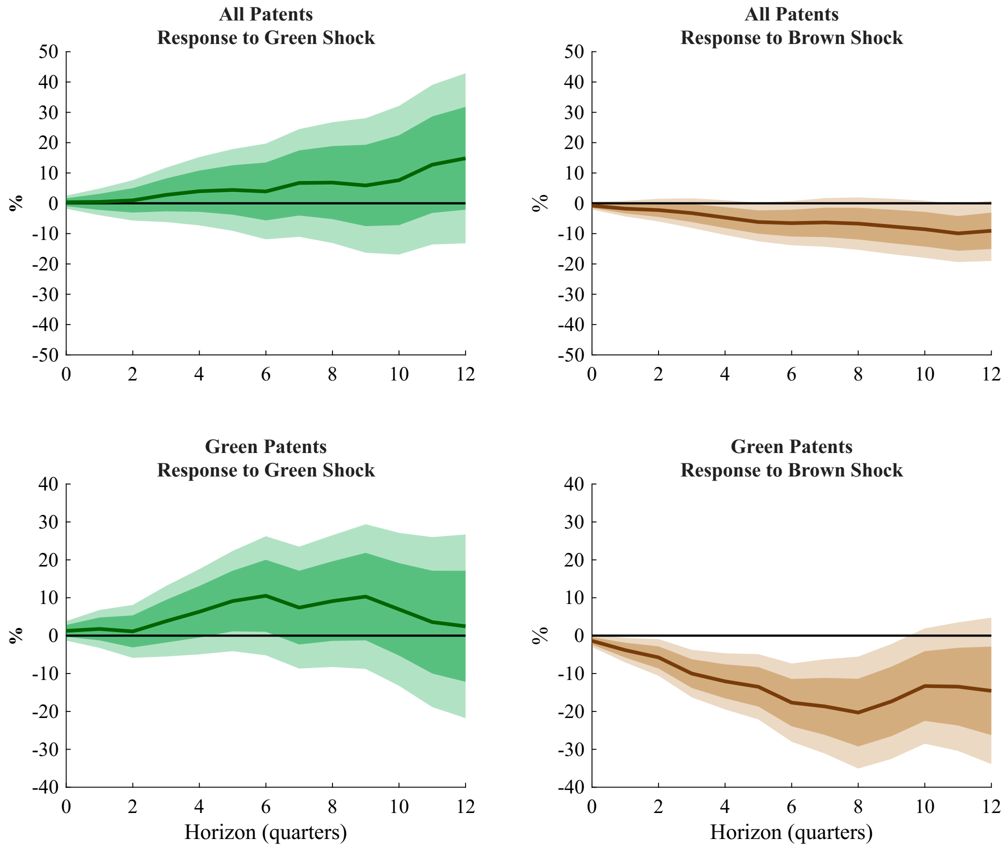
Sample: 2011Q1–2023Q4. Impulse variables: Log procurement p.c. Response variable: GDP per capita. Interpretation: % change in GDP p.c. to a 1-standard deviation shock to the impulse variable h quarters after the shock. Solid line: low uncertainty state (World Uncertainty Index below its sample mean); Dashed line: high uncertainty state (World Uncertainty Index above its sample mean). Shading: 68% CIs.

evant metric for comparing the fiscal effectiveness of procurement composition, and on this measure green procurement consistently outperforms brown procurement.

The effects of procurement composition also depend on the level of aggregate uncertainty. Figure 13 splits the sample according to the World Uncertainty Index, using its sample mean as the threshold. Green procurement generates substantially larger and more persistent output responses during periods of high uncertainty than during periods of low uncertainty. GDP rises by around 0.3% on impact, peaks above 0.5% in the second year, and gradually dissipates thereafter, whereas the response under low uncertainty remains close to zero throughout the horizon. By contrast, brown procurement exhibits little state dependence, with similar output responses under both high- and low-uncertainty regimes. Together, these findings suggest that procurement composition becomes particularly important when uncertainty is elevated, with green procurement providing substantially stronger macroeconomic stabilisation than brown procurement.

5.5 Long Run Effects: Innovation

Figure 14: Patents Effects



Sample: 2011Q1–2021Q4, IE excluded. Impulse variable: Log procurement p.c. Response variable: Log All Patents (first row), Log Green Patents (second row). Interpretation: Percentage change to a 1-standard deviation shock to the impulse variable h quarters after the shock.

The preceding results focus on the short-run macroeconomic consequences of procurement composition. We conclude by asking whether these differences extend to longer-run outcomes. Figure 14 examines innovation, measured by triadic patent-family filings, distinguishing between total patenting and green patenting. Green procurement is associated with modest, though imprecisely estimated, increases in both measures. By contrast, brown procurement reduces total patenting by around 9% after three years and has an even larger effect on green innovation, lowering green patent filings by around 20% after two years and 14.6% after three years. These findings suggest that procurement composition influences not only short-run macroeconomic performance but also the direction of technological change, with brown procurement appearing to discourage innovation, particularly in green technologies, consistent with directed technical change (Acemoglu et al., 2023).

5.6 Robustness

We subject the baseline results to two sets of checks, reported in Appendix D and Appendix E. First, we re-estimate the impulse responses under the three alternative identification schemes, the purged shock and the SVAR-based Cholesky and Max-Share shocks: the green output response is preserved, though attenuated under the SVAR schemes, while the brown response is more sensitive to the choice of scheme. Second, we re-estimate the baseline local projections with lag augmentation, restricted sample periods, and under a leave-one-out exclusion of each country. The main conclusions are unaffected.

6 Conclusion

This paper has estimated the macroeconomic effects of green and brown government spending using a new quarterly panel of public procurement contracts for ten Eurozone economies over 2011–2023, classified by Common Procurement Vocabulary codes and identified through the institutional timing of award announcements, with three alternative schemes for robustness (Appendix D). Impulse responses are estimated with panel local projections.

Green procurement has an impact multiplier of 0.69 and a cumulative multiplier above one within a year, while the brown multiplier is near zero for the first two years; the 3-year estimates are too imprecise to interpret. Both shocks transmit as demand shocks but with different timing, and both are amplified in recessions and high uncertainty, green far more so: its recession-state multiplier exceeds one and is sustained over the horizon, while the brown one is smaller.

In the energy market, the two shocks have near-symmetric effects: green spending reduces energy prices, industrial production, and fossil fuel import dependence, with oil import dependence (the ratio of net oil imports to inland oil consumption – 96.6% for the EU in 2024) falling by up to 4.6 percentage points at peak. Brown procurement increases energy industrial production and energy prices. Cumulating the energy price impulse responses over the horizon reveals that green spending delivers a net gain to households through persistently lower energy prices, while brown spending is approximately neutral. Finally, brown procurement significantly depresses total and green patent filings.

The results carry several policy implications. First, the green multiplier above one implies that public green spending more than pays for itself in output terms, reducing the net fiscal cost of the green transition and strengthening the case for green public investments to reduce the €477 billion annual investment gap. Even changing the composition of spending from brown to green should see a net gain in terms of economic activity. Second, the strong countercyclical properties of green spending suggest that directing fiscal stimulus toward green activities during downturns delivers larger stabilisation gains than equivalent brown spending, with the added benefit of advancing the low-carbon transition simultaneously. Third, the energy market results suggest that substituting away from brown and toward green public procurement can improve households' welfare in terms of energy costs.

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A Green and Brown CPV Codes

Table A.1: Green CPV code list (138 codes)

Code	Description	Code	Description
RENEWABLE ENERGY & ENERGY EFFICIENCY			
09330000	Solar energy	34144910	Electric buses
09331000	Solar panels	45251120	Hydroelectric plant construction work
09331100	Solar collectors for heat production	45251141	Geothermal power station construction work
09331200	Solar photovoltaic modules	45251160	Wind power installation works
09332000	Solar installation	45251240	Landfill-gas electricity generating plant construction work
31121300	Wind-energy generators	45261215	Solar panel roof-covering work
31121310	Windmills	45261250	District-heating plant construction work
31121320	Wind turbines	45261410	Roof insulation works
31121330	Wind turbine generators	45321000	Thermal insulation work
31121340	Wind farm	71314300	Energy-efficiency consultancy services
31121350	Wind-power generators	71314310	Thermal engineering services for buildings
34144900	Electric vehicles		
POLLUTION & ENVIRONMENTAL PROTECTION			
34516000	Pollution-control vessels	90721400	Protection of protected species services
38344000	Pollution monitoring devices	90721500	Protection of marine environment services
38433020	Emission measurement equipment	90721600	Protection of historical or natural heritage services
42914000	Recycling equipment	90721700	Verification of environmental compliance services
45213270	Construction works for recycling station	90721800	Environmental protection services for public areas
45262640	Environmental improvement works	90722000	Environmental rehabilitation
60651300	Anti-pollution ship services	90722100	Industrial site rehabilitation services
71313000	Environmental engineering consultancy services	90722200	Environmental decontamination services
71313100	Noise control consultancy services	90722300	Environmental cleaning services
71313200	Sound insulation and room acoustics consultancy services	90730000	Pollution tracking, monitoring and rehabilitation
71313300	Environmental risk and hazard assessment for construction	90731000	Air pollution management services
71313400	Environmental impact assessment for construction	90731100	Air pollution control services
71313410	Risk or hazard assessment for construction	90731200	Air quality management services
71313420	Environmental standards for construction	90731210	Carbon trading services
71313430	Environmental indicators analysis for construction	90731300	Air pollution reduction services
71313440	Environmental impact assessment (EIA) services for construction	90731400	Carbon management and sequestration services
71313450	Environmental monitoring for construction	90731500	Air pollution monitoring services
80540000	Environmental training services	90731600	Air pollution sampling services
90514000	Refuse recycling services	90731700	Air pollution measurement services
90700000	Environmental services	90731800	Air quality investigation services
90710000	Environmental management	90731900	Air quality index services
90711000	Environmental impact assessment other than for construction	90732000	Soil pollution services
90711100	Risk or hazard assessment other than for construction	90732100	Soil pollution assessment services
90711200	Environmental standards other than for construction	90732200	Soil pollution advice services
90711300	Environmental indicators analysis other than for construction	90732300	Soil pollution measurement services
90711400	Environmental impact assessment (EIA) other than for construction	90732400	Soil pollution sampling services
90711500	Environmental monitoring other than for construction	90732500	Soil pollution removal services
90712000	Environmental planning	90732600	Soil treatment or remediation services
90712100	Urban environmental development planning services	90732700	Soil decontamination services
90712200	International environmental planning services	90732800	Soil or groundwater recovery services
90712300	Countryside environmental development planning services	90732900	Soil protection services
90712400	Environmental management planning services	90733000	Water pollution tracking, monitoring and rehabilitation services
90712500	Environmental sustainability planning	90733100	Surface water pollution services
90713000	Environmental issues consultancy services	90733200	Surface water pollution prevention services

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Code	Description	Code	Description
90713100	Urban environmental issues consultancy services	90733300	Surface water pollution assessment services
90714000	Environmental audit services	90733400	Surface water pollution monitoring services
90714100	Environmental benchmarking services	90733500	Surface water pollution measurement services
90714200	Environmental investigation services	90733600	Surface water pollution cleaning services
90714300	Environment data analysis and reporting services	90733700	Surface water pollution treatment services
90714400	Environmental risk assessment services	90733800	Groundwater pollution treatment services
90714500	Environmental quality management and control systems	90733900	Groundwater pollution prevention services
90714600	Environmental information systems	90740000	Pollutant tracking, monitoring and rehabilitation services
90715000	Pollution investigation services	90741000	Services related to oil pollution
90715100	Soil and groundwater pollution investigation services	90741100	Oil spillage monitoring services
90715110	Soil pollution investigation services	90741200	Oil spillage control services
90715120	Groundwater pollution investigation services	90741300	Oil spillage rehabilitation services
90715200	Chemical and petrochemical pollution investigation services	90742000	Noise-pollution services
90715210	Chemical pollution investigation services	90742100	Noise-pollution reduction services
90715220	Petrochemical pollution investigation services	90742200	Noise-pollution measuring services
90716000	Contingency planning services for environmental accidents	90742300	Noise-pollution prevention services
90720000	Environmental protection	90742400	Noise-pollution rehabilitation services
90721000	Environmental safety services	90743000	Toxic-substance tracking, monitoring and rehabilitation services
90721100	Environmental protection from natural hazards services	90743100	Toxic-substance monitoring services
90721200	Protection against soil erosion services	90743200	Toxic-substance rehabilitation services
90721300	Protection of habitats services		
CLIMATE ADAPTATION			
45243300	Coastal defence works	45246200	Flood embankment works
45246000	River regulation and flood control works	45246400	Flood prevention works
45246100	River bank reinforcement work	45246410	Flood-defences maintenance works

Table A.2: Brown CPV code list (220 codes)

Code	Description	Code	Description
FOSSIL FUELS			
09100000	Fuels	09200000	Petroleum, coal and oil products
09110000	Solid fuels	09210000	Lubricating preparations
09111000	Coal and coal-based fuels	09211000	Lubricating oils and lubricating agents
09111100	Coal	09211100	Motor oils
09111200	Coal-based fuels	09211200	Compressor lube oils
09111210	Hard coal	09211300	Turbine lube oils
09111220	Briquettes	09211400	Gear oils
09111300	Fossil fuels	09211500	Reductor oils
09112000	Lignite and peat	09211600	Oils for use in hydraulic systems and other purposes
09112100	Lignite	09211610	Liquids for hydraulic purposes
09112200	Peat	09211620	Mould release oils
09113000	Coke	09211630	Anti-corrosion oils
09120000	Gaseous fuels	09211640	Electrical insulating oils
09121000	Coal gas, mains gas or similar gases	09211650	Brake fluids
09121100	Coal gas or similar gases	09211700	White oils and liquid paraffin
09121200	Mains gas	09211710	White oils
09122000	Propane and butane	09211720	Liquid paraffin
09122100	Propane gas	09211800	Petroleum oils and preparations
09122110	Liquefied propane gas	09211810	Light oils
09122200	Butane gas	09211820	Petroleum oils
09122210	Liquefied butane gas	09211900	Lubricating traction oils
09123000	Natural gas	09220000	Petroleum jelly, waxes and special spirits
09130000	Petroleum and distillates	09221000	Petroleum jelly and waxes
09131000	Aviation kerosene	09221100	Petroleum jelly
09131100	Kerosene jet type fuels	09221200	Paraffin wax
09132000	Petrol	09221300	Petroleum wax
09132100	Unleaded petrol	09221400	Petroleum residues
09132200	Leaded petrol	09222000	Special spirits
09132300	Petrol with ethanol	09222100	White spirit
09133000	Liquefied Petroleum Gas (LPG)	09230000	Petroleum (crude)
09134000	Gas oils	09240000	Oil and coal-related products
09134100	Diesel oil	09241000	Bituminous or oil shale
09134200	Diesel fuel	09242000	Coal-related products
09134210	Diesel fuel (0,2)	09242100	Coal oil
09134220	Diesel fuel (EN 590)	24327200	Wood charcoal
09135000	Fuel oils	24327300	Oils and products of the distillation of high-temperature coal tar, pitch and pitch tar
09135100	Heating oil	24327310	Coal tar
09135110	Low-sulphur combustible oils	39225400	Gas fuels for lighters
EXTRACTION AND PRODUCTION			
31121100	Generating sets with compression-ignition engine	76340000	Core drilling
31121200	Generating sets with spark-ignition engine	76400000	Rig-positioning services
42112300	Gas turbines	76410000	Well-casing and tubing services
42113300	Parts of gas turbines	76411000	Well-casing services
42113320	Gas-injection module	76411100	Well-casing crew services
42113390	Fuel-gas systems	76411200	Well-casing planning services
43130000	Drilling equipment	76411300	Well-casing milling services
43131000	Offshore production platforms	76411400	Well-casing completion services
43131100	Offshore equipment	76420000	Well-cementing services
43131200	Offshore drilling unit	76421000	Liner cementing services
43132000	Oil drilling equipment	76422000	Plug cementing services
43132100	Drilling machinery	76423000	Foam cementing services
43132200	Drilling rig	76430000	Well-drilling and production services
43132300	Drills	76431000	Well-drilling services
43132400	Line equipment	76431100	Well-drilling control services
43132500	Line hangers	76431200	Well-drilling pickup services
43133000	Oil platform equipment	76431300	Well-drilling laydown services
43133100	Skid units	76431400	Rathole well-drilling services
43133200	Skid-mounted modules	76431500	Well-drilling supervision services
43134000	Oil-field machinery	76431600	Well-drilling rig monitor services
43134100	Submersible pumps	76440000	Well-logging services
43135000	Subsea equipment	76441000	Cased hole logging services
43135100	Subsea control systems	76442000	Open hole logging services
43136000	Downhole equipment	76443000	Other logging services
43122000	Coal or rock-cutting machinery	76450000	Well-management services
43414100	Coal pulverising mills	76460000	Well-support services
43613000	Parts of coal or rock cutting machinery	76470000	Well-testing services
43613100	Parts of coal cutting machinery	76471000	Well fracture testing services
44166000	Oil country tubular goods	76472000	Well site inspection or testing services
66519100	Oil or gas platforms insurance services	76473000	Well equipment testing services
76000000	Services related to the oil and gas industry	76480000	Tubing services
76100000	Professional services for the gas industry	76490000	Well-completion services

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Code	Description	Code	Description
76110000	Services incidental to gas extraction	76491000	Well-plugging services
76111000	Regasification services	76492000	Well-positioning services
76120000	Diving services incidental to gas extraction	76500000	Onshore and offshore services
76121000	Subsea well diving services	76510000	Onshore services
76200000	Professional services for the oil industry	76520000	Offshore services
76210000	Services incidental to oil extraction	76521000	Offshore installation services
76211000	Liner-hanger services	76522000	Offshore supply-vessel services
76211100	Lining services	76530000	Downhole services
76211110	Test pit lining services	76531000	Downhole logging services
76211120	Well site pit lining services	76532000	Downhole pumping services
76211200	Mudlogging services	76533000	Downhole recording services
76300000	Drilling services	76534000	Downhole underreaming services
76310000	Drilling services incidental to gas extraction	76535000	Downhole hole opening services
76320000	Offshore drilling services	76536000	Downhole vibration control services
76330000	Turbine drilling services	76537000	Downhole tool services
76331000	Coiled turbine drilling services	76537100	Downhole oilfield tools services
CONSTRUCTION AND INFRASTRUCTURE			
39340000	Gas network equipment	45255100	Construction work for production platforms
45223720	Petrol/gas stations construction work	45255110	Wells construction work
45231100	General construction work for pipelines	45255120	Platforms facilities construction work
45231110	Pipelaying construction work	45255121	Topside facilities construction work
45231111	Pipeline lifting and relaying	45255200	Oil refinery construction works
45231112	Installation of pipe system	45255210	Oil terminal construction work
45231113	Subsea pipelines construction work	45255300	Gas terminal construction work
45231200	Construction work for oil and gas pipelines	45255400	Fabrication work
45231210	Construction work for oil pipelines	45255410	Offshore fabrication work
45231220	Construction work for gas pipelines	45255420	Onshore fabrication work
45231221	Gas supply mains construction work	45255430	Demolition of oil platforms
45231222	Gasholder works	45255500	Drilling and exploration work
45231223	Gas distribution ancillary work	45255600	Coiled-tubing wellwork
45251150	Cooling tower construction works	45255700	Coal-gasification plant construction work
45251210	Gas-fired heating station construction work	45255800	Gas-production plant construction work
45252150	Coal-handling plant construction work	45333000	Gas-fitting installation works
45255000	Construction work for the oil and gas industry	51133100	Installation services of gas turbines
DISTRIBUTION AND STORAGE			
34512800	Tanker ships	63121110	Gas storage services
39721410	Gas appliances	65200000	Gas distribution and related services
39721411	Gas heaters	65210000	Gas distribution
44161100	Gas pipelines	44611410	Oil-storage tanks
44161110	Gas-distribution network	44612000	Liquefied-gas containers
50531200	Gas appliance maintenance services	44612100	Gas cylinders
60651100	Coastal tanker-chartering services	44612200	Gas tanks

B Data

This appendix documents the construction of the procurement dataset. It provides the full green and brown CPV classifications, details the treatment of mixed contracts, describes the construction of macroeconomic, energy, and innovation variables, and presents supplementary descriptive statistics referred to in the main text.

B.1 Classifying Procurement as Green or Brown

To construct the green procurement series, we first identify which procurement contracts can be categorised as 'green'. There are multiple approaches for green-tagging contracts. One way to identify green contracts would be to identify which contracts contain 'green criteria' in the tendering process. For example, in the TED contract notices there are six categories which describe the criteria taken into consideration by the contracting public authority when choosing to award the contract to a bidding supplier, one of them being environmental criteria. An alternative approach would be similar to the definition used in the national accounts' Environmental Protection Expenditure statistics, by identifying as green all contracts awarded by public authorities and agencies whose main area of activity is the Environmental Protection COFOG function. A third approach would be to follow the European Commission (2008) definition of Green Public Procurement (GPP) as a "process, whereby public authorities seek to procure goods, services and works with a reduced environmental impact throughout their life cycle when compared to goods, services and works with the same primary function that would otherwise be procured" – green contracts are those in which green goods and services are purchased.

The first approach is not followed due to data limitations. While Opentender provides information as to how many criteria were used in the award decision, it does not clearly separate which criteria were used nor the weight assigned to each. The second definition can be implemented as Opentender provides the COFOG function of the contracting authority for each contract; however, as was discussed in the literature, this is a less accurate definition of 'green spending' than the third.

We therefore implement the third classification of green contracts by relying on each contract's standardised Common Procurement Vocabulary (CPV) codes, which identify the product category of the goods and services being stipulated in each contract. We define a list of ‘green’ CPVs, starting from the green CPVs provided by Poltoratskaia et al. (2024). We then manually parsed through all CPV codes and sub-codes to identify additional green codes. The final list of 138 CPVs is shown in Table A.1, which can be divided into three broad themes: Renewable Energy and Energy Efficiency, Pollution and Environmental Protection, and Climate Adaptation. The Opentender data was then filtered so that only contracts with at least one green CPV code were kept.

One possible approach to categorise brown contracts would be to use the Open Risk (2022) mapping of CPV codes to NACE Level 2 production sectors, then use Eurostat’s sectoral emission intensity data to identify which NACE sectors are the most polluting, and define the CPV codes which are mapped to such sectors as brown. However, this poses several problems. First, one would need to select an arbitrary threshold of the NACE sectoral emission intensity distribution such that above this level, a sector would be classified as brown. Second the classification would be very asymmetric: the brown list would be constructed from the top of the sectoral emission intensity distribution, while the green list would not constructed as its mirror image from the bottom. Third, the emission intensity data underlying the brown classification are measured at broad NACE sector levels, which does not allow to distinguish the production technology used to produce a product identified by a CPV code. A CPV code falling within an emission-intensive NACE sector would be classified as brown regardless of whether the specific product procured was generated using fossil fuels or renewable sources. For example, a contracting authority that purchases electricity (CPV code 09310000, which maps to NACE sector D) which was produced with a renewable source will nonetheless have that contract tagged as brown since NACE sector D is the second-most emission-intensive sector.

To address these limitations, we identify as brown those CPV codes whose primary object is fossil-fuel-related goods and services. The 220 identified codes are presented in Table A.2, where four broad categories can be distinguished. The first covers the energy products themselves — solid fuels including coal, lignite, peat, and coke; gaseous fuels including natural gas, propane, and butane; petroleum and its distillates including crude oil, diesel, aviation kerosene, petrol, and fuel oil. The second covers the extraction and production process — offshore platforms, drilling and mining equipment, and the full hierarchy of oil and gas field services. The third covers the construction of fossil fuel infrastructure — pipelines for oil and gas distribution, power station construction, gas-fired heating plants, oil refineries, coal-gasification plants, and gas installation works. The fourth covers distribution, storage, and ancillary services — gas distribution networks, tanker ships, liquefied gas containers, oil storage tanks, and gas storage services.

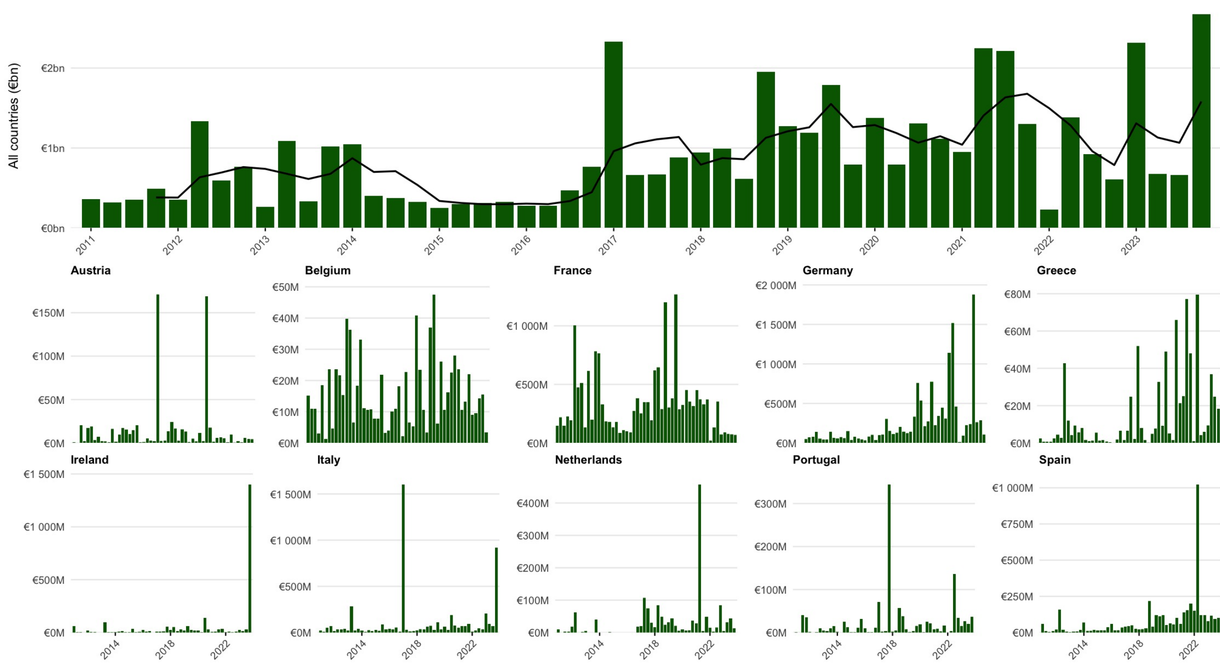
A further problem is that in the data, contracts may carry simultaneously both a green and brown CPV. For example, a contract's lot (a subdivision of a tender) can have the brown CPV 09100000 (Fuels) and the green CPV 09332000 (Solar installation). This problem is quantitatively minor, as mixed lots account for a negligible share of total brown and green contracts. Mixed contracts are resolved through a two-stage decision rule. In the first stage, we count the number of green and brown CPV codes assigned to each lot and classify the contract according to whichever category has the higher count: a lot with more green than brown codes is classified as green, and vice versa. In the second stage, applicable only to lots where the number of green and brown codes is exactly equal, for example a lot carrying one green and one brown code, we apply a specificity rule: among the green and brown CPV codes assigned to the lot, we identify the most specific, defined as the code with the fewest trailing zeros in its eight-digit representation, since trailing zeros indicate higher levels of the CPV hierarchy and therefore less precise classification. The lot is then classified according to whether this most specific code is green or brown, on the grounds that a contracting authority who assigned a highly granular code was more deliberately describing the primary object of procurement, while a broader code is more likely to reflect a generic category assignment. In the event of a further tie, where the most specific green and the most specific brown code share the same level of precision, green classification is prioritised as the tiebreaker.

To obtain a quarterly series of green and brown procurement, we implemented the following procedure. Each row in the Opentender data corresponds to a lot of a tender, where each tender can contain multiple lots. We thus aggregated all lot-level monetary values to obtain tender-level data. In a second step, to aggregate the tender-level data up to quarterly level, contracts must be assigned to specific months. In the raw data, each contract contains multiple dates, corresponding to different stages in the tendering process. We find that for most of the tenders there are missing observations for the last call for publication, award decision and contract signature dates. The variable with the least share of missing values is the first award notice date, making it a good candidate for the date used for aggregation. More importantly, this is also the date within the tender process which corresponds closely to 'news' in procurement spending, which will be discussed later in the causal identification section. Therefore, we first assign each tender an announcement quarter according to the date on which the contract award announcement was published, and then aggregate all tenders' monetary values by grouping on the award publication quarter and country.

B.2 Time series properties

Figures B.1 and B.2 plot nominal green and brown procurement value (final, not imputed) aggregated to the quarter of contract's award announcements, for the panel aggregate (top sub-panels of each chart) and for each countries individually, with the black line representing the 4-quarter moving average. Aggregate green procurement is highly volatile at quarterly frequency, ranging from under €500M in the early sample to over €2.5 billion in peak quarters. The four-quarter rolling average reveals a clear upward trend throughout the sample period, rising from below €1 billion per quarter before 2019 to consistently above €1 billion after 2019. Two episodes stand out: a pronounced spike of approximately €2.5bn around early 2017, driven primarily by large contracts in Italy and Portugal, and large spikes after 2021, consistent with European green recovery expenditure.

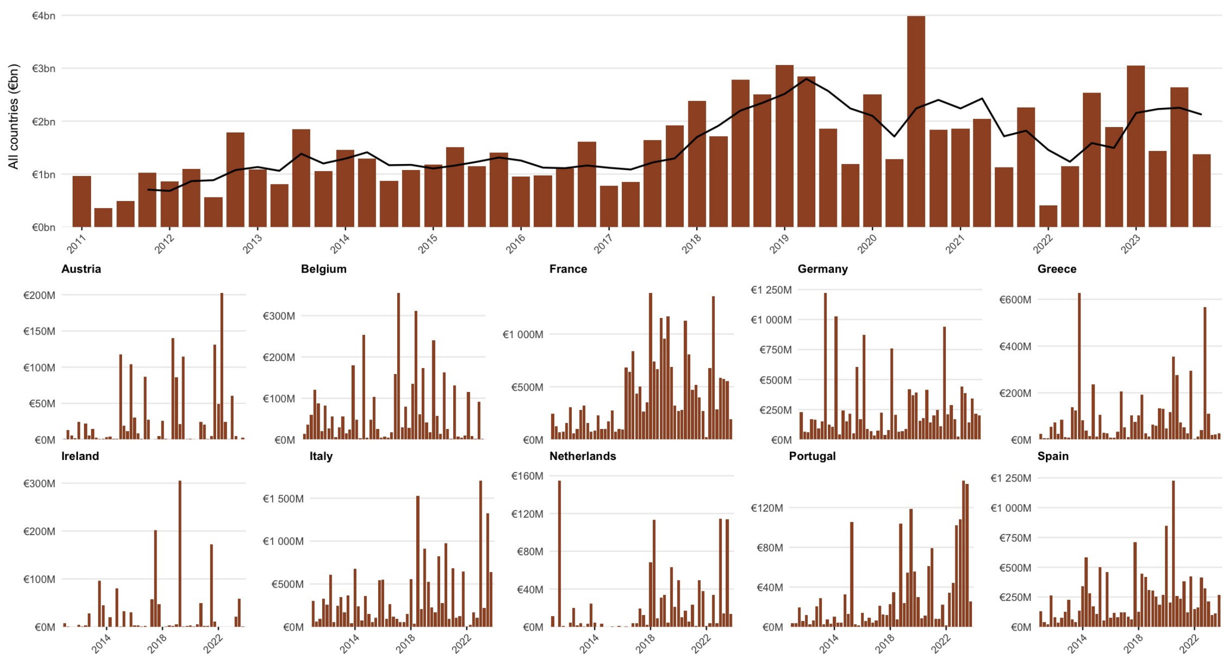
Figure B.1: Quarterly Green Procurement Value



Notes: Nominal final value aggregated by quarter of contract award announcement. Line = 4-quarter rolling average.

Aggregate brown procurement (lower chart) is substantially larger in magnitude and also trends upward. The moving average of quarterly brown procurement is typically €1 billion in the first half of the sample and rises to €2-3 billion after 2017. The volatility of brown procurement is also high, though visibly less than green procurement. As can be seen in the country-level time series, brown procurement exhibits less extreme quarterly spikes than green procurement, especially in Austria, Ireland, Italy, Netherlands, Portugal and Spain.

Figure B.2: Quarterly Brown Procurement Value



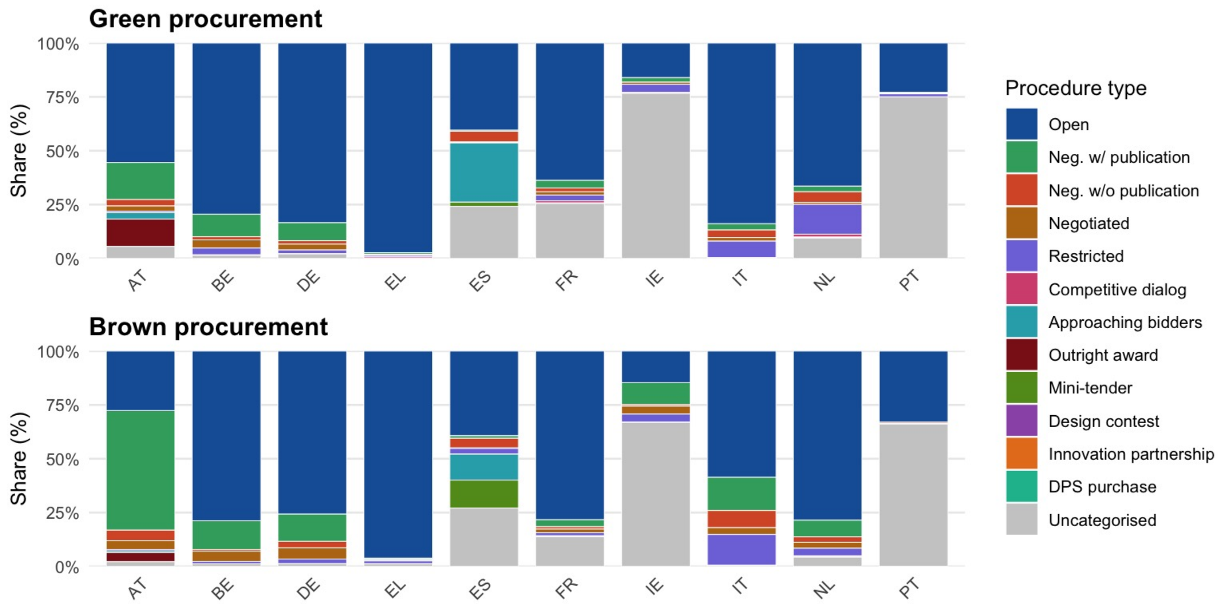
Notes: Nominal final value aggregated by quarter of contract award announcement. Line = 4-quarter rolling average.

B.3 Tender structure and competition

In addition to the decomposition of procurement by supply type shown in Figure 2 in the main text, Figures B.3–B.5 further characterise the institutional features of the procurement data. They document the procurement procedures through which contracts are awarded and the degree of competition among bidders, providing additional context for the identification strategy discussed in Section 4.

Figure B.3 shows the breakdown by tender procedure type. The open competitive pro-

Figure B.3: Composition of Procurement Tenders by Procedure Type

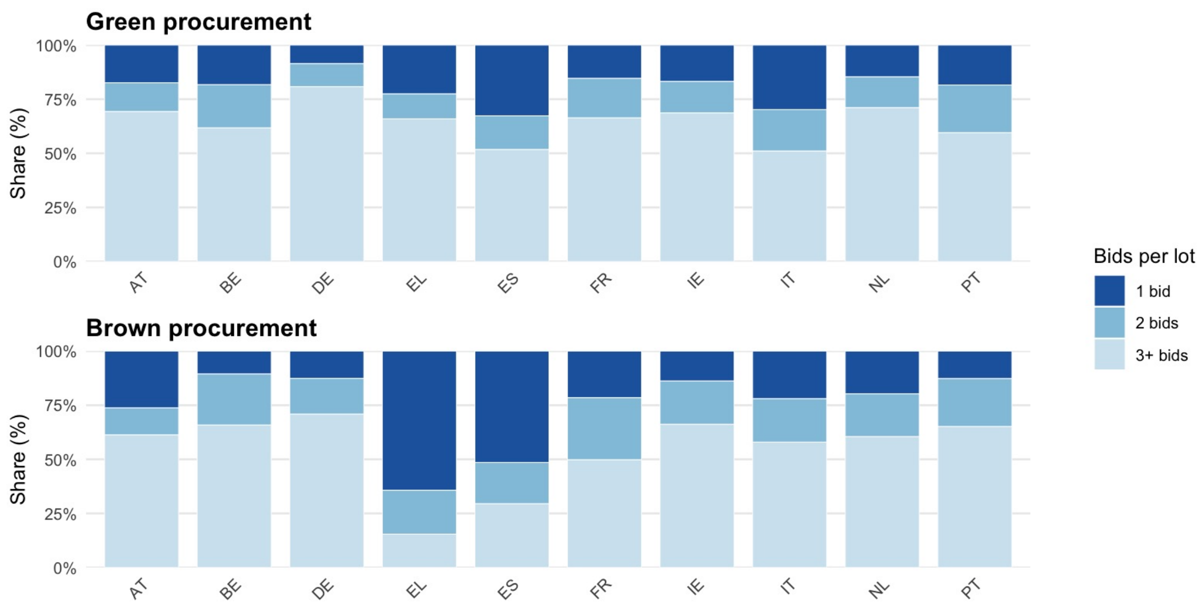


Notes: Percentage share of tenders from 2011 to 2023 by procedure type for the ten considered countries.

cedure dominates in most countries for both green and brown procurement. The Open tender procedure is the most accessible procedure, defined as a tender in which ”any interested economic operator may submit a tender in response to a call for competition” (European Parliament & Council of the European Union, 2014). The second-most used procedure is Negotiated with Publication, whereby ”any economic operator may submit a request to participate in response to a call for competition” (Ibid.), and after being shortlisted, selected candidates submit initial tender bids, which can be further negotiated with the contracting authority. The fully Restricted procedure is less common, being only relevant in Italy and Netherlands, which requires a request for participation as in Negotiated with Publication, but entails a final bid with no possibility of negotiation.

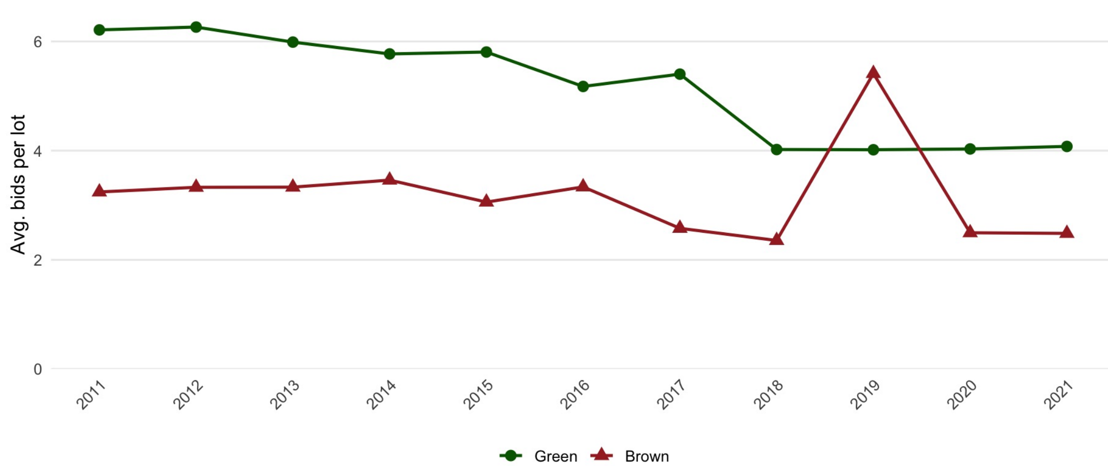
Figures B.4 and B.5 characterise the degree of competition of green and brown tenders. The majority of green tenders attract at least two bids, and in every country at least 50% of green tenders attract at least three bids. Competition in brown procurement is more heterogeneous: Greece and Spain stand out with substantially higher shares of single-bid brown tenders, indicating more limited supplier competition. Figure B.5 traces the average number of bids per lot over time. Green tenders consistently attract more bids than brown throughout the sample, but both see a trending decline in competition. Green averages approximately 6 bids per lot in 2011 and declines gradually to around 4 by 2021, while brown averages just above 3 bids in 2011 and falls to approximately 2.5 by 2021. Taken together, these patterns suggest that while brown and green tenders do not differ in the level of accessibility and openness when looking at the tender procedure type, green tenders attract more competition from tender suppliers.

Figure B.4: Composition of Procurement Tenders by Bid Count



Notes: Percentage share of tenders from 2011 to 2023 by number of bids received.

Figure B.5: Average Number of Bids per Lot



B.4 Macroeconomic, Energy, and Innovation Data

The macroeconomic variables used in the empirical analysis are drawn from four sources, summarised in Table B.1. The primary source is the Euro Area Mixed-frequency Database (EA-MD-QD), which provides harmonised and seasonally adjusted quarterly and monthly time series for all ten sample economies. From this database we draw the main national accounts aggregates (real GDP, real private consumption, real government consumption, and real gross fixed capital formation), as well as labour market variables (employment, unemployment rate, real labour productivity, wages and salaries), the GDP deflator, headline Harmonised Index of Consumer Prices (HICP), industrial production indices (IP) for manufacturing and energy sectors, the producer price index (PPI) for energy, long-term government bond yields (10-year), the Economic Sentiment Indicator, and national stock price indices. Monthly series are aggregated to quarterly frequency by averaging (for stock variables) or summing (for flow variables).

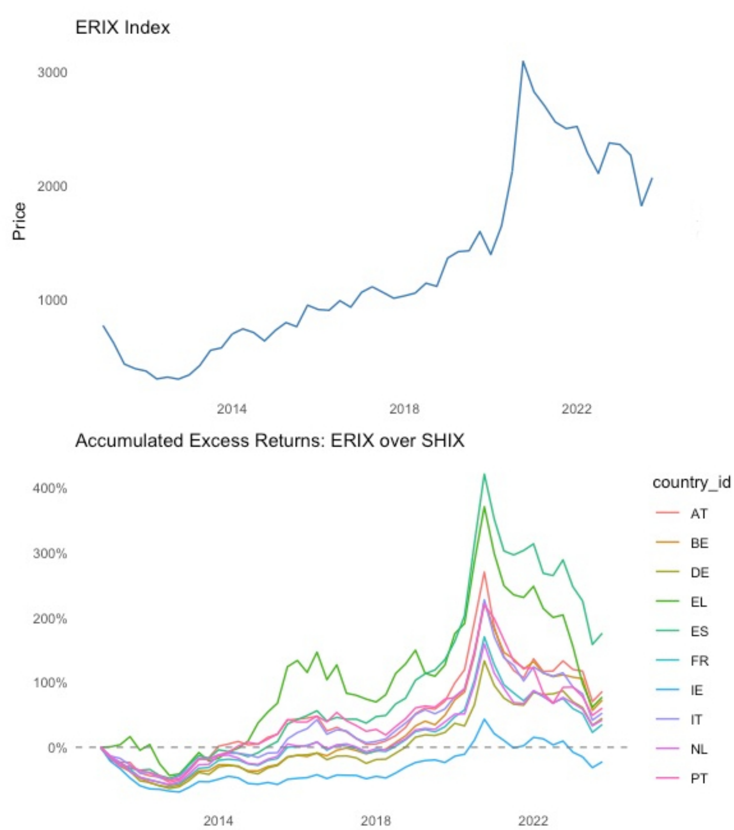
A further macroeconomic variable used is the excess stock market returns of the renewable energy sector relative to the returns of the broad stock market. We use the stock price of the European Renewable Energy Total Return (ERIX) Index, which tracks the performance of European renewable energy companies that are active in biofuels, geothermal, marine, solar, water, and wind sectors. For the benchmark stock index against which excess returns are measured, we use the national stock market indices provided in EA-MD-QD. An accumulated excess return series is constructed as the cumulative difference between ERIX quarter-on-quarter returns and the corresponding national stock index returns, capturing the relative outperformance of green energy equities net of general market movements. The time series are shown in Figure B.6.

Additional energy disaggregates are obtained from Eurostat: HICP sub-indices for electricity, gas, and liquid fuels, as well as physical volume series for electricity, natural gas, and oil products covering imports, exports, and total consumption. These series are used to trace the energy market transmission channel of procurement shocks. Since energy trade and consumption data exhibit a seasonal pattern, we apply seasonal adjustment to each energy import, export, and consumption variable prior to computing import dependency rates. For each country and each variable, the raw quarterly series is adjusted using an X-11 filter. The filter decomposes the energy series into trend-cycle, seasonal, and irregular components, and the seasonally adjusted series is obtained as the difference between the original series and the estimated seasonal component. A logarithmic transformation is applied prior to decomposition, implying a multiplicative decomposition. This is appropriate for energy series, where the magnitude of seasonal swings varies with the overall level of consumption, such that an additive decomposition would understate seasonality in high-consumption periods and overstate it in low-consumption periods. Energy import dependency rates for electricity, gas and oil products are then constructed from the seasonally adjusted components as:

$$\mathrm{Dep}_{i,t} = \frac{\mathrm{Imp}_{i,t}^{SA} - \mathrm{Exp}_{i,t}^{SA}}{\mathrm{Consumption}_{i,t}^{SA}}$$

where i denotes the country and t the quarter, and SA denotes the seasonally adjusted series.

Figure B.6: Stock Market Returns



Sample: 2011Q1 – 2023Q4. Accumulated Excess Return = Cumulative Excess of ERIX quarter-on-quarter returns over baseline national index (SHIX) quarter-on-quarter returns.

Table B.1: Macroeconomic Variables

Source	Description	Frequency	Unit
EA-MD-QD	Real Gross Domestic Product	Quarterly	Millions EUR
	Real Household Final Consumption Expenditure	Quarterly	Millions EUR
	Real Government Final Consumption Expenditure	Quarterly	Millions EUR
	Real Gross Capital Formation	Quarterly	Millions EUR
	Real Gross Fixed Capital Formation	Quarterly	Millions EUR
	Real Exports of Goods and Services	Quarterly	Millions EUR
	Real Imports of Goods and Services	Quarterly	Millions EUR
	Wages and Salaries	Quarterly	Millions EUR
	GDP Deflator	Quarterly	Index, 2015=100
	Real Labour Productivity	Quarterly	Index, 2015=100
	Total Employment (domestic concept)	Quarterly	000s of persons
	Unemployment Rate, Total	Monthly	%
	Long-term Interest Rate (10-year gov. bond)	Monthly	% per annum
	HICP, Overall	Monthly	Index, 2015=100
	HICP, Energy	Monthly	Index, 2015=100
	Producer Price Index, Energy	Monthly	Index, 2021=100
	Industrial Production, Manufacturing	Monthly	Index, 2021=100
	Industrial Production, Energy	Monthly	Index, 2021=100
	Economic Sentiment Indicator	Monthly	Index
	National Stock Price Index	Monthly	Index
Eurostat	HICP, Electricity	Monthly	Index, 2015=100
	HICP, Gas	Monthly	Index, 2015=100
	HICP, Liquid Fuels	Monthly	Index, 2015=100
	Electricity Exports	Monthly	Gigawatt-hours
	Electricity Imports	Monthly	Gigawatt-hours
	Electricity Available to Internal Market	Monthly	Gigawatt-hours
	Natural Gas Exports	Monthly	Terajoules
	Natural Gas Imports	Monthly	Terajoules
	Natural Gas Inland Consumption - Observed	Monthly	Terajoules
	Oil Products Exports	Monthly	Thousand Tonnes
	Oil Products Imports	Monthly	Thousand Tonnes
	Oil Products Gross Inland Deliveries - Observed	Monthly	Thousand Tonnes
	Employed persons by detailed occupation (ISCO-08 two digit level)	Yearly	000s of persons
OECD Intellectual Property Statistics	Triadic Patent Families	Daily	Count
Investing.com	ERIX Total Return Index	Monthly	EUR
Ahir et al. (2022)	World Uncertainty Index	Quarterly	Index

Notes: Monthly series aggregated to quarterly frequency by averaging (stock variables) or summing (flow variables) within each quarter.

To measure the effects of green and brown procurement on innovation, we rely on the OECD's Triadic Patent Families (TPF) database, February 2026 Release (Dernis & Khan, 2004; Martinez, 2010; OECD, 2009), which aggregates patent family data from the United

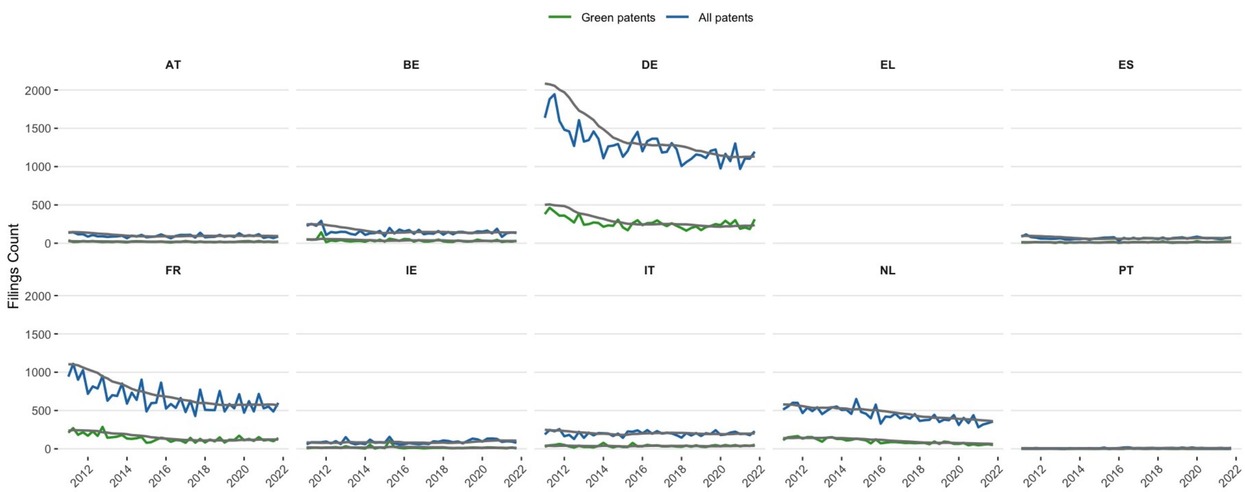
States Patent and Trademark Office, European Patent Office, and Japan Patent Office. A patent family is defined as a set of patents filed in multiple countries to protect a single invention, identified by a common Family identifier variable. We obtain all patents to measure overall innovation, and green-related patents to measure green innovation. Green patent families are identified by matching each family's patent classification codes against a list of green technology codes. Patent classification systems assign every patent to one or more technology categories based on the technical content of the invention. The two systems available in the TPF database are the International Patent Classification (IPC) and the Cooperative Patent Classification (CPC). The IPC organises all technology into eight sections (A through H), each subdivided into classes, subclasses, groups, and subgroups. The CPC is a more granular extension of the IPC, and importantly it adds the further Y02 and Y04S tags, which specifically identify climate-change-mitigation technologies (Angelucci et al., 2018). This tag is applied to patents which contribute to emissions reduction or climate adaptation, even when the underlying technology falls under a primary class that is not inherently environmental. Y02 subcategories include technologies for adaptation to climate change (Y02A), climate mitigation technologies related to buildings (Y02B), carbon capture and storage (Y02C), renewable energy technologies (Y02E), sustainable industrial processes (Y02P), transport-related climate mitigation technologies (Y02T), and waste-related climate mitigation technologies (Y02W). Y04S include smart grids. To further capture patents that might relate to green innovation, we also specify a list of green IPC codes. The IPC Green Inventory[2] provides a list of IPC codes related to green innovation, and we supplement this by identifying codes related to waste and pollution control, recycling, and environmental cleanup. The full list of green CPC and IPC codes is shown in Table B.2.

To assign patents to countries, we rely on the nationality of the patent applicant recorded in the TPF Applicants file. For each green family, all distinct applicant countries are extracted, so that a family with applicants in multiple countries contributes to each country's count. To assign a date to when patents were filed, we rely on the First_prio variable, which records the date of the earliest priority filing in the family. Summing the family count variable Count_prio by applicant country and quarter yields a quarterly country-level panel of patent filings for the 10 Eurozone countries in our analysis sample. This procedure is done twice, once to obtain all patent filings, and the second time to filter only green patent filings. Since quarterly patent filings are very noisy, we smooth the

[2]Provided by Méndez-Morales (2025): https://data.mendeley.com/datasets/yd3x3dbpbn/1

series by taking the three-year trailing moving average for each country, calculated by starting with pre-2011 data. Furthermore, since patents normally take a long time to be recorded and updated in TPF, we restrict the sample to 2021Q4 rather than 2023Q4 to prevent end-of-sample undercounting. The time series of patent filings are shown in Figure B.7. The largest innovators, by both overall and green patent filings, are Germany, France and the Netherlands.

Figure B.7: Patent Filings Count by Country



Notes: 2011Q1-2021Q4. Grey smoothed lines = 3-year trailing moving average.

Table B.2: Green CPC and IPC codes

Code	Description	Code	Description
CPC CLIMATE-CHANGE MITIGATION TAGS (Y02 / Y04)			
Y02A	Climate change adaptation	Y02B	Climate change mitigation – buildings and heating
Y02C	GHG capture, storage and disposal	Y02D	Climate change mitigation – ICT
Y02E	Low-carbon energy generation and distribution	Y02P	Climate change mitigation – production and processing
Y02T	Low-carbon transportation	Y02W	Wastewater treatment and waste management
Y04	Systems integrating technologies from multiple fields	Y04S	Smart grid systems
WIND ENERGY			
F03D	Wind motors		
SOLAR ENERGY			
F24S	Solar heat collectors and solar heat systems	H02S	Generation of electric power by photovoltaic conversion
F02C 1/05	Gas-turbine plants operating on solar energy	F03G 6/00	Solar machinery
GEOTHERMAL ENERGY			
F24T	Geothermal collectors and geothermal systems	F24T 10/00	Geothermal collectors using working fluids
F24T 20/00	Geothermal collectors using ground water	F24T 30/00	Geothermal systems using dry steam
F24T 40/00	Details of geothermal systems	F24T 50/00	Geothermal systems with heat storage
F24V 30/00	Collection of thermal energy	F24V 40/00	Production of thermal energy
F24V 50/00	Use of thermal energy		
OCEAN, WAVE AND TIDAL ENERGY			
F03G 5/00	Wave energy motors (pneumatic)	F03G 5/01	Wave energy – horizontal rotation axis
F03G 5/02	Wave energy – vertical rotation axis	F03G 5/03	Wave energy – oscillating bodies
F03G 5/04	Wave energy – wave impact	F03G 5/05	Wave energy – overtopping
F03G 5/06	Wave energy – movable bodies	F03G 5/07	Wave energy – pressure differences
F03G 5/08	Tidal stream energy	F03G 7/05	Ocean thermal energy conversion (OTEC)
BIOMASS AND BIOFUELS			
C10J	Producer gas from solid carbonaceous materials	C10J 3/02	Producer gas using steam and air
C10J 3/46	Producer gas from waste materials	C10B 53/00	Carbonisation of biomass
C10L 3/00	Synthetic and bio natural gas	C10L 5/00	Solid fuels from biomass
C10L 5/42	Briquettes from peat	C10L 5/44	Briquettes from wood and agricultural waste
C10L 5/46	Briquettes from industrial waste	C10L 5/48	Briquettes from municipal solid waste
C10G 1/10	Bio-oil from animal or vegetable fats	F02C 3/28	Gas-turbine plants using biofuels
F02B 43/00	Engines characterised by use of gaseous fuels	F02M 21/02	Apparatus for supply of non-liquid fuels
F02M 27/02	Fuel preheating and prevaporising	F23B 90/00	Solid fuel combustion apparatus
F23G	Incineration and destruction of waste	F23G 5/00	Waste incineration apparatus
F23G 5/027	Incineration with waste pretreatment	F23G 7/00	Incineration of liquid waste
F23G 7/06	Incineration of waste gases	F23G 7/10	Incineration of industrial waste gases
C05F	Organic fertilisers from waste or refuse	C05F 7/00	Fertilisers from household waste
HYDROGEN AND FUEL CELLS			
H01M 4/86–4/98	Electrodes for fuel cells (various types)	H01M 8/00–8/24	Fuel cells (all electrolyte types)
H01M 12/00–12/08	Hybrid electrochemical cells		
NUCLEAR ENERGY			
G21	Nuclear physics and engineering (all subclasses)	G21C 13/10	Nuclear reactor safety systems
G21F 9/00	Treatment of radioactively contaminated material		
ELECTRIC AND HYBRID VEHICLES			
B60K 6/00	Plural prime-movers for mutual propulsion (HEV)	B60K 6/10	Hybrid – engine and motor in parallel
B60K 6/20	Hybrid – engine and motor in series	B60K 6/28	Electric propulsion with power-split
B60K 6/30	Hybrid – engine driving electric generator	B60K 16/00	Propulsion from force of nature
B60L 3/00	Electric propulsion safety equipment	B60L 7/10	Regenerative braking (resistors)
B60L 7/22	Regenerative braking with battery charging	B60L 8/00	Propulsion from force of nature
B60L 9/00	Propulsion with external power supply	B60L 50/30	Fuel cell vehicle propulsion
B60W 10/26	Control of energy storage for propulsion	B60W 20/00	Control systems for hybrid vehicles
B61	Railways (all subclasses)	B61D 17/02	Lightweight rail vehicle bodies
B62D 35/00	Aerodynamic streamlining of vehicles	B62D 35/02	Road vehicle aerodynamic streamlining
B62D 67/00	Demountable or modular vehicle bodies	B62K	Cycles and cycle frames
B62M 1/00	Rider propulsion of wheeled vehicles	B62M 3/00	Rider propulsion with steering
B62M 5/00	Foot-driven propulsion devices	B62M 6/00	Electric propulsion of cycles
B63B 1/34–1/40	Hydrodynamically optimised vessel hulls	B63B 35/32	Anti-pollution vessels
B63H 9/00	Ship propulsion by sails	B63H 13/00	Ship propulsion by rotors
B63H 16/00	Ship propulsion by kites	B63H 19/02	Ship propulsion combined with wind
B63H 19/04	Ship propulsion combined with solar	B63H 21/18	Electric ship propulsion
B63J 4/00	Ship waste-water treatment	B64G 1/44	Spacecraft attitude control – solar
F16H 3/00	Toothed gearings for HEV transmission	F16H 3/78	Epicyclic gearings for HEV power split
F16H 48/00	Differential gearings	F16H 48/30	Locking differentials
H02K 29/08	Dynamo-electric machines for HEV	H02K 49/10	Magnetic couplings for HEV
ENERGY STORAGE			
H01G 11/00	Hybrid capacitors (supercapacitors)	H01M 10/44	Nickel–metal hydride batteries
H01M 10/45	Lithium secondary batteries	H01M 10/46	Non-aqueous electrolyte batteries
H02J	Power supply and distribution networks	H02J 3/28	Grid-level energy storage integration

Continued on next page…

Code	Description	Code	Description
H02J 7/00	Battery charging circuits	H02J 9/00	Emergency and standby power supply
H02J 15/00	Electric energy storage	F03G 7/08	Flywheel energy storage
C09K 5/00	Heat transfer and storage materials	F24H 7/00	Combined heating devices
F28D 20/00	Heat-exchange apparatus for heat storage	F28D 20/02	Storage using non-water heat storage media
SMART GRIDS AND ENERGY MANAGEMENT			
G01R	Measuring electric variables (smart metering)	G06Q	Data processing for energy management
G08G	Traffic control systems (eco-driving)		
ENERGY-EFFICIENT BUILDINGS AND INSULATION			
E04B 1/62–1/90	Insulated building elements (various types)	E04B 2/00	Walls with insulating cores
E04B 5/00	Insulated floors	E04B 7/00	Roofs and roof coverings
E04B 9/00	Insulated ceilings	E04C 1/40–2/296	Insulating structural elements and panels
E04D 1/28	Insulating roofing slates	E04D 3/35	Insulating roofing sheets
E04D 13/16	Insulated and ventilated roofs	E04F 13/08	Insulating facade materials
E04F 15/18	Insulating flooring material	E04H 1/00	Buildings with insulation measures
E06B 3/263	Multiple glazing (energy-efficient windows)		
EFFICIENT LIGHTING			
F21K 99/00	LED and semiconductor light sources	F21L 4/02	Battery-powered portable lighting
H01L 33/00–33/64	LED semiconductor devices and packages	H01L 51/50	Organic light-emitting devices (OLEDs)
H05B 33/00	Electroluminescent light sources		
CARBON CAPTURE AND STORAGE			
B01D 53/14	Gas absorption for CO_2 capture	B01D 53/22	Membrane separation for CO_2 capture
B01D 53/62	Separation of carbon dioxide	B65G 5/00	Underground material storage
C01B 32/50	Carbon dioxide	E21B 41/00	Bore holes for CO_2 storage
E21B 43/16	CO_2 injection for enhanced recovery / CCS	E21F 17/16	Gas storage monitoring
F25J 3/02	Cryogenic separation of gas constituents		
POLLUTION CONTROL AND EXHAUST TREATMENT			
B01D 45/00	Gravity-based particle separation	B01D 51/00	Electrostatic particle separation
B01D 53/00	Gas separation and purification	B01D 53/92	Membrane gas separation
B01D 53/96	Chemical conversion of gas impurities	B03C 3/00	Electrostatic dust separation
C10B 21/18	Flue gas purification in coking	C10L 10/02	Combustion-improving fuel additives
C10L 10/06	Emission-reducing fuel additives	C21B 7/22	Blast furnace gas cleaning
C21C 5/38	Dust removal from steel-making furnaces	F01N 3/00	Exhaust gas treatment apparatus
F01N 3/38	Exhaust apparatus with afterburning	F01N 9/00	Exhaust monitoring and control
F23B 80/02	Low-emission solid fuel combustion	F23C 9/00	Low-emission pulverised fuel combustion
F23J 7/00	Removal of combustion solid residues	F23J 15/00	Flue gas cooling and by-product removal
F27B 1/18	Furnaces with waste heat recovery	F27B 15/12	Furnaces with emission controls
G08B 21/12	Pollution alarm systems		
WATER TREATMENT AND MANAGEMENT			
C02F	Treatment of water, wastewater and sewage	C02F 1/00	Physical processes for water treatment
C02F 3/00	Biological treatment of water	C02F 9/00	Multi-stage water treatment
E02B 15/04	Water surface pollution control barriers	E03C 1/12	Water-saving plumbing installations
E03F	Sewers and cesspools		
WASTE MANAGEMENT			
B09B	Disposal of solid waste	B09B 3/00	Chemical treatment of solid waste
B09C	Reclamation of contaminated soil	B65F	Gathering and removal of refuse
RECYCLING			
A43B 1/12–21/14	Footwear from recycled materials	B03B 9/06	Gravity sorting of solid waste
B22F 8/00	Metal powder from scrap	B29B 17/00	Recovery of waste rubber and plastic
C04B 7/24–7/30	Cement from waste and slag	C04B 18/04–18/10	Building materials from rubble and sludge
C08J 11/00	Reclaiming and reprocessing polymers	C08J 11/04–11/28	Recovery of rubber and plastic by dissolution
C09K 11/01	Luminescent materials from recycled sources	C11B 11/00–13/04	Recovery of fatty acids and oils
C14C 3/32	Tanning using waste materials	C21B 3/04	Processing blast furnace slag
C22B 7/00–7/04	Metal recovery from scrap and slag	C22B 19/30–25/06	Zinc and lead recovery from waste
C25C 1/00	Electrolytic metal recovery	D01F 13/00–13/04	Recycled and regenerated textile fibres
D01G 11/00	Disintegration of fibrous waste	D21B 1/08–1/32	Paper-making from waste
D21C 5/02	Pulp from recycled paper	H01J 9/50–9/52	Cathode ray tube recycling
H01M 6/52	Disposal of primary batteries	H01M 10/54	Reclamation of used batteries
ENVIRONMENTAL REMEDIATION			
A61L 11/00	Disposal of medical waste	A62D 3/00–101/00	Rendering hazardous substances harmless
C09K 3/22	Sealing materials for chemical containment	C09K 3/32	Waterproofing for environmental protection
AGRICULTURE AND FORESTRY			
A01G 23/00	Forestry (carbon sink)	A01G 25/00	Water-efficient irrigation systems
A01N 25/00	Natural biocides and plant protection	A01N 65/00	Plant-based biocides
C09K 17/00	Soil conditioning materials	E02D 3/00	Ground improvement and stabilisation

C Endogeneity and Predictability of Procurement

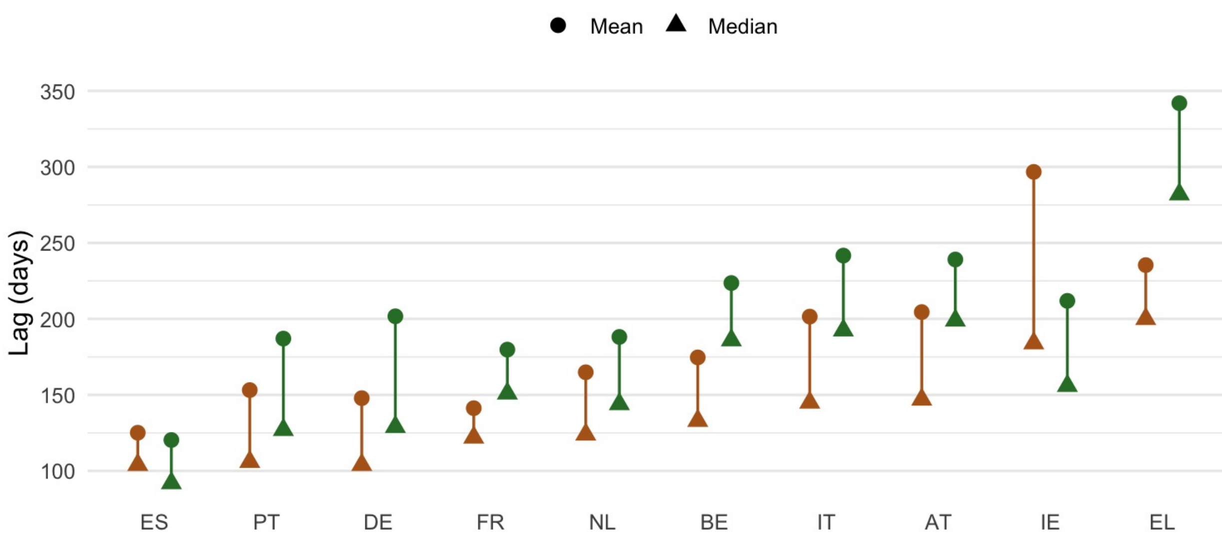
This appendix collects the figures and tables underlying the endogeneity and predictability checks discussed in Section 4.

Simple correlations point to no systematic relationship. Within-country scatter plots and pooled regressions (Figures C.2–C.4) show only weak and inconsistent associations between procurement and macroeconomic variables, and a lead-lag analysis following Briganti (2023) (Figure C.5) finds that past government spending does not predict current procurement, nor procurement future spending. These bivariate correlations ignore country and time fixed effects, however, so we now turn to formal tests.

For a more thorough test of the dynamic correlations with different macroeconomic variables, we conduct Granger causality tests, which are often used in the fiscal literature to gauge whether an identified shock is predictable (Ramey, 2011). Before applying Granger causality tests, it is necessary to verify the stationarity of all series tested, since standard Granger tests are invalidated by the presence of unit roots (Shojaie & Fox, 2022). Table C.1 reports Im-Pesaran-Shin panel unit root tests, which test the null hypothesis that all panels contain a unit root (Im et al., 2003). Following the sequential testing procedure of (Dolado et al., 1990), each variable is tested first under a specification including both a constant and a linear trend. Log GDP per capita, log government consumption, log industrial production (manufacturing and energy), log labour productivity, and log accumulated excess returns are all stationary in log levels with a trend. Log HICP fails to reject a unit root under any specification; year-on-year HICP growth is also non-stationary, but the acceleration rate of HICP is stationary and is therefore used in subsequent tests. The unemployment rate is stationary with a trend but has a unit root without a trend, and is accordingly detrended before use. The long-term interest rate is treated as level-stationary with a constant only. Both log green and log brown procurement per capita are strongly stationary across all specifications.

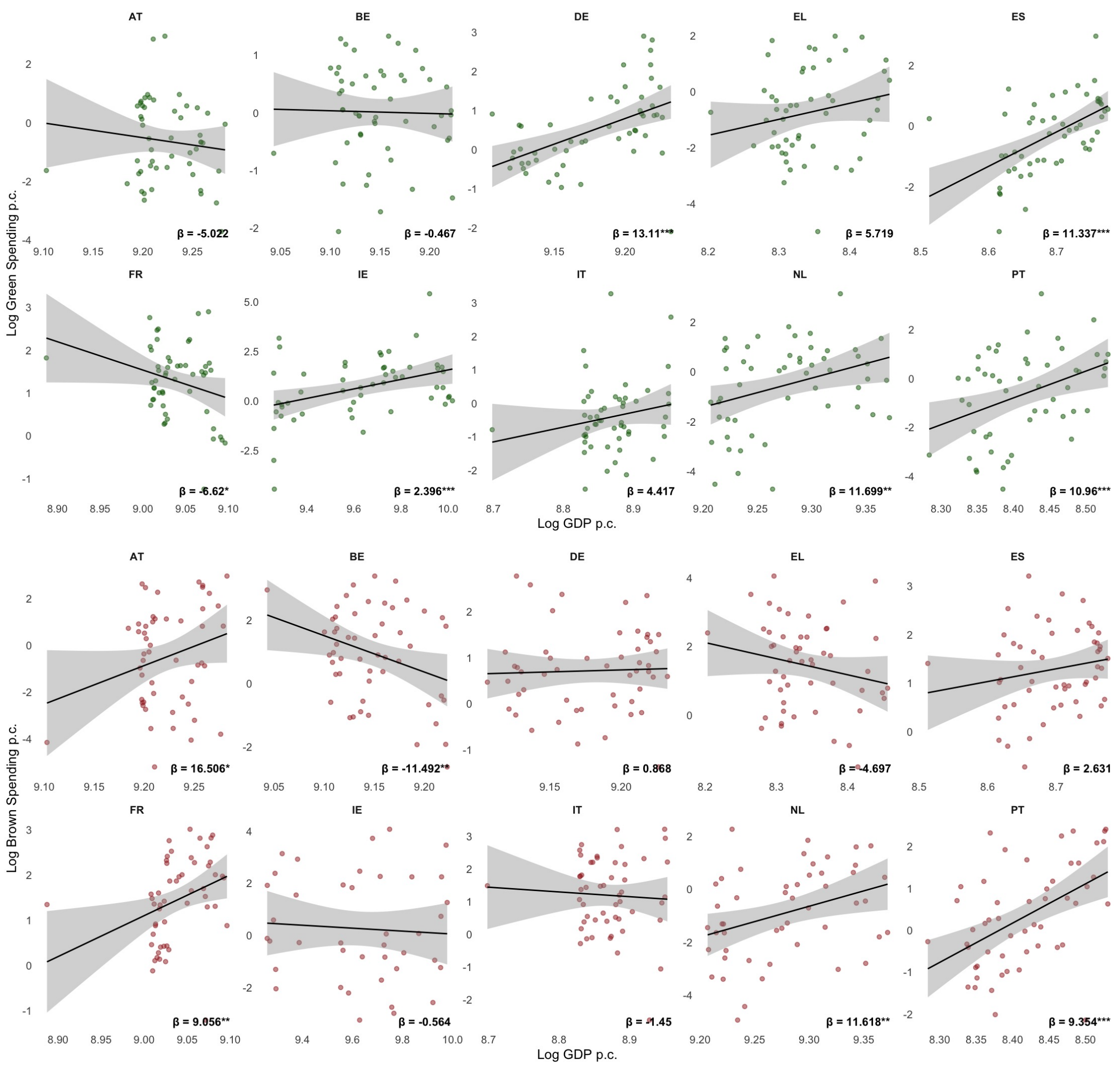
Granger causality tests are conducted as bivariate country-by-country regressions in which each variable is regressed on four of its own lags and four lags of the procurement variable, with the null hypothesis of no Granger causality tested using a country-level F-test. Table C.2 reports the median F-statistic and p-value across countries, along with the count of countries for which the null is rejected at the 10% level. The results offer no systematic evidence of Granger causality in either direction. For the direction macro $\rightarrow$ green procurement, median F-statistics range from 0.56 to 1.53 across all predictors, with all median p-values above 0.2. The highest country-level rejection rate is 4 out of 10 for accumulated excess ERIX returns, but no predictor generates consistent rejection across countries. For macro $\rightarrow$ brown procurement, the evidence is again weak. In the reverse direction, both green and brown procurement do not predict macroeconomic variables, although out of all variables, they best predict government consumption (2 out of 10 countries for both brown and green).

Figure C.1: Implementation Lag by Country: Green vs. Brown



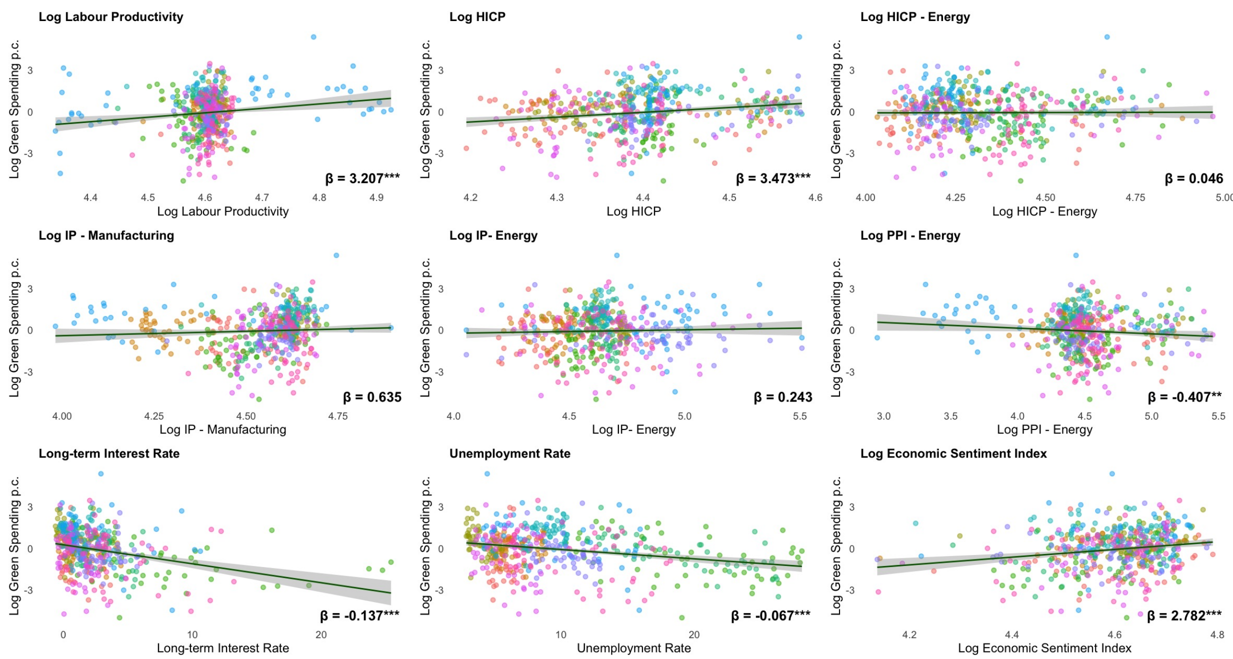
Sample: 2011-2021. Implementation lag = Number of days between tender notice date and tender award publication date.

Figure C.2: Procurement vs GDP, Within-Country



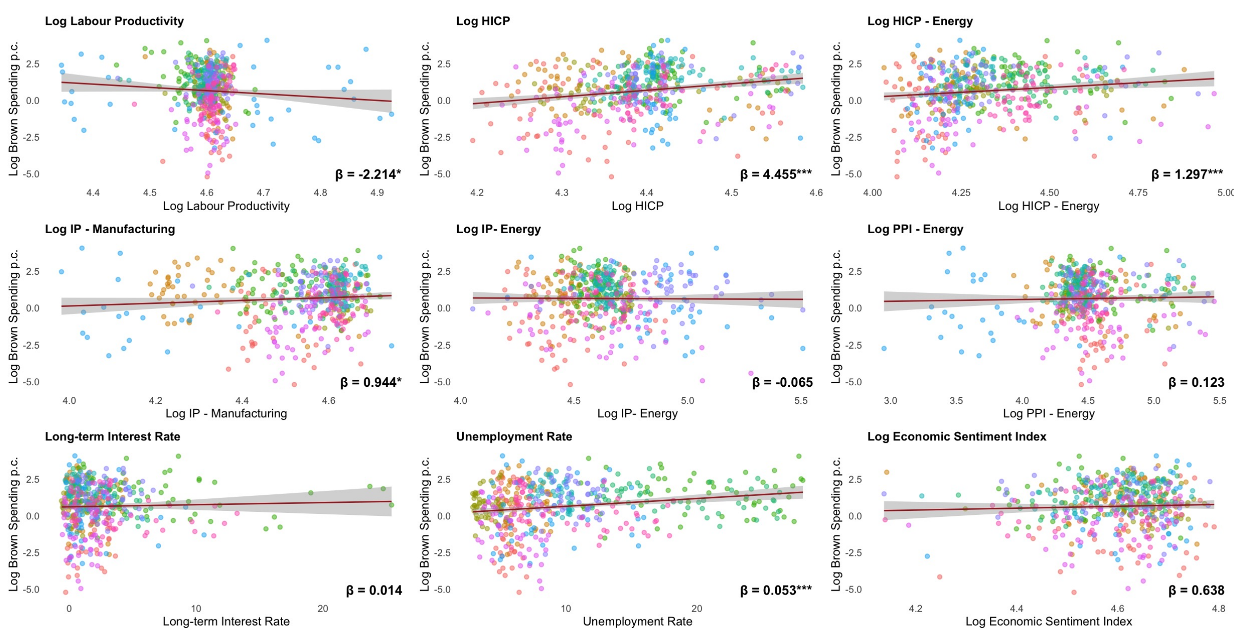
Sample: 2011Q1 – 2023Q4. Green dots = green procurement; Brown dots = brown procurement. Logs of real per-capita variables. Black line = OLS fit. $p < 0.01^{***}$, $p < 0.05^{**}$, $p < 0.1^{*}$.

Figure C.3: Green Procurement vs Macroeconomic Variables



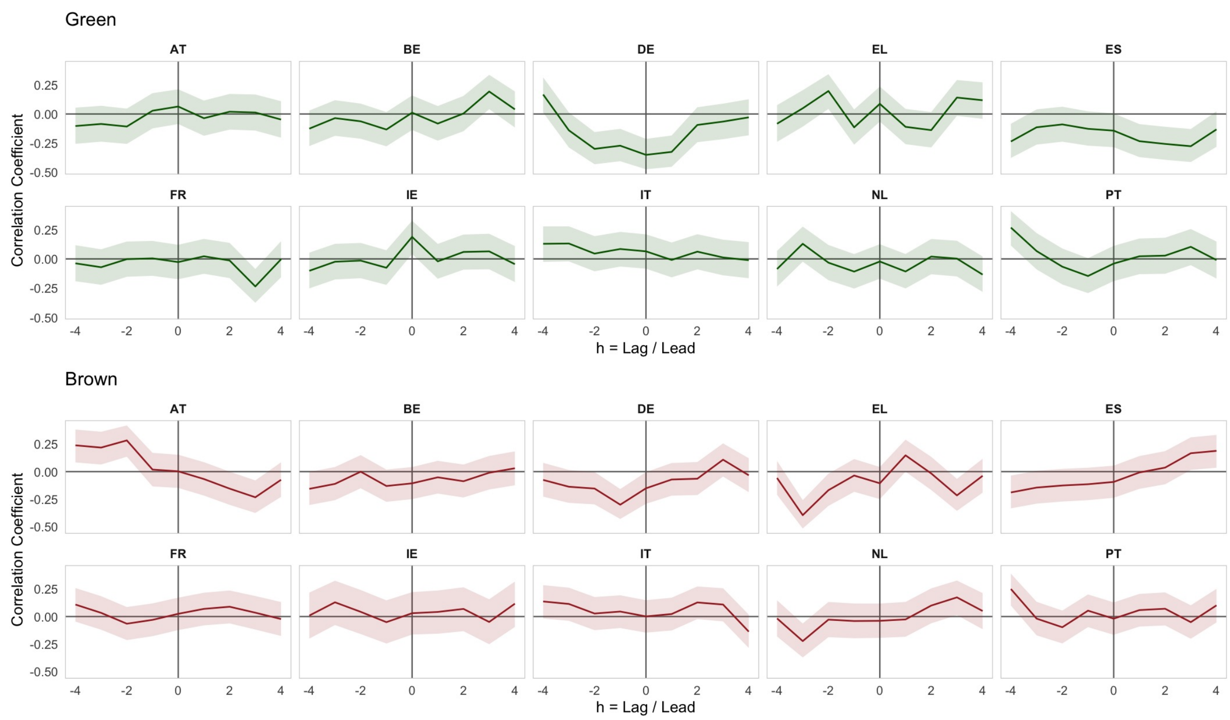
Sample: 2011Q1 – 2023Q4. Each point = country-quarter. Black line = pooled OLS fit.

Figure C.4: Brown Procurement vs Macroeconomic Variables



Sample: 2011Q1 – 2023Q4. Each point = country-quarter. Black line = pooled OLS fit.

Figure C.5: Lead-Lag Correlation, Procurement Growth vs Government Spending Growth



Sample: 2011Q1 – 2023Q4. Correlation coefficient at each h shows the correlation between the year-on-year growth rate of real green/brown procurement per capita at time t and the year-on-year growth rate of real government consumption per capita at time $t + h$. Shading = 68% CIs.

Table C.1: Stationarity Tests

Sample: 2011Q1 – 2023Q4. Im-Pesaran-Shin Panel Unit Root Tests. Lag selection: AIC. H_0: all panels contain a unit root. $p < 0.01^{***}$, $p < 0.05^{**}$, $p < 0.1^{*}$

Variable	Specification	W-stat	p-value	Result
Procurement				
Green p.c. (levels)	Constant + Trend	-15.6	0.000	Stationary***
Brown p.c. (levels)	Constant + Trend	-17.1	0.000	Stationary***
Log Green p.c.	Constant + Trend	-17.3	0.000	Stationary***
Log Brown p.c.	Constant + Trend	-16.2	0.000	Stationary***
Green p.c. Growth YoY	Constant + Trend	-17.0	0.000	Stationary***
Brown p.c. Growth YoY	Constant + Trend	-17.5	0.000	Stationary***
Rate variables (levels)				
Unemployment Rate	Constant + Trend	-3.06	0.001	Stationary***
Unemployment Rate	Constant	1.85	0.968	Unit Root
Long-term Interest Rate	Constant + Trend	3.68	1.000	Unit Root
Long-term Interest Rate	Constant	-2.94	0.002	Stationary***
Log level variables				
Log GDP p.c.	Constant + Trend	-5.56	0.000	Stationary***
Log Gov. Consumption p.c.	Constant + Trend	-3.08	0.001	Stationary***
Log Industrial Production	Constant + Trend	-6.50	0.000	Stationary***
Log Labour Productivity	Constant + Trend	-6.50	0.000	Stationary***
Log Accumulated Excess Returns	Constant + Trend	-4.67	0.000	Stationary***
Log HICP	Constant + Trend	6.62	1.000	Unit Root
HICP transformations				
HICP Growth YoY	Constant	1.63	0.949	Unit Root
HICP Acceleration YoY	Constant	-14.3	0.000	Stationary***

Table C.2: Granger Causality Tests – Green and Brown Procurement
Sample: 2011Q1 – 2023Q4. 4 lags of the predictor, controlling for 4 lags of the predicted. Sig. Countries = number of countries significant at 10%.

Predicted	Predictor	F (median)	p (median)	Sig. Countries
Macro → Green Procurement				
Log Green p.c.	Log Accumulated Excess Returns	1.08	0.382	4/10
Log Green p.c.	HICP Acceleration	1.45	0.240	2/10
Log Green p.c.	Log Gov. Consumption p.c.	1.16	0.343	2/10
Log Green p.c.	Long-term Interest Rate	1.12	0.363	1/10
Log Green p.c.	Log GDP p.c.	1.36	0.267	1/10
Log Green p.c.	Unemployment (detrended)	0.79	0.538	1/10
Log Green p.c.	Log Labour Productivity	0.56	0.694	1/10
Log Green p.c.	Log Economic Sentiment	0.62	0.649	0/10
Log Green p.c.	Log Industrial Production	0.93	0.457	0/10
Log Green p.c.	Log Industrial Production – Energy	1.17	0.340	0/10
Macro → Brown Procurement				
Log Brown p.c.	HICP Acceleration	1.05	0.397	3/10
Log Brown p.c.	Log Economic Sentiment	0.99	0.428	2/10
Log Brown p.c.	Log Gov. Consumption p.c.	0.88	0.486	2/10
Log Brown p.c.	Log Industrial Production – Energy	0.90	0.481	2/10
Log Brown p.c.	Unemployment (detrended)	0.79	0.561	1/10
Log Brown p.c.	Log GDP p.c.	0.74	0.573	1/10
Log Brown p.c.	Log Labour Productivity	0.99	0.432	1/10
Log Brown p.c.	Long-term Interest Rate	0.90	0.479	0/10
Log Brown p.c.	Log Accumulated Excess Returns	0.71	0.593	0/10
Log Brown p.c.	Log Industrial Production	0.98	0.432	0/10
Green Procurement → Macro				
Log Gov. Consumption p.c.	Log Green p.c.	1.18	0.337	3/10
Long-term Interest Rate	Log Green p.c.	0.79	0.542	1/10
Log Accumulated Excess Returns	Log Green p.c.	1.05	0.397	1/10
Log GDP p.c.	Log Green p.c.	0.72	0.585	1/10
Log Industrial Production	Log Green p.c.	0.87	0.490	1/10
Log Labour Productivity	Log Green p.c.	0.78	0.546	1/10
Unemployment (detrended)	Log Green p.c.	0.94	0.452	0/10
HICP Acceleration	Log Green p.c.	0.63	0.644	0/10
Log Economic Sentiment	Log Green p.c.	0.45	0.774	0/10
Log Industrial Production – Energy	Log Green p.c.	0.46	0.767	0/10
Brown Procurement → Macro				
Log Gov. Consumption p.c.	Log Brown p.c.	1.01	0.413	2/10
Long-term Interest Rate	Log Brown p.c.	1.19	0.335	1/10
HICP Acceleration	Log Brown p.c.	0.78	0.549	1/10
Log Accumulated Excess Returns	Log Brown p.c.	0.71	0.595	1/10
Unemployment (detrended)	Log Brown p.c.	0.47	0.758	0/10
Log Economic Sentiment	Log Brown p.c.	0.66	0.626	0/10
Log GDP p.c.	Log Brown p.c.	0.60	0.665	0/10
Log Industrial Production	Log Brown p.c.	1.03	0.406	0/10
Log Industrial Production – Energy	Log Brown p.c.	0.61	0.656	0/10
Log Labour Productivity	Log Brown p.c.	0.65	0.632	0/10

Table C.3: Predictive Panel Regressions, Two-way FE
Dependent variable: Real Log Procurement Value p.c.

	(1) Base Macro	(2) +HICP	(3) +Unemp.	(4) +Long Rate	(5) +Productivity	(6) +IP-Manuf.	(7) +Energy	(8) +Sentiment	(9) +Stocks	(10) +Excess Return
Panel A: Dependent Variable = Log Green Procurement										
Log GDP p.c.	0.963	−0.216	−1.544	−1.643	2.051	3.073	2.536	1.344	3.822	3.221
	(1.354)	(1.522)	(1.206)	(1.188)	(4.142)	(4.067)	(4.249)	(4.166)	(4.939)	(6.778)
Log Gov p.c.	1.898	3.171	4.154*	4.743**	4.795**	4.963	5.121*	7.195**	7.066**	6.941**
	(2.317)	(2.109)	(2.025)	(2.005)	(1.942)	(2.887)	(2.634)	(2.542)	(2.642)	(2.866)
Log HICP		−8.590**	−2.825	−1.215	−0.603	1.057	1.987	4.843	6.933	7.373
		(3.765)	(4.113)	(5.187)	(5.111)	(4.536)	(4.578)	(4.408)	(5.292)	(5.686)
Unemployment Rate			−0.123**	−0.117**	−0.094*	−0.089	−0.096	−0.095	−0.078**	−0.087
			(0.047)	(0.046)	(0.050)	(0.053)	(0.060)	(0.055)	(0.034)	(0.058)
Long-term Interest Rate				−0.035	−0.026	−0.047	−0.051	−0.040	−0.042	−0.035
				(0.043)	(0.043)	(0.037)	(0.037)	(0.039)	(0.039)	(0.041)
Log Productivity					−4.078	−4.877	−4.367	−3.651	−4.854	−3.986
					(4.669)	(4.378)	(4.943)	(4.596)	(4.869)	(8.203)
Log IP Manufacturing						−0.882	−0.542	−0.426	−0.872	−0.961
						(0.777)	(0.924)	(0.863)	(0.947)	(0.933)
Log IP Energy							−0.265	−0.276	−0.310	−0.333
							(0.337)	(0.343)	(0.372)	(0.349)
Log PPI Energy							−0.621	−0.729	−0.886	−0.851
							(0.612)	(0.641)	(0.680)	(0.694)
Log Economic Sentiment								3.551***	3.897***	3.895***
								(1.040)	(0.849)	(0.828)
Log Stock Index									−0.632	−1.213
									(0.703)	(2.536)
Log Excess Return										−0.665
										(3.120)
Num. Obs.	517	517	517	517	517	501	501	501	501	501
R^2	0.369	0.380	0.396	0.397	0.398	0.424	0.426	0.435	0.437	0.437
R^2 Within	0.012	0.029	0.054	0.055	0.057	0.061	0.064	0.079	0.082	0.082
Panel B: Dependent Variable = Log Brown Procurement										
Log GDP p.c.	−1.379	−2.028*	−2.309**	−2.310*	2.052	7.398	5.507	5.241	2.871	3.928
	(0.881)	(0.927)	(1.019)	(1.038)	(7.446)	(9.086)	(8.549)	(8.490)	(8.587)	(8.632)
Log Gov p.c.	−1.506	−0.779	−0.619	−0.610	−0.523	−1.803	−2.211	−1.815	−1.672	−1.427
	(2.041)	(2.084)	(2.011)	(2.112)	(2.154)	(2.797)	(2.935)	(2.700)	(2.630)	(2.406)
Log HICP		−4.560	−3.417	−3.391	−2.736	−1.461	−0.371	0.172	−1.722	−2.527
		(3.768)	(3.531)	(4.052)	(4.417)	(4.371)	(4.473)	(4.039)	(4.766)	(5.398)
Unemployment Rate			−0.024	−0.024	0.004	0.039	0.020	0.020	0.004	0.021
			(0.050)	(0.047)	(0.049)	(0.060)	(0.057)	(0.057)	(0.067)	(0.078)
Long-term Interest Rate				−0.001	0.011	−0.009	−0.018	−0.016	−0.013	−0.027
				(0.020)	(0.025)	(0.031)	(0.030)	(0.031)	(0.031)	(0.030)
Log Productivity					−4.780	−5.103	−3.259	−3.119	−2.004	−3.556
					(7.884)	(8.151)	(7.366)	(7.298)	(7.309)	(7.443)
Log IP Manufacturing						−1.737	−1.494	−1.470	−1.028	−0.851
						(1.389)	(1.397)	(1.367)	(1.442)	(1.673)
Log IP Energy							−0.676	−0.675	−0.643	−0.599
							(0.536)	(0.535)	(0.512)	(0.495)
Log PPI Energy							−0.241	−0.270	−0.131	−0.194
							(0.626)	(0.603)	(0.604)	(0.607)
Log Economic Sentiment								0.660	0.349	0.361
								(1.160)	(1.261)	(1.283)
Log Stock Index									0.588	1.637
									(0.383)	(1.953)
Log Excess Return										1.199
										(2.172)
Num. Obs.	504	504	504	504	504	493	493	493	493	493
R^2	0.364	0.367	0.368	0.368	0.369	0.379	0.382	0.383	0.384	0.384
R^2 Within	0.009	0.013	0.014	0.014	0.015	0.012	0.018	0.018	0.020	0.021
Country FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Time FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓

$^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$
Standard Errors clustered by country.

D Alternative Identification Strategies

This appendix describes the alternative identification schemes used as robustness checks for the baseline announcement-based procurement shocks. In addition to the baseline identification presented in the main text (Identification I), we consider three alternative measures of procurement shocks: (Identification II) a procurement series purged of its macroeconomically predictable component following Barattieri et al. (2023); (Identification III) a recursive (Cholesky) structural VAR shock; and (Identification IV) a Max-Share news shock. Throughout the appendix and the robustness figures, these alternative identification schemes are referred to simply as Identifications II, III, and IV. Although each relies on different identifying assumptions, they produce qualitatively similar impulse responses, supporting the robustness of the baseline results. The remainder of this appendix describes their construction in detail.

Identifications III and IV recover procurement shocks from a panel structural VAR following Pedroni (2013). Let $\mathbf{y}_{i,t}$ denote the $k \times 1$ vector of endogenous variables for country $i = 1, \ldots, N$ observed at time $t = 1, \ldots, T$. The panel VAR(p) with country and time fixed effects is

$$\mathbf{y}_{i,t} = \boldsymbol{\alpha}_i + \gamma_t + \sum_{j=1}^{p} \mathbf{B}_{i,j} \mathbf{y}_{i,t-j} + \mathbf{u}_{i,t}, \tag{5}$$

where $\boldsymbol{\alpha}_i$ captures time-invariant country heterogeneity, γ_t captures common time effects, and $\mathbf{u}_{i,t}$ denotes the vector of reduced-form residuals with covariance matrix

$$\boldsymbol{\Sigma}_i = E[\mathbf{u}_{i,t} \mathbf{u}'_{i,t}].$$

The fixed effects are removed using the standard two-way within transformation,

$$\tilde{\mathbf{y}}_{i,t} = \mathbf{y}_{i,t} - \bar{\mathbf{y}}_i - \bar{\mathbf{y}}_t + \bar{\mathbf{y}}, \tag{6}$$

yielding

$$\tilde{\mathbf{y}}_{i,t} = \sum_{j=1}^{p} \mathbf{B}_{i,j} \tilde{\mathbf{y}}_{i,t-j} + \mathbf{u}_{i,t}. \tag{7}$$

The endogenous variables comprise log procurement (green or brown), GDP per capita, government consumption per capita, industrial production in the energy sector, and HICP energy. The lag order is fixed at $p = 4$, and the VAR is estimated separately for each country by OLS. This yields reduced-form residuals

$$\hat{\mathbf{u}}_{i,t} = \tilde{\mathbf{y}}_{i,t} - \sum_{j=1}^{p} \hat{\mathbf{B}}_{i,j} \tilde{\mathbf{y}}_{i,t-j}, \tag{8}$$

from which the country-specific covariance matrix is constructed as

$$\hat{\mathbf{\Sigma}}_i = \frac{1}{T} \sum_{t=1}^{T} \hat{\mathbf{u}}_{i,t} \hat{\mathbf{u}}'_{i,t}, \tag{9}$$

The covariance matrices $\hat{\mathbf{\Sigma}}_i$ provide the input for the structural identification schemes described below.

The first structural identification recovers procurement shocks using recursive (Cholesky) restrictions. Assume that the reduced-form VAR admits the structural representation

$$\mathbf{y}_t = \sum_{\tau=0}^{\infty} \mathbf{C}_\tau \mathbf{A} \boldsymbol{\varepsilon}_{t-\tau}, \tag{10}$$

where $\boldsymbol{\varepsilon}_t$ denotes the vector of mutually orthogonal structural shocks, $\mathbf{A}$ is the contemporaneous impact matrix, and $\mathbf{C}_\tau$ collects the dynamic impulse responses.

Recursive identification sets

$$\tilde{\mathbf{A}} = \text{chol}\left(E[\mathbf{u}_t \mathbf{u}_t']\right),$$

which, for a stylised three-variable system, takes the lower-triangular form

$$\mathbf{A} = \tilde{\mathbf{A}} = \begin{pmatrix} a_{11} & 0 & 0 \\ a_{21} & a_{22} & 0 \\ a_{31} & a_{32} & a_{33} \end{pmatrix}, \tag{11}$$

The structural shocks are then recovered as

$$\hat{\boldsymbol{\varepsilon}}_t = \tilde{\mathbf{A}}^{-1}\mathbf{u}_t.$$

Green (or brown) procurement is ordered first in the VAR, implying that procurement responds only to its own structural innovation within the quarter, while all remaining variables may respond contemporaneously to procurement shocks (Blanchard & Perotti, 2002).

The second structural identification follows the Max-Share procedure of Ben Zeev and Pappa (2017) and Ben Zeev et al. (2025). Rather than identifying an unexpected procurement innovation, this approach recovers the procurement news shock that explains the largest share of future procurement fluctuations while having no contemporaneous effect on procurement.

Formally, the news shock is the rotation vector

$$\mathbf{q}_j^* = \arg\max_{\mathbf{q}_j} \Theta_{i,j}(H) \quad \text{subject to} \quad \mathbf{q}_j'\mathbf{q}_j = 1, \qquad (\mathbf{q}_j)_i = 0, \tag{12}$$

where $\Theta_{i,j}(H)$ denotes the share of the forecast error variance of variable i explained by structural shock j at horizon H.

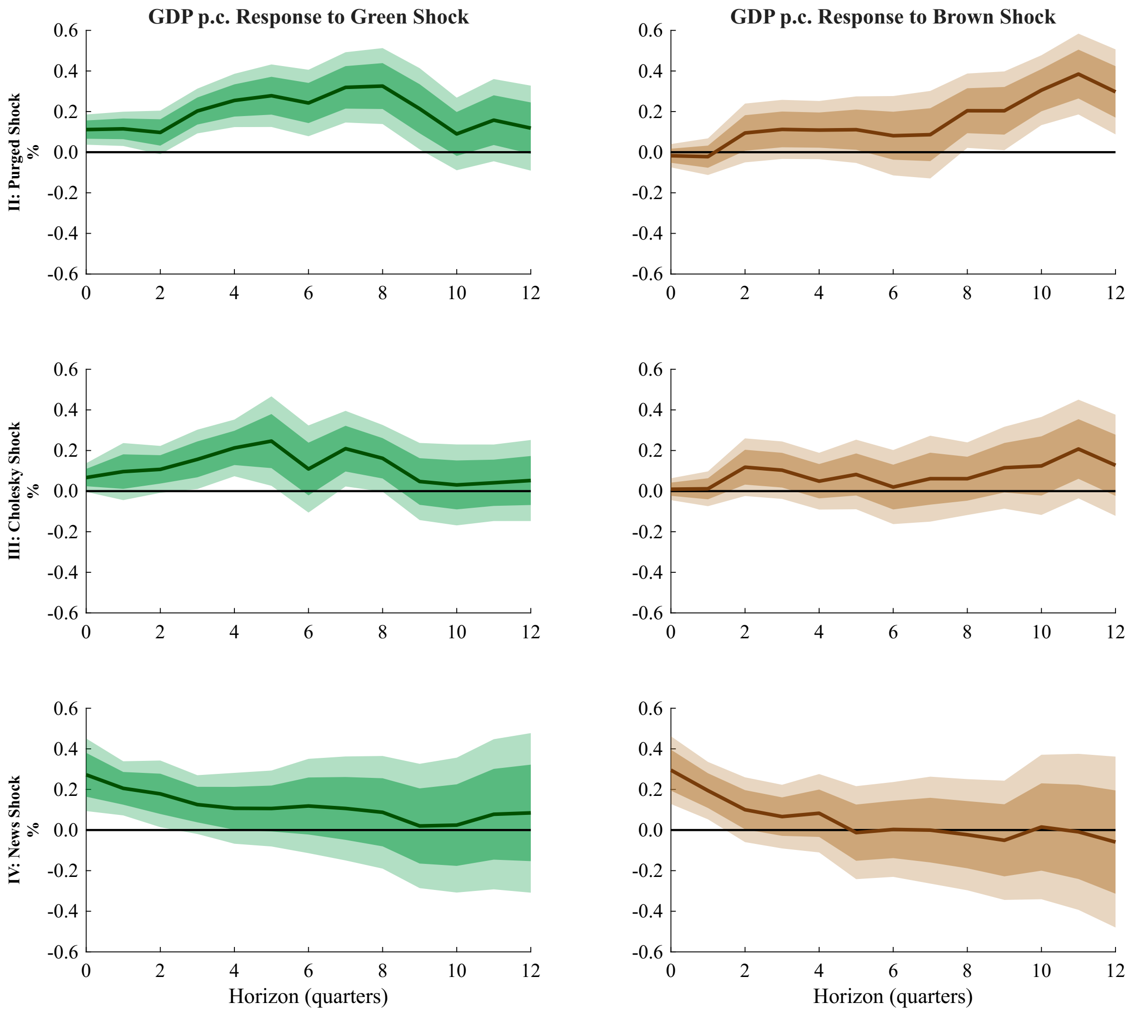
The unit-length restriction preserves the orthonormality of the rotation matrix $\mathbf{Q}$, while the zero-impact restriction,

$$(\mathbf{q}_j)_i = 0,$$

ensures that procurement does not respond contemporaneously to the identified news shock, although it is free to respond at longer horizons. In our application, procurement is ordered first in the VAR, so that $i = 1$ corresponds to green or brown procurement and structural shock $j = 2$ is interpreted as the procurement news shock.

Figure D.1 compares the GDP responses obtained under Identifications II, III, and IV with the baseline announcement-based shock. Overall, the qualitative conclusions remain remarkably similar across identification schemes: green procurement generates positive output effects during the first two years, whereas the response to brown procurement is weaker and more delayed.

Figure D.1: GDP Response – Alternative Shocks



Sample: 2011Q1–2023Q4, IE excluded. Impulse variable: green shocks II-IV (LHS), brown shocks II-IV (RHS). Response variable: GDP per capita. Interpretation: % change in GDP p.c. to a 1-standard deviation shock to the impulse variable *h* quarters after the shock.

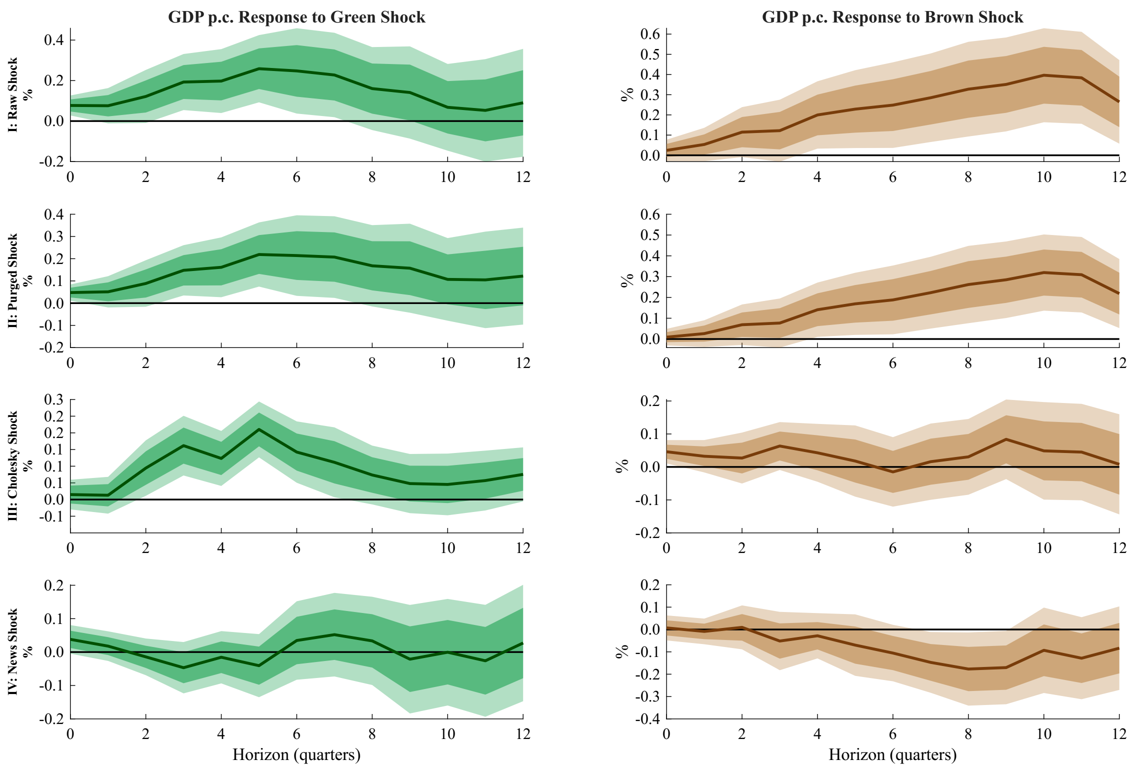
Identification II (purged procurement shocks) produces impulse responses that closely resemble the baseline. Green procurement continues to increase GDP over the first two years before gradually dissipating, while brown procurement displays a delayed response. The estimated magnitudes differ somewhat—the green response peaks at 0.33% rather than 0.28%, while the brown response peaks at 0.38% instead of 0.52%—but the overall dynamics remain unchanged.

Identification III (recursive Cholesky shocks) yields a more attenuated green response, which remains positive and statistically significant for roughly the first eight quarters before returning to zero. By contrast, the positive GDP response to brown procurement largely disappears under this identification. Identification IV (Max-Share news shocks) instead identifies short-lived news effects: both green and brown news shocks increase GDP on impact (around 0.3%), but the responses become statistically insignificant after only a few quarters.

These differences reflect the distinct economic objects identified by each approach. Recursive identification isolates unexpected procurement innovations, whereas the Max-Share procedure identifies news about future procurement. In our setting, however, the baseline procurement series is already constructed using the timing of award announcements, the earliest point at which committed spending becomes public information. The announcement-based identification therefore already captures much of the fiscal foresight that the Max-Share approach is designed to recover. Taken together, the similarity of the impulse responses across all four identification schemes suggests that the main conclusions of the paper do not depend on the particular identification strategy employed.

Figure D.2 further assesses the robustness of the results by restricting the sample to the pre-pandemic period (2011Q1–2019Q4). Across all four identification schemes, the qualitative pattern of the impulse responses remains unchanged. Green procurement continues to generate positive output effects over the first two years, while the response to brown procurement remains delayed and generally weaker. The magnitudes differ somewhat from the full-sample estimates, reflecting the exclusion of the large fiscal interventions associated with the COVID-19 pandemic and subsequent energy crisis, but the central finding—that procurement composition matters for macroeconomic outcomes—is unaffected.

Figure D.2: GDP Response – Restricted Sample Period



Sample: 2011Q1–2019Q4. Impulse variables: green shocks I-IV (LHS), brown shocks I-IV (RHS). Response variable: GDP per capita. Interpretation: % change in GDP p.c. to a 1-standard deviation shock to the impulse variable *h* quarters after the shock.

E Robustness Checks

Multiplier distribution across lag specifications. The pooled Monte Carlo distribution of the cumulative multiplier across lag specifications, discussed in Section 5, is shown in Figure E.1.

Lag-Augmented Local Projections. The baseline local projection specification in equation (2) includes no lagged controls, which may leave the impulse response estimates sensitive to serial correlation in the error term and to near-unit-root behaviour in the dependent variable. Montiel Olea and Plagborg-Møller (2021) show that augmenting local projections with lags of both the shock and the outcome variable restores standard inference under a range of data-generating processes, including $I(1)$ non-stationary processes, without requiring pre-testing for unit roots or to difference the data. Intuitively, the additional lags absorb serial correlation in $u_{i,t+h}$, preventing it from biasing the coefficient of interest β_h^s, while the lagged shock terms account for the possibility that the identified shock $\varepsilon_{i,t}^s$ itself exhibits autocorrelation. We therefore re-estimate (2) but add P lags of both the shock and the cumulated outcome variable included as controls:

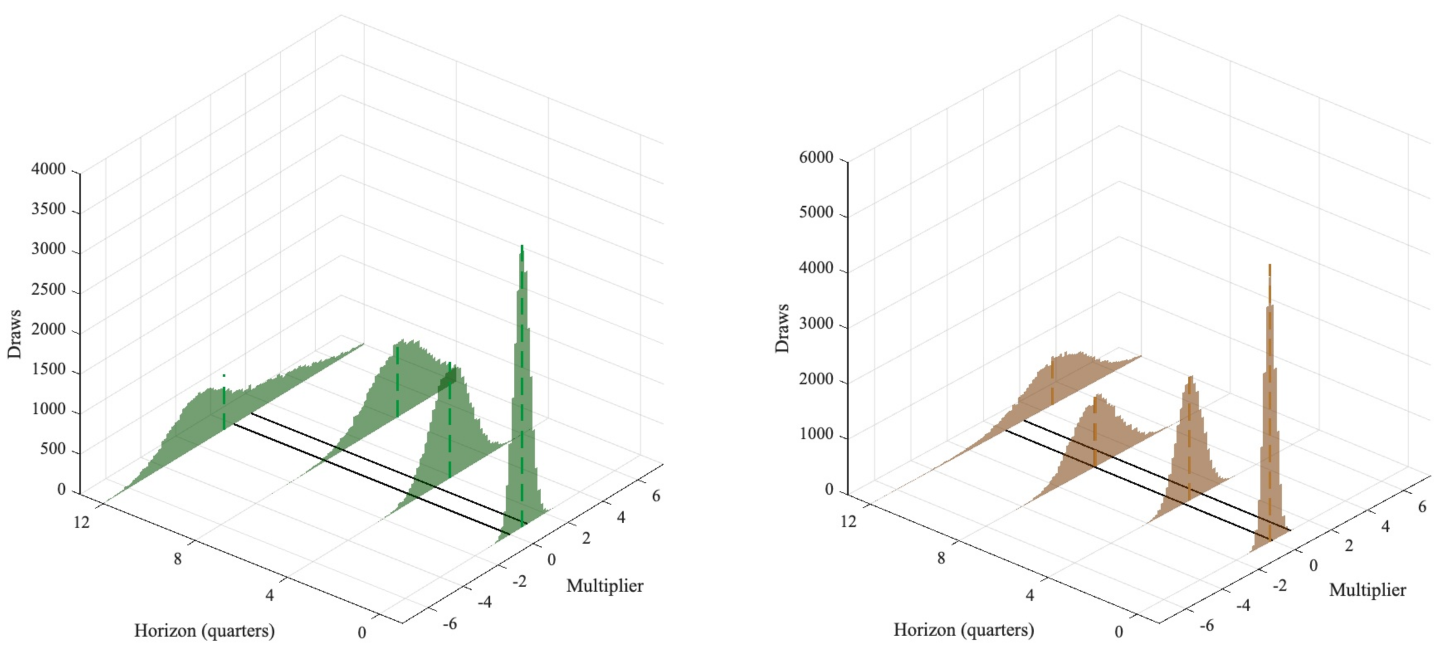
$$\sum_{j=0}^{h} \Delta y_{i,t+j} = \alpha_i^h + \gamma_t^h + \beta_h^s \varepsilon_{i,t}^s + \sum_{p=1}^{P} \phi_p^{h,s} \varepsilon_{i,t-p}^s + \sum_{p=1}^{P} \delta_p^h \Delta y_{i,t-p} + u_{i,t+h}$$

We repeat the estimation with 4, 8 and 12 lags. Results for the main GDP estimation, for all identified shocks, are shown in Figure E.2. At the three different lag lengths, the LPs estimate very similar impulse responses at all horizons, and the results do not change substantially compared to the baseline 0 lags specification.

Sample Periods. Estimates of the sizes and shapes of the impulse response functions to fiscal shocks are highly sensitive to which sample period is chosen (Ascari et al., 2023; Ramey, 2011). This poses a two-fold problem for this study: first, the sample itself captures a small time period, so the results are have limited external validity. Second, results might be highly distorted by the period 2020-2023, which includes major events which could affect public procurement - the Covid-19 recession and the EU National Recovery and Resilience Plan, which allocated a lot of funds to green spending. To mitigate both problems while retaining a large enough sample, we restrict the baseline GDP and multiplier estimations to 2019Q4, plotted in Figures D.2 and E.3. For green shocks, the impact response is much lower, but the shape is again broadly similar: positive and significant in the first two years, and returning to 0 and insignificant in the third year. Brown shocks change significantly. For baseline and II shocks, GDP starts to become positive and significant already by the fourth quarter rather than the final year, showing quicker stronger response. The early news shock effects disappear entirely. Howevere, when computed in multiplier terms, results are less positive for brown procurement. As Figure E.3 shows, in the restricted sample the brown multiplier becomes not statistically different from 0 even in the 4-quarter specification. The green multiplier instead becomes statistically above 1 even at the 90% confidence level between horizon 3 and 10, peaking at €4.4 in the 9th quarter. Therefore, GDP effects were mixed: brown shocks in the restricted sample have more positive and lasting effects than green, but in terms of fiscal return this was not the case.

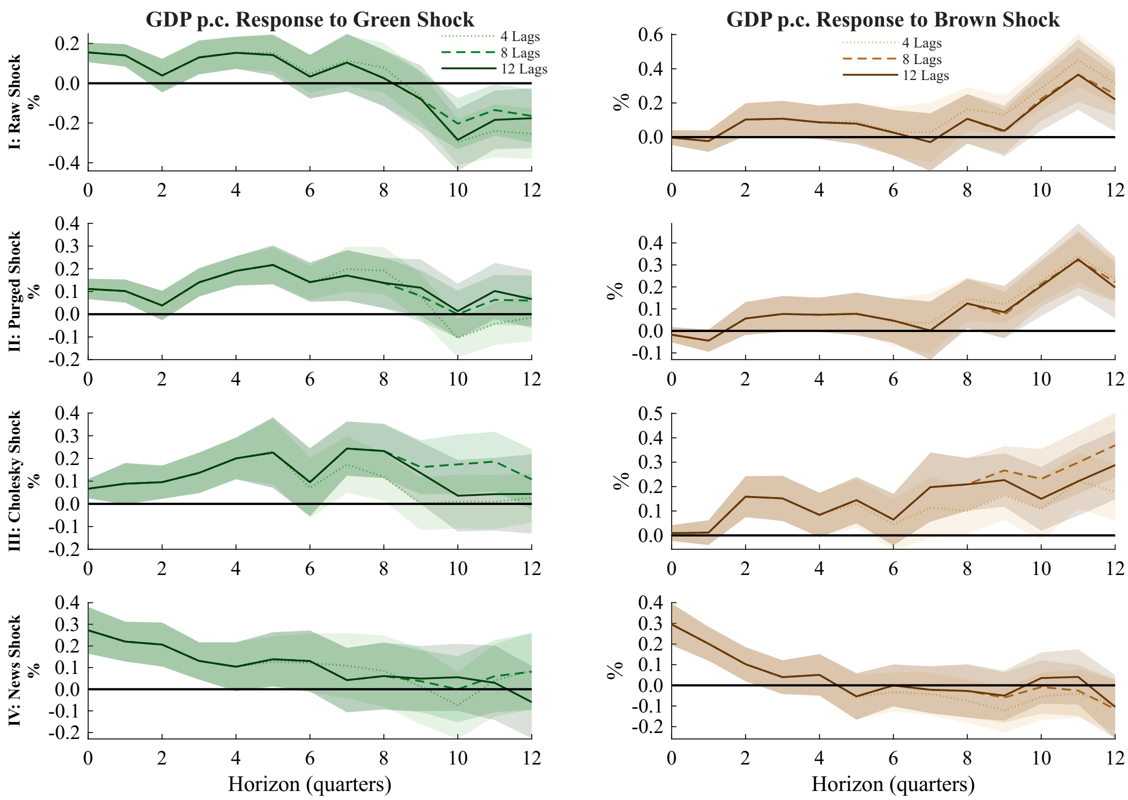
Excluding Countries. As a last exercise, we perform a leave-one-out analysis, which estimates the baseline LP for GDP, but sequentially leaves out only one country, which is then re-added and another is excluded. Results for the point estimates are shown in Figure E.4. The estimates are very close to each other, confirming that no country is an outlier which is driving the results. The only exception is Spain, whose exclusion reduces by a significant amount the response to a green shock I and II.

Figure E.1: Cumulative Multipliers: Monte Carlo Draws Across Specifications



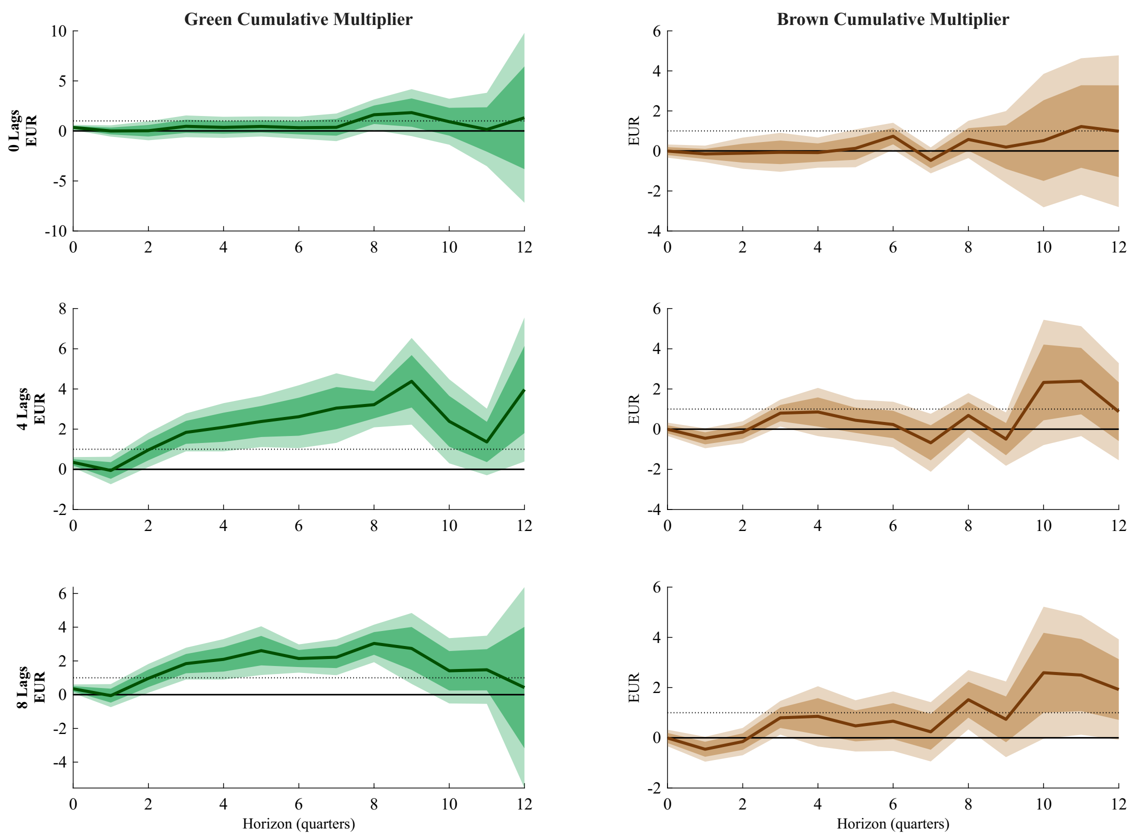
Notes: Pooled distribution of cumulative fiscal multiplier estimates for green (LHS) and brown (RHS) procurement at horizons $h \in \{0, 4, 8, 12\}$, constructed by drawing $R = 1{,}000$ realisations from the asymptotic sampling distribution of each lag specification $p \in \{0, \ldots, 12\}$. Solid black lines denote multiplier of 0 and 1. Dashed vertical coloured lines denote the mean of each distribution.

Figure E.2: GDP Response – Lag-Augmented Local Projections



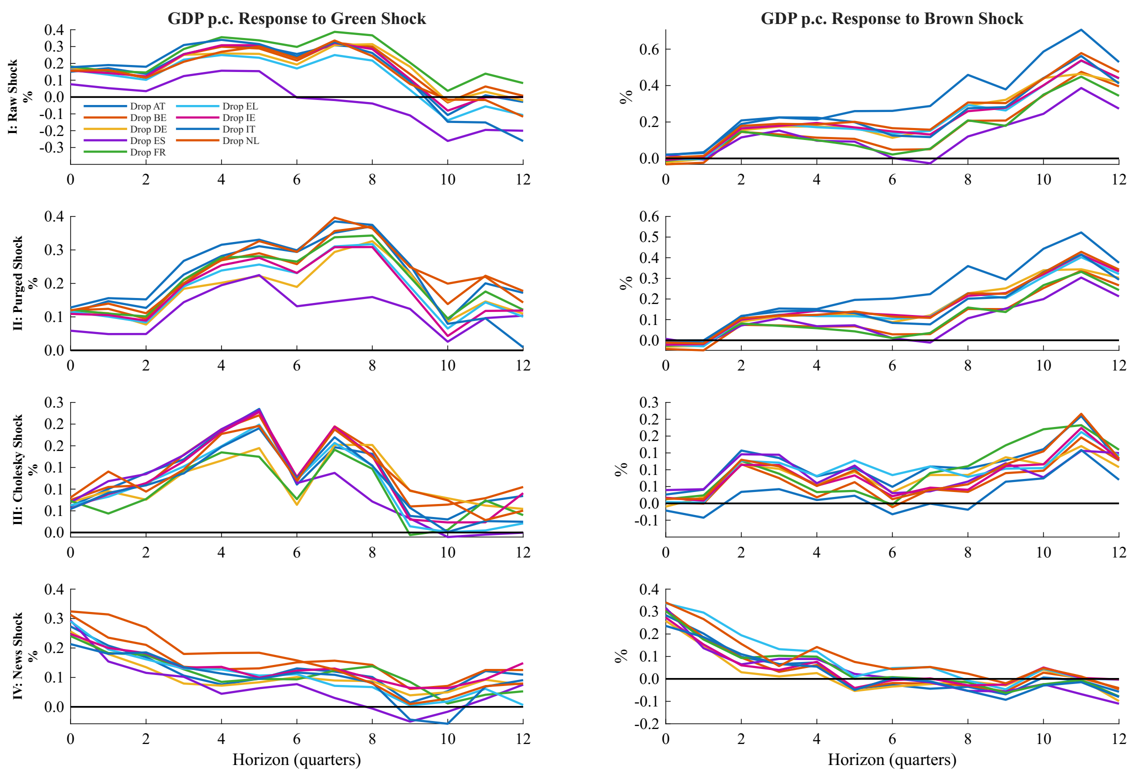
Sample: 2011Q1–2023Q4. Impulse variables: green shocks I-IV (LHS), brown shocks I-IV (RHS). Response variable: GDP per capita. Interpretation: % change in GDP p.c. to a 1-standard deviation shock to the impulse variable h quarters after the shock. Impulse responses at 4 lags (dotted line), 8 lags (dashed line), 12 lags (solid line). Shading: 68% CIs.

Figure E.3: Cumulative Multiplier – Restricted Sample Period



Sample: 2011Q1–2019Q4. Impulse variable: cumulative change of green/brown procurement per capita normalised by lagged GDP per capita. Controls: 0, 4 and 8 lags of dependent variable and impulse variable. Dashed line: multiplier of 1.

Figure E.4: GDP Response – Excluding Countries



Sample: 2011Q1–2023Q4. Impulse variables: green shocks I-IV (LHS), brown shocks I-IV (RHS). Response variable: GDP per capita. Interpretation: % change in GDP p.c. to a 1-standard deviation shock to the impulse variable h quarters after the shock. Lines: point IRF estimates with 1 country excluded from the estimation.

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