Assessing policy co-ordination in government: text and network analysis of the UK’s economic strategies

Diane Coyle\textsuperscript{a,1,*} and Adam Muhtar\textsuperscript{a,**}

\textsuperscript{a} Bennett Institute for Public Policy, University of Cambridge, Cambridge, UK

\textsuperscript{1} Corresponding author email: dc700@cam.ac.uk

Alison Richard Building, 7 West Road, Cambridge CB3 9DT, UK.

\textsuperscript{*} https://orcid.org/0000-0001-7243-1641

\textsuperscript{**} https://orcid.org/0000-0001-8330-5704

\textbf{Abstract} Lack of consistency has long been noted as a weakness in government policy-making, but it has previously been difficult to assess the extent of the absence of strategic co-ordination. This paper investigates this shortcoming by applying computational linguistics and network tools to provide some evidence on the lack of policy co-ordination in the UK. We use two key economic strategy documents produced during the Johnson administration—the 2021 Plan for Growth and the 2021 UK Innovation Strategy—to analyse all subsequent policy documents produced by the same administration. The extent of linguistic discontinuity provides some indication of the extent of the absence of policy co-


ordination in that administration’s economic policies, reinforced by analysis showing a similar lack of ‘joining up’ in government departmental networks.

**Keywords:** Policy co-ordination, economic strategy, networks, text as data

**JEL Codes:** D72, D78, C80
Highlights

Textual analysis of policy documents can reveal extent of government 'joined-upness'

Scant reference in UK Johnson government policies to overarching economic strategies

Network analysis can document highly centralised structure of UK government
Introduction

When governments announce flagship economic strategies, to what extent does the machinery of government—ministries, civil service, and public sector agencies—mobilise into co-ordinated action? And are policies whose effects may take many years to materialize applied consistently over time, or is there ‘policy myopia’?

Scholars and policymakers alike have long noted the importance of an integrated approach to delivering policies, variously termed the “whole-of-government” approach or “joined-up government”, as the cornerstone of effective policymaking practice (Pollitt 2003; Christensen and Lægreid 2007). Indeed, many complex economic and societal challenges, from geographic rebalancing of economic growth to addressing climate change, do not fit neatly within any single traditionally defined policy domains such as education, transportation, or industrial development, but rather require co-ordinated efforts. Scope for strategic complementarities arising from co-ordination exist in many areas of policymaking (Rodrik 1996; Dixit et al. 1997; Grassi and Sauvagnat 2019; Scott and Gong 2021). A lack of consistency or coherence in government policies may sometimes occur for unavoidable reasons, such as data lags or budget constraints (Aidt & Dutta 2007). At the same time, policy uncertainty is negatively linked with favourable economic outcomes: macro level evidence indicates that
increases in policy uncertainty have adverse effects on economic outcomes (Kelly et al 2016, Caldara et al 2019, Davis 2019).

The UK’s system of government is highly centralised by the standards of most other OECD countries, with national government departments led by a minister having domain responsibilities that cascade down to other levels of government and public agencies (eg Richards & Smith 2016; McCann 2022). This structure has been identified as contributing – among other shortcomings – to the ‘siloiisation’ of policy actions (Pabst & Westwood 2021, Myrodias 2022). Officials and ministers in a department are accountable ‘upwards’, formally to Cabinet and Parliament, in practice to the central co-ordinating departments, the Cabinet Office and the Treasury. Cross-departmental policy development and co-ordination is secondary as there is little incentive for either politicians or officials to do so. Horizontal co-ordination is further discouraged by the rapid pace of policy development in the central ministries, with officials often having only a few months at best to prepare documents.

While there have been estimates of policy uncertainty, to date the degree of policy consistency within what is explicitly presented as a strategic economic framework has not been estimated empirically. This paper proposes a novel method using text analysis of all government policy documents over a 16-month period of a single administration in the United Kingdom – that of Boris Johnson in 2021-22 – to demonstrate a striking lack of consistency between the decisions of
government departments and agencies and the two major statements of national economic strategy.

As the corpus of documents were published in a short period by the same administration, the lack of textual continuity is a possible indicator of the absence of policy consistency; more detailed departmental documents might be expected to refer back to the flagship strategic framework documents published recently and speaking to a central Government agenda, that of ‘levelling up’ poorer UK regions. While there was some political turmoil, it occurred in the later part of the 16 month period covered. Jennings et al (2021) have suggested that the two main economic strategic documents were intended as symbolic rather than practical statements of policy, governing “through symbols, language and tokens of action,” creating a narrative of success instead of policy impact. This is a plausible alternative explanation of lack of expressed joined-upness, particularly given contemporaneous comment on the character of the then-Prime Minister (cited in Jennings et al 2021). Nevertheless, it seems reasonable to expect that subsequent policy documents might pay lip service to the narrative, even if officials elsewhere in government did not take them seriously as strategy documents. This is particularly so as “levelling up”, a central theme, had been so prominent in the Government’s election manifesto. As a number of authors have noted (eg Pabst 2021, Warner et al 2022), government structures in the UK have become increasingly complex, making the role of a unifying narrative more important. We therefore consider the documents in this study constitute a
reasonable test, despite the nature of the Johnson government and the challenges of that post-Brexit period: the Government had a large Parliamentary majority whose factions were not divided about the importance of the productivity and ‘levelling up’ economic agenda. We do not, however, have a benchmark for what degree of textual consistency would be expected; this would require a number of studies over time and across jurisdictions, and is an important question for future work.

National economic strategies often play a prominent role in policymaking, as the primary vehicle through which governments deploy a suite of initiatives to achieve specified strategic objectives. Examples of such strategies around the world are plentiful: Japan has a string of initiatives related to the Society 5.0 agenda which binds together industrial support of future economic growth engines with long-term societal aims; the European Union’s European Green Deal and EU Industrial Strategy are multi-country projects aimed at, among many other things, turning Europe into the first climate-neutral continent by 2050, improving economic resilience, and closing the widening technological gap between the EU and the US; the US passed the 2021 US Innovation and Competition Act with bipartisan support with the express purpose of boosting American capabilities along dimensions ranging from rebuilding key industries such as semiconductor and electronics production, to strengthening core US comparative advantages such as scientific research, artificial intelligence development, and space exploration (Balawejder and Monahan 2020; Coyle and
The UK is no different in this regard, having gone through successive economic or industrial strategies newly announced by its governments in the past decades. One iteration of these strategies was the 2021 Plan for Growth, which replaced the previous 2017 Industrial Strategy, and was further supplemented by the UK Innovation Strategy later in 2021. Both the Plan for Growth and Innovation Strategy set out the long term aims typical of such key policy documents.

The scope of policies announced under national economic strategies is often wide-ranging and not confined to the domain of any single government department. As with most economic strategies, the Plan for Growth-UK Innovation Strategy duo follows this pattern of packaging a host of measures aimed at a number of strategic priorities. What is often unclear is the uptake of these policy measures across the wider state apparatus from other departments to delivery bodies. Who does what? Do different parts of government with different remits and operate in different policy domains collaborate and co-ordinate with each other? How extensive are these co-ordination and collaboration efforts? For an important element in an economic strategy’s success (or otherwise) is the ability to mobilise and co-ordinate the various parts of the government machinery effectively in a sustained fashion (Industrial Strategy Council, 2020). Indeed, some of the most transformative strategies are

---

1 The examples mentioned are often referred to as industrial policies rather than economic strategies. We use the terms interchangeably.
often those that have been able achieve a significant degree of policy co-
ordination across the various government departments and agencies over
medium- to long-term horizons.\(^2\) This is a particularly salient issue in the UK
given the extensive literature claiming a lack of cross-public sector co-ordination
in the country. Studies have found a lack of joining up in areas ranging from
health policy (Lorne et al., 2019) to food policy (Barling et al., 2003), and
between local and national policies (Barling et al., 2003), and indeed across the
board (Ling, 2002; Trein et al., 2019).

Answering the question about the extent of co-ordination requires a stocktake of
the suite of policies and their uptake by different parts of the government. To
perform such an undertaking requires bulk information retrieval from the corpus
of policy documents published by the government following publication of the key
economic strategies. We do this for the UK governments documents following
publication of the two key 2021 strategies. The Data and Methods section details
the process by which this information is obtained. These documents are obtained
by web scraping, text extraction, and text pre-processing Python scripts, with
each document also accompanied by metadata such as government document
classification, publication date, and the institution publishing it. We then carry out
textual analysis on this dataset by measuring all the instances in which a given
policy is cited in the corpus of policy documents. For the measure construction,

\(^2\) For examples, see Nezu, 2007; Fuchs, 2019; Balawejder & Monahan, 2020
we employ a simple pattern-based sequence-classification method, known as dictionary techniques, developed in computational linguistics (Manning et al. 2008; Bholat et al. 2015). The patterns are based on a dictionary of search terminologies that we constructed, comprising a selected list of names of policy programmes and special policy delivery entities (e.g. “Strength in Places Fund”, “Net Zero Strategy”, “Office for Investment”, etc.) announced under the Plan for Growth and the UK Innovation Strategy. By choosing these context-specific terms over generic policy-related words (e.g. “R&D incentives”, “sector support”, “regional funding”, etc.), we aim to ensure that the meaning of these terms and close variations of them maintain a consistent meaning throughout the corpus. Instances where these search terms or close variations appear in the corpus of policy documents are tallied, providing a count of how frequently a given policy is cited. We then perform validation exercises such as n-gram and manual audits (Cao 2021) to ensure that the meaning and context of our search terms remains consistent throughout the whole corpus of policy documents.

The resulting frequencies of these search terms, or term frequencies, are then visualised as heatmaps and networks to illustrate the extent to which the policy measures set out in the key strategic documents are incorporated into the policy publications of UK ministerial departments, non-ministerial departments, and public agencies. These heatmaps indicate that a substantial proportion of these policy measures remain completely uncited by the wider government. We also analyse a subset of this dataset—the policy publications produced only by
ministerial departments—as a network, with each ministry acting as a node and a weighted measure of term frequencies being the weights of the links between nodes. Finally, by measuring centrality among UK inter-ministry relationships through various conceptual frameworks such as distance, connectivity, and relative importance (the concepts and formulas are described in the Appendix), we are able to measure the extent of centrality among ministries within the context of Plan for Growth and UK Innovation Strategy. These network results add weight to long-held notions of that policymaking practice in the UK is extremely centralised.

There are some important caveats to this analysis. First, we do not claim causal channels. The analysis here assesses the absence of coordination simply by linguistic discontinuity in policy documents issued within a short period by a single administration. It is possible that certain aspects of policymaking or branches of government are systematically more likely than broad economic strategies to involve coordination. While it would be desirable to compare the administration studied here with others at other times or in other countries, there is no methodology at present in text and network analysis to undertake the type of causal identification familiar from econometric modelling. Whether the findings
of this paper generalise to policy frameworks in other settings involves empirical questions for future research to help set points of comparison.

The second caveat concerns the interpretation of our measure constructed in our analysis. A primary assumption in our analysis is that use of a search term implies some policy intent by the authoring institution. Although the constructed measure of search terms derived from the economic strategy documents is shown to capture the instances of such policies being cited in any given policy publication, this does not reveal the context in which these terms are being used in the documents. While we have constructed our search terms to ensure that their specific meanings remain fixed throughout the corpus—by selecting only proper noun terms and subsequently auditing n-gram plots—we cannot interpret directly the context of their citation. Establishing this fact for all such instances requires qualitative interpretation of each search term within the context of the wider document, which is unfeasible to implement at this scale.

Third, our analysis encompasses only the key policies announced under the Plan for Growth and UK Innovation Strategy; there may be measurement errors if policies are simply re-branded in later publications, although this risk is mitigated
by the relatively short time period as the sampling frame is policy documents published between March 2021 and July 2022, and within a single administration.

**Institutional Background**

Policymaking in the UK is often characterised as an ‘impositional’ (top-down), where policy proposals originate at the political level, i.e. ministers and their personal advisory staff, as opposed to a ‘consensual’ (bottom-up) style of policymaking, which emphasises collaborative and deliberative policymaking process via networks of stakeholders and relevant civil servants (Richardson 2018). This style of policymaking is enabled by the British mode of government; the UK’s Westminster model of majoritarian democracy confers a significant degree of latitude for the ruling party to make nearly unilateral executive decisions (Liphart 2012).

The result of this policymaking process over time is an approach to economic strategy that has largely been ad-hoc and haphazard, driven by political cycles. Looking back at the overarching direction of British economic policy in the past decades, episodes of policy change generally follow ideological lines reflecting the prevailing paradigm of the day: from large-scale government intervention in the form of subsidies and nationalisations of the post-war years to the 1950s, power-sharing arrangements of government, businesses, and workers in the 1960s and 1970s, to mass privatisations and fiscal consolidation of the 1980s
and 1990s (Crafts 1991; Bailey and Driffield 2007; Norris and Adam 2017). This haphazard pattern can also be observed when administrations change despite originating from the same political party. The Conservative-led government of recent years under the leadership of Theresa May launched the 2017 Industrial Strategy before it was scrapped and replaced with the Plan for Growth by Boris Johnson’s administration in 2021.  

This announcement, replacing the previous 2017 Industrial Strategy was unexpected and deemed by many unnecessary (BEIS Committee 2021)—especially in the context of the relative successes of the previous strategy (NAO 2021), and the concurrent abolition of the only agency dedicated to monitoring the implementation of industrial policy measures, the Industrial Strategy Council. There were objections from various parties including businesses, industry associations, public sector officials, and academics, among others (for a review, see Coyle and Muhtar 2021). Content-wise, the Plan for Growth represented a reduction in scale and scope compared to the 2017 Industrial Strategy, but still retained a number of common areas of focus. These areas include bolstering three identified “core pillars of growth”—infrastructure, skills, and innovation—alongside three thematic areas to improve on, namely tackling regional imbalances, catalysing transition towards carbon neutrality, and supporting British trade (HM Treasury 2021). The Plan for Growth also included an explicit

\[3\] Itsself since replaced by a Growth Plan in September 2022 and a different Growth Plan in early 2023.
mention of a follow-up white paper, namely the UK Innovation Strategy, addressing gaps in innovation support policies that were left in limbo from the dismantling of the previous Industrial Strategy. The UK Innovation Strategy white paper further outlined four focus pillars, namely ‘Unleashing Business’, ‘People’, ‘Institutions & Places’, and ‘Missions & Technologies’. While the Plan for Growth-UK Innovation Strategy duo contains a number of other strategies which would later become separate policy papers—such as ‘Net Zero Strategy’, ‘Export Strategy’, ‘National AI Strategy’—these key documents together provide the framework for the UK Government’s economic strategy throughout 2021 and the first half of 2022.

Data and Methods

In order to assess the extent of policy co-ordination throughout the various arms of the UK government around these key documents, we create a novel dataset that directly mines the texts of all the policy papers produced by the UK government during the relevant time period. Text mining these papers presents several unique challenges stemming from their unstructured nature and non-uniform document file formats. We use purpose built web-scraping (BeautifulSoup and urllib.request), text extraction (BeautifulSoup,

---

4 An open letter from high-level ministers in light of the backlash from the 2017 Industrial Strategy’s rollback clarified the government’s commitment to review of the mission-oriented elements of the previous Industrial Strategy, further highlighting the role of the UK Innovation Strategy as a stop-gap for the shortcomings of the Plan for Growth (Sunak and Kwarteng 2021; Pickard and Thomas 2021).
pdfplumber, and pypandoc), text pre-processing (re, string, and unicodedata), natural language processing (spaCy and scikit-learn), and network analysis (NetworkX) packages in Python to construct this dataset. Figure 1 illustrates the workflow for this study.

**Figure 1.** Web-scraping, text extraction, text pre-processing, natural language processing, and analysis workflow.

**Web-scraping, text extraction, text pre-processing, and tokenisation.** The first step in this process is obtaining document files of all policy papers of interest. These are from the UK government’s public sector information website,
GOV.UK, which provides a single point of access for all publicly available documents from all branches of the UK government, including documents produced by all ministries, non-ministerial departments, and public sector agencies. This repository categorises government produced content into one of six categories—‘services’, ‘guidance and regulation’, ‘news and communications’, ‘research and statistics’, ‘policy papers and consultations’, and ‘transparency and freedom of information releases’. We focus on the ‘policy papers and consultations’ content category, where documents are further classified as either ‘policy papers’, ‘consultations (open)’, or ‘consultations (closed)’ (GOV.UK, n.d.); for simplicity and consistency, only document files classified as ‘policy papers’ are scraped with our text mining script. Additionally, only policy papers published between 3 March 2021 and 8 July 2022 are included; restricting the range of publication dates to this time period ensures that we only consider policy papers published after the Plan for Growth up to the week of Prime Minister Boris Johnson’s resignation speech. This time frame provides the benefit of restricting our analysis to a single political administration, avoiding potential confounding factors such as changes in administration which often lead to a revamp of government policy (Bailey and Driffield 2007; Norris and Adam 2017; Coyle and Muhtar 2021) or simply a change in political rhetoric. Finally, government institutions regularly update policy papers after their original publication dates;

---

5 Following a large wave of resignations from ministers and civil servants alike, Boris Johnson’s resignation speech on 6 July 2022 (Prime Minister’s Office 2022) was taken to mark the de facto end of his administration.
our text mining script takes in the latest available versions of the publications.\textsuperscript{6} This process of web-scraping yields the uniform resource locators (URLs) of 2,158 unique document files in the ‘policy papers’ category within the specified period. Of these URLs, we mine texts of publications published in either HyperText Markup Language (HTML), Portable Document Format (PDF), text files, or Microsoft Word formats.\textsuperscript{7} Our script also records the institution that publishes the document.\textsuperscript{8} These extracted texts are pre-processed to convert them into analysable forms.\textsuperscript{9} The result is a dataset of texts extracted from 2,012 unique policy papers published across 83 government institutions (see Figure 2).\textsuperscript{10} Finally, the extracted and pre-processed texts are parsed through a tokeniser—splitting a given text into meaningful discrete elements or tokens (Manning et al. 2008)—via a natural language processing application

\begin{quote}
\textsuperscript{6} The policy papers’ respective GOV.UK pages places the most recent version of the paper as the first link. The script takes in the first hyperlink reference attribute that points to the policy paper content as the URL link to be scraped, ensuring our script only scrapes the latest version of the paper.
\textsuperscript{7} A small remainder of these policy publications cannot be extracted as they are either published in non-text formats (e.g. videos or spreadsheets) or non-searchable PDFs. Manual inspection of these remaining policy publications show that these mostly relate to operational matters of specific projects (e.g. general vesting declarations for High Speed Two (HS2) projects) and would not materially affect this analysis in any significant way. Excluding these special cases, our text mining script captures \textasciitilde 93\% of all publications within our sampling frame.
\textsuperscript{8} If a policy paper lists more than one institution as its author, we note the first institution as the primary author of that paper.
\textsuperscript{9} This includes steps such as translating unicode strings into normal characters, converting all characters into lower case form, removing unnecessary punctuation symbols, and removing excess white spaces.
\textsuperscript{10} A number of ministerial departments and public agencies, such as the Attorney General’s Office or the Small Business Commissioner, do not appear in our text mining analysis, indicating that these institutions have not produced any policy papers within this time frame. Publications by agencies such as the National Infrastructure Commission or UK Government Investments fall outside our text mining catchment and are not included as their publications are hosted on websites separate to GOV.UK, reflecting the institutional independence of the bodies concerned.
\end{quote}
programming interface (API) to enable detection of trigger phrase patterns from our dictionary of search terms.

Figure 2. Number of policy papers mined from GOV.UK, by institution, top 20 institutions. Dark green bars represent ministerial departments, while light green bars represent non-ministerial departments and other public agencies. See Appendix Figure A4 for full list.

Dictionary of search terms. The primary motivator behind the use pattern-based sequence-classification or dictionary technique (as opposed to document similarity methods such as vector space modelling or latent variable models) is
the need to preserve the meaning of patterns identified across different
documents, ensuring comparability for all instances of positive pattern matches.

To obtain frequencies of specific terms of interest, we first build a dictionary of
search terms containing the names of key policy programmes, measures or
purpose-built policy delivery entities listed within the Plan for Growth and UK
Innovation Strategy. For the Plan for Growth, the terms are predominantly
sourced from the table of policies listed at the end of every section of the report,
which encompasses policies aimed at addressing the three core growth pillars as
well as supporting the ‘Levelling Up’, ‘Net Zero’, and ‘Global Britain’ agendas
(HM Treasury 2021). For the UK Innovation Strategy, the terms are
predominantly sourced from the full list of actions listed in the final section of the
white paper (BEIS 2021, pp. 103-107); they comprise 44 high-level actions aimed
at tackling four pillars of focus identified within the document. Throughout the
dictionary-crafting process, only terms that are proper nouns are included in our
dictionary, whereas generic verb or common noun terms are excluded. A key
differentiator between the former and the latter is the capitalisation of their
spelling. As an example, some of the announced measures under the
‘innovation’ pillar of the Plan for Growth includes sentences like (a) “£14.6 billion
government investment in R&D in 2021-22, boosting existing and emerging R&D
strengths across the UK” and (b) “£800 million of funding for the Advanced
Research & Invention Agency (ARIA), helping to cement the UK’s position as a
global science superpower” (HM Treasury 2021, p. 65). In the case of the first
sentence, we do not include any subset of words from this sentence into our dictionary—terms such as “£14.6 billion government investment in R&D”—as these sequences of words do not have a fixed and definite meaning across all policy papers and could change depending on the context. In the second sentence, we include the term ‘Advanced Research & Innovation Agency’ into our dictionary as the meaning and context of these sequence of words are fixed across any policy domain and setting, as they refer to the newly formed entity, called ARIA. Additionally, our dictionary focuses on new policy measures announced under the Plan for Growth and UK Innovation Strategy rather than the continuation of past policies. While the dictionary is not an exhaustive list of all measures announced within those white papers, the choice of terms selected for inclusion in the dictionary reasonably covers the majority of their key policies; the full dictionary of search terms is given in Appendix Table A1.

Search terms are then mapped onto their respective sets of trigger phrases to ensure variations of the same term would still be detected; from the example earlier, terms such as ‘ARIA’ or ‘Advanced Research and Invention Agency’ would still be detected as a match for the term ‘Advanced Research & Invention Agency’. We utilise spaCy’s PhraseMatcher API to configure an efficient rule-based matching programme that searches for all instances of our trigger phrases in our text dataset. To ensure that our dictionary of search terms is valid – i.e. that our search terms have a consistent meaning throughout the corpus – we checked the top 20 n-grams (with n = 6, 8, and 10) (see A1 in the Appendix).
Auditing these n-grams confirms our intuition that these terms have a consistent meaning throughout the corpus.

**Term frequency.** The frequency of trigger phrases corresponding to each search term forms the basis of measurement in our analysis. An unweighted term frequency count for each search term-UK institution pair is calculated based on instances where the code returns a positive match for the trigger phrase patterns with the patterns of the underlying texts. That is, the term frequency, $tf_{t,i}$, of term, $t$, cited by institution, $i$, is defined as the number of times that the trigger phrase for $t$ occurs within the set of all documents produced by $i$, $D_i$:

$$tf_{t,i} = \sum_{d \in D_i} \sum_{t} \text{trigger phrase}_{t,d}$$

**Network graphs.** Our analysis also includes a network analysis at the ministry level. That is, we utilise the term frequencies of search terms from documents published by UK ministerial departments to generate undirected network graphs (with no self-loops) that illustrate the degree of connectedness between UK ministerial departments. Each ministerial department can be represented as a node (vertex) while each edge (link) emanating from a node represents the extent of connectedness between any two ministries within the context of Plan for Growth/UK Innovation Strategy.
The network graphs are generated using two force-directed algorithms, the Fruchterman-Reingold layout\textsuperscript{11} and Kamada-Kawai methods. The former assigns a repelling force to all vertices in the graph and an attraction force for all vertices linked via edges (Fruchterman and Reingold 1991). This configuration effectively pushes vertices apart while simultaneously applying an attractive force between each linked vertices pair, pulling those vertices closer in proportion to weight of the edge (similar to the effect of springs with differing pulling strengths). The latter algorithm treats the graph a dynamical system of springs such that the optimal configuration of vertices is a state in which the total spring energy of the system is minimal (Kamada and Kawai, 1989). Each configuration provides an intuitive way to understand the underlying relationships in the network; the former visualises the relative positioning of each node given the strength of their connections to other nodes while the latter visualises the relative order of nodes by according to the strength of their connections.

To construct the network, $G$, ministries are represented as a set of nodes $V$ while the set of edges, $E$, represents the number of times a Plan for Growth/UK Innovation Strategy policy is cited by all ministry pairs in our dataset. We propose a simple measure to measure the weight of each edge for visualisation purposes; for any given ministry pairs $(u, v) \in V$, their weighted edge, $e_{u,v} \in E$, is given by

\textsuperscript{11} Within the NetworkX package, this is also known as the spring layout
\[ e_{u,v} = \frac{\sum_t w_{t,u,v}}{n} \]  
where 
\[ w_{t,u,v} = \begin{cases} 
1 & \text{if } tf_{t,u} > 0 \text{ and } tf_{t,v} > 0 \\
0 & \text{otherwise}
\end{cases} \]

Here, \( w_{t,u,v} \) represents the total number of instances where a given search term, \( t \), is cited at least once in publications from ministries \( u \) and \( v \), separately. In other words, for a given term, \( t \), \( w_{t,u,v} \) takes the value 1 if the term frequency, \( tf \), for that term is non-zero for both ministries \( u \) and \( v \). \( n \) is the total number of search terms in the dictionary. As an example, the term frequency for the search term “freeports’ is 11 and 16 for the Cabinet Office and BEIS respectively. Since \( tf \) freeports is non-zero for both the Cabinet Office and BEIS, \( w_{\text{freeports,Cabinet Office,BEIS}} \) takes the value 1. Conversely, the term frequency for the search term 'levelling up fund' is 2 and 0 for the Cabinet Office and BEIS, respectively. Here, \( w_{\text{levelling up fund,Cabinet Office,BEIS}} \) takes the value 0 since \( tf \) levelling up fund is 0 for at least one of the ministries in this pair. This measure of weighted edges captures instances when a given Plan for Growth or UK Innovation Strategy policy is cited by two ministries, highlighting the presence of that specific policy within both ministries’ policy domains.

From these network graphs, we calculate each department’s clustering coefficients and centrality within the overarching economic strategy framework.

Since the concept of centrality can mean different things within different contexts, this study utilises centrality measures that can be broadly categorised into four
conceptual frameworks: degree, closeness, betweenness, and eigenvector centralities (Newman, 2018). Figure 3 provides an overview of the intuition behind these different centrality measures.

![Diagram of different concepts of network centrality](image)

**Figure 3.** Different concepts of network centrality, adapted from (Newman, 2018; Ortiz-Arroyo, 2010)

**Results**

**Term frequency heatmaps.** We visualise the term frequencies for each search term-UK institution pair as heatmaps shown in Figures 4 and 5. Figure 4 visualises the term frequencies for Plan for Growth terms, while Figure 5 show the term frequencies for Innovation Strategy terms. Higher term frequencies correspond to increased ‘pixel’ brightness in these heatmaps.

What is immediately striking from these figures is the overwhelming lack of any citation of the majority of the policies. Term frequencies with a value of zero (i.e. \( tf_{t,i} = 0 \)) make up 94% and 96% for the Plan for Growth and UK Innovation Strategy heatmaps in Figure 4 respectively; in Figure 5, the proportions are 77%
and 90% respectively. In other words, the subsequent policy documents make almost no reference to the earlier strategic texts, whereas one might expect more reference – bright areas – with the central department of the Cabinet Office, for example, citing a wider range of policies rather than just over quarter, or the Committee on Fuel Poverty making some reference to home building policy or the many green policies. From a combinatorics perspective, the heatmaps also allow us to calculate all instances of a search term being cited more than once for a given pair of institutions, i.e. \( tf_{i,i} \) and \( tf_{i,j} \) are both non-zero for any \((i, j)\) pair. In Figure 4, there were 1,317 such pairs among the Plan for Growth search terms out of a total maximum of 200,777 possible pairs (0.7% of all possible pairings) whereas among UK Innovation Strategy search terms, there 123 such pairs out of a total maximum of 85,075 possible pairs (0.1% of all possible pairings). For Figure 5, there were 985 such pairs for Plan for Growth search terms out of a total maximum of 11,210 possible pairs (8.8% of all possible pairings), whereas there were 108 such pairings for UK Innovation Strategy search terms out of a total maximum of 4,750 possible pairs (2.3% of all possible pairings). While we would not necessarily expect that every possible combination of institution pairs to cite every policy from the economic strategy documents, and do not know what the ‘correct’ level of referencing would be, the large gaps identified here are indicative of a substantial lack of co-ordination among government institutions.
Figure 4. Heatmaps of Plan for Growth terms cited in all UK policy papers published between March 2021 and July 2022. Search terms are sorted according to their weighted averages and ministries are listed alphabetically in (a) to (d).

(a)
Figure 5. Heatmaps of (UK Innovation Strategy terms cited in UK ministries’ policy papers published between March 2021 and July 2022. Search terms are sorted according to their weighted averages and ministries are listed alphabetically in (a) to (d).
A closer inspection of the heatmaps reveals that this lack of verbal joining up extends to key policy instruments in principle central to the economic strategies. For example, the UK Shared Prosperity Fund (UKSPF) is a £2.6 billion fund that forms a central pillar of the government’s ambitious Levelling Up agenda and supports place-based growth across the UK by “building pride in place, supporting high quality skills training, supporting pay, employment and productivity growth and increasing life chances,” (DLUHC 2022). Yet the heatmaps show zero citations of the UKSPF terms for all ministries except for the Department for Levelling Up, Housing & Communities (DLUHC) and HM
Treasury—the ministries that own and fund the initiative, respectively. In the context of wider government, only the Social Mobility Commission has cited this term once. Many ministries and agencies are small and/or have specific areas of responsibility, so it is not surprising that some of these such as Defence, Foreign Office or Overseas Development do not refer to the core economic strategies or instruments. It is more surprising that many of the ministries with economic responsibilities – such as Work and Pensions or Health and Social Care do not cite broad terms such as ‘plan for growth’. Analysing what level of cross-reference to expect is a matter of judgment about the specificity of the terms and the policy domain of the department or agency. This kind of analysis partitioning the policy terms and departments would produce heat maps with a warmer overall shade.

The level of referencing to be expected is also a matter of judgment depending on the purpose, number and length of the documents; and will require a number of similar exercises to be carried out to help develop benchmarks. Refining the technique to develop a rigorous approach to partitioning and normalising the metrics is a direction for future work. However, there are still surprising zeroes or low single figures, such as no reference in Ministry of Defence policy documents to ‘defence and security industrial strategy’, or by the Department for Business, Energy and Industrial Strategy, which holds the budget for government-funded R&D, to the ‘R&D places strategy’ intended to focus on the spatial allocation of that spending.
The heatmaps also show a degree of heterogeneity in the number of citations for policies with similar or overlapping objectives. Policy instruments strongly related to the UKSPF—such as Levelling Up Fund, Community Renewal Fund, and Community Ownership Fund, among others—have varying amounts of citations within policy papers from ministries such as the Cabinet Office, BEIS, Department for Culture, Media & Sport (DCMS), Department for Environment & Rural Affairs (Defra), DLUHC, Department for Transport (DfT), HM Treasury, Ministry of Defence (MoD), and the Prime Minister’s Office (PMO). At face value, ministries such as the Department for Health & Social Care (DHSC), Department for Education (DfE), Department for International Trade (DIT), appear to be disconnected from these policies. Similar domain-specific policies such as improving local and regional transport networks (e.g. ‘Integrated Rail Plan’, ‘Union Connectivity Review’, etc.) are usually concentrated on the ministry in charge (i.e. DfT or DLUHC) and core ministries (i.e. HM Treasury and PMO).

**Network graphs.** Figures 6 and 7 depict the network of relationships between ministries from the perspective of Plan for Growth and UK Innovation policies—that is, for any instance that any two ministries cite the same search term in their respective policy papers. The networks’ general properties are listed in Table 1, while each ministries’ degree, clustering, and centrality measures are listed in Appendix Tables A2 and A3.
### Network Properties and Local Clustering Coefficients

<table>
<thead>
<tr>
<th>Network Properties</th>
<th>Plan for Growth</th>
<th>UK Innovation Strategy</th>
</tr>
</thead>
<tbody>
<tr>
<td>Nodes</td>
<td>20</td>
<td>14</td>
</tr>
<tr>
<td>Edges</td>
<td>106</td>
<td>33</td>
</tr>
<tr>
<td>Average degree</td>
<td>5.30</td>
<td>2.36</td>
</tr>
<tr>
<td>Average clustering coefficient</td>
<td>0.751</td>
<td>0.422</td>
</tr>
<tr>
<td>Global clustering coefficient (transitivity)</td>
<td>0.841</td>
<td>0.765</td>
</tr>
</tbody>
</table>

Figure 6 confirms visually the highly centralised nature of British government with core ministries (HM Treasury, Prime Minister’s Office, and BEIS) taking on central roles in economic policies; Figure A3 in the Appendix visualises the extensive links of HM Treasury with nearly all other ministerial departments. Conversely, the Office of the Secretary of State for Scotland (Scotland Office), Office of the Secretary of State for Wales (Wales Office), and the Northern Ireland Office (NIO) are barely connected to any other ministries at all, reflecting the UK’s devolution settlement and yet raising a question about the geographic and practical scope of central government strategies. On average, ministries are connected to 5.3 and 1.65 other ministries for Plan for Growth and UK Innovation Strategy policies respectively. The average weighted clustering coefficient, which measures the proportion of a ministry’s ‘partner’ (in the sense of the same policy
cited in their respective policy papers) which are themselves partners with the ministry’s other partners—a broad measure of co-operation and collaboration in this network—is 0.121 and 0.152 for the Plan for Growth and UK Innovation Strategy respectively.

Figure 6

(a) Plan for Growth
Figure 6. Network graphs for (a) Plan for Growth policies and (b) UK Innovation Strategy policies using Fruchterman-Reingold method. Ministries with larger edge weights are depicted with thicker and brighter lines, and vice versa—reflecting more instances of Plan for Growth/UK Innovation Strategy policies that are cited in policy publications of the linked ministries.

The centrality measures in Tables A2 and A3 provide specific centrality and clustering measures for each ministry. Across measures such as betweenness and eigenvector centralities and weighted local clustering coefficients, ministries such as HM Treasury, the Prime Minister's Office, and BEIS consistently score as the most central among all UK ministries in our sample. The opposite can be
said for ministries such as the Scotland, Wales, Northern Ireland Offices, as well as a host of other line ministries such as UK Export Finance (UKEF), Home Office, and DHSC, among others.

**Conclusion**

Bearing in mind the caveats noted earlier, we have demonstrated a striking lack of reference to two key UK government strategy documents, the 2021 Plan for Growth and Innovation Strategy, in other government policy documents published within a single administration.

Specifically, we have been able to give empirical meaning to the claim that UK government policies are unco-ordinated across departments and other public bodies, and that reference to key levers for large-scale and transformative policies such as those listed in the national economic strategy documents rest solely with the core government machinery (i.e. HM Treasury and the Prime Minister’s Office). The traditional demarcation of ministerial powers poses challenges to government co-ordination, as many aspects of effective co-ordination tie together various policy domains (such as export support, financing, R&D initiatives, public procurement, capability development, etc.). New policy issues such as promoting development of new technologies, or climate change mitigation and adaptation, are even more likely to require policy measures that extend beyond traditional ministerial jurisdictions. Our results suggest that policy-
makers could better co-ordinate policies, as empirical analysis of the documents exposes co-ordination failures, or at a minimum failures of consistency in strategic narratives. The metrics developed here could also be used as a basis to assess policy consistency in other contexts and to enable comparison of network structures in different jurisdictions. Such work would allow the development of benchmarks of what is ‘typical’ or to be expected. Although we do not have a benchmark for comparison across countries or time periods, it seems reasonable to conclude that this study has identified something at or near a lower bound.

**Data Availability**

Code and data have been deposited in


**Acknowledgments**

D.C. gratefully acknowledges funding support from the ESRC’s Productivity Institute (grant number ES/V002740/1). A.M. gratefully acknowledges funding support from the Gatsby Foundation.
References


GOV.UK, Policy papers and consultations (n.d.)


Norris, E., R. Adam, All Change: Why Britain is so prone to policy reinvention, and what can be done about it, (Institute for Government), Technical report (2017).


Prime Minister’s Office, Prime Minister Boris Johnson’s statement in Downing Street: 7 July 2022 (2022).


Table A1. Dictionary of search terms, in alphabetical order

<table>
<thead>
<tr>
<th>Plan for Growth</th>
<th>UK Innovation Strategy</th>
</tr>
</thead>
</table>
Table A2. Centrality and clustering measures for Plan for Growth network nodes, sorted by degree.

<table>
<thead>
<tr>
<th>Node</th>
<th>Degree</th>
<th>Degree Centrality</th>
<th>Closeness Centrality</th>
<th>Betweenness Centrality</th>
<th>Eigenvector Centrality</th>
<th>Clustering Coefficient</th>
</tr>
</thead>
<tbody>
<tr>
<td>Treasury</td>
<td>16</td>
<td>0.842</td>
<td>22.082</td>
<td>0.027</td>
<td>0.45</td>
<td>0.203</td>
</tr>
<tr>
<td>DLUHC</td>
<td>16</td>
<td>0.842</td>
<td>22.082</td>
<td>0.027</td>
<td>0.401</td>
<td>0.186</td>
</tr>
<tr>
<td>PMO</td>
<td>16</td>
<td>0.842</td>
<td>23.381</td>
<td>0.027</td>
<td>0.385</td>
<td>0.182</td>
</tr>
<tr>
<td>Defra</td>
<td>16</td>
<td>0.842</td>
<td>22.713</td>
<td>0.027</td>
<td>0.273</td>
<td>0.149</td>
</tr>
<tr>
<td>BEIS</td>
<td>15</td>
<td>0.789</td>
<td>16.914</td>
<td>0.014</td>
<td>0.386</td>
<td>0.209</td>
</tr>
<tr>
<td>DCMS</td>
<td>15</td>
<td>0.789</td>
<td>26.498</td>
<td>0.021</td>
<td>0.244</td>
<td>0.146</td>
</tr>
<tr>
<td>DfT</td>
<td>14</td>
<td>0.737</td>
<td>26.498</td>
<td>0.009</td>
<td>0.284</td>
<td>0.185</td>
</tr>
<tr>
<td>Cabinet</td>
<td>13</td>
<td>0.684</td>
<td>24.089</td>
<td>0.005</td>
<td>0.251</td>
<td>0.2</td>
</tr>
<tr>
<td>DfE</td>
<td>13</td>
<td>0.684</td>
<td>22.082</td>
<td>0.006</td>
<td>0.115</td>
<td>0.127</td>
</tr>
<tr>
<td>MoJ</td>
<td>13</td>
<td>0.684</td>
<td>31.798</td>
<td>0.007</td>
<td>0.037</td>
<td>0.063</td>
</tr>
<tr>
<td>DIT</td>
<td>12</td>
<td>0.632</td>
<td>20.92</td>
<td>0.003</td>
<td>0.163</td>
<td>0.172</td>
</tr>
<tr>
<td>Department</td>
<td>Closeness</td>
<td>Betweenness</td>
<td>Local Clustering Coefficients</td>
<td>Eigenvector Centrality</td>
<td></td>
<td></td>
</tr>
<tr>
<td>------------------</td>
<td>-----------</td>
<td>-------------</td>
<td>-------------------------------</td>
<td>-------------------------</td>
<td></td>
<td></td>
</tr>
<tr>
<td>MoD</td>
<td>0.579</td>
<td>19.874</td>
<td>0.001</td>
<td>0.12</td>
<td></td>
<td></td>
</tr>
<tr>
<td>DWP</td>
<td>0.526</td>
<td>24.089</td>
<td>0.001</td>
<td>0.041</td>
<td></td>
<td></td>
</tr>
<tr>
<td>DHSC</td>
<td>0.474</td>
<td>21.485</td>
<td>0</td>
<td>0.047</td>
<td></td>
<td></td>
</tr>
<tr>
<td>FDCO</td>
<td>0.474</td>
<td>24.842</td>
<td>0</td>
<td>0.044</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Home Office</td>
<td>0.474</td>
<td>28.391</td>
<td>0</td>
<td>0.027</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Scotland Office</td>
<td>0.263</td>
<td>22.082</td>
<td>0</td>
<td>0.013</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Wales Office</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td></td>
<td></td>
</tr>
<tr>
<td>UKEF</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td></td>
<td></td>
</tr>
<tr>
<td>NIO</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Note: Closeness takes in each edge weight as distance between nodes; this means low values for more central nodes and high values for less central ones, which is the opposite of other centrality measures (Newman, 2018). Betweenness centrality measures do not make use of the networks’ edge weights; documentation in the NetworkX package highlights issues of zero edge weights, which can produce an infinite number of equal length paths between pairs of nodes (NetworkX, n.d.). Eigenvector centrality and local clustering coefficients utilises the edge weights in the network graph.
**Table A3.** Centrality and clustering measures for UK Innovation Strategy network nodes, sorted by degree.

<table>
<thead>
<tr>
<th>Node</th>
<th>Degree</th>
<th>Degree Centrality</th>
<th>Closeness Centrality</th>
<th>Betweenness Centrality</th>
<th>Eigenvector Centrality</th>
<th>Clustering Coefficient</th>
</tr>
</thead>
<tbody>
<tr>
<td>Treasury</td>
<td>9</td>
<td>0.474</td>
<td>6.925</td>
<td>0.035</td>
<td>0.474</td>
<td>0.203</td>
</tr>
<tr>
<td>BEIS</td>
<td>9</td>
<td>0.474</td>
<td>7.31</td>
<td>0.061</td>
<td>0.424</td>
<td>0.182</td>
</tr>
<tr>
<td>DCMS</td>
<td>8</td>
<td>0.421</td>
<td>7.31</td>
<td>0.024</td>
<td>0.425</td>
<td>0.186</td>
</tr>
<tr>
<td>DfT</td>
<td>8</td>
<td>0.421</td>
<td>8.224</td>
<td>0.008</td>
<td>0.237</td>
<td>0.146</td>
</tr>
<tr>
<td>MoD</td>
<td>7</td>
<td>0.368</td>
<td>7.31</td>
<td>0.004</td>
<td>0.339</td>
<td>0.149</td>
</tr>
<tr>
<td>Cabinet</td>
<td>6</td>
<td>0.316</td>
<td>6.266</td>
<td>0.001</td>
<td>0.373</td>
<td>0.209</td>
</tr>
<tr>
<td>DLUHC</td>
<td>6</td>
<td>0.316</td>
<td>7.31</td>
<td>0.001</td>
<td>0.236</td>
<td>0.185</td>
</tr>
<tr>
<td>DIT</td>
<td>5</td>
<td>0.263</td>
<td>8.224</td>
<td>0</td>
<td>0.128</td>
<td>0.172</td>
</tr>
<tr>
<td>PMO</td>
<td>5</td>
<td>0.263</td>
<td>8.224</td>
<td>0</td>
<td>0.124</td>
<td>0.16</td>
</tr>
<tr>
<td>Home Office</td>
<td>2</td>
<td>0.105</td>
<td>3.987</td>
<td>0</td>
<td>0.125</td>
<td>0.2</td>
</tr>
<tr>
<td>Defra</td>
<td>1</td>
<td>0.053</td>
<td>4.873</td>
<td>0</td>
<td>0.029</td>
<td>0.127</td>
</tr>
<tr>
<td>NIO</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0.101</td>
</tr>
<tr>
<td>UKEF</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0.099</td>
</tr>
<tr>
<td>Wales Office</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0.087</td>
</tr>
<tr>
<td>MoJ</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0.079</td>
</tr>
<tr>
<td>Scotland Office</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0.078</td>
</tr>
<tr>
<td>FDCO</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0.063</td>
</tr>
<tr>
<td>DfE</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>DWP</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>DHSC</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
</tbody>
</table>

Note: Closeness takes in each edge weight as distance between nodes; this means low values for more central nodes and high values for less central ones, which is the opposite of other centrality measures (Newman, 2018). Betweenness centrality measures do not make use of the networks' edge weights; documentation in the NetworkX package highlights issues of zero edge weights, which can produce an infinite number of equal length paths between pairs of nodes (NetworkX, n.d.). Eigenvector centrality and local clustering coefficients utilises the edge weights in the network graph.
This appendix next describes the method used to increase confidence in the dictionary of search terms constructed in the main paper and then provides the formulas used for the calculations of network properties, clustering coefficients and network centralities.

**Dictionary validation exercise (auditing top n-gram)**

To bolster our confidence on the validity of our choice of search terms, we obtain the contiguous sequence of n tokens surrounding the search term tokens (a modification of the standard n-grams); that is, we check instances in which the tokens matches with one of the search term trigger phrases, and then takes in a set number of tokens preceding and after these tokens to capture the content of interest. We then manually check the most frequent n-grams, i.e. n-grams with the highest term frequency (tf) score and show that the choice of those search terms intuitively makes sense in terms of having a consistent underlying meaning. We replicate this again for n-grams with the highest term frequency-inverse document frequency (tf-idf) score, which is an alternative measure of weighted term counts that identify the most distinctively frequent terms in a given corpus. Formally, for a term, t, and document, d,

\[
    tf-idf(t, d) = tf(t, d) \times idf(t), \quad \text{where } idf(t) = \log \left(1 + \frac{n + 1}{df(t) + 1}\right)
\]
where $n$ is the total number of documents in the document set, and $df$ is the number of documents in the document set that contain term $t$. The term frequency, $tf$, upweights terms according to their frequency while $idf$ downweights terms that appear frequently across the corpus. We utilise the spaCy package to create the $n$-grams and sklearn package’s vectoriser functions to compute term frequencies and $tf-idf$ scores, which normalises the resulting $tf-idf$ vectors the Euclidean norm:

$$v_{\text{norm}} = \frac{v}{\|v\|^2} = \frac{v}{\sqrt{v_1^2 + v_2^2 + \cdots + v_n^2}}$$

$n$ is set to 6, 8, and 10 to capture context of search terms within different contiguous lengths. The resulting $n$-grams, visualised in Figures A1, A2, and A3, indicate that the terms have consistent underlying meaning, referring to the same policy programme or entity throughout the corpus.
Figure A1. Frequency of the top $tf$ and $tf$-$idf$ 6-grams.
Figure A2. Frequency of the top tf and tf-idf 8-grams.
Figure A3. Frequency of the top tf and tf-idf 10-grams.

Network properties, clustering coefficients, and centralities

Degree. For an undirected network $G = (V, E)$, where $V$ is the set of nodes and $E$ is the set of edges, the simplest structural property of a node is the node’s degree. This degree is simply the total number of neighbouring nodes it is connected (e.g. a node with 5 connections will have a degree of 5). The concept adjacency of provides useful mathematical notations to describe a network; two nodes, $u$ and $v$ where $u, v \in V$, are adjacent if they are joined by an edge $(u, v) \in E$. A graph can therefore be described by its adjacency matrix $A = a_{u,v}$, resulting in a square $|V| \times |V|$ matrix. Each entry $a_{u,v}$ is either 0 or 1, where

$$a_{u,v} = 1 \text{ if and only if } (u, v) \in E$$

Therefore, for an undirected network, $G$, the degree centrality, $\text{deg}(u)$, of a node $u \in V$ is the number of edges $e$ which involve $u$ as an endpoint:

$$\text{deg}(u) = \sum_v a_{u,v}$$

Local clustering coefficients. Local clustering coefficient of node $u$ is, intuitively, the proportion of “friends” who are friends themselves. Geometrically,
the proportion of friends that are friends form triangles in the network graph; this
metric provides a measure of how ‘dense’ the graph is within the local vicinity of
the node \( u \). Mathematically, this is the proportion of neighbours for node \( u \in V \)
which are neighbours themselves (Newman 2018). For networks with weighted
edges, such as the ones used in our main paper, the local clustering coefficient
of a node \( u \) is defined as the geometric average of the subgraph edge weights
(Onnela 2005)

\[
LCC(u) = \frac{1}{\text{deg}(u)(\text{deg}(u) - 1)} \sum_{vw} (\hat{w}_{uv}\hat{w}_{uw}\hat{w}_{vw})^{1/3}
\]

where, the edge weights \( \hat{w}_{uv} \) are normalised by the maximum weight in the
network, i.e. \( \hat{w}_{uv} = \frac{w_{uv}}{\max(w)} \). Additionally, we adopt the convention that the
value of \( LCC(u) \) is assigned to 0 if \( \text{deg}(u) < 2 \). The network average clustering
coefficient is thus simply defined as the average of local clustering coefficients for
all nodes in the network:

\[
\overline{LCC} = \frac{1}{|V|} \sum_{u \in V} LCC(u)
\]

**Centrality measures.** A class of functions known as network centralities assigns
scores to nodes based on their structural properties within the context of the
network. These metrics provide a way to ascertain the nodes' rankings relative to
each other as well as quantifying their importance, which determines the magnitude of their relative importance within the network. While different measures of network centrality often identify the same set of important nodes in the network, the amount of importance assigned to each node depends on the concept of centrality in question. In this section, we describe four different concepts of centrality: degree, closeness, betweenness, and eigenvector centralities.

**Degree centrality.** The definition of degree centrality used here, also known as normalised degree centrality, extends the concept of degree by normalising $\text{deg}(u)$ with the maximum possible number of connections to other nodes without self-loops, i.e. $n-1$, where $n$ is the number of nodes in $G$ (e.g. for a graph with maximum possible degree of 20, $n-1$ would be 19).

$$C_{\text{degree}}(u) = \frac{\text{deg}(u)}{n-1}$$

**Closeness centrality.** Another class of centrality metrics makes use of the network's global structural information, by measuring how close a node is to all other nodes in the network. Formally, closeness centrality of a node $u$ is the reciprocal of the average shortest path distance to $u$ over all reachable nodes (with no self-loops), $n-1$, of the component of the network where the node is located. This term is normalised to the proportion of $n-1$ over $N-1$ where $N$ is the...
total nodes in the network (Wasserman and Faust 1994). This results in a proportion of the fraction of nodes in the group that are reachable, to the average distance from the reachable nodes:

$$C_{\text{closeness}}(u) = \frac{n - 1}{N - 1} \frac{n - 1}{\sum_{u} d(v,u)}$$

where $d(v,u)$ is the shortest-path distance computed using Dijkstra’s algorithm with the edge weight taken as ‘distance’ between nodes. This concept of ‘distance’ yields low values for more central nodes and high values for less central ones, which is the opposite of other centrality measures (Newman 2018).

**Betweenness centrality.** Betweenness is another class of centrality concepts, which captures the importance of a node's connectivity, or the property of a node acting as a ‘gatekeeper’ to other nodes. Betweenness centrality quantifies the number of times a node acts as a bridge along the shortest path between two other nodes. Mathematically, betweenness centrality of a node $u$ is the sum of the fraction of all-pairs shortest paths that pass through $u$:

$$C_{\text{betweenness}}(u) = \sum_{s,t \in V} \frac{\sigma(s, t \mid u)}{\sigma(s, t)}$$
where $\sigma(s, t)$ is the number of shortest $(s, t)$-paths, and $\sigma(s, t|u)$ is the number of those paths passing through node $u$ between $s$, $t$. If $s = t$, $\sigma(s, t) = 1$, and if $u \in s$, $t$, then $\sigma(s, t|u) = 0$ (Brandes 2008). We do not utilise the edge weights in the betweenness centrality as the documentation in the NetworkX package highlights issues of zero edge weights, which can produce an infinite number of equal length paths between pairs of nodes (NetworkX n.d.).

**Eigenvector centrality.** While the number of neighbours often determines a node's degree centrality, one could also imagine scenarios where the identity of these neighbours also affects a node's importance. For example, a node connected to many unimportant nodes may be less important than a node with a few neighbours of high importance. The final class of centrality explored here are eigenvector centralities, which attempts to capture this type of importance. Thus, nodes with high eigenvector centrality may not necessarily be highly linked (the node might have few but important edges). The eigenvector centrality for node $u$ is the $u$-th element of the vector $\vec{x}$ defined by the equation:

$$A\vec{x} = \lambda \vec{x}$$

where $A$ is the weighted adjacency matrix of the graph $G$ with eigenvalues $\lambda$ (Newman 2018) (Jackson 2010).
Figure A3. Network graphs for (a) Plan for Growth policies and (b) UK Innovation Strategy policies using Kamada-Kawai method. Ministries with larger edge.
weights are depicted with thicker and brighter lines, and vice versa—reflecting more instances of Plan for Growth/UK Innovation Strategy policies that are cited in policy publications of the linked ministries.

Figure A4. Full list of departments & bodies, (expanded Figure 2 main text)

Figure 2. Number of policy papers mined from GOV.UK, by institution. Dark green bars represent ministerial departments, while light green bars represent non-ministerial departments and other public agencies.

Appendix references: