National Physical Laboratory

NPL REPORT IEA 22

VISUALISING THE LOCATIONS OF NPL'S SED DEPARTMENTS AND DESIGNATED NMS LABORATORIES WITHIN AN IMPACT SPACE

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MARCH 2024

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ABSTRACT

This report presents a scoping study that contains the beginnings of a quantitative framework to construct and analyse department-level metrics. These metrics help enhance our understanding of the portfolio of NPL's SED departments and how they occupy different bits of the impact scape. We extend this analysis to include NEL and NML. We construct department-level metrics from NMS indicators data and analyse them using Principal Component Analysis. The analysis reveals heterogeneity in the work that the NEL, NML, and different SED departments within NPL specialise in. The key takeaway from the PCA is that the departments face an apparent trade-off between activities that generate Current Impacts and activities that have the potential to generate Future Impacts. Moreover, the analysis provides insights into how the departments vary across generating direct, monetizable current impacts and indirect, non-monetizable current impacts (spillovers / externalities). Under the assumption that there is no slack in the system, the analysis provides a neat way to infer the scale of externalities / spillovers that a department might be generating.

ISSN 2633-4194

https://doi.org/10.47120/npl.IEA22

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This work was funded by the UK Government's Department for Science, Innovation & Technology through the UK's National Measurement System programmes.

Approved on behalf of NPL by
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EXECUTIVE SUMMARY

This report presents a scoping study that contains the beginnings of a quantitative framework to construct and analyse department-level metrics. These metrics help enhance our understanding of the portfolio of NPL's SED departments and how they occupy different parts of the science impact landscape. We extend this analysis to include NEL and NML.

We construct department-level metrics from NMS indicators data and analyse them using Principal Component Analysis (PCA). The analysis reveals heterogeneity in the work that the NEL, NML, and different SED departments within NPL specialise in. The main contribution of the analysis comes in the form of a key takeaway that there is an apparent trade-off between activities that generate Current Impacts and activities that have the potential to generate Future Impacts. Time and resource constraints make it difficult to specialise in both types of activities, which can partly explain the trade-off. Moreover, we believe that Current Impacts are comprised of two bits: direct, monetizable impacts and indirect, non-monetizable impacts (or spillovers). In practice, the metrics only allow us to observe the first bit. Thus, the second contribution of the analysis is that it provides a way to infer the scale of non-monetizable impacts that the NEL, NML, and different SED departments within NPL generate.

The analysis presented in this report has certain caveats and there is scope for addressing these caveats in future work. More years of data, combined with the ongoing NMS metrics revision will eventually provide a bigger dataset that will enable the analysis to become more powerful. Despite the caveats, this report establishes a new quantitative framework that provides a foundation to better understand the similarities and differences in the activities of NEL, NML, and NPL's different SED departments.

1 INTRODUCTION

1.1 INTRODUCTION TO NATIONAL PHYSICAL LABORATORY

The National Measurement System (NMS) is the backbone of the UK's measurement standards. It ensures that the country has a consistent and internationally recognized basis for measurement that caters to a wide range of activities in trade, industry, and regulation. The Department for Science, Innovation & Technology (DSIT) supports the NMS through six core measurement laboratories that maintain, develop, and disseminate measurement standards. Over 80% of the entire NMS funding goes to the National Physical Laboratory (NPL), which is a public corporation owned by the DSIT and specializes in metrology (measurement science). Much of the remaining NMS funding is received by the National Measurement Laboratory (NML) hosted at LGC (formerly the Laboratory of the Government Chemist) and the National Engineering Laboratory (NEL).

NPL's research facilitates the development of primary standards and cutting-edge instrumentation. It also interacts with private businesses, hospitals, and academic institutions through collaborative R&D as well as supplying commercial calibration, testing, consultancy, measurement, and training services to such organizations. Much of the scientific work at NPL happens under the Science & Engineering Directorate (SED), which is divided into nine departments, and each department is further divided into groups. Figure 1 presents the organisational chart for the SED, as of February 2024. The red boxes represent the departments, and the green boxes represent the respective groups under each department.

1.2 INTRODUCTION TO NMS INDICATORS

Each year, NPL collates a list of NMS indicators on behalf of the DSIT, which are designed to gather evidence against the delivery of the themes of the UK Measurement Strategy published in March 2017. These indicators, outlined in Table 1, show the activities and outputs within the three main NMS laboratories: NPL, NML at LGC, and NEL. The indicators support the NMS in delivering its strategy and cover the key themes of research, trade and standards, innovation, and skills / knowledge transfer.

Table 1: Mapping of Existing NMS Indicators on to the Strategic Themes

Theme Title	Theme Description	Activities	Outputs
Research	Delivering a world-leading measurement infrastructure.	1.1 Number of academic collaborators	1.2 Number of peer reviewed papers
Trade & Standards	Ensuring good policy, standards, and regulation.	2.1 Number of active measurement services and reference materials	2.2 Income from measurement services and reference materials 2.3 Publication of new or amended standards with an NMS contribution
Innovation	Getting better connected to end users to deliver impact.	3.1 Number of business collaborators 3.2 Number of new active measurement services and reference materials	3.3 Leveraged income from collaborative R&D and consultancy
Skills	Improving the UK's measurement skills.		4.1 Number of people accessing measurement training through web resources 4.2 Participation in face-to-face training

1.3 RATIONALE FOR FOCUSING ON DEPARTMENT-LEVEL METRICS

Our primary objective for undertaking this analysis is to understand NPL's portfolio of scientific work and how it occupies different bits of the science impact landscape. This will help us capture heterogeneity in the activities of different parts of the organisation. We also want to understand how the NEL and NML fit into the different bits of the science impact landscape.

For the NPL, data on NMS indicators is compiled annually at the group level. However, there are over 30 scientific groups that sit under 9 departments, as shown in Figure 1. Any analysis that aims to identify patterns across different parts of the organisation would get intractable very quickly if use the scientific groups as the units of analysis. Moreover, an analysis containing so many groups will also make any kind of data visualisation a challenge. On the other hand, it will be easier to analyse, identify patterns, and visualise data across departments since there are a fewer number of them. This provides the primary rationale to focus on department-level metrics. Moreover, frequent restructuring of the SED in response to the changing needs and priorities means that groups can merge / split over time, making it difficult to track the same set of groups across different years.[1] Comparatively, departments are more stable over time. Although even departments have merged and split over the years, it is easier to map groups (past & existing ones) to the departments under the current

[1] An example of group restructuring: "Materials Characterisation (Matchar)" and "Materials Testing (Mattest)" used to be two different groups under the Materials and Mechanical Metrology department until 2021, but they were merged into a single group called "Advanced Engineering Materials (AEM)" in 2022. So, if we perform any analysis at group level, we will observe discontinuity where Matchar and Mattest would show up in the data until 2021, and AEM would show up only 2022 onwards. More importantly, the analysis gets tougher when a group splits as there will be no history of the newly formed groups or when a group permanently shuts down.

organisational structure.[2] This provides a secondary rationale to track department-level metrics.

However, since the data on NMS indicators is compiled at the group level, additional steps are required to correctly compute indicators at the department-level. Simply aggregating the indicators for all the groups that lie under a department might lead to double counting of certain indicators (especially count variables such as number of papers, collaborators, etc.). For example, suppose two groups within the same department collaborate on a research paper. In the group-level indicators data, that paper will be tagged to both groups. However, when we are constructing department-level indicators, that paper should be counted only once for the department (because both groups belong to the same department). Thus, simply adding up the number of papers for each group in a department to obtain the department's total would lead to double (or multiple) counting of such papers and lead to an overcount of the total number of papers published by the department. On the other hand, if two or more groups from different departments collaborate on a research paper, then that paper should be counted for each of the respective departments separately. Therefore, a crucial step while computing department-level indicators involved de-duplicating count variables. Appendix 1 presents a snapshot of double counting errors that would have occurred without de-duplication for two such count variables.

[2] An example of department restructuring: At the start of 2019, the SED was called the Operations Directorate and it comprised of four departments – Chemical, Medical & Environmental Science; Engineering, Materials & Electrical Science; Quantum Science; & Data Science. The current nine departments were created by further splitting these four departments.

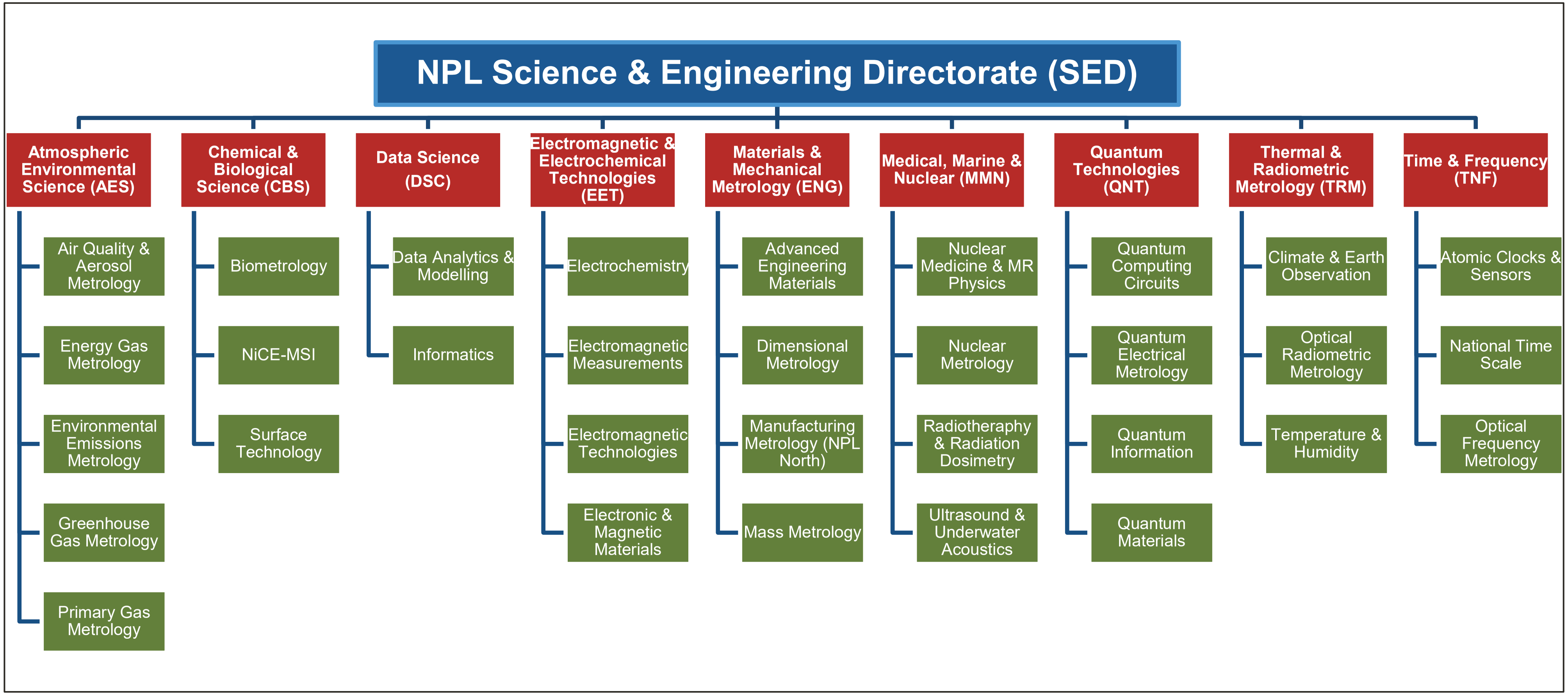

Figure 1: Organisational Chart for NPL's Science & Engineering Directorate

2 DATA

In this report, we utilise the NMS indicators data from 2017-2022.[3] The reason for using 2017 as the starting point for this analysis is that the SED at NPL underwent a major organisational re-structuring in 2016-17. Although, we have data on NMS indicators going back to 2015, mapping some of the old scientific groups that existed prior to 2017 to the current departments is not straightforward. Therefore, it is not possible to construct department-level metrics for some indicators in our dataset prior to 2017. The NEL and NML are comparable in size and the amount of NMS funding they receive to some of NPL's departments. Therefore, in this analysis, we treat them as "departments" that lie under the NMS. This report presents two types of results: one that includes NEL and NML along with NPL's nine SED departments, and the other that only contains NPL's SED departments.

3 METHOD

3.1 DIMENSIONALITY REDUCTION AND PRINCIPAL COMPONENT ANALYSIS

Up until 2022, there were ten NMS indicators being tracked annually, as shown in Table 1. Appendix 2: Definitions of Existing NMS INdicatorspresents the definitions of these indicators. Comparing different SED departments across each of those indicators would get cumbersome, possibly intractable, and difficult to visualise. To overcome the problem of high dimensionality[4], there are techniques in statistics that transform the data from a high-dimensional space into a low-dimensional space such that the low-dimensional representation retains most of the variance from the original dataset. In simple terms, the goal of dimensionality reduction techniques is to transform original data such that most of the meaningful information in the data can be captured with fewer variables. Such techniques are commonly divided into linear and nonlinear approaches.

Principal Component Analysis (PCA) is a dimensionality reduction technique that performs a linear mapping of the original data to a lower dimensional space in such a way that the variance of the data in the low-dimensional space is maximised. It helps in reducing the number of variables in an analysis by describing a series of uncorrelated, unit-length linear combinations of the variables, called principal components, that contain most of the variance. Thus, the first principal component has the maximal overall variance of all possible unit-length linear combinations of the variables. The second principal component has maximal overall variance among all unit-length linear combinations that are uncorrelated to the first principal component, and so on. And the last principal component has the smallest variance among all unit-length linear combinations of the variables. All principal components combined contain the same information as the original data, however, the important information is partitioned over the components in a particular way: the components are orthogonal (uncorrelated) to each other, and earlier components contain more information than later components. In this way, PCA helps increase interpretability while preserving maximum amount of information, thus enabling easier visualisation of multidimensional data.

3.2 EIGENVALUE CRITERION IN PCA

Technically speaking, the amount of variance retained by each principal component is measured by its eigenvalue. The first principal component has the highest eigenvalue, followed by the second principal component, and so on. The sum of the eigenvalues of each principal component is equal to the number of variables entered into the PCA; however, the eigenvalues will range from greater than one to near zero. An eigenvalue of 1 means that the principal component would explain about one variable's worth of the variability. Since we

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[3] All monetary indicators (e.g., income from measurement services and reference materials) are in real terms. That is, they have been deflated (using 2022 as the base year) to ensure consistency across different years by accounting for inflation. GDP deflators used in this analysis are based on the Office for National Statistics (ONS) Quarterly National Accounts release for September 2023, which can be downloaded using the following link: https://www.gov.uk/government/statistics/gdp-deflators-at-market-prices-and-money-gdp-september-2023-quarterly-national-accounts

[4] In statistics, the number of input variables or features for a dataset is often referred to as its dimensionality.

perform PCA for dimensionality reduction, ideally, a component would be relevant if it explains at least one variable's worth of the variance. Otherwise, we are better off using the variable instead of the component. Therefore, the eigenvalue criterion states that only components with eigenvalues greater than 1 should be retained.[5]

3.3 SIMPLE GRAPHICAL DEPICTION OF PCA

For example, consider a simple dataset containing two variables $\boldsymbol{x}$ and $\boldsymbol{y}$ as shown in Figure 2. Then, we can think of a linear transformation of the original data in terms of the rotated axes $\boldsymbol{u}$ and $\boldsymbol{v}$, such that $\boldsymbol{u}$ and $\boldsymbol{v}$ are orthogonal, linear combinations of the original axes $\boldsymbol{x}$ and $\boldsymbol{y}$. That is, we can write the expressions:

$$\boldsymbol{u} = a_1\boldsymbol{x} + b_1\boldsymbol{y}$$

$$\boldsymbol{v} = a_2\boldsymbol{x} + b_2\boldsymbol{y}$$

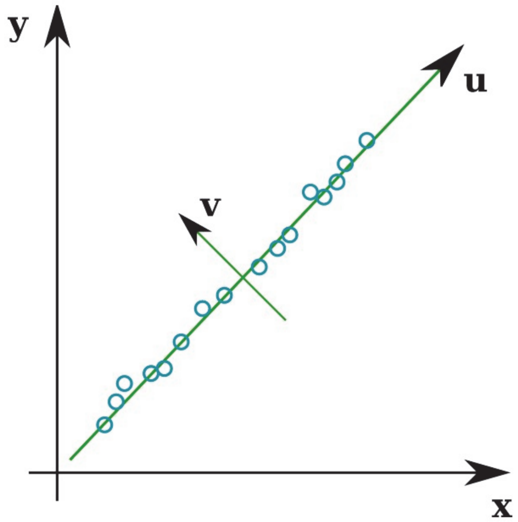

Figure 2: Visual representation of PCA

where a_1, a_2, b_1, and b_2 can be thought of as the weights (loadings) of each existing variable in the new principal components. The transformation allows us to see that most of the variance in the original data is captured along the $\boldsymbol{u}$-axis, whereas there is very little variance along the $\boldsymbol{v}$-axis. It is also important to note that by performing such transformations, the new axes might have new interpretations that are different from the original variables. The next section presents results when we apply PCA to department-level metrics. In the analysis that follows, all indicators/variables have been normalised in per staff terms before applying PCA. This is done to account for the size difference across departments. That is,

$$\text{Normalized Variable} = \frac{\text{Value of the Variable}}{\text{Staff Count of the Department}}$$

4 RESULTS

4.1 PCA APPLIED TO NPL'S NINE SED DEPARTMENTS

We start by applying PCA to the dataset containing NPL's nine SED departments. Out of the ten indicators shown in Table 1, we drop the ones that are discrete and sparsely populated as they do not impact the analysis. These include variables like 'number of training participants (web and face-to-face)' and the 'number of new active measurement services and reference materials.' We also notice that excluding 'leveraged income from collaborative R&D and consultancy' does not impact the analysis. Lastly, we exclude the 'number of active

[5] The eigenvalue criterion is not a hard rule of thumb. In some cases, a component with an eigenvalue marginally less than 1 may be retained if it demonstrates a useful relationship between variables that would not be captured if the component is not retained.

measurement services and reference materials' from the analysis.[6] Therefore, the main specification of the analysis consists of the remaining five variables as shown in Table 2.

We observe that the first principal component has an eigenvalue of 2.79 and accounts for roughly 56% of the variance in the original data. The second principal component has an eigenvalue of 0.97, which is marginally less than 1, but it accounts for roughly 19% of the variance.[7] Together, the first two principal components account for more than 75% of the total variability in the data. As the next step, we apply rotations to these principal components while preserving their orthogonality.[8]

Next, we examine the loadings of each variable in the two rotated components. The following three variables have the highest weights in the first rotated component: number of academic collaborators, number of business collaborators, and number of peer reviewed papers. These variables reflect activities and outputs that pertain to R&D and innovation. Therefore, we interpret the first component as a dimension along which we can measure "Collaborative Innovation." Likewise, the following variables have the highest weights in the second rotated component: income from measurement services and reference materials, and publication of new or amended standards with an NMS contribution. Both these variables reflect activities and outputs that pertain to pertain to core measurement capabilities. Hence, we interpret the second component as a dimension along which we can measure "Measurement Services" capability. Another way to interpret the two components is in terms of the impacts they capture. Measurement services and standards reflect the current, direct impacts that NPL and other NMS laboratories generate by supporting UK businesses. On the other hand, R&D activities and collaborations are more reflective of future impacts.

Table 2: Rotated Components with Variable Loadings

Variable	**Component 1 *(Collaborative Innovation)***	**Component 2 *(Measurement Services)***	**Unexplained[9]**
Income from measurement services and reference materials	-0.2341	0.4848	0.3503
Number of academic collaborators	0.5787	-0.1005	0.1192

[6] The reason for excluding this variable is explained in Appendix 3: Alternate Specifications for PCA. Moreover, in Appendix 3: Alternate Specifications for PCA we perform PCA with an alternate specification where we include 'number of active measurement services and reference materials' and 'number of new active measurement services and reference materials.'

[7] Although component 2 has an eigenvalue that is marginally less than 1, we retain it as it shows an important relationship between variables that is crucial for the analysis. Moreover, currently we only have six years of data. But we expect that more years of data in a future analysis will enable this component to capture a higher variance.

[8] We use the default *varimax* rotation, which maximizes the variance of the squared loadings within the principal components. Rotating the principal components helps improve the interpretability and meaning of the components. By default, PCA selects the principal components that maximize the variance of the data, without considering the relationships between the variables. However, this can sometimes result in components that are difficult to interpret and may not capture the underlying structure of the data. Therefore, rotating the principal components can enhance the interpretability of the components by aligning them with the underlying patterns in the data. This can make the results of PCA more useful and actionable for data analysis and decision-making. The first rotated component accounts for roughly 46% of the variance in the data (as compared to 56% accounted by the first principal component). On the other hand, the second rotated component accounts for roughly 29% of the variance in the data (as compared to 19% accounted by the second principal component). Note that the two rotated components cumulatively account for the same amount of variance (~75%) as the first two principal components, which is not surprising. In other words, rotation has the effect of trading off the importance of the first principal component to improve interpretability. But it does not impact the total variance captured by the two components.

[9] As discussed in the previous section, all principal components combined contain the same information as the original data. However, since we only retain two principal components here, there is some loss of information compared to the original data. That is, some of the variances in the original variables are unaccounted for or "unexplained." The last column captures the residual variance for each variable that is unaccounted for by the two principal components.

Number of business collaborators	0.588	0.0911	0.2757
Number of peer reviewed papers	0.4826	-0.0727	0.3985
Publication of new or amended standards with an NMS contribution	0.1779	0.861	0.09606

Using the relative weights for the variables in each component from Table 2, we can predict the "scores" along that component for each department in a given year. Figure 3 presents the average score from 2017-2022 for the nine SED departments along the two components: Collaborative Innovation & Measurement Services. It is worth noting that the scores are centred around zero, that is, the red lines passing through (0,0) represent the average scores for the respective components across the nine departments. Therefore, Figure 3 represents the position of each department along the two components with respect to the overall NPL average. In other words, the red lines divide the graph into four regions / quadrants:

- The bottom left quadrant denotes scores below the NPL average along both components.
- The bottom right quadrant denotes scores above the NPL average along the "Collaborative Innovation" component but scores below the NPL average along the "Measurement Services" component.
- The top left quadrant denotes scores below the NPL average along the "Collaborative Innovation" component but scores above the NPL average along the "Measurement Services" component.
- The top right quadrant denotes scores above the NPL average along both components.

By design, it is not possible for all departments to lie in the top right quadrant. The light blue line represents the line of best fit for the nine points.

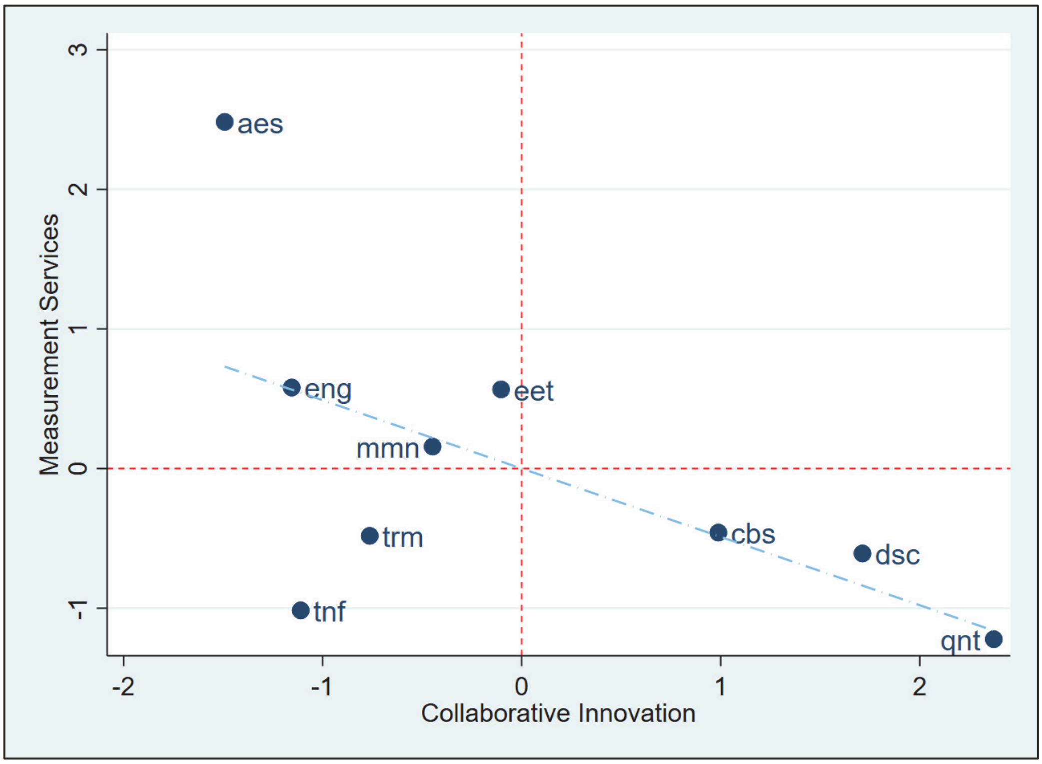

Figure 3: NPL's portfolio across Collaborative Innovation & Measurement Services[10]

4.1.1 Key takeaways / Commentary

Here are the key takeaways from Figure 3:

- **There is an apparent trade-off between Collaborative Innovation and Measurement Services, as denoted by the downward sloping line of best fit.** That is, departments either specialise primarily in the provision of measurement services and reference materials or in collaborative activities that result in innovation. However, resource and time constraints would mean that it is difficult for departments to prioritise both kinds of activities. Another way to interpret this result is that there is a "Production Possibility Frontier," where departments are trading off Current Impacts (i.e., provision of measurement services) for Future Impacts (i.e., collaborative innovation activities).
- **Broadly speaking, the specialisation of a department can be categorised by the "age" of the field it operates in.** Departments that score highly along the Collaborative Innovation component include Quantum Technologies, Data Science, and Chemical & Biological Sciences. All three departments operate in fields that either are relatively new and at nascent stages of their development. Therefore, their natural focus is more towards R&D activities. On the other hand, departments that rank highly along the Measurement Services component include Atmospheric Environmental Science, Materials and Mechanical Metrology, Electromagnetic & Electrochemical Technologies, and Medical, Marine & Nuclear. These departments operate in fields that have been around for longer and where the R&D is relatively more established, thereby enabling departments to focus more on activities that use this existing R&D to generate high current impact.

[10] Acronyms: aes – Atmospheric Environmental Science; cbs – Chemical & Biological Sciences; dsc – Data Science; eet – Electromagnetic & Electrochemical Technologies; eng – Materials and Mechanical Metrology (previously known as Engineering); mmn – Medical, Marine, & Nuclear; qnt – Quantum Technologies; tnf – Time & Frequency; trm – Thermal & Radiometric Metrology.

- **Most departments lie close to the line of best fit, but there are some outliers.** One of these outliers is the Time & Frequency (TNF) department, which is significantly below average along both components. However, we believe that its true position on the vertical axis is possibly downward skewed. Recall that income from measurement services and reference materials is one of the two variables that has a high weight in the Measurement Services component. Departments receive this kind of income from paid-for-services and providing UKAS accredited calibrations. However, unlike other departments, the TNF department gives away its primary measurement services for free in the form of broadcast signals. Calibrations are not an important part of its repertoire either. Thus, there are spillovers / fanout benefits from the service that TNF department provides that are not entirely captured in this principal component. As for the Collaborative Innovation component, in recent years the focus of the department has shifted more towards delivering the National Timing Centre (NTC) programme. We are currently undertaking an ambitious programme of monitoring and evaluation specifically for the NTC programme, where we aim to track new indicators beyond the NMS indicators. Over time, we might be able to capture more benefits that come out of the TNF department.
  The other outlier is the Atmospheric Environmental Science (AES) department, which scores very highly on the Measurement Services component. There are a couple of factors at play here. First, it offers crucial services in environmental monitoring and gas standards that have been widely adopted by commercial and non-commercial customers. This has consistently placed AES among the top two or three departments in terms of revenue generated through measurement services and reference materials. Moreover, remember that in this analysis, we normalise the variables by staff count and AES usually lies near the median (in terms of staff count). Therefore, it is not surprising to see AES have a very high value for these variables in per staff terms.
- **We hypothesize that in its present form, the Measurement Services component mainly captures direct, monetizable impacts. In other words, being below the line of best fit along this component does not necessarily imply that the department is poor at generating Current Impacts.** We think that Current Impacts are comprised of the following two bits: direct, monetizable impacts and indirect, non-monetizable impacts. The latter bit can be thought of as a measure of externalities or spillovers. Therefore, there is an additional dimension in Figure 3 that measures the scale of indirect, non-monetizable impacts. But this third dimension is unobservable in practice because the metrics only allow us to measure the first bit (i.e., the direct, monetizable impacts).
  If we assume that there is no slack in the system and that there is no underutilisation of resources in any department[11], then we can infer the scale of the indirect, non-monetizable impacts by using the vertical distance of a department from the line of best fit in Figure 3. The idea here is that we can think of a three-dimensional space, where the axes represent the following: monetizable bit of the current impacts, non-monetizable bits of the current impacts, and future impacts. Under the assumption that there is no slack in the system, each department would be at the production possibility frontier (which would be a plane in the 3-D space). The total current impacts are a sum of the monetizable and the non-monetizable bits. However, since we cannot observe the non-monetizable bit, the residuals (i.e., vertical distance from the line of best fit) in Figure 3 can used to infer this bit.
  Therefore, as seen in the above example for the T&F department, it is possible that a department might be providing measurement services that are not being monetized but are still generating benefits. Therefore, being below the line reflects the possibility

[11] That is, we assume that each department is operating at the frontier. Note that we interpreted the line of best fit as representing a production possibility frontier. In the case of a three-dimensional space, the production possibility frontier becomes a plane (instead of a line).

of spillovers / fanout that are not captured via the variables included in the Measurement Services component. This does not mean that a department with a positive score does not generate spillovers, but it just reflects a better ability of these departments to monetize the services that generate current impacts. In this way, the PCA provides a neat way to visualise the scale of externalities / spillovers that a department might be generating.

4.2 PCA APPLIED TO NPL'S NINE SED DEPARTMENTS + NEL + NML

Next, we extend the PCA to include NEL and NML. Although NEL and NML are independent laboratories, their sizes are comparable to some of the larger SED departments at NPL. Therefore, we treat NEL and NML as departments here and the following analysis is based on data for eleven "departments." Results from the analysis are presented in Next, we examine the loadings of each variable in the two rotated components, which look like the loadings in Table 2. We interpret the first component as a dimension along which we can measure "Collaborative Innovation" or "Future Impacts" and the second component as a dimension along which we can measure "Measurement Services" or "Current Impacts."

Table 3, which look similar to the NPL-only analysis from the previous section.

There are two principal components with eigenvalues greater than 1. We observe that the first principal component has an eigenvalue of 2.66 and accounts for roughly 53% of the variance in the original data. The second principal component has an eigenvalue of 1.07 and accounts for roughly 21% of the variance. Together, the first two principal components account for approximately 75% of the total variability in the data. As the next step, we apply rotations to these principal components while preserving their orthogonality.[12]

Next, we examine the loadings of each variable in the two rotated components, which look like the loadings in Table 2. We interpret the first component as a dimension along which we can measure "Collaborative Innovation" or "Future Impacts" and the second component as a dimension along which we can measure "Measurement Services" or "Current Impacts."

Table 3: Rotated Components with Variable Loadings

Variable	Component 1 *(Collaborative Innovation)*	Component 2 *(Measurement Services)*	Unexplained
Income from measurement services and reference materials	-0.2247	0.5247	0.3541
Number of academic collaborators	0.5919	-0.0871	0.09985
Number of business collaborators	0.506	0.0003	0.3972
Number of peer reviewed papers	0.5519	0.0054	0.2864
Publication of new or amended standards with an NMS contribution	0.1964	0.8468	0.1307

Using the relative weights for the variables in each component from Table 3, we can predict the "scores" along that component for each of the eleven "departments". Figure 4 presents the average score from 2017-2022 for the eleven "departments" along the two components: Collaborative Innovation & Measurement Services. It is worth noting that the scores are centred around zero, that is, the red lines passing through (0,0) represent the average scores

[12] The first rotated component accounts for roughly 47% of the variance in the data (as compared to 53% accounted by the first principal component). On the other hand, the second rotated component accounts for roughly 28% of the variance in the data (as compared to 21% accounted by the second principal component). Note that the two rotated components cumulatively account for the same amount of variance (~75%) as the first two principal components.

for the respective components across the eleven "departments". The light blue line represents the line of best fit for the eleven points.

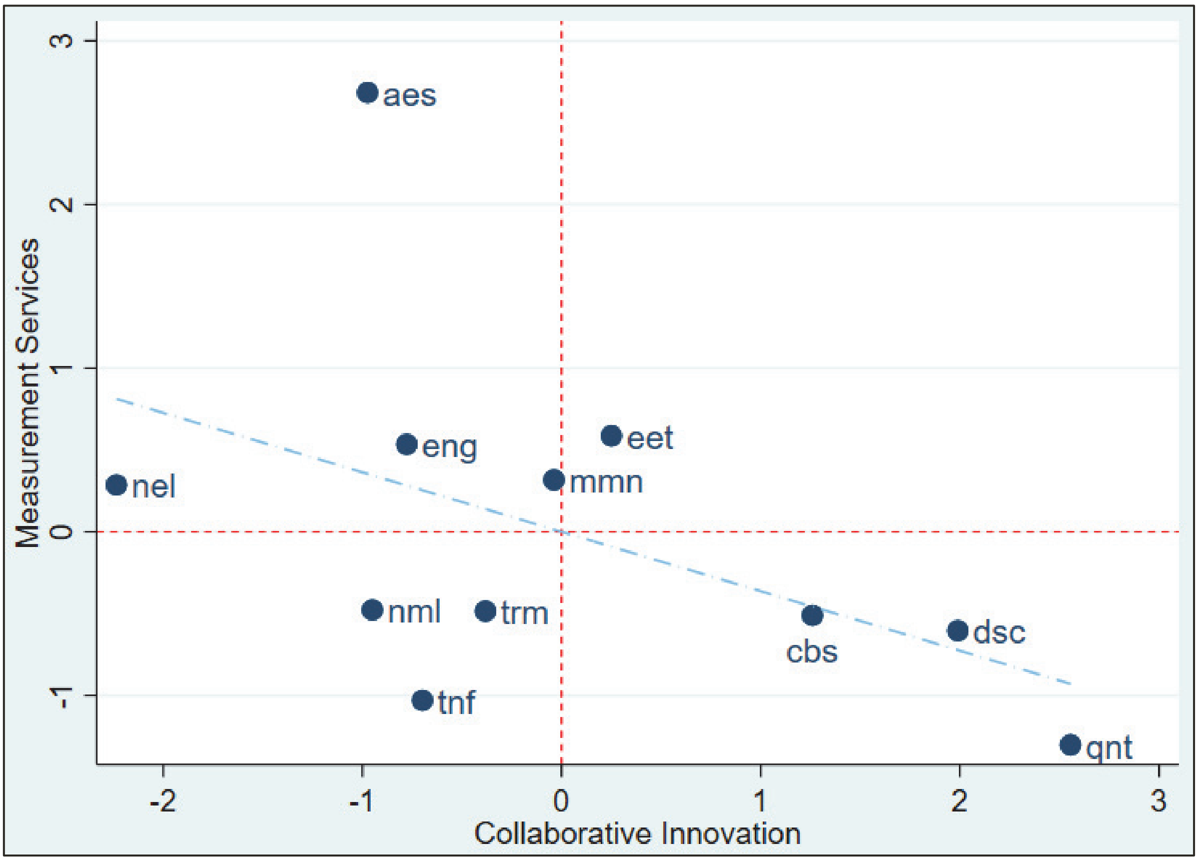

Figure 4: NPL's, NEL's & NML's portfolio across Collaborative Innovation & Measurement Services[13]

4.2.1 Key Takeaways / Commentary

Here are the key takeaways from Figure 4:

- **The trade-off between Collaborative Innovation and Measurement Services is evident, as denoted by the downward sloping line of best fit, even after adding NEL and NML into the analysis.** The rationale for this result is the same as in the previous section. Departments either specialise primarily in the provision of measurement services and reference materials or in collaborative activities that result in innovation. However, resource and time constraints would mean that it is difficult for departments to prioritise both kinds of activities. Another way to interpret this result is that there is a "Production Possibility Frontier," where departments are trading off Current Impacts (i.e., provision of measurement services) for Future Impacts (i.e., collaborative innovation activities).
- **NML lies in the bottom left quadrant.** However, we believe that its position along the vertical axis is possibly downward skewed. NML specialises in the provision of a very large number of measurement services and reference materials, even though the income it generates through those services is relatively smaller compared to

[13] Acronyms: aes – Atmospheric Environmental Science; cbs – Chemical & Biological Sciences; dsc – Data Science; eet – Electromagnetic & Electrochemical Technologies; eng – Materials and Mechanical Metrology (previously known as Engineering); mmn – Medical, Marine, & Nuclear; nel – National Engineering Laboratory; nml – National Measurement Laboratory; qnt – Quantum Technologies; tnf – Time & Frequency; trm – Thermal & Radiometric Metrology.

certain other departments.[14] However, since we do not include the variables 'number of active measurement services and reference materials' and 'number of new measurement services and reference materials' into the analysis here, that fails to capture the breadth of NML's impact through the provision of such services. In Appendix 3: Alternate Specifications for PCA, we present an alternate specification that includes these variables.

- **NEL lies in the top left quadrant.** This is not surprising because NEL does very little in terms of R&D. Its primary focus is on flow measurement, which leads to the provision of niche services that are highly monetizable.

5 CONCLUSION AND SCOPE FOR FUTURE WORK

This report presents a scoping study that contains the beginnings of a quantitative framework to construct and analyse department-level metrics. These metrics help enhance our understanding of the portfolio of NPL's SED departments and how they occupy different bits of the science impact landscape. We extend this analysis to include NEL and NML.

We apply Principal Component Analysis to the department-level metrics that are constructed using NMS indicators data. The analysis reveals heterogeneity in the nature of work that the NEL, NML, and different departments within NPL specialise in. The key takeaway from the PCA is that their activities can be categorised into two broad buckets: Measurement Services (i.e., activities that generate Current Impacts) and Collaborative Innovation (i.e., activities that have the potential to generate Future Impacts). There is an apparent trade-off between the two kinds of activities, which can possibly be explained by time and resource constraints as it is difficult for departments to allocate resources to both kinds of activities. Moreover, different departments operate in fields that are in very different stages of development, which can also explain heterogeneity across these departments. Moreover, we believe that Current Impacts are comprised of the observable, monetized impacts (i.e., direct impacts) and the unobservable, non-monetized impacts (i.e., indirect impacts / spillovers / externalities). Under the assumption that there is no slack in the system, the PCA provides a neat way to visualise the scale of externalities / spillovers that a department might be generating.

The current analysis has certain caveats and scope for improvement that can be addressed in future work. First, the analysis is based on a relatively small sample set of nine departments (eleven after including NEL and NML) and six years of data (2017-2022). As we accumulate more years of data, we can expect the analysis to become more powerful. Second, currently we rely on variables coming from the NMS indicators data. The ongoing work on NMS metrics revision will provide an expanded list of indicators for use in the future analyses. Third, it is possible to gain additional insights by splitting existing indicators. For example, measurement services and reference materials are bundled in the existing indicators data.[15] However, the two represent slightly different ways of supporting measurement capabilities and the ability to monetise them might be hugely different. It would be interesting to see whether any new patterns would emerge in the PCA if we separated the income earned from (and count of) measurement services and reference materials. Lastly, there is scope to expand the analysis to include new variables that do not feature in the NMS indicators but still capture a wealth of information about how the different laboratories operate. Despite these caveats, this report establishes a new quantitative framework that

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[14] For instance, in 2022, NML provided 124 measurement services and reference materials. This is higher than any other department's count. The total income it made from sales of those services and reference materials was £720k. On the other hand, NEL only provided 12 services and reference materials but had an income of £2.83 million from the sales of those services and reference materials. Likewise, NPL's Atmospheric Environmental Science department also made a similar income (£2.83 million) from the sales of 28 measurement services and reference materials.

[15] That is, the current indicators include 'number of active measurement services and reference materials' and 'income from the sales of measurement services and reference materials.' In the future, we can use the annual Esteem Survey as a guide to develop a more comprehensive capability-level study.

provides a foundation to better understand the similarities and differences in the activities of NEL, NML, and NPL's different departments.

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7 APPENDICES

7.1 APPENDIX 1: IMPORTANCE OF DE-DUPLICATING COUNT VARIABLES

The table below presents a snapshot of double counting errors for two variables – the counts of academic and business collaborators. The first two columns represent the values before de-duplication, where we simply aggregate the group-level counts for the respective variables to obtain the department totals. The next two columns present the de-duplicated values. The last two columns show the double counting errors, defined as the difference between the aggregate and the de-duplicated values. For some departments, double counting error would have been a significant fraction of the true (de-duplicated) values.

Table 4: Snapshot of Double Counting Errors

		Aggregate Values (Non de-duplicated)		De-duplicated Values		Double Counting Error	
Year	Department	No. of Academic Collaborators	No. of Business Collaborators	No. of Academic Collaborators	No. of Business Collaborators	No. of Academic Collaborators	No. of Business Collaborators
2021	Atmospheric Environmental Science	73	81	63	74	10	7
	Chemical & Biological Sciences	158	217	122	189	36	28
	Data Science	123	82	109	82	14	0
	Electromagnetic & Electrochemical Technologies	233	243	168	205	65	38
	Materials and Mechanical Metrology (Engineering)	149	233	116	220	33	13
	Medical, Marine & Nuclear	273	180	199	167	74	13
	Quantum Technologies	237	246	177	201	60	45
	Time & Frequency	145	51	115	51	30	0
	Thermal & Radiometric Metrology	179	148	120	113	59	35
2020	Atmospheric Environmental Science	86	82	78	63	8	19
	Chemical & Biological Sciences	177	125	146	116	31	9
	Data Science	137	143	103	100	34	43
	Electromagnetic & Electrochemical Technologies	244	299	178	264	66	35
	Materials and Mechanical Metrology (Engineering)	152	180	112	167	40	13
	Medical, Marine & Nuclear	251	107	184	74	67	33
	Quantum Technologies	297	269	197	173	100	96
	Time & Frequency	90	55	61	48	29	7
	Thermal & Radiometric Metrology	79	51	75	52	4	-1

7.2 APPENDIX 2: DEFINITIONS OF EXISTING NMS INDICATORS

Indicator	Definition
Number of academic collaborators	The collaboration includes below mechanisms: • Collaborative publications (peer-reviewed papers), • Collaboration in grant funded projects, • Collaboration in commercial research contracts, • Collaborations in terms of joint students, guest workers, and secondments, • Collaborations in NMS-run inter-laboratory studies Every unique academic organization collaborated within above mechanisms is counted as an 'academic collaborator'. Type of an organization is decided using 'Global Research Identifier Database (GRID)'
Number of peer reviewed papers	The number of papers published in peer-reviewed journals from the NMS laboratories in year, excluding conference proceedings papers.
Number of active measurement services and reference materials	This indicator represents a count of the types of measurement services and reference materials available from the NMS laboratories that received any income within the year. A service type is defined as the measurement, or

	calibration of a physical property or material, with no subdivision of services made by measurement range or environment. A reference material type is defined by the main element/material and its carrier but are not sub-divided by concentration or any other physical property.
Income from measurement services and reference materials	Revenue accrued in year, from the sales of the measurement services and reference materials described in 2.1.
Publication of new or amended standards with an NMS contribution	Number of publications of new or amended standards by the NMS contribution.
Number of business collaborators	The collaboration mechanism includes below mechanisms: • Collaborative publications (peer-reviewed papers), • Collaboration in grant funded projects, • Collaboration in commercial research contracts, • Collaborations in terms of joint students, guest workers, and secondments, • Collaborations in NMS-run inter-laboratory studies Every unique company collaborated within above mechanisms is counted as an ‘business collaborator’. Type of an organization is decided using ‘Global Research Identifier Database (GRID)’
Number of new active measurement services and reference materials	This indicator represents a count of new active measurement services and reference materials available from the NMS laboratories.
Leveraged income from collaborative R&D and consultancy	Revenue accrued in year, from the sales of collaborative R&D and consultancy services.
Number of people accessing measurement training through web resources	The total number of people accessing measurement training through web resources within a year. Web resources include both ‘e-learning’ and using the ‘online’ platforms.
Participation in face-to-face training	The total number of people accessing measurement training through physically participating into a classroom within a year.

7.3 APPENDIX 3: ALTERNATE SPECIFICATIONS FOR PCA

In the main specification presented in Section 4, we excluded “number of active measurement services and reference materials” and “number of new measurement services” from the PCA as these variables are quite sparsely populated. However, we believe that excluding these variables might put certain “departments” at a disadvantage. For example, NML specialises in the provision of a massive number of measurement services and reference materials, even though the income it generates through those services is relatively smaller compared to certain other departments. In the main specification, NML scores low along the Measurement Services component despite consistently providing the highest number of measurement services among all departments. Therefore, we introduce the two variables to understand how they impact the analysis.

7.3.1 Alternate Specification Applied to NPL's Nine SED Departments

We rerun the PCA using the alternate specification for NPL's nine SED departments, which gives two principal components with an eigenvalue greater than 1. The first principal component has an eigenvalue of 3.27 and accounts for roughly 47% of the variance in the original data. The second principal component has an eigenvalue of 1.20 and it accounts for roughly 17% of the variance. Together, the first two principal components account for approximately 64% of the total variability in the data. Next, we apply rotations to these principal components while preserving their orthogonality.[16]

Next, we examine the loadings of each variable in the two rotated components. The results are presented in Table 5. The first component looks very similar to the Collaborative Innovation component from the main specification, with the following three variables carrying the highest weights: number of academic collaborators, number of business collaborators, and number of peer reviewed papers. Of the two new variables included in this specification, the 'number of active measurement services and reference materials' now has the highest weight in the second component, along with 'income from measurement services and reference materials' and 'publication of new or amended standards with an NMS contribution.' Thus, the interpretation of the second component remains the same as in the main specification, i.e., it is a dimension along which we can measure Measurement Services capabilities. However, it is evident that in addition to the value (income) from the provision of measurement services and reference materials, the number of measurement services and reference materials are also important to understand a department's capability along this dimension.

Table 5: Rotated Components with Variable Loadings

Variable	Component 1 *(Collaborative Innovation)*	Component 2 *(Measurement Services)*	Unexplained
Number of active measurement services and reference materials	0.0646	0.6322	0.2123
Income from measurement services and reference materials	-0.0634	0.6157	0.09229
Number of academic collaborators	0.5312	-0.13	0.1699
Number of business collaborators	0.3712	-0.193	0.4539
Number of peer reviewed papers	0.6155	0.1056	0.2363
Publication of new or amended standards with an NMS contribution	-0.0101	0.3533	0.7231
Number of new measurement services	-0.4391	-0.1764	0.6481

Using the relative weights for the variables in each component from Table 5, we can predict the "scores" along that component for each of the departments. Figure 5 presents the average score from 2017-2022 for the nine departments along the two components: Collaborative Innovation & Measurement Services. It is worth noting that the scores are centred around zero, that is, the red lines passing through (0,0) represent the average scores for the respective components across the nine departments. The light blue line represents the line of best fit for the nine points.

[16] The first rotated component accounts for roughly 33% of the variance in the data (as compared to 47% accounted by the first principal component). On the other hand, the second rotated component accounts for roughly 31% of the variance in the data (as compared to 17% accounted by the second principal component). Note that the two rotated components cumulatively account for the same amount of variance (~64%) as the first two principal components.

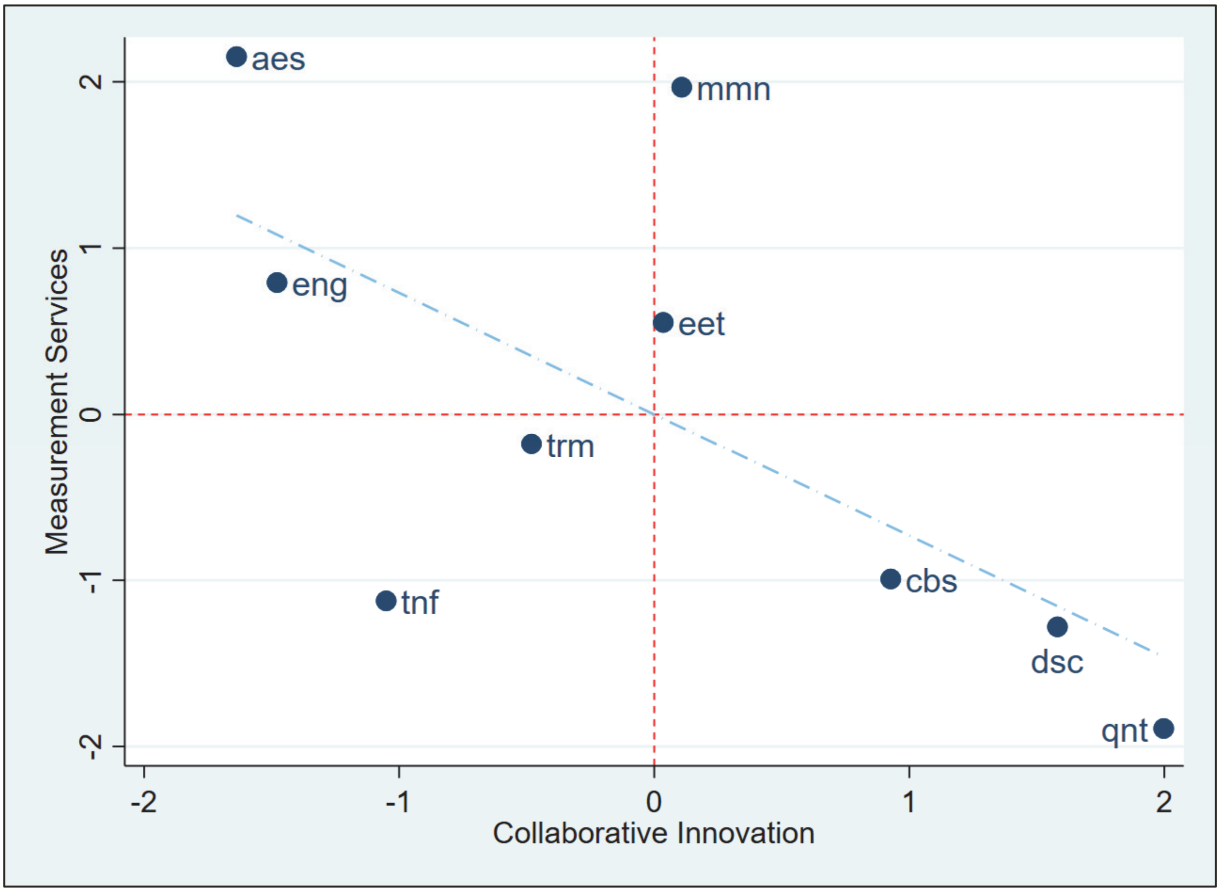

Figure 5: NPL's portfolio across Collaborative Innovation & Measurement Services

Comparing Figure 5 with Figure 3, we notice one stark difference. The Medical, Marine, & Nuclear (MMN) department moves up considerably along the vertical axis in the alternate specification. That is because MMN ranks as NPL's top department within all the years when it comes to the number of active measurement services and reference materials. MMN operates in a highly specialist and regulated areas like defence, nuclear, radiation dose symmetry research, etc. There aren't many players other than NPL that can provide these kinds of specialist services. Thus, there is a good reason why MMN ranks highly on the Measurement Services dimension. Since this variable has a high weightage in the Measurement Services component, that considerably pushes up MMN's score along this dimension. Also, under the alternate specification, MMN and EET are two departments that marginally lie in the upper right quadrant.

7.3.2 Alternate Specification Applied to NPL's Nine SED Departments + NEL + NML

Next, we extend the alternate specification to include NEL and NML as well. Applying PCA to this specification reveals an interesting new pattern. It gives three principal components with an eigenvalue greater than 1. The first principal component has an eigenvalue of 2.91 and accounts for roughly 42% of the variance in the original data. The second principal component has an eigenvalue of 1.39 and it accounts for roughly 20% of the variance. The third principal component has an eigenvalue of 1.08 and it accounts for roughly 15% of the variance. Together, the first three principal components account for approximately 77% of the total variability in the data. Next, we apply rotations to these principal components while preserving their orthogonality.[17]

Next, we examine the loadings of each variable in the three rotated components. The results are presented in Table 6. The first component looks very similar to the Collaborative Innovation component from the main specification, with the following three variables carrying the highest weights: number of academic collaborators, number of business collaborators, and number of peer reviewed papers. On the other hand, the second and third components reveal an interesting pattern. In the NPL-only analysis for the alternate specification, the variables with the highest weights in the second component were the 'number of active measurement services and reference materials', 'income from measurement services and reference materials' and 'publication of new or amended standards with an NMS contribution.' However, once we include NEL and NML, it seems that this component gets split into two. The second component now consists of only the 'number of active measurement services and reference materials' and 'number of new measurement services' as variables with the highest weights. We interpret this as representing the "Breadth of Measurement Services," as a larger number of services possibly mean that a department provides a wider variety of services and reference materials.[18] Meanwhile, there is now a third component that consists of only 'income from measurement services and reference materials' and 'publication of new or amended standards with an NMS contribution' as variables with the highest weights. We interpret this as representing the "Depth of Measurement Services," as a higher income from measurement services and reference materials represents the provision of nice, high value services.

Table 6: Rotated Components with Variable Loadings

Variable	**Component 1** *(Collaborative Innovation)*	**Component 2** *(Breadth of Measurement Services)*	**Component 3** *(Depth of Measurement Services)*	**Unexplained**
Number of active measurement services and reference materials	-0.0077	0.6679	0.2021	0.2102
Income from measurement services and reference materials	-0.237	-0.09	0.5589	0.2722
Number of academic collaborators (deduped)	0.5983	0.0061	-0.0572	0.1002
Number of business collaborators (deduped)	0.4814	-0.0035	-0.0524	0.4084
Number of peer reviewed papers (deduped)	0.5636	-0.0313	0.0758	0.2662
Publication of new or amended standards with an NMS contribution	0.1891	0.1	0.7667	0.2351

[17] The first rotated component accounts for roughly 34% of the variance in the data (as compared to 42% accounted by the first principal component). On the other hand, the second rotated component accounts for roughly 22% of the variance in the data (as compared to 20% accounted by the second principal component). The third rotated component accounts for roughly 21% of the variance in the data (as compared to 15% accounted by the third principal component). Note that the three rotated components cumulatively account for the same amount of variance (~77%) as the first three principal components.

[18] This component, in some ways, can also be thought of as a measure of the externalities / spillovers that we discussed in Section 4.1.1.

Number of new measurement services	-0.0266	0.7313	-0.2171	0.1307

Using the relative weights for the variables in each component from Table 6", we can predict the "scores" along that component for each of the "departments." Figure 6 presents the average score from 2017-2022 for NEL, NML and NPL's nine departments along the two components: Collaborative Innovation & Breadth of Measurement Services. It is worth noting that the scores are centred around zero, that is, the red lines passing through (0,0) represent the average scores for the respective components across the eleven "departments." The light blue line represents the line of best fit for the eleven points.

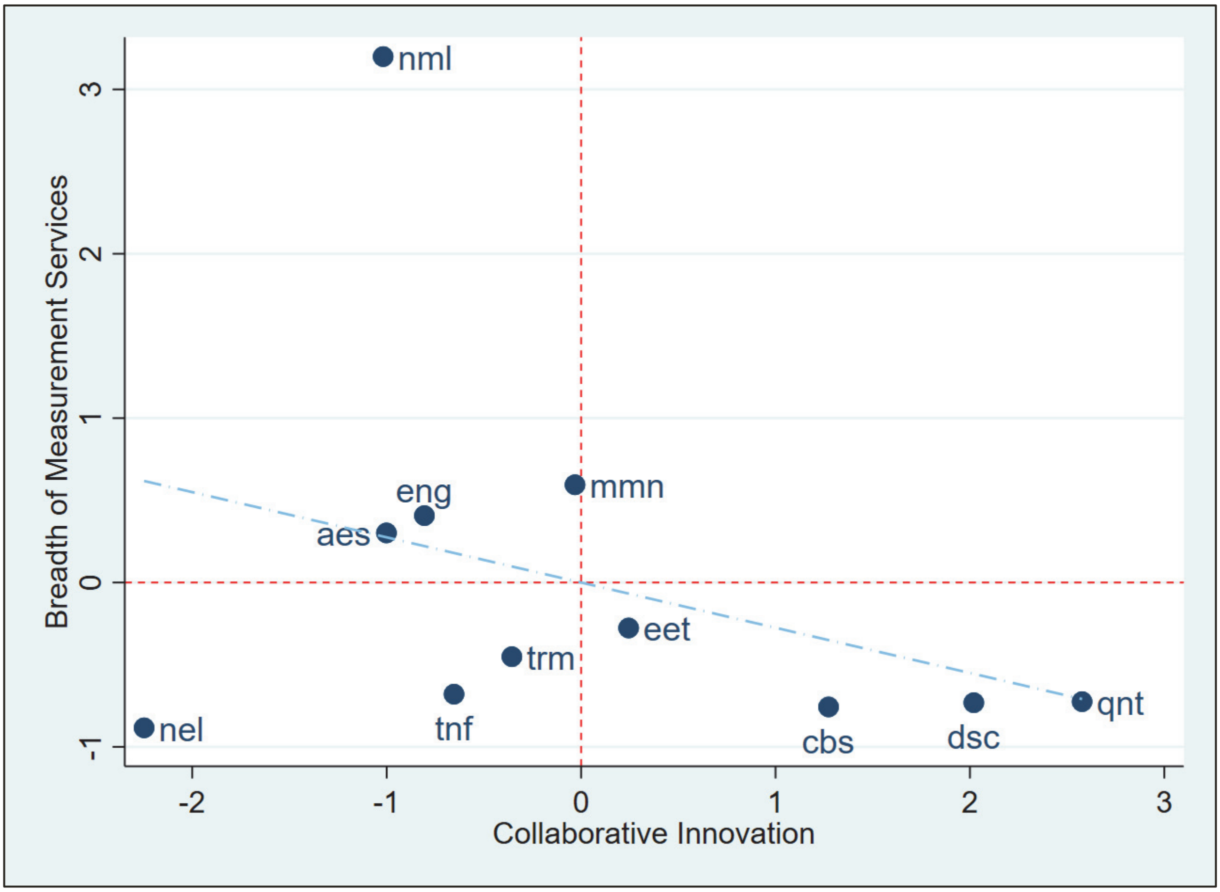

Figure 6: NPL's, NEL's & NML's portfolio across Collaborative Innovation & Breadth of Measurement Services

The key takeaway from Figure 6 is the position of NML along the vertical axis. It looks like an outlier compared to any other department when it comes to the provision of measurement services and reference materials. This is exactly what we had hypothesized in Section 4.2.1. NML specialises in the provision of a massive number of measurement services and reference materials. Hence, after we account for the number of active and new services in our PCA, it is unsurprising that the NML scores favourably on the component where these variables have a high weight. The other outlier in Figure 6 is the NEL, which lies in the bottom left quadrant much below the line of best fit. Again, this result is unsurprising given that the NEL provides very few measurement services, but they are all very niche. This is reflected in Figure 7, where we plot the average score from 2017-2022 for NEL, NML and NPL's nine departments along the two components: Collaborative Innovation & Depth of Measurement Services. We observe that NEL is located above zero along the vertical axis, which is reflective of the high value of the services it provides.

An intriguing result to come out of this analysis is that the difference in the nature of work that the NML and NEL perform is so vast that including them in the analysis leads to the splitting of the second component from the NPL-only analysis into two different components – one that captures the breadth (or number) of measurement services while the other that captures the depth (or value) of measurement services. In summary, NML provides a very high number of relatively low-value measurement services and reference materials. And NEL provides a low number of nice, high-value measurement services and reference materials. Thus, even comparing the two laboratories along a general broad umbrella of measurement services would not entail an apples-to-apples comparison.

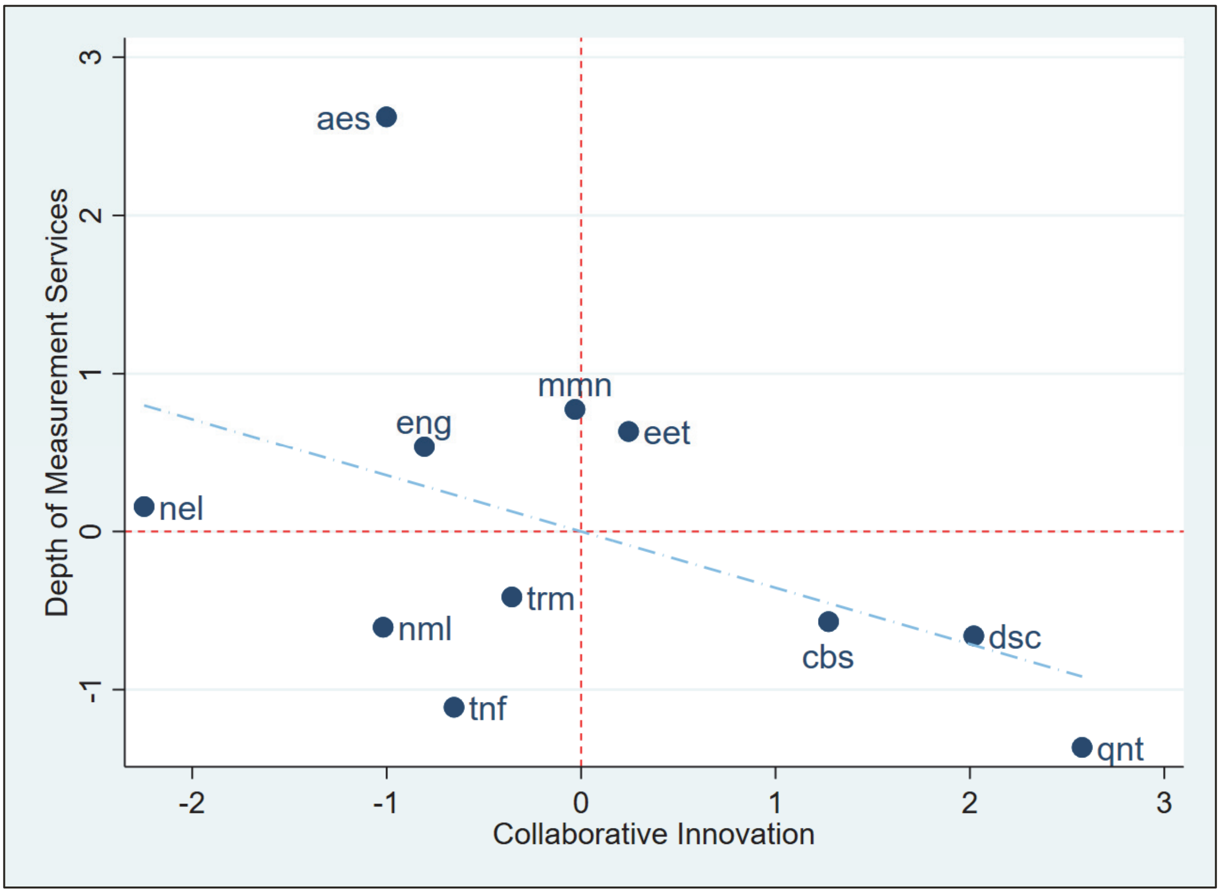

Figure 7: NPL's, NEL's & NML's portfolio across Collaborative Innovation & Depth of Measurement Services

Finally, Figure 8 presents the average score from 2017-2022 for NEL, NML and NPL's nine departments along the two components: Breadth of Measurement Services & Depth of Measurement Services. The light blue line represents the line of best fit for the eleven points. It is upward sloping, which is intuitive because we can expect the breadth (number) of measurement services to be highly correlated with the depth (value / income) of measurement services. As expected, the NEL and NPL's departments such as AES and MMN lie above the line of best fit. As discussed earlier, these "departments" are generally associated with the provision of niche, high-value services and reference materials. On the other hand, the NML and NPL's Time & Frequency department lie below this line. As discussed, they are associated with the provision of services and reference materials that are probably not being monetised to the true potential.

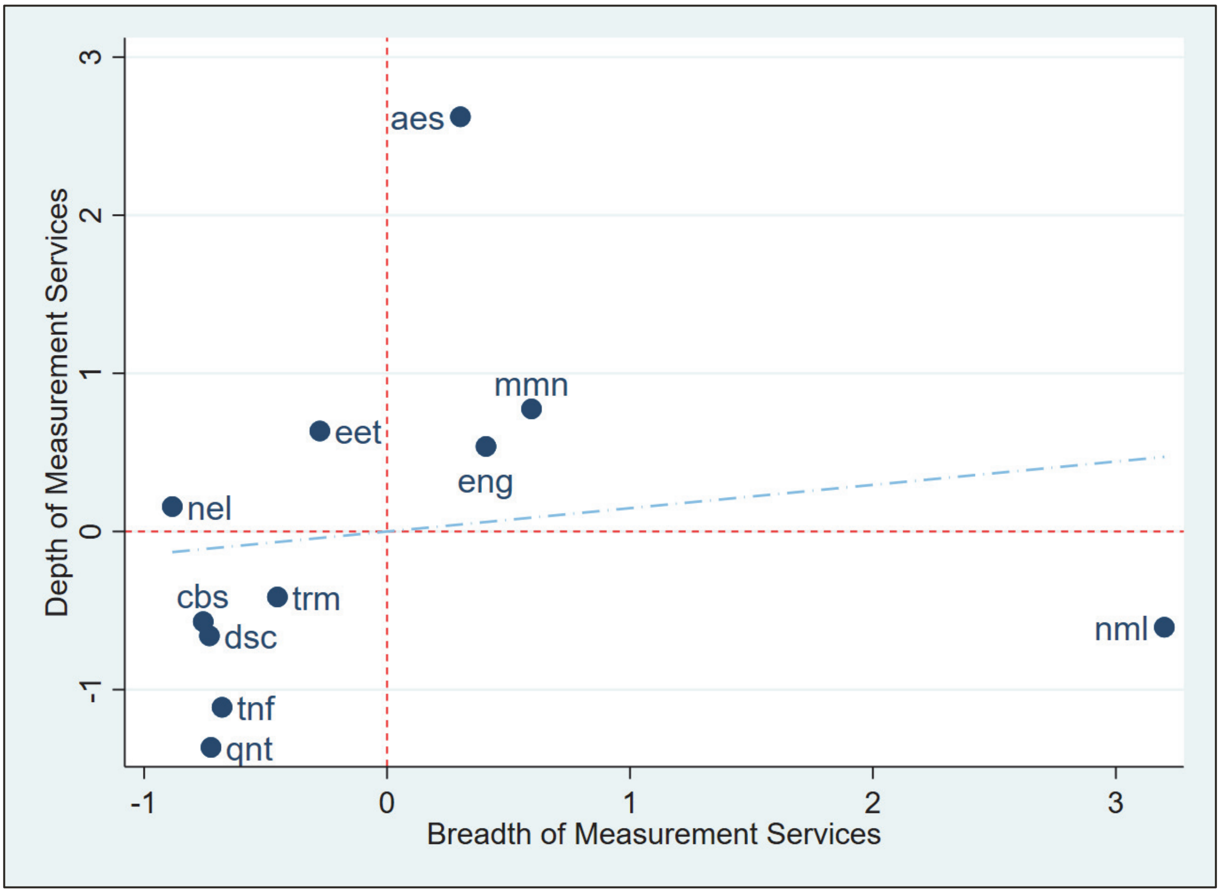

Figure 8: NPL's, NEL's & NML's portfolio across Breadth & Depth of Measurement Services