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GROWTH AND SURVIVAL OF SUPPORTED FIRMS

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Growth and Survival of Supported Firms

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ABSTRACT
NPL’s direct economic impact is positively related on the number of UK-based firms that regularly use its measurement services, or that collaborate with its scientists; where the firms’ use of services or their engagement in collaboration are to be counted as instances of “support” from NPL to these firms. The approach taken in this study is motivated by the findings of an independent analysis, done by consultants from Belmana (entitled ‘*Public Support for Innovation and Business Outcomes*’), according to which firms who regularly pay for NPL’s measurement services, or that collaborate with its scientists, saw statistically significant wage and employment growth. This study follows on from Belmana’s analysis and details the development of a metric based on counting the number of "regularly supported" firms, defined as those who’d worked with NPL five (or more) times during a six-year period. A couple of supplementary metrics have also been created, counting the number of firms who “sometimes” or “occasionally” receive support from NPL.

Over a long period of time, it’s natural for firms to "transition" from one type of status (e.g., being "unknown to NPL") to another type of status (e.g., being “regularly supported”). Thus, assessing the dynamics of this flow is one of the many analytical uses of this metric and the underlying data. Although our analysis focussed on finding correlations, it confirmed that regularly supported firms tend to perform better than those that have stopped being supported, where “performance” is judged based on the firms’ survival and growth. Lastly, enhanced performance among the supported firms seems to scale positively with the regularity of the support being received by a given firm (more support, lower probability of death, and higher probability of growth).

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EXECUTIVE SUMMARY

Existing econometric studies have found that support supplied by NPL to businesses increased their productivity, leading to enhanced survival rates and attributable economic growth. However, alongside these highly credible econometric studies, publicly funded institutions like NPL are increasingly required by government to establish indicators capable of tracking yearly changes in the flow of attributable economic benefits. Hence, it has become important for NPL to establish a method by which to monitor yearly changes in the scale of attributable economic benefit being channelled through the private sector.

This report begins by detailing why the preferred indicator for such yearly impact tracking is the count of NPL's regularly supported UK-based businesses. This is grounded in Belmana (2019), which found that regularly supported firms have superior outcomes when compared to other supported firms. It should be noted that there is a distinction between econometrics and count-metrics, of which our headline metric is the latter. The middle sections of this report describe the construction of this metric: First, outlining the data sources, then explaining the formula for calculating the number of Regularly Supported firms, and lastly constructing time-series graphs for the number of regularly supported firms. Also, there's an analysis of the graph (time-series) for the number of regularly supported firms to determine whether there has been a significant change in its trend over time. The final section details further analytical uses of this metric. This includes an "associative" (correlation-based) impact analysis, assessing whether the regularly supported firms seem to perform better (in terms of growth and survival) than similar firms who only got occasional support. This section also features an operational analysis detailing the movement of firms between different forms of support. The last piece of analysis reviews the number of regularly supported firms working with specific scientific areas (NPL's sectors), which is currently limited by a lack of data. The report concludes with a section concerning ideas for further studies that could be derived from this report, along with a discussion of its implications.

Context & Background: Establishing a metric for the number of regularly supported firms allows for an annual assessment of the total amount of impact generated by NPL through the improved productivity of its supported firms. It also makes it possible to track the yearly increases, or decreases, in the amount of attributable economic growth. The justification of the use of this metric is as follows:

1. There's strong evidence that a core group of regularly supported firms have a much better survival rate than comparable firms within the pool of potential users.

2. Using a sample of regularly supported firms, an econometric analysis found statistically significant effects on employment growth, as well as significant wage increases for new employees joining such firms. In contrast, a sample of other firms, whom NPL had only sometimes, or occasionally supported, didn't see significant increases in employment.

3. Despite making up only 20% of the UK-based firms on NPL's customer database, this special group of firms accounts for over 70% of the UK-based, private revenue. [1]

This metric for regular support is a crucial part of the Business Case Model, used to estimate the Net Present Value (NPV) of the support that NPL supplies to the private sector - the value of the economic growth generated by NPL's work with the private sector.

1 Treated firms account for approximately 70% of invoices and income from 2012-2021

An important piece of context to keep in mind whist reading this report is the following clarification regarding what's meant by the term "metric". There are two distinct ways in which the word “metric” often appears in analysis documents. The first use of the term "metrics" occurs as a shorthand for the word “econometrics”, and so refers to statistics in an empirical analysis that's testing whether a programme or institution has had a causal effected the economy. The other use of the term "metrics" refers to what may be called “count-metrics”, which are counts of observable things (events or entities) that may be connected to impacts, and so counting these things serves as a good proxy for the amount of impact: The number of regularly supported firms is a good proxy for economic impact because there's robust econometric evidence of enhanced growth among such firms.

All count-metrics amount to a sum of observable things, while econometrics looks to supply evidence concerning a causal connection between the events or entities being counted and the ultimate impacts. Count-metrics, such as the number of regularly supported firms, could feature in the scoreboard used to assess NPL's success and to see how NPL has done against its objectives. In the case of this metric, for the number of regularly supported firms, the associated goal is economic impact, which is directly linked to ambitions set out in the “*Impact-from-Science*” strategy. Hence, this report recommends a metrics-based approach - already discussed with NPL's board - by which to assess how NPL is doing with regards to its declared goal of supporting the UK's economic growth. As this “*Impact-from-Science”* strategy is a core part of NPL's overarching 5-year corporate plan, the number of regularly supported firms may ultimately feature in a “scoreboard” to tack NPL's future success.

Construction & Visualisations: To create the count-metric discussed above, comprehensive records of the events (i.e., instances of support) as detailed before, can be found within NPL's administrative data (e.g., invoicing records). The frequency of a firm's usage of NPL's services, along with its engagement with NPL's scientists, can be tracked using data that's already assembled to construct the annual NMS Indicators. (These internal data sources include NPL's Order Management System (OMS) and its Events Database.) During a given year, the firms that either paid for one of NPL's services or had worked closely with its scientists on an R&D project were deemed to have been “supported” in that year. Notice that a firm's “support status” can vary on a yearly basis: a binary variable for a firm's yearly “support status” is set to ‘1’ if the firm was supported in that year, and its “support status” is set to ‘0’, otherwise.

Borrowing a little terminology from medical trials, we now introduce the criterion for a firm to have been ‘treated’ in a given year: A ‘treated’ firm must have been supported by NPL during at least five of the previous six years. Hence, a firm's treatment status is determined using a moving average of its yearly support status based on a time window that spans six years. As the dataset starts in 2007, and our criteria for treatment depends on six years of data, the first year for which regular support can be assessed is 2012. This study also introduces two other concepts that are derivatives of our criteria for treatment, namely, “pathway to treated” and “close to treatment”. These concepts form the basis of leading indicators for assessing the movement of firms from initial support through to full treatment. This is aided by the fact that the data is at firm-level, allowing for the identification of firms whose ‘status’ was close to moving into, or out of, being ‘regularly supported’; whilst also assessing ways to assure these firms become (or at least remain) ‘regularly supported’. In time, there could be the development of forecasting methods to estimate the anticipated scale of NPL's impact on the private sector in the future.

The main headline is that there was a steady increase in the number of treated firms from 2012 up until 2017, reaching a maximum of 287 firms in 2016; after which, the number of treated firms started to trend downwards, dropping by 11% over the next four years. The change in direction observed in this time-series, between the two periods, was found to be statistically significant. This suggests that there was a structural break in the time-series, with a hypothesis needed regarding its cause. One hypothesis regarding the cause of this decline is the significant reforms that took place at NPL following a change of ownership (from Serco to BEIS) in 2014, as well as the disruption caused by a series of lockdowns during the COVID crisis in 2020. However, on a more positive note, the time-series also shows that in 2020 there was a 40% increase in the number of firms that were “close to treatment”. It may be that the introduction of grant-funded collaboration programmes, such as, A4I and M4R, contributed to this marked increase in recent uptake. Again, this is speculation and so requires separate piece of analysis to properly investigate the main drivers of the shift of direction seen in the time-series; metrics give good information about ‘when’ something happened but little explanation of ‘why’ it happened. Finding such explanations is very much the domain of more qualitative social research techniques, such as, semi-structured interviews.

Analytical Uses: The significant changes identified in the time-series are in-and-of themselves, important pieces of analysis. However, this analysis goes beyond just spotting changes in the overall direction of this metric and investigated whether there’s a relationship between firms being regularly supported and subsequent changes in business outcomes for such firms (survival and growth), where the comparators are those firms that were only sometimes supported. It was found that the “death rate” analysis seen in Belmana (2019) could be replicated using accounting data from the FAME database, with the ‘regularly supported’ firms seeing significantly higher survival rates when compared to a group of firms that hadn’t worked with NPL for between 6 to 8 years (referred to in our study as firms who’d had ‘No Recent Interaction’ with NPL). It was found that the greater the frequency of support received by a firm, the lower the probability of death faced by that firm. Although survival is an important indicator of NPL’s ability to impact on business outcomes, critics might argue that NPL’s support is providing a form of “life-support” – keeping a firm afloat when really it should be allowed to dissolve, with its resources (capital and employees) re-allocated to better uses across the economy. However, a subsequent piece of analysis looked at the probability of seeing a firm’s total assets grow, given its level of support. What was seen is that after a firm has been assigned a level of support (‘Treated’, ‘Close to Treated’, ‘Pathway to Treated’, ‘No Recent Interaction’), the more support a firm has, the greater the probability of that firm seeing growth in its total assets – meaning that the ‘regularly supported’ firms aren’t “treading water” but expanding, presumably, in response to increased economic opportunity.

The metrics as defined above can be viewed very much as impact related metrics, that are motivated by the evidence found in Belmana (2019), as well as the statistical analysis that’s been written up in this study. However, the new metrics also have some potential to be used as operational metrics, as well. As roughly 70% of NPL’s invoices and income come from its treated firms, it’s in NPL’s commercial interest to really understand this special group of firms - the composition of this group and its likely growth trend. Furthermore, as a firm can “flow” from one status to another over time, a regime-switching model has been constructed, based on the conditional probability of a firm changing from its current status to another alternative status in the following year. (That is, the conditional probability of moving from one level of support – ‘Pathway to Treated’ – to another level of support – ‘Close to Treated’.) Assessments based on tracking the progress of specific kinds of firm, towards becoming treated, could be made to better understand how a firm’s characteristics influence its likely interactions with NPL. Using these probabilities, forecasts can be made concerning the likely breakdown of NPL’s supported firms in the following year. These forecasts can be done on a cross-sectional basis, using the probability of moving from one support category to another (as well as, of course, just remaining in that category). In addition to this cross-sectional analysis, a dynamic analysis was conducted to investigate the composition of a given category in the years prior to assignment, along with where such firms move to in the years post assignment. (This dynamic analysis focussed on the lineage and evolution of the firms in a given support category.)

Finally, the supported firms have been segmented according to NPL's challenge areas, which are Prosperity, Health, Security and Environment. Currently, due to data limitations, only an assessment of each challenge's breakdown in 2020 can be done at present. However, from 2020 onwards, we will be able to assess the supported firms not only by challenge area but also by Science & Engineering Departments, representing areas of research, such as, Quantum Technologies and Electromagnetic Materials.

Further Work: The purpose of this report is to detail a metric that can be used to assess impact, together with several, associative pieces of analysis - using correlations - that can be built on in the future to test for causal relationships. However, this metric's development has allowed for a range of new work packages, representing a major step forward in NPL's evaluation capabilities.

Firstly, by combining this metric with an Input-Output analysis, we would be able to estimate the impact of NPL's private sector work on Health and the Environment. Secondly, this spawns a new area of research: Impact Metrics. These entail the tracking of NPL's impact year-on-year, potentially, with yearly bulletins detailing how NPL has done. Deeper analysis of these metrics focussed on firm-level characteristics could be used to determine if there were underlying factors driving the changes in the kinds of regularly supported firms that NPL works with over a given period.

Secondly, there are, also, operational uses of the metric, given that the majority of NPL's income is from the regularly supported firms and, therefore, improving NPL's financial performance is strongly correlated with increasing the number of such firms. These work packages would all be new to NPL and would also require experimenting with a multitude of methods. Given that some of these work packages would be dedicated to helping NPL generate more commercial revenue (e.g., the operational metrics), funding sources other than the NMS should be considered for this kind of analysis.

Lastly, the econometric evidence featured in Belmana (2019) is core to the justification and motivation for this choice of impact metric. Nonetheless, it's important to keep in mind that the data used in Belmana's analysis comes from the period before schemes like A4I existed. Hence, it may be that future econometric analysis finds that certain kinds of one-off interaction (e.g., support received through the A4I programme) has a positive effect on business outcomes, or that grant-funded collaborations turns out to be a key channel through which new firms are encouraged to seek regular support from NPL.

To sum up, it can be inferred from the econometric evidence that NPL seems to require long-term relationships with its customers to generate measurable impact, with a need for these relationships to be cultivated over time. This point is evidenced by looking at the time-series for the number of regularly supported firms, which has seen a structural break, with the increase up to 2016 in regularly supported firms followed by a decrease. However, on a more positive note, a recovery can be seen in the health of NPL's "*pipeline*", with the number of firms on the "*pathway towards treatment*" increasing significantly in recent years.

The metrics can also be used analytically, with two main applications detailed in this analysis. The first analytical use is to assess the impact of the support that NPL provides to the private sector, while the second analytical use is an operational application, given that regularly supported firms contribute the vast majority of NPL's income and invoices. Secondly, these metrics can also be done at a sectoral level, assessing the frequency of different kinds of support (collaboration or services) provided to firms in each sector. At the moment, this analysis can't be done, due to only having one cohort of sufficiently detailed data, but this can be developed in 2023, by when three more years of such data will be available. This analysis will, hopefully, be extended to assess NPL at SED level, as well. Lastly, although the metric is appropriate for benefits channelled through the private sector, impacts on the public sector aren't yet accounted for as the data only relates to support going to firms. This might be remedied by developing models to estimate NPL's impact on greenhouse gas emissions, along with economy-wide input-output models to track the flow of indirect inputs (e.g., embodied R&D) from NPL into non-market sectors, such as, healthcare and defence.

1 INTRODUCTION

This document explains why counting the number of UK-based firms in receipt of regular support from NPL serves as a proxy for the benefit being channelled through the private sector. Moreover, this document argues that NPL should adopt this proxy as its headline metric for impacts on the nation's 'prosperity'. The discussion contained in this document fits into a well-established framework for the monitoring and evaluation of publicly funded programmes. Hence, it's helpful to begin by explaining some of its constituent concepts and terminology. It's also helpful to describe the limitations of such a metric, as well as, introducing the evidence that motivated a focus on the number of regularly supported firms in the first place. Thus, this section sets up the discussion and provides context for the rest of the document.

Different types of benefit: Given that this document is exclusively focused on direct economic impacts, it should be noted at the outset that there are other forms of impact, beyond the direct benefit that's channelled through the private sector. Following the methodological framework used in a recent meta-analysis of impact case studies ('good news stories')[2], the impact detailed in this document links to what has been called "direct benefits", where NPL provides benefits directly to specific organisations who either use its measurement services or who work closely with its scientists in collaborative projects. However, this is only one of the three types of benefit that feature in this meta-analysis, with the remaining two types of benefit being:

- Indirect benefits: This is where NPL's activities benefit third parties, who are not directly involved in NPL's transactions with customers or collaborators. The underlying causes of indirect benefit are:
    - Knowledge spillovers, where third parties derive benefits from technology without needing to make any payments to NPL.
    - Non-market goods, where NPL supports public goods, such as, Environment and Security.

- Future benefits: This is where NPL's knowledge, contributes to future research and innovation, which constitutes an 'impact on science' rather than producing a near-term benefit for the economy or citizens. Nonetheless, if applications and innovations follow from such advances in knowledge, then benefits will be generated in the future.

It's important to keep in mind that 'indirect' and 'future' benefits aren't properly accounted for by this metric, and so further thinking is required in order to develop ways to measure these missing forms of benefit.

Defining what's meant by 'impact': Since references to impacts generated by NPL occur frequently throughout this document, it's helpful to begin by explaining what's meant by the term 'impact' in this context. The definition of impact found in HMT's Green Book involves comparing, outcomes including some contribution from a publicly funded programme, against outcomes in a hypothetical 'counterfactual' world in which the programme didn't exist, whilst everything else remains the same. Hence, the amount of 'impact' generated by a programme is found by subtracting this 'counterfactual' outcome (e.g., economic growth without support) from the observed outcome (e.g., economic growth with support), to find the net-additional

2 Dias, C. and King, M. (2022). A Meta-Analysis of NPL's Impact Case Studies: Charting NPL's Economic and Societal Benefit Mechanisms

benefit (e.g., extra growth) that's attributable to the programme. According to this definition, impact isn't directly observable, and so can only be inferred through econometric/statistical analysis.

Econometric evidence for impacts: The Green Book definition of 'impact' presents an obvious challenge for analysts: the outcome that occurs with support is easily observable, whereas the outcome in the hypothetical 'counterfactual' world, clearly, isn't directly observable. This means that the outcomes for a control group is often used as stand-in for 'counterfactual' outcomes. Hence, in practice, 'impact' is defined as the net-additional benefit among members of a supported group when compared to that for members of a matched control group, who went without the support. In the case of NPL (and the NMS labs), the growth among a group of regularly supported firms was compared to that of a group of similar firms who weren't regularly supported, with impact being the differences in growth between these two groups. The notion of "regular support" was coined in 2019 by a report entitled: 'Public Support for Innovation and Business Outcomes'. This report was written by consultants from Belmana and was based on an econometric analysis that has been peer-reviewed by independent academics, operating on behalf of BEIS. What this analysis identified was the significance of firms being in receipt of regular support from NPL (and the NMS labs) as an observable criterion for there being probable impacts on firms' survival, employment growth, and wages. The headline findings were:

- For a seven-year period, firms in the matched control group had a death rate of 12%, whereas the 'regularly supported' firms had a death rate of just 4%.

- On average, a regularly supported firm grows by around 6.31 employees a year due to support from the NMS labs. In contrast, there was no statistically significant effect on employment among the sometimes-supported firms.

- On average, the weekly wages of new staff joining a supported firm increase by around £78.30. Since there are 52 weeks in a year, this weekly wage-premium translates into an annual wage-premium of £4,083.

The purpose of econometric evidence in programme evaluation (as opposed to metrics) is that it's making claims about the causal effects of public support, as opposed to just focusing on correlations between support and the outcomes. The 'magic' of econometrics is that it's a set of methods for trying to find the net-additional effect of a programme on certain outcomes, as outlined in HMT's guidance on what's expected in an evaluation. In practice, econometrics is really a set of tools for reducing, or diluting, the bias that comes from self-selection, rather than fully removing it.

There are many different types of econometric analysis but at their core is an attempt to account for self-selection (the endogeneity of the support). In our case, firms were matched according to their propensity to receive support from NPL (and the NMS labs), where these propensity scores are based on the characteristics of the firms (e.g., industry), as well as previous levels of R&D and patenting as proxies for past innovation. The effect of unobservable differences between firms is partially removed by 'differencing', which amounts to focusing on changes in employment, rather than looking at raw differences in the level of employment between two different firms (e.g., comparing employment at a 'treated' firm to that an 'untreated firm).

Modelling economic impacts: The net-additional "treatment effects" found in an econometric analysis, such as the one mentioned above, provide a basis upon which to derive the estimates of economic impact found within submissions to BEIS made during spending reviews and as part of the scrutiny applied to business cases. It ought to be recognised that the headline "treatment effects", concerning firm-level wage and employment growth, represent the average impact on a "regularly supported" firm. The reality is likely to be more heterogenous, with a distribution of "treatment effects" among the firms who'd been receiving regular support. The econometric evidence from Belmana's report forms the basis of a simple model for the quantifying the economic benefit being channelled through the private sector. As outlined below, the modelled impacts are based on multiplying the average impact on a "regularly supported" firm by a count of the number of such firms; and so, there's a close connection between the metric and the following model for estimating NPL's impact on the private sector:

- In total, the NMS labs provide meaningful help to approximately 360 regularly supported firms each year. At these firms, a wage premium of £4,083 and an increase of 6.31 employees was found. This increase in the wage premium suggests an overall increase in gross economic benefit (gross value added) of roughly £12,188 for each new employee.

- When the increase in economic output from an individual worker is scaled by the total number of jobs being generated, and the period of time over which such benefits typically endure (6 years), it is estimated that the value of the flow of direct benefits to regular users in the private sector is around £142 million.

- After applying an established '2:1' multiplier for the positive externalities created by technological knowledge spilling over to non-payers, a total economic benefit of £426 million was found. Accounting for the cost of public funding, and innovation spending among the supported firms, yielded a net benefit of £254 million.

A count-metric as a proxy for impact: A key part of context-setting is a clarification regarding what's meant by the term "metric". There are two distinct ways in which the word "metric" often appears in analysis documents, and so there's the potential for these two meanings to be accidentally conflated. The first use of the term "metrics" occurs as a short-hand for the word "econometrics", and so refers to statistics in an empirical analysis that's testing whether something has had a causal effected the economy. (An example of this type of statistical analysis is the Belmana report, as detailed above.) The other use of the term "metrics" refers to what might be better called "count-metrics", which are counts of observable things (events or entities) that are connected to impacts, and so counting these things serves as a good proxy for the amount of impact. (The number of regularly supported firms is a proxy for impact because there's evidence of enhanced growth among such firms.) All count-metrics amount to a sum of observable things, whilst it's left to econometrics to supply evidence that there's a general connection between the things being counted and the impacts. Hence, it's important to update the underlying econometric analysis from time-to-time to maintain the reliability and relevance of the underlying evidence. It is important to note that within this report, econometrics will be described as such, while count-metrics will be shortened to metrics as the focus of this report is the latter rather than the former.

Associative evidence of impact: Count-metrics, as detailed above can be used to find evidence of impact. The evidence developed here is different to econometric evidence, which looks to find net-additional benefits to the work done at NPL, using a control group to compare. Rather, the analysis done here is more associative in nature, rather than causal. This entails the use of the linear probability model, assessing the probability of a firm seeing growth in its total assets or "dying" given its status. These findings have to be taken with "a pinch of salt" but can indicate whether further analysis is merited to find causal relationships. Furthermore, if regressions are used, control variables are easily introduced in order to introduce some causality.

Operational uses: Although the metrics were developed in order to assess the impact of NPL, the importance of these firms to NPL's operations is still an important measure. Treated firms contribute far more with regards to invoices and income in comparison to their untreated counterparts. Therefore, assessing how many treated firms there are year-on-year and a benchmark for how NPL does concerning the movement of firms from brand new partners to treated ones is important to determine the success of initiatives.

2 CONTEXT

The work of NPL's executive team could be assisted by access to non-financial metrics to monitor the organisation's performance. Such metrics would go some way towards helping NPL to satisfy two basic public accountability requirements: Firstly, the executives managing a company have a well-established fiduciary duty to act in the best interest of its owners, and so to ensure a good return on funds provided. It follows that, as NPL is owned by the Department for Business, Energy, and Industrial Strategy (BEIS), NPL has a duty to ensure that the organisation supports the UK's economy and delivers value-for-money to society as a whole. Secondly, any institution in receipt of significant public funding must monitor and evaluate its programmes in accordance with HM Treasury guidance, to ensure accountability to taxpayers, and to better inform the allocation of future funding. Since NPL receives around £110 million of public funding each year, it must therefore ensure that it can account for this funding in terms of the impacts that are generated because of its programmes. Lastly, whilst helping to satisfy these public accountability requirements, having such metrics strengthens the ability of NPL's own management to set objectives for the organisation, which can then be measured so that the organisation's progress can later be analysed.

In the case of a privately owned company, financial metrics for a company's performance (e.g., turnover and net-margin) go a long way towards evidencing the fulfilment of this fiduciary duty. However, because of its special ownership status, NPL requires, at least, some non-financial metrics to demonstrate that it's tracking the impact of its programmes on the UK's economy and the wider society. This document details a metric that NPL has been adopted to assess the direct impact coming from the NMS. It is derived from an econometric analysis used during last year's spending review, which found that benefits going to the private sector are channelled through a core group of regularly supported firms. As such, the metric detailed in this report, connects strongly to supporting economic growth and 'prosperity', but misses many benefits channelled through the public sector, as well as the benefits from helping to maintain public goods, such as, 'environment' and 'security'. Hence, beyond this report, further work will be needed to advance the metrification of benefits that are not being channelled through the private sector, and so won't be picked up in the 'prosperity' metric set out in this report.

3 WHY TRACK THE NUMBER OF "REGULARLY SUPPORTED" FIRMS?

This section explains the reasons for wanting to track the number of "regularly supported" firms. This comes down to providing evidence of a probable association between firms in receipt of regular support and an observed increment in their employment and wage growth, that can't easily be explain away as a consequence of other factors. There are two distinct strands of justification: one based on deductions from economic theory; and another based on supportive empirical evidence.

3.1 THEORETICAL JUSTIFICATION

It's intuitive that if a firm keeps on returning to NPL on a regular basis, then NPL must be providing something important that the firm can't easily find elsewhere. (It's not that a one-off user necessarily fails to receive any benefit, rather it's that we can't be too sure they valued the support unless we see them return for ongoing support.) However, the connection between firms being in receipt of regular support and their enhanced economic growth requires further explanation. Hence, this subsection outlines a theory explaining the economic mechanisms (product innovation) connecting the firms' enhanced employment growth to their regular 'in-sourcing' of technological knowledge from NPL.[3]

The employment within firms tends to adjust in responses to changes in their turnover.[4] A firm's turnover is composed of sales across a portfolio of products, each of whose lifetime depends on the likelihood of a more efficient competitor 'stealing' the market, as well as the rate at which products are made obsolete through 'creative destruction'. However, as older products leave the portfolio, there's potential for their place to be taken by the introduction of new products.[5] A firm's size grows (or declines) if the 'birth rate' for new products entering the portfolio is greater than (or less than) the 'death rate' for older products exiting the portfolio. New inventions (or ideas) have potential to become the basis of new products, but successful product innovation only happens if the resulting products are economically viable.[6] That is, the willingness-to-pay among potential buyers must exceed the lowest attainable unit-cost of the firm's production process. (The unit-cost acts like a hurdle that must cleared before ideas can become the basis of innovations.) Access to relevant technological knowledge raises the firm's Total Factor Productivity (TFP) and helps to lower the unit-cost of its production process, which increase the chance that an invention (or idea) leads to a successful product innovation. Lastly, increasing the rate of product innovation among a group of firms (raising the 'birth rate' of new products), increases the perceived economic opportunity, leading them to expand output, increase their turnover, and so to employ more staff.

NPL offers access to unique expertise that's particularly relevant to engineering-based firms, who are looking to secure competitive advantage through access to measurement technologies that underpin effective production and product verification techniques.[7] Indeed, there exists a core group of roughly two hundred and sixty UK-based firms in receipt of regular support from NPL.[8] In effect, these firms are 'renting' knowledge from NPL, where

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3 NPL is a source of (almost) unique measurement expertise because its scientists can become world experts in the subject during their long careers at NPL. Arguably, NPL Management Ltd can't own this knowledge but rather rents it by paying its scientists a salary. If so, NPL's stock of useful knowledge will tend to diminish following a period in which there's been a high turnover of scientific and technical staff.

4 Aggregate employment at the whole economy level is assumed to be, essentially, fixed by exogenous macroeconomic factors (monetary and fiscal policy) that are outside this model. Hence, the changes in employment, discussed in this note, are assumed to occur between firms, as their sizes wax and wane in response changes in relative competitiveness.

5 From evidence in the UK Innovation Survey and the NMS customer survey, the average life of a product each firm has about 6 years

6 A more complex model would seek to explain (or endogenize) the mechanisms through which inventions (or ideas) arise but, for our purposes, it's sufficient to use an analogy in which firms buy raffle tickets, some of which lead to winning a prize. The "raffle tickets" are inventions (or ideas) and the "prizes" are successful product innovations. The buying of raffle tickets is analogous to spending on R&D projects, but we will leave this as an exogenous process, fuelled by people pursuing scientific enquiry and seeking out opportunities to exercise their creativity.

7 There is a strong connection between employing reliable measurement process and having effective product verification procedures and conformance-testing. This is often a pre-condition for being part of international supply chains. More generally, putting effective product verification procedures in place lowers transaction costs, and so makes it easier to access new markets.

8 In the 1990s, Paul Romer's ground-breaking work on endogenous growth theory established that accounting for the contribution of technological knowledge (ideas) is very different for accounting for the factors of production (labour and capital). Romer's analysis demonstrated that innovative firms can't be price-takers in an equilibrium in which they buy regular access to partially excludible knowledge. That is, these innovative firms must engage in a form of monopolistic competition, so that they always have some supernormal profits, out of which payments can be made for accessing proprietary knowledge.

such knowledge is either embodied in NPL's technical services or accessed through long-term collaborations with its scientists.[9] This sustains an increment in the firm's accessible stock of technological knowledge, which allows for the firm to benefit from capabilities that they could never own. In a sense, this is like companies paying an annual subscription for the use of *Microsoft Office*, which provides functionalities that most individual firms couldn't develop or sustain by themselves.[10]

Trust has been built up between individual firms and Microsoft that its products will work as advertised and will remain consistent over time. This kind of trust enables firms to rely on such capabilities in the long-term, expediting the sort of planning and investment decisions, often concerning the introduction of new products, that underpins employment growth. That is, firms wanting to capitalise on a perceived increase in economic opportunity require a dependable base of technology on which to build and expand. Hence, it's conceivable that this kind of confidence has been built up among NPL's long-term customers, leading the measurable impacts on their employment growth that can't be found for NPL's less frequent or occasional users.[11]

3.2 EMPIRICAL JUSTIFICATION

The empirical reasons for us recommending a yearly count of the number of regularly supported firms as an indicator of economic impact are as follows: Firstly, the death rate amongst the sample of regularly supported businesses was found to be just 4% over a seven year period.[12] This is lower than the death rate for a comparison group of similar firms, and much lower than the death rate for the general population of firms in the UK's economy.[13] (For a seven year period, the matched control group has a death rate of 12%, whereas the general population of businesses had a death rate of 35%.)

Secondly, NPL's regularly supported firms saw statistically significantly employment growth, as well as positive wage premiums for new employees. The average treated firm grows by about 6.31 employees a year due to NMS support, while the weekly wages of new staff

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This 'profitability requirement' helps to explain why large OEMs (Original Equipment Manufacturers) feature so prominently among firms making regular payments to NPL. https://web.stanford.edu/~chadj/RomerNobel.pdf

9 Every time that a calibrated instrument is used to calibrate another instrument, or to take measurements, there's a small chance of little knocks or disturbances that might cause it to go out of specification. Hence, the probability that calibrated instrument has remained in specification decreases with time and usage, which is why this core group of firms must return each year to get their instruments recalibrated.

10 Although, this will not be explored in this document, the comparison to *Microsoft Office* is germane, because of its role as a common de-facto standard for assembling and disseminating information. That is, a large part of utility of *Microsoft Office* is derived from its status as a platform, easing communication between different organisations and across the world. Moreover, the value that's derived from conventionality is inherently connected to regularity of usage and ubiquity. This is like the network externalities associated with the NMS (National Measurement System). The positive externalities coming from the comparability of measurements, made by many different organisations, are underpinned by a distributed system of calibrations that are traceable back to a common reference standard at NPL. The scale of adoption determines how effectively the system lowers transaction costs, thereby increasing scope for specialisation, and so enabling gains from inter-industry trade. That is, the greater the number of users adopting the system, the higher the value of the system itself.

11 Another good analogy is the example of going to a physiotherapist for an issue one may have. One session may diagnose the problem but won't treat it, while repeated sessions over a period of time will hopefully solve the problem.

12 The relationship between 'survival rate' and 'death rate' is as follows: 'survival rate' = 100% − 'death rate'.

13 The main ONS (Office of National Statistics) database used for the analysis set out in the Belmana's report was the Business Structure Database (BSD).

joining a treated firm see an annual wage premium of approximately £4,083. In comparison, the study found insignificant effects for users that were being only sometimes supported.[14] The Belmana report uses this as evidence to show that these regularly supported firms constitute the main route through which NPL (and the other NMS labs) channel economic benefits to the private sector, whose results were detailed above.[15]

Lastly, to accompany their headline analysis, based on using a binary '*treatment*' indicator, Belmana's economists also experimented with '*dose response*' models, looking at how firms' employment growth responds to continuous measures of support. The most convincing '*dosage response'* model found an approximately linear relationship between the employment growth, attributable to NPL's support, and the number of invoices that NPL had sent to a firm during a six-year period. This suggests that, to a first approximation, the impact on employment growth scales linearly with the number of invoices sent to a firm. This further strengthens the case for focussing on the 'treated' firms because there's clearly a strong connection between firms being sent multiple invoices, for the multiple services they've used, and them being in receipt of regular support.

Building off of the work conducted in the dosage response model, we can extrapolate impacts for the 'sometimes-supported' firms, based on what we know about the scale of impact on the treated firms. This was done by using an estimate of the aggregate increase in employment across the population of "treated" firms that's attributable to the support. That is, the '6.31' extra employees per "treated" firm was multiplied by the '360' firms classed as being "treated", which yields a total of 2,272 extra employees. This aggregate increase in employment, among the 'regularly supported' firms, accounts for the impacts associated with about 78% of NPL's invoices. Therefore, it's logical to suppose the remaining 22% of aggregate impact on employment is spread amongst the 'sometimes-supported' firms. If 74% of NPL's invoices creates 2,272 jobs, then a simple estimate of NPL's total impact on employment is given by the following calculation: 2,272 / 0.74 = 3,070 jobs. Moreover, 26% of the 3,070 jobs, yields 798 jobs as an estimate of the net-additional jobs created among the 'sometimes-supported' firms. This isn't a fully justified empirical result, but this extrapolation leads us to believe that among the 'sometimes-supported' firms, 60% of them saw one extra employee a year.

3.3 IMPORTANCE TO NPL'S REVENUE

The focus of these metrics was to track the impact NPL has on its direct users with regards to their employment and wage growth. However, the treated firms can also be very important to NPL. These firms make up only 18% of NPL's supported firms each, yet they account for 69% and 74% of NPL's income and invoices respectively. As a private company, it is in NPL's interest to grow its revenue. These firms are a key part of NPL's revenue, so their number and health should be assessed and maintained.

3.4 OTHER ADDITIONAL METRICS

On top of the Regularly Supported metric, two other metrics were also created; Pathway to- and Close to Treated. These metrics will be defined below but help to track the journey a firm takes with regards to its working relationship with NPL and are collectively known as the

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14 Every firm has a unique Companies House Reference Number (CRN), which is identifiable within the FAME database.

15 "Eureka" moments have happened in the science of measurement, as illustrated by the legendary story of Archimedes solution to the problem of density measurements. (Once a good idea about how to measure something has been created, it can be used repeatedly without coming back to the source of that idea.) Hence, whilst the focus of our document is on "regular support", this is not to deny the possibility that a one-off project can sometimes create enduring benefits by solving a difficult measurement problem. But these highly impactful one-off projects don't seem to have been the dominant channel through which NPL's impacts on employment growth have occurred.

"Pipeline to Treated". It is hoped that firms would look to intensify its working relationship with NPL over time, but this isn't assumed as the standard direction firms take.

Unlike the Treated firms, the firms in these lower levels of support intensities didn't see a significantly different level of employment/wage growth as their treated counterparts. However, this is partially due to the fact the study by Belmana didn't segregate the firms in the untreated group into levels of intensity as is done here. This doesn't mean that firms on the Pipeline don't see impact, which is something that is tested by association here and can be assessed in a causal manner as part of a potential future study.

All the variables detailed here are relatively "easy" to track year-on-year and have been adopted by NPL's directors in order to measure NPL's impact from Science on the Economic Prosperity of the UK.

4 FIRM-LEVEL DATASET

The dataset used for this analysis is maintained by the Analysis & Evaluation (A&E) team and complied each year using internal administrative data from a range of sources, such as, the Order Management System (OMS) and Eventbrite. This section outlines some of the issues surrounding this dataset, but a fuller discussion can be found in the annex. The data itself pose several challenges that need to be overcome whilst assembling the dataset, and A&E's attempts to deal with these issues constitute a kind of data 'cleaning' process:

Firstly, questions of identity sometimes arise for large firms with multiple business sites, due to their ability to spread activities across different locations. This can lead to issues when trying to avoid double counting these multi-site firms. Fortunately, the ambiguity around what might constitute a firm can be dealt with by using Companies Reference Numbers (CRNs) as the primary way to tag and identify companies. Moreover, the invoicing data, found in the Order Management System (OMS), includes the firms' addresses, which can be matched to Companies Reference Numbers (CRNs) by searching for a firm's address in a comprehensive database (referred to as 'FAME') of company accounts.[16]

Secondly, there are issues concerning the collaboration data. The data comes from the esteem survey, meaning that tagging is a manual process. This requires human judgement which could lead to inconsistencies.[17] These errors are minimised as unique ID codes are used for collaborators, but yearly updates of this register can lead to instances of duplication in cases where a search of the pre-existing codes mistakenly draws a blank, due to a small error in how the code has been entered (such as a space within the string). This issue has been reviewed and is being progressively dealt with by manual inspection, with 60 problem codes identified and corrected, which implies that 0.6% of the dataset had to be corrected. Other issues have arisen concerning the accidental tagging of hospitals as companies, but this is accounted for in other areas of the data and has also now been corrected.

16 The challenge posed by multi-site firms becomes more of an issue for information from other sources, such as, that from Eventbrite, where more of a judgement call is required over matters of identity. However, because events are classified as a form of engagement, rather than a form of "*support*", the issues with data from Eventbrite do not affect the current analysis.

Further details on the dataset are found in the attached note "The User Database – Zahrah Qureshi"

17 The collection of NPL's collaboration data needs to be greatly improved and should receive special attention during the transformation of its ICT systems. It should be managed in a similar manner to the invoices, with each instance of collaboration being recorded rather like an invoice.

Finally, an issue is created by using a 'fuzzy matching' algorithm, which is used to match the names of companies found in invoices, or the register of collaborations, to those in our existing database.[18] The A&E team has developed its own 'fuzzy matching' tool, with the use of Python's software library (referred to as "pandas"). This algorithm isn't perfect, but it was found to be a little more accurate than Excel's 'fuzzy matching' tool. Nonetheless, errors do occur and these need to be spotted and corrected manually.

The data itself is in panel form, utilising both unique subjects and a time index. The unique subjects in this instance are each of the private companies, tagged by CRNs, while the time index are years, from 2007 to 2020. Further detail concerning the dataset can be found in the attached document "User Database by Zahrah Qureshi".

5 HOW TO TRACK SUPPORTED FIRMS

To define *Support* and *Treatment*, the following forms of interaction are used as the base variables:

Paid: This form of interaction is where NPL invoiced an organisation for its use of a paid-for product or service. The data for this mode of interaction is found in NPL's internal invoicing database, which pulled information from the Order Management System. This data was subsequently tagged by members of the Analysis & Evaluation team to identify unique private-sector companies.

Collaborations: This form of interaction is where the employees of a firm worked alongside NPL's scientists on a joint project.[19] The data collected for the annual NMS indicators report was tagged to unique companies found within the Analysis & Evaluation team's customer database.

Using these two specific types of interaction, flags for two broader classes of interaction were created:

Support: This form of interaction is where a firm either conducts a "*collaboration*" or has a "*paid-for*" interaction. Instances of *paid-for* support and *collaboration* indicate that the other party in the exchange sees value in the work that NPL does and the services it provides.[20] This is the same definition as that used within the Belmana report.

Treatment: This form of interaction is where, during a six-year time window, a firm receives "*support*" in at least <u>five out of the possible six years.</u>[21] This is in step with Belmana's definition of "*treatment*", which is: "*there being an incidence of NMS support for the businesses in over 85% of the years that the business is in the ONS [Office of National Statistics] data.*"

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18 This 'fuzzy matching' is performed once commonly occurring endings have been removed (such as, "LTD" and "PLC").

19 These are cases where NPL isn't paid for their work but rather works closely with the other party on a joint project.

20 The economic value of something to a given user depends on that user's "*willingness-to-pay"* for it. In the case of the use of a paid-for service, evidence for its users' having some 'willingness-to-pay' is obvious. In the case of a collaborative project, evidence for the existence of some 'willingness-to-pay' comes from the collaborating firm having committed resources in-kind to the R&D project. For example, the firm commits the time of its staff, along with, perhaps, some data and other materials.

21 Admittedly, there's a degree of arbitrariness to the window of time used in the definition of 'regular support'. However, 6-years feel about right, because it corresponds to typical number of years for which a product continues to generate sales for a firm. This tallies with what was seen in the NMS customer survey and the UK innovation survey

Within the dataset that's being maintained by staff in the Analysis & Evaluation team, there are other forms of interaction recorded in the data. In particular, 'Events' and 'Training' are also tracked, but these forms of interaction are deemed to be a lot weaker than *paid-for* support and *collaboration.* These weaker forms of interaction are markers of interest in the work that NPL does, but we don't believe that they should be classed as an instance of "*support*". As this analysis focuses on "*support*" and "*treatment*", these weaker types of interaction do not feature in this report.

The dataset used in this analysis, currently, provides reliable information on instances of support received by UK-based firms for the period 2007-2020. (Please note that it takes a few months of arduous and complex data work, over the first quarter of a year, to update this dataset so that it includes information for the previous year.)

To formally define our variables, it's helpful to introduce an index (i = 1, 2, … , N) running over the firms in our dataset; and a second index (t = 1, 2, … , T) running over the years that are covered by our dataset. Let a_t^i denote a count of the number of invoices sent by NPL to firm i during year t. Let b_t^i denote a count of the number of collaborations that NPL's scientists had with firm i during year t.

Binary variables for each year were generated, denoting whether a company had been sent an invoice or had engaged in collaboration. Let β_k^i be a binary variable indicating whether firm i had been '*supported*' during year t:

$$\beta_t^i = \begin{cases} 1 \text{ if } a_t^i + b_t^i > 0 \\ 0 \text{ if } a_t^i + b_t^i = 0 \end{cases}$$

where a_t^i is a count of invoices sent to firm i in year t; and b_t^i is a count of collaborations NPL have had with firm i in year t. To help us to identify and track the '*treated'* firms, a moving average was constructed by summing these binary dummies for yearly *'support'* over a six-year period. Let x_t^i denote the number of years for which support was given to a firm during a six-year period beginning in year t-5 and ending in year t:

$$x_t^i = \beta_t^i + \beta_{t-1}^i + \beta_{t-2}^i + \ldots + \beta_{t-5}^i = \sum_{k=0}^{5} \beta_{t-k}^i$$

Since the data on collaborations only went back as far as 2007, x_t^i can only be constructed from 2012 onwards, as for each year denoted by the subscript 't', six years of data had to be checked. That is, to construct x_t^i for t = 2012, we need full data on both invoices and collaborations for 2007-2012.

x_t^i will now be used to construct an indicator for each firm's treatment status in a given year, as well as the other two indicators for the 'pipeline' of firms who are on the path towards treatment:

1. Close to Treatment – This is where a firm has worked with NPL three or four times in the previous six years, suggesting they are either very close to being treated or have only dropped out of treatment for a year or so.

2. Pathway to Treatment – This is where a firm has worked with NPL once or twice in the previous six years, suggesting that they could be on the way towards being treated.

There is also a third indicator which can be counted as a status but isn't part of the pipeline. This is called No Recent Interaction, where a firm hasn't worked with NPL for six to eight years. *Treatment, Close to Treatment, Pathway to Treatment and No Recent Interaction* collectively are known as the *Status of Supported firms* (or Status(es) for short). It can also be assumed that the four statuses refer to intensities of support, with treatment being the highest level of support, followed by close to treatment, then pathway to treatment, with no recent interaction representing only residual support.

For ease of description, when referring to firms flagged by these indicators, they will be referred to as on the "*pathway to treatment*" or "*close to treatment"*. There has been no specific econometric analysis concerning firms that are either "*close to treatment"* or on the *"pathway to treatment"*. However, there has been some associative analysis concerning these metrics, which are detailed in section 12 and 13. Nevertheless, it's useful for NPL to see the amount of activity occurring at these somewhat lower grades of interaction, because they are both leading indicators, which may forecast the future number of "*treated*" firms. That is, an increase in the number of firms on the "*pathway to treatment"* is likely to be followed by to an increase in the number of firms "*close to treatment"*; which in turn, should lead to an increase in the number of "*treated*" firms a few years down the line. By construction there will be a two-year time lag, but these variables should still provide a good indication of our firms' progress towards becoming treated.[22]

The definitions for these indicators are as follows:

If $5 \leq x_t^i \leq 6$, then firm *i* is "*treated"* in year *t*.
If $3 \leq x_t^i \leq 4$, then firm *i* is "*close to treatment"* in year *t*.
If $1 \leq x_t^i \leq 2$, then firm *i* is on the "*pathway to treatment"* in year *t*.
If $x_t^i = 0$, then firm *i* is deemed to have had "*no recent interaction"* in year *t23*.

Treatment status is determined annually on a firm-by-firm basis, after which the number of firms at a given stage of treatment journey are summed up across the whole database of firms. To construct annual indicators this process was repeated for each year over the period 2012-2020.

22 Using the government's COVID metrics as an analogy, it's like the relationships that 'Cases', 'Hospitalisations', and 'Deaths' have to one another, by feeding into each other, sequentially.

23 If, after two periods (years), $x_t^i = 0$, then the firm is deemed to no longer have a status. It would be defined as "falling into the void".

6 TIME-SERIES FOR THE COUNT OF TREATED FIRMS

The chart below tracks the number of "*treated*" firms over the period 2012-2020. Each year, detailed in the graph below, is based on assessing the regularity of the support going to firms over a 6-year period that's inclusive of the year itself. (For example, "*treatment*" in 2012 relates to support delivered over the period 2007-2012.)

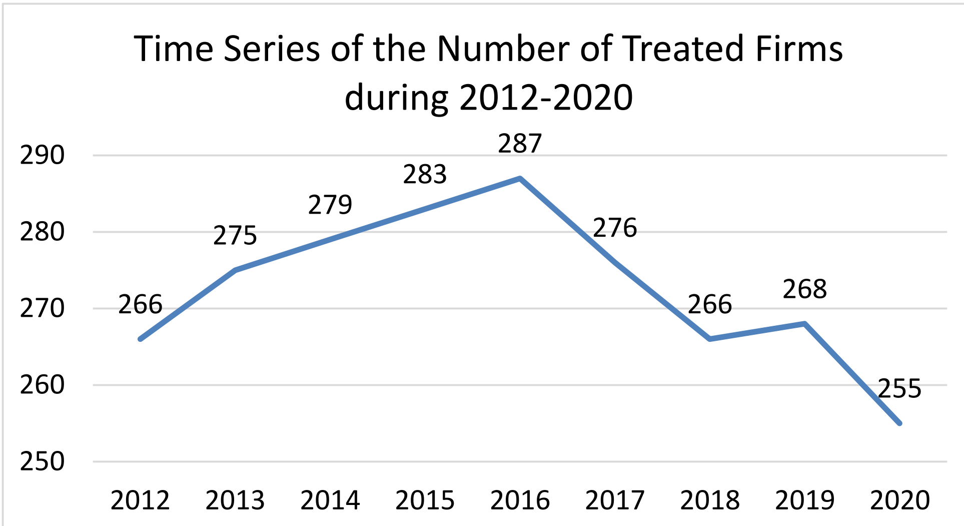

Figure 1

The metric above shows that in the first half of the series there was consistent growth in the number of "*treated*" firms. This growth continued up until 2017, reaching a high of 287 "*treated*" firms in 2016. From 2017 onwards, a decline appears to have set in, reaching a new low of just 255 "*treated*" firms in 2020. It should also be noted that firms "dying off" isn't the main driver of this decline in numbers, rather it appears that some of the previously 'treated' firms are no longer working with NPL on such a regular basis.[24]

The time-series for the number of treated firms seems to be following a random-walk, but with a systematic component to its movements represented by a drift parameter.[25] That is, the count of firms for year *t* is the count for year *t*-1 plus a small constant parameter (called the 'drift'), alongside a residual term (representing yearly shocks) that's drawn randomly from some symmetric distribution with a mean of zero. Although, these shocks are assumed to average-out over several years, the residual will be positive or negative in any given year: 'good' years have a positive residual; and 'bad' years have a negative residual. As such, our time-series, itself, can't be stationary, but a time-series formed from its 'first-differences' (yearly differences) should be approximately stationary, and so is much more susceptible to statistical analysis. A change in the direction of the trend corresponds to a change in the sign of the drift parameter.

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24 Ceasing activity, becoming dormant or another version of closing down.

25 Suppose that time can be divided into time periods (years) that are indexed by *t* = 0, 1, 2, … , T. Let y_t denote the value of a time-series at time *t*; and let y_{t-1} denote the value of the same time-series in the previous time period (t-1). If the series follows a random-walk with a systematic drift, then it can be represented by the following expression: $y_t = y_{t-1} + \theta + u_t$, where θ is the drift parameter, and $u_t \sim \mathcal{N}(0, \sigma^2)$ is a normally distributed (mean zero) residual representing random yearly shocks, occurring due to a multitude of factors that are changing each period.

The data falls neatly into two four-year time periods: 2013-2016 and 2017-2020.[26] Due to the apparent structural break in 2017, these two four-year time periods were specifically constructed to assess whether the apparent changes are statistically significant. This was done by analysing the year-on-year differences in the two periods, as detailed in the tables below:

Calendar Year	*4-Year Period*	*Obs. no. within each Period*	*Count of 'Treated' Firms*	*Yearly Differences*	*Diff. of Yearly Differences*
2012	N/A	N/A	266	N/A	N/A
2013	1st	1st	275	9	N/A
2014	1st	2nd	279	4	N/A
2015	1st	3rd	283	4	N/A
2016	1st	4th	287	4	N/A
2017	2nd	1st	276	-11	-20
2018	2nd	2nd	266	-10	-14
2019	2nd	3rd	268	2	-2
2020	2nd	4th	255	-13	-17

Table 1: Time-Series Data for the Number of "Treated" Firms

Using the yearly differences, significance testing has been used to determine whether the apparent change in the direction of the drift can be explained away as an artifact of random fluctuations caused by the yearly shocks. The analysis looked for evidence of a positive (upward) drift in the first period, and a negative (downward) drift in the second period.

- 1st period: the null hypothesis is that the drift is zero and the alternative is that its positive.
- 2nd period: the null hypothesis is that the drift is zero and the alternative is that its negative.

The difference between the yearly differences in the two periods was also assessed; with two observations being paired-up according to their observation numbers.[27] A change in the trend is equivalent to a change in the drift parameter characterising the evolution of our series. The question of whether there was a structural change in the time-series in 2017 comes down to whether something caused a change in this parameter. The null hypothesis is that there was no change in the parameter, and the alternative hypothesis is that there was a change in the parameter. The results of this analysis are detailed in the table below:

26 We lose one year's worth of data because of the construction of yearly differences, in which the number of firms classed as treated in year *t*-1 is subtracted from the number of firms treated in year *t*.

27 For example, the yearly difference for 2013 was subtracted from the yearly difference for 2017, because 2013 and 2017 are the first year of the first and second periods, respectively.

	Yearly Differences (1st Period)	*Yearly Differences (2nd Period)*	*Diff. of Yearly Differences*
Mean	5.25	-8.00	-13.25
Standard Deviation	2.50	6.78	7.89
Standard Error (SE)	1.25	3.39	3.94
t-values	4.20	-2.36	-3.36
One-tailed p-value	0.012	0.050	0.022
Two-tailed p-value	0.025	0.099	0.044

Table 2: Statistical Analysis of the Time-Series for the Number of "Treated" Firms

The table above provides strong (5% significant) evidence that the drift parameter was positive in the first period, and slightly weaker (10% significant) evidence that this drift parameter was negative in the second period. When tested directly, strong evidence is found that the value of this drift parameter differed significantly between the two time periods. Hence, this analysis found evidence of statistically significant changes in the rate of growth (or rate of decline) in the number of "*treated*" firms. Also, the scale of the decline isn't trivial, amounting to a 11% decrease between 2016 and 2020 (an annualised drop of just under 3% each year).

There is room for a little speculation as to the cause of the structural-break in the time-series, that seem to have occurred shortly after 2016. The decline may have been triggered, at least in part, by the disruption to staff and routines that accompanied the instigation of essential reforms following the end of Serco's management contract in 2015.[28] However, there was also some evidence of this decline starting to be reversed in 2019, with a slight uptick compared to 2018, but this rally was presumably then choked-off by the effects of the COVID crisis of 2020. Nonetheless, a slight note of caution is warranted: following a major event, one may observe changes in a time-series but, on its own, this isn't sufficient to prove a causal connection between the event and the change in the time-series. That said, constructing a list of major events that occurred just before the change in the time-series does allow for plausible hypotheses to be formed that are worthy of further examination.

28 These reforms led to a one-time loss of over 20% in NPL's scientific staff, which is likely to have contributed to the drop-off in the number of "treated" firms. Furthermore, there was probably a time lag between reforms commencing and the subsequent impact on NPL's output.

7 TIME-SERIES FOR THE COUNT OF SUPPORTED FIRMS

Having analysed the time-series for our headline indicator of economic impact it remains to analyse the time-series for our other indicators showing the number of firms in the 'pipeline' and heading towards being treated. It's also important to note that the firms in this pipeline receive some benefits on their journey towards 'treatment', even though the econometric evidence suggests that this impact is typically of a lower order of magnitude.[29] Hence, we now look at the number of firms receiving any form of support over a six-year period, as illustrated by the chart below:

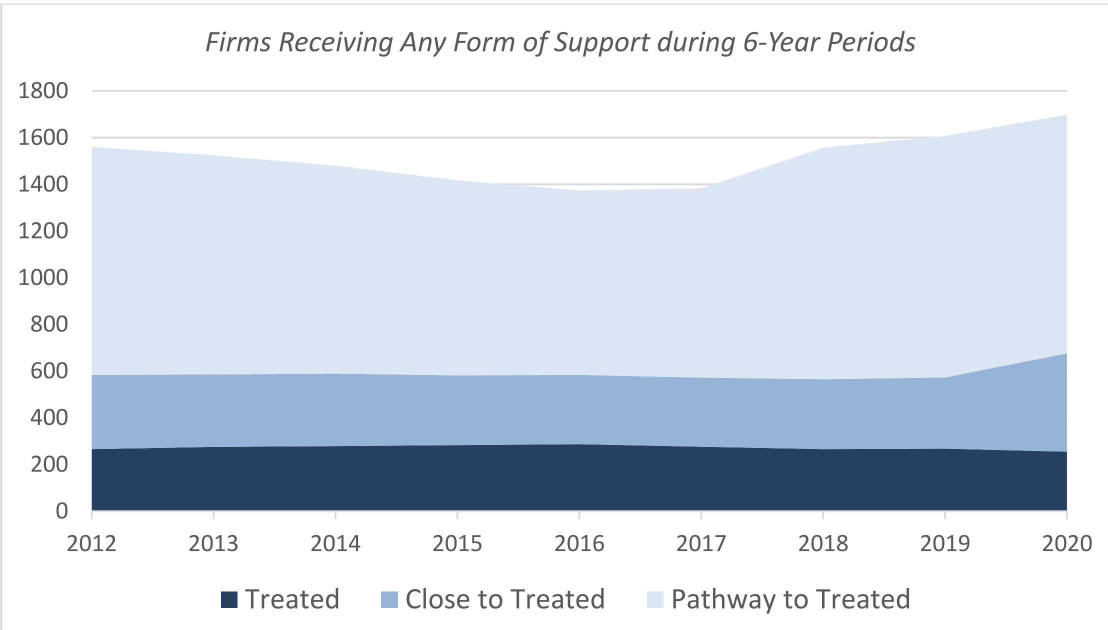

Figure 2

The chart above stacks all three of the indicators discussed in this report on the same axis. The darkest area of the staked line graph, given above, follows on from the previous line graph in that it's only tracking the number of "*treated*" firms. The lighter areas of this staked line graph track our metrics for the "*pipeline"* to treatment. As before, each of the years, detailed in the graph, is assessing a six-year period inclusive of the year itself. (For example, 2012 assesses support delivered to firms during the period 2007-2012.)

There was a consistent decline in the number of firms on the "*pathway to treatment"* from 2012 up until 2017. One hypothesis for why this decline occurred is that the closure of the *Measurement for Innovators* (MfI) programme, as well as stricter limits on the number of EMPIR projects, made it more difficult for scientists to engage with new firms, and so less firms entered the "*pathway to treatment"*.[30] However, in 2018, there was a ~28% <u>increase</u> in the number of firms on the "*pathway to treatment"*. This increase in firms entering the "*pipeline*" saw a large spike in 2018 and was followed by consistent, though lower, levels of growth after. The cause of the spike in 2018 is currently unknown but appears to be

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29 Evidence from a '*dose response*' model (based on a count of invoices) suggests that the huge number of sometimes-supported firms, found in the pipeline towards '*treatment*', only accounts for around 17% of NPL's attributable impact on firms' employment growth.

30 Because NPL generates most of its private sector revenue from its 'treated' firms, a drop in grant-funded projects may have encouraged a focus on winning more commercial work from regular customers, as opposed to broadening the userbase by trying to attract new customers.

correlated with Advanced Manufacturing.[31] After 2018, A4I and its sister programmes “take up the slack”, with a notable proportion of new firms to NPL in 2020 coming from A4I et al.[32]

The number of firms *“close to treatment”* had been almost constant up to 2012, with only a very slight decline over time. However, this changed in 2020, with a dramatic 40% increase, that took the total number of such firms to 421. This increase is likely to have been a delayed effect of the introduction of the *Analysis-for-Innovators* (A4I) programme in 2017. That is, by construction, there’s a two-year lag before an increase in the number of firms on the “*pathway to treatment*” can feed through to a change in the number of firms that are “*close to treatment*”.[33]

8 HYPOTHESES CONCERNING THE MOVEMENT OF TREATED FIRMS

There is strong evidence of a decline in the number of ‘treated’ firms after 2016, but why this happened isn’t entirely clear. However, one possible explanation runs as follows:

It’s possible that cause of the decrease in the number of “treated” firms seen in the 2nd period actually originates in changes that occurred in the 1st period, namely, the closure of the MfI programme and a restriction on access to funding from EMPIR. This could have led to a greater focus on winning commercial income from the “regularly supported” firms, which would tally with an increase in the number of “treated” firms, as seen in the 1st period. It can be hypothesised that, a greater focus on the “regularly supported” firms, came at the detriment to firms that might otherwise have been encouraged to enter the "pipeline", which would tally with a decline in the number of firms on the "pathway to treatment", as was also seen in the 1st period.

In the 2nd period, the effect of neglecting the "pipeline" in 1st period, ultimately, fed through to a drop in the number of “treated” firms. This was probably compounded by a very high ‘churn’ among NPL’s staff, that accompanied the reforms that took place following the end of Serco’s contract in 2015. In particular, the spike in churn in 2016 was due to a portfolio rebalancing exercise, leading to redundancies across NPL.

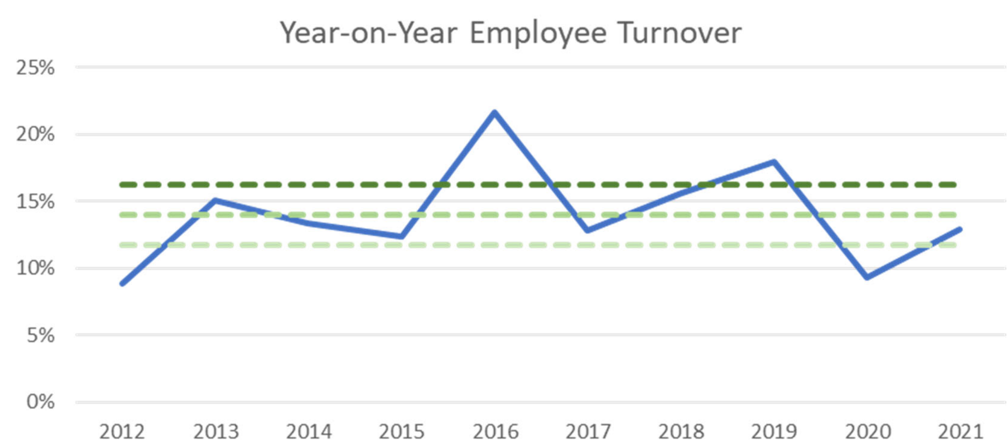

Figure 3

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31 See annex 18.4 for more information concerning new firms
32 The apparent plateau in 2019-2020 is likely due to firms graduating from being on the “*pathway to treatment*” to being “*close to treatment*”.
33 Although we can’t see this yet in the data, we’d expect the same two-year lag between the series for the number of firms “*close to treatment*” and the series for the number of “*treated*” firms.

We currently have staffing data back to 2012, showing that 2018-2019 saw a larger proportion of leavers, relative to total headcount at the time, when compared to the ‘churn’ that was observed in other years. Of course, the demand for support from the private sector will also be influenced by macro-economic factors that affect the general level of business investment. Hence, there may have been other exogenous factors that have led to the changes in the “treated” firms, such as the Brexit vote in 2016 which created a period of uncertainty and so dampened private sector investment for a while. This is not to deny that Brexit may have long-term benefits, but the immediate aftermath of the decision had a negative impact on private sector investment. The impact of Covid has likely impact the spend of businesses on R&D, likely causing the drop in treated firms from 2019 to 2020.

Lastly, a final remainder that the causal story sketched above isn’t yet proved, although, it has enough plausibility to warrant some further investigation, because understanding why things happened in the past gives us more control over them in the future.

9 SUMMARY OF THE COUNT METRIC ANALYSIS

Up until this point, an analysis of the time-series for the number of “treated” firms (defined as firms in receipt of regular support from NPL) has been conducted. The time-series for the number of “treated” firms appears to follow a random-walk process with drift, and the resulting series trends up or down depending on the sign of the drift parameter. However, there is evidence that structural break occurred around 2016, involving a statistically significant change in the value of the drift parameter (likely, going from positive to negative), where the change in this drift parameter reflects something structural occurred that led to a decline in the number of “treated” firms over multiple years.

Why a decline in the number of “treated” firms set-in after 2016 (the material cause) isn’t too clear, but two possible explanations are as follows: (1) disruption to working routines that accompanied reforms taking place following the end of Serco’s contract in 2015; and (2) a narrowing of the “pipeline”, of new firms on the path to “treatment”, due to a decrease in the availability of grant-funded projects that involved industrial partners. The downward pressure from structural influences (whatever changed the sign of the drift parameter) was almost certainly compounded by the onset of the COVID crisis in 2020. Indeed, what may have been the beginnings of a systematic bounce-back in 2019 appears to have been choked-off by the COVID crisis.

As discussed, this document has also analysed the time-series for the number of firms on the path to becoming “treated”, which is referred to as the “pipeline”. The number of firms on the “pathway to treatment” has been increasing since 2018; and the number of firms “close to treatment” increased significantly in 2020. This time lag suggests that it takes two years before an increase in the number of firms on the “pathway to treatment” feeds through to the number of firms “close to treatment”. A plausible explanation for growth in the number of firms entering the “pipeline” is the introduction of the Analysis for Innovators programme in 2017.

Finally, there should be a two-year lag between a change in the number of firms “close to treatment” and a change in the number of “treated” firms. Hence, we’d expect to see the number of “treated” firms to begin to bounce-back in 2022 as a consequence of the increase in the number of firms “close to treatment” that was already witnessed in 2020. Therefore, given that the COVID crisis is starting to pass, we’d expect to see the number of “treated” firms stabilise in 2021, followed by a strong bounce-back in 2022.

10 ANALYTICAL USES OF THE METRICS

The development of the support metrics provides valuable information to NPL on their own. However, the metrics can be used in analysis to garner more information in several different areas. At this point in time, through the finding of Belmana (2019), we assume that firms that are treated see improved survival rates, higher employment, and higher wage rates. However, the Belmana study is somewhat narrow in its analysis. It was based on a single window of time (2009-2017) and used a binary treatment variable, treated or untreated. This is not demeaning the study in any way shape or form; its findings are incredibly important to making the economic case for the NMS, but it could be extended.

Rather than using a binary treatment, a categorical one could be developed using the statuses, showing different levels of outcome. This would enrich the analysis and provide evidence of impact for firms who receive less support than treated. Furthermore, rather than using one period of data, several "cohorts" of data could be used. These would be stacked upon one another and would help to reduce the statistical noise, improving the signal from the data used, a la Frontier Economics (2016).[34] What is done here is an associative version of that analysis. It is out of the scope of this paper to conduct a causal analysis due to the time and effort needed to develop a control group and run an analysis of that manner, rather an analysis based on association can be run, assessing if there are differences between the statuses with regards to growth of assets and survival rates. This would inform the development of a re-run of Belmana (2019), determining whether it would be beneficial to have a categorical treatment variable.

Although the primary use of this analysis is to assess the impact of NPL on the private sector, this analysis also has the potential to help inform the operations of the organisation. As will be detailed in section 13, the treated firms account for the vast majority of NPL's income and invoices, clearly indicating their value to the financial performance of NPL. It would be in the best financial interest of the organisation to increase their number over time, in order to increase revenue from the private sector. However, creating treated firms requires the development a strong relationship with the prospective customer due to the time required to move a firm towards treatment. What the metrics can do here is provide a baseline for the probability of firms moving towards treatment over the last 9 years. By providing a baseline for what has happened, an assessment can be made concerning actions moving forward to increase the number of supported and treated firms. Also, bottlenecks can be identified concerning not only the movement of firms from newly supported to treated, but how firms fall out of the system and the "point of no return", where they are very unlikely to work with us again.

34 Frontier Economics. 2016. "The Impact of Public Support for Innovation on Firm Outcomes."

11 KEY CONCEPTS

For the analysis in this section, there are two concepts that are the bedrock upon which it is built. The description below will be mainly theoretical descriptions. When utilised, it will be noted and contextualised.

11.1 LINEAR PROBABILITY MODEL

Where a regression formula has been used within the analysis in this report, the *Linear Probability Model* (or LPM) has been used as the outcome variables are all binary (either 0 or 1). The standard linear regression model is as follows:

$$Y_i = \beta_0 + \beta_1 X_{1i} + \beta_2 X_{2i} + \ldots + \beta_k X_{ki} + u_i$$

Where Y_i is the dependent variable over i observed values, β_0 is the intercept, X_{ki} represents k number of independent variables over i observed values, β_k representing the coefficients of k independent values and u_i representing the error term. If Y_i were to be a binary value, the model would no longer be a linear regression model but would now change to an LPM, where:

$$E(Y_i|X_1, X_2, \ldots, X_k) = P(Y = 1|X_1, X_2, \ldots, X_3) = \beta_0 + \beta_1 X_{1i} + \beta_2 X_{2i} + \ldots + \beta_k X_{ki} + u_i$$

Therefore, β_k can be represented as the change in probability that $Y_i = 1$, when holding the other k-1 dependent variables constant. As with multiple regression, the β_k can be estimates using OLS.[35] In the analysis done here, either binary or 4 category variables are used as independent variables. Therefore, the coefficients produced are the probability of $Y_i = 1$ given $X_{ki} = \{0,1\}$ or $\{1,\ldots,4\}$. LPM can be used a first step for modelling as it is very simple to estimate and produces easy-to-understand coefficients.

However, LPM does have its issues. Firstly, the relationship between the independent and dependent variables can't have a linear relationship, as probabilities must be constrained within 0 and 1 (e.g., impossible to have a probability greater than 1 – would mean an event has a greater than 100% chance of occurring). There are also issues concerning heteroskedasticity, as the variance of Y_i depends on the values of X_{ki}. These can be corrected for by using robust standard errors, but even still the robust standard errors aren't totally correct as they aren't normally distributed. As detailed before, this model is used as a first step within the modelling process, which is how it is used here. If this analysis was taken further, it may be more appropriate to use either logit or probit model, which manage some of the issues detailed above. However, at this point in time, using the LPM provides early indications concerning the impact of the statuses, when compared to one another. This can be expanded upon in subsequent work.

35 https://www.econometrics-with-r.org/11-1-binary-dependent-variables-and-the-linear-probability-model.html

11.2 RELATIVE YEARS

In order to explain relative years, the diagram here shows how an example firm would look like in the data. The years support was given to a firm are reported, along with the duration of each of the cohorts:

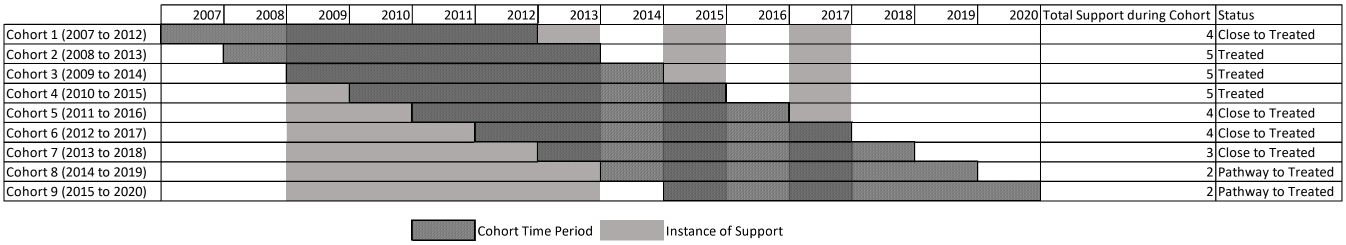

Figure 4

This exemplar firm has worked with NPL seven times in the 15 years of data at hand for tracking support. The firm can have a different status in each of the cohorts. Using these cohorts, they can be stacked on top of each other and assessed as a totality. This is a method that was used by *Frontier Economics (2016)* when assessing the impact of public support for innovation on firm outcomes. This study stacked its cohorts then looked x number of years after treatment (treatment in the Frontier Economics study meant receiving NMS or Innovate UK support). This utilised a “propensity score matching approach combined with a difference-in-difference estimation”. The analysis done here is more like a generalised propensity score analysis, which uses a non-binary form of treatment. The standard version of generalised propensity score uses continuous forms of treatment, which this data isn’t. But there is literature concerning the use of multi-categorical treatment variables within a generalised propensity score framework.[36]

This use of relative years is also similar to a Kalman filter, as it uses a series of measurements observed over time that reduces the noise that can be generated by estimates using a single observation. Using the diagram above. the development of a series of measurements observed over time is the process of generating the cohorts and stacking them on top of each other, rather than just using the observations. A critique of this method is that the use of repeat observations is done merely to reduce the standard error, allowing for significance to be found which wouldn’t be otherwise.

To present the analysis, the final years of each cohort are reported as the year of assignment. This year of assignment can also be referred to as the base year or year 0 in graphs. By holding all of the cohorts at their base years, the data can be aggregated, and assessments can be made moving forwards and backwards where possible. the time index is years but rather than calendar year, relative years are used, which merely respond to how many years the data point is away from the base year.

This method means that the analysis provides greater insight than standard pieces of association analysis. The use of this sequencing method allows for an assessment of how differing levels of support can lead to different levels of outcome. This still isn’t strict causality, but if differences were found, further statistical investigation with the use of a

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36 Hu, A. and Mustillo, S.A. (2015). Recent development of propensity score methods in observational studies: Multi-categorical treatment, causal mediation, and heterogeneity. *Current Sociology*, [online] 64(1), pp.60–82. doi:10.1177/0011392115589599.

The above report shows the viability of the technique but requires further work to adapt and implement.

control group could be warranted. Even if the statistical investigation wasn't conducted, Belmana (2019) shows the economic impact over a specific period of time, one that could be adopted to assess the GVA growth of NPL's support. This is seen in the NPL business case, with further details are in Annex 18.1.

12 ASSOCIATIVE IMPACT ANALYSIS

The first area of analysis that will be presented is an early attempt to ascertain the impact of residing in one of the support categories/statuses. This analysis isn't of the same ilk as Belmana (2019), but rather looks at association rather than causation. The development of an external counterfactual is outside of the scope of this report, but the work done here could inform the development of a report a la Belmana (2019) moving forward. The purpose of this section is to look at the movement of the averages within the datapoints, assessing the general patterns of NPL's user database. It should be noted that outliers can exist (i.e., individual firms could see greater than average impacts) within the database, but this isn't comparable to the vast majority of firms that work with NPL.

12.1 DEATH RATE

An important indicator for the impact of NPL on the private sector is the survival of firms. This was done by using the FAME database's category known as company status. This indicates if a firm is "active" or not. Within the active category, there are a range of subcategories which were assumed to be "death", these included *Dissolved, Dormant* and *In Administration* to name a few.

Using this definition of death, a binary indicator was used in order to assess if a firm had "died" – entered one of the definitions of death. This binary indicator was used as the outcome variable in a set of regressions, where forward operators were used to account for relative years as the interest was concerning the likelihood of death after a firm had been assigned a status. the following regression formula was used:

$$D_{i,t+n} = \beta_1 + \sum_{\kappa=2}^{4} \gamma_\tau^\kappa . \mathbb{I}(S_{it} = \kappa) + \varepsilon_{it}$$

Where:

- t = Calendar year
- $D_{i,t+n}$= Binary Indicator assessing if a firm I had died in year t (± τ years)
- β_1 = constant representing the probability of Treated firms dying
- S_{it} = Status of firm i in year t where S_{it} ∈ {Close to Treated, Pathway to Treated, No Recent Interaction}
- γ_τ^κ= Coefficient given relative year and status
- ε_{it} = Error term

The linear probability model assumes that the coefficients on the explanatory variables are the probability of a firm with that characteristic – in this instance, their status – of being "dead" (where the explanatory variable = 1). By using forwards operators, an assessment can be made moving forwards, looking τ number of years after assignment to see how the probability of death increases.

The γ_τ^κ are collected and plotted for each status and relative year. They will be presented in two ways. Firstly, a panel containing a bar graph for each status will be used to show the trends, as it'll allow for error bars to be used for each status without the graphs looking too messy. Succeeding the panel will be a line graph for all the main statuses, with the relative years comprising the x axis and the probability of death comprising the y axis:

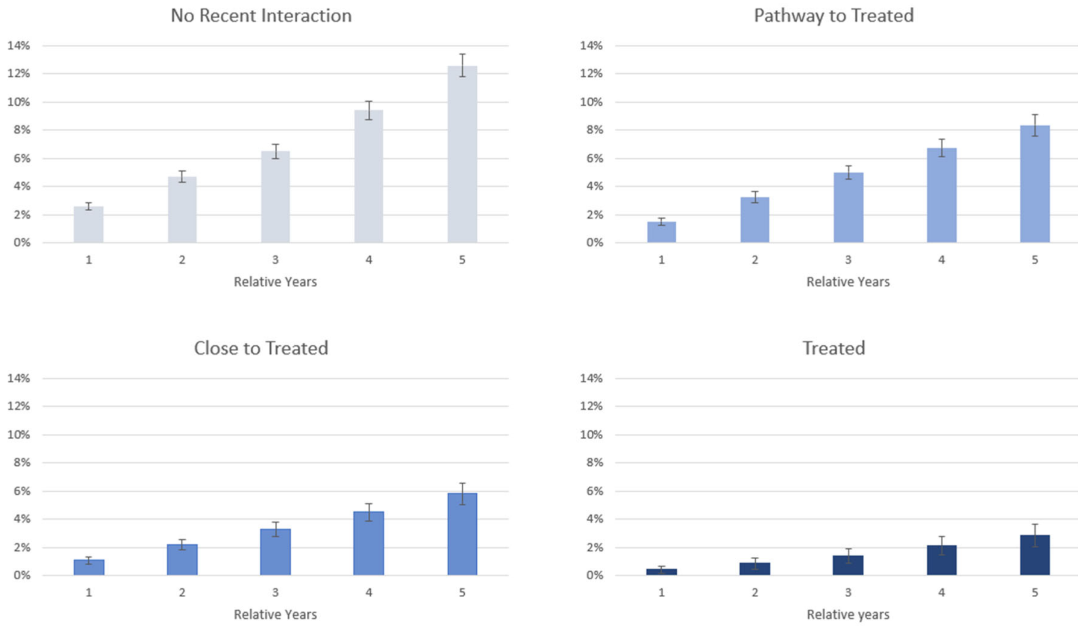


Figure 5

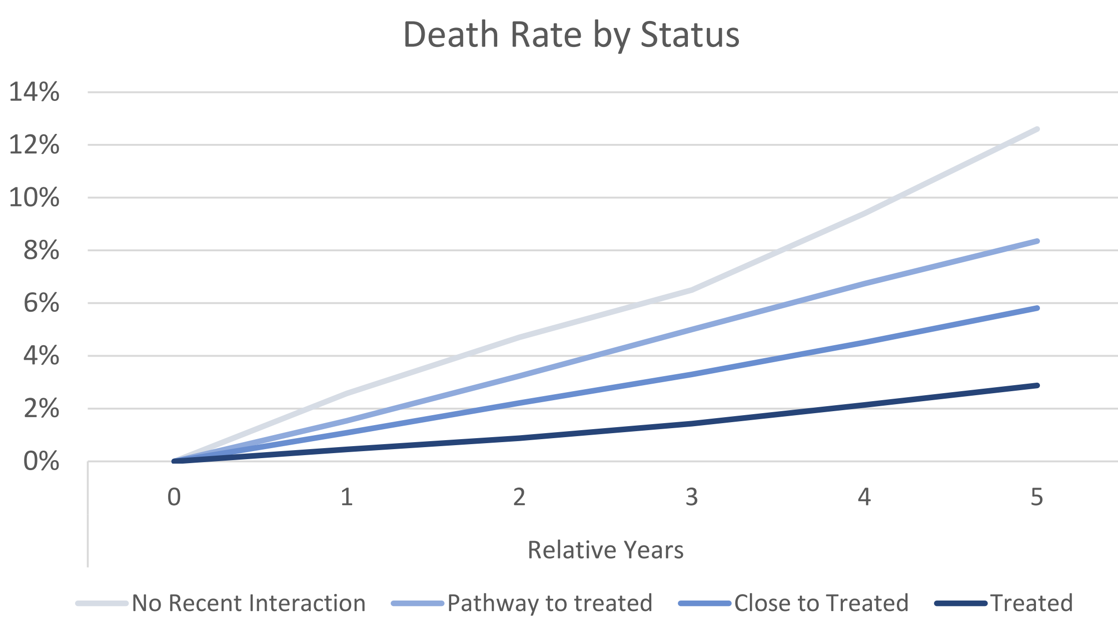


Figure 6

What is seen the time and status effects on a firm's death rate. The likelihood of a firm dying increases over time from the point of a firm being assigned a given status. That trend is constant for each status. But what is notably different is the gradients for each status. They all start in the same point, but the higher the level of support you receive, the lower your death rate is. It should also be noted that the error bars increase in size as you move further forward, this is due to the dataset shrinking the further away you get from 0 relative years (years of assignment).[37]

Although this analysis is merely associative, an attempt to introduce controls has been done, with the statuses remaining as a significant factor in determining an average firm's probability of growing its assets.[38]

12.2 CHANGE IN ASSETS

Although survival is important, it could be argued that NPL is merely keeping firms afloat, allowing "zombie" firms to stay alive when really, they should be allowed to die. This would allow for that firm's assets and employees to be recycled back into the economy and re-enter the labour market. This can be tested by assessing whether the firms NPL work with are growing, seeing whether the firms are the "zombie" firms detailed above or are in fact thriving businesses. This is done by assessing their assets, seeing if they had grown between years. For this analysis, total assets were used rather than gross assets. This was due to the fact that gross assets often comprise of the capital a firm has, which may not be the most representative measure of growth for NPL.

This would lend more weight towards manufacturing firms[39], for whom growth can be measured more accurately by assessing an increase in capital (i.e. more machinery for the production of goods). Therefore, using total assets, which would include (among other things) cash assets from sales, would be a better measure of the growth of NPL's supported firms. Another thing to account for is the issue concerning the differences between percentage and absolute growth for the supported firms. A small firm's growth may be much smaller when compared to a large firm's growth when compared in absolute terms, but as a percentage growth, it would be much more significant. Therefore, binaries were used to deal with this issue, allowing for the utilisation of the Linear Probability Model, with each of the coefficients for the statuses assumed to be the probability of an average firm seeing I = 1 given their status (i.e., an average firm seeing growth in its assets given their status).

This was done by taking the first differences between years for each unique firm, then assigning a binary if the following held true:

$$I_{i,t+\tau} \ = \ 1 \ if \ A_{i,y_{t+\tau}} > A_{i,y_t}$$

$$I_{i,t+\tau} \ = \ 0 \ if \ A_{i,t+\tau} \leq A_{i,y_t}$$

Where:

- $I_{i,t+\tau}$ = Binary Indicator assessing if a firm i's assets has grown in year $t+\tau$
- A_{y_t} = Assets for firm i in year=t (where t=year of assignment of status)
- $A_{y_{t+\tau}}$= Assets for firm i in year=t+τ (where t + τ = τ number of years after t assignment year)

I is used as the outcome variable in the regression, with the statuses as explanatory variables, as seen below:

$$I_{i,t+\tau} \ = \ \sum_{\kappa=1}^{4} \theta_{\tau}^{\kappa}.\mathbb{I}(S_{it} = \kappa) \ + \ \varepsilon_{it} \text{ or } \mathbb{E}\,[I_{i,t+\tau}] = \ \sum_{\kappa=1}^{4} \theta_{\tau}^{\kappa}.\mathbb{I}(S_{it} = \kappa)$$

where:

- t = Calendar year of assignment
- τ = Relative year

37 See Annex 18.3

38 See Annex 18.1

39 These are firms who fit within SIC hierarchy section C: Manufacturing (Divisions 10 – 33)

- S_{it} = Status of firm i in year t where $S_{it} \in$
  {Treated, Close to Treated, Pathway to Treated, No Recent Interaction}
- θ_{τ}^{κ}= Coefficient given relative year and status
- ε_{it} = Error term

As seen in the death rate analysis, the coefficient θ_{τ}^{κ} are collected and plotted for each status and relative year. The use of lag and forward operators can be represented as the relative years, with year of assignment held constant. This allows for each cohort of firms to be stacked on top of each other, reducing statistical noise and allowing for the signal to feed through.[40]

The analysis looks at three main periods, Pre-, During and Post-Assignment of status. For simplicity, let's assume that the assignment year in question is 2017. As the assignment of status given the level of support requires 6 years, the support period looks at the current year and previous five (2012-2017). Then, the years preceding their treatment (before 2012) are assessed to see what their growth looked like then (for a firm being assessed in 2017, the pre-support period would be from 2007-2011). It should be noted that the earlier in the pre-support period you go, the smaller the data set is and the higher the standard deviations (therefore accuracy of the points) are[41].

It should be noted that support can/does occur through the entire time period, but the focus of this analysis is on the support that occur in the *During Assignment* period, where status is determined. An analogy that can be used is one similar to the education system and its outcomes. Assignment of status in year 0 can be seen as a firm's "grade", assessed in a continuous manner like the IB[42], where it is assumed that working more with NPL increases your grade (Treated = 7, Close to Treated = 5, etc..). It is hypothesized that the grade a firm receives correlates with a firm's "success". In the analogy, success would be viewed as doing better in life (higher earnings, better quality of life, etc.). In the model, success is viewed as having a greater probability of growth. The support firms receive before and after the assignment period are deemed to be similar to attending primary school and university. The focus of this analysis is seeing how firms do in "secondary school" before (as a baseline) and after.

Below is the graph for Treated and No Recent Interaction firms:

40 Any value obtained by a measurement contains two components: one carries the information of interest, the **signal**, the other consists of random errors, or **noise**, that is superimposed on the first component. These random errors are, of course, unwanted because they diminish the accuracy and precision of the measurement. http://www.statistics4u.com/fundstat_eng/cc_signal_noise.html

41 See Annex 18.3 for more details.

42 The International Baccalaureate (IB) diploma is an academic programme which is an alternative to A levels, but uses continuous assessments rather than examinations.

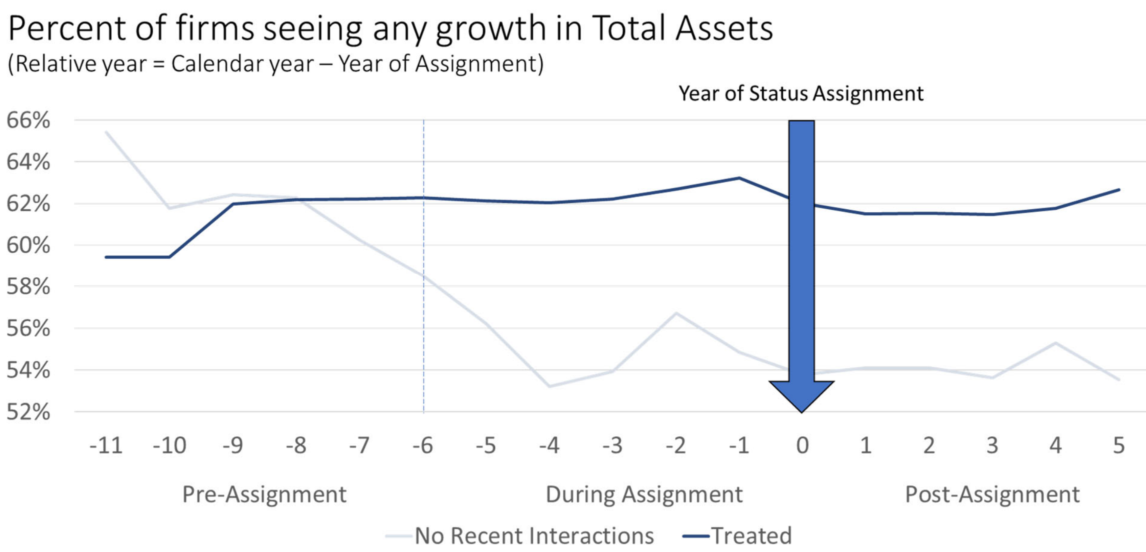


Figure 8

The main point that can be drawn from the graph is that a greater proportion of treated firms see growth than the no recent interaction firms. That is fairly self-explanatory but should be noted is that they both start at fairly similar points with regards to growth probability. What occurs is a drop off in growth for the No Recent Interaction firms which isn't reciprocated by treated firms. This is assumed to be the benefit of NPL's support helping to maintain growth levels for these respective firms. Only two statuses were used here as the statuses are noisy, leaving the signal from the data tricky to identify. Therefore, multi-year averages were used to reduce noise and strengthen the signal.

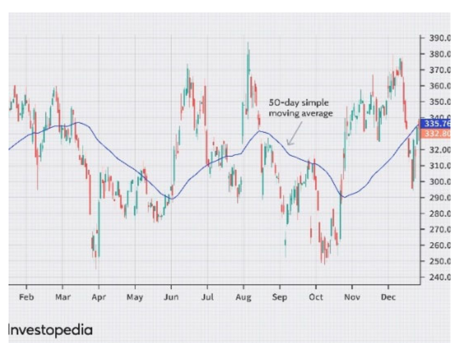


Figure 7

Multi-year or moving averages are used in various different areas of research in order to filter out noise from short-term fluctuations. An application of this is seen above in financial data, where the movement of day-to-day tick bars are averaged out by the 50-day moving average. A time period within the dataset is taken, and an average is provided. The time period used for the analysis conducted in this report is 6 years as it ties into the definition of support periods used in assignment of status.

The “smoothing” of each of the curves going from raw scores to moving average allows for the general trends of the data to be assessed.

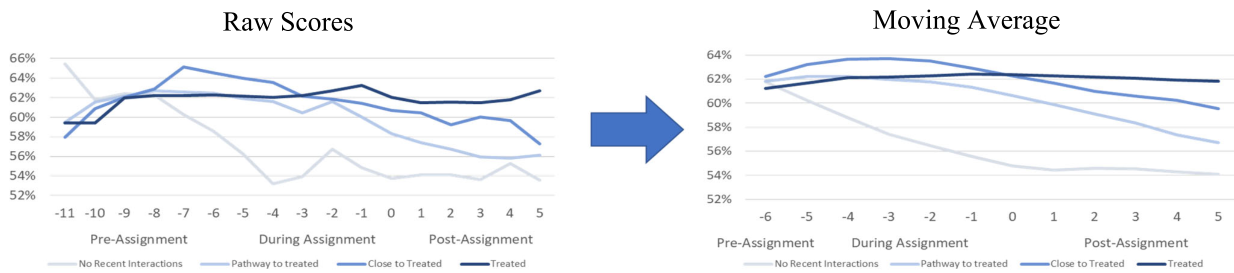


Figure 9

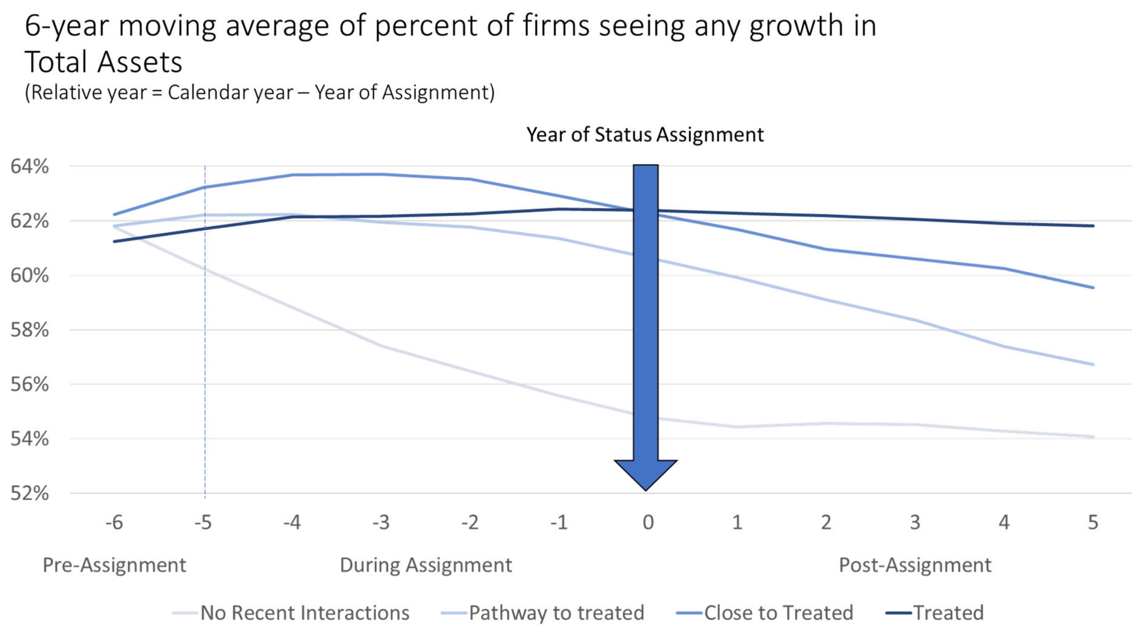


Figure 10

The description of *no recent interaction* and *treated* firms holds, while the other two statuses mirror each other, with Pathway to Treated set slightly below Close to Treated. Pathway to Treated and Close to Treated are in between the two extremes, seeing better growth than the No Recent Interaction but unable to maintain the same proportion of growth as the treated. Building on the education analogy used earlier, these are the people within the group who apply themselves partially, with those in the Close to Treated applying themselves more than the Pathway to Treated. One interesting point is that the Close to Treated firms appear to do better earlier than the treated firms. These could be viewed as the high achievers in school. Generally speaking, this group does better earlier than everyone, but after a while they tail off and do worse due to a lack of application. The only group that does consistently well are those who are treated. This is seen better when averages are taken for each period:

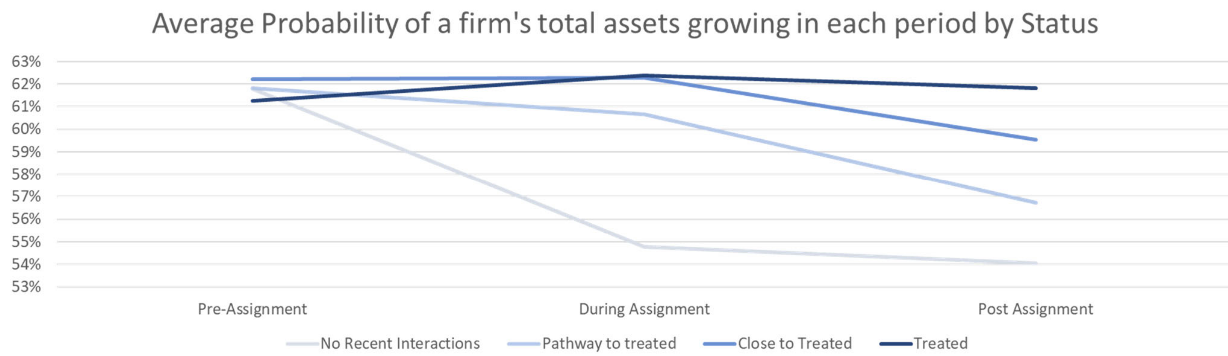


Figure 11

As can clearly be seen here, the statuses are very similar pre-assignment, then diverge during- and post-assignment. These trends can be seen but can be tested in further detail.

A time trend analysis was subsequently conducted in order to prove significant differences between the relative years and the trends seen for each sector. If there were notable differences seen, this would suggest that a causal relationship exists between the statuses and probability of a growth in total assets. This causal relationship is purely internal to NPL and isn't an indicator of growth of firms scaling when compared to firms that haven't received support from NPL.

To conduct the analysis, the dependent variable used were the coefficients plotted in the section before (θ_{τ}^{κ}), done by taking the first differences between each period. These coefficients were regressed on an interaction term between a continuous time variable to account for the relative years and the statuses in categorical form. This interaction term assesses the relationship between the coefficients over both status and time. The Statuses, with regards to the coefficients, are all compared to the Treated Coefficients. The formula of the regression is as follows:

$$G_{i\tau} = \lambda\tau + \psi \sum_{\kappa=1}^{4} \mathbb{I}(S_i = \kappa) + \ \phi_{\tau}^{\kappa} \sum_{\kappa=1}^{4} [\mathbb{I}(S_i = \kappa) \times \tau]$$

Where:

- τ = Relative year
- S_i = Status of firm i where $S_i \in$ {Treated, Close to Treated, Pathway to Treated, No Recent Interaction}
- G_{τ}^{κ} = Probability of growth given relative year and status (the Θ^{k}_{τ} from the previous regression).
- $\varepsilon_{i\tau}$ = Error term

The analysis done here doesn't care about the intercepts. Rather, the main focus concerning the coefficients ϕ_{τ}^{κ}, which represent the slope of each line, given status. The significance and sign of these coefficients show the difference between the treated group and other respective groups. This regression is done twice with two different time restrictions to see assess changes in slopes around a given point.

- During Assignment – Between relative years 0 and -5
- After Assignment – From Relative year 1 and onwards

	Before Assignment year		After Assignment year	
Difference between Statuses when compared to Treated	Coefficient	P-Value	Coefficient	P-Value
No Recent Interaction	-0.0127	0***	-0.00059	0.787
Pathway to Treated	-0.0039	0.04**	-0.00588	0.014**
Close to treated	-0.0015	0.431	-0.00648	0.008***

Table 3

Here we see the trends of the probabilities of growth among the firms in their respective status when compared to the probabilities of those who are treated. In Period 1, No Recent Interaction and Pathway to Treated's coefficients are falling significantly more than the Treated coefficients, with Close to Treated being insignificantly different to Treated, though it does have a negative significance.

In Period 2, Pathway to- and Close to Treated both see a significant declining trend in comparison to Treated, with No Recent Interaction following the same trend. This is due to No Recent Interaction "bottoming out" with regards to their coefficients, which can be assumed to be the lowest point a firm that has worked with NPL can reach. This is what is seen in the 6-year graphs above but proves the statistical significance of it. This "Bottoming-out" effect, along with the other details can be visualised when fitted values are used and plotted. Fitted Values are generated as a regression's prediction of the mean response values, predicting what the data looks like given the coefficients produced by the regression.[43]

As two regressions were used with two different time periods (before and after assignment year), the fitted values were used from their respective time period

- Fitted values from pre-assignment regression are used for relative years less than or equal to zero
- Fitted values from post-assignment regression are used for relative years greater than zero

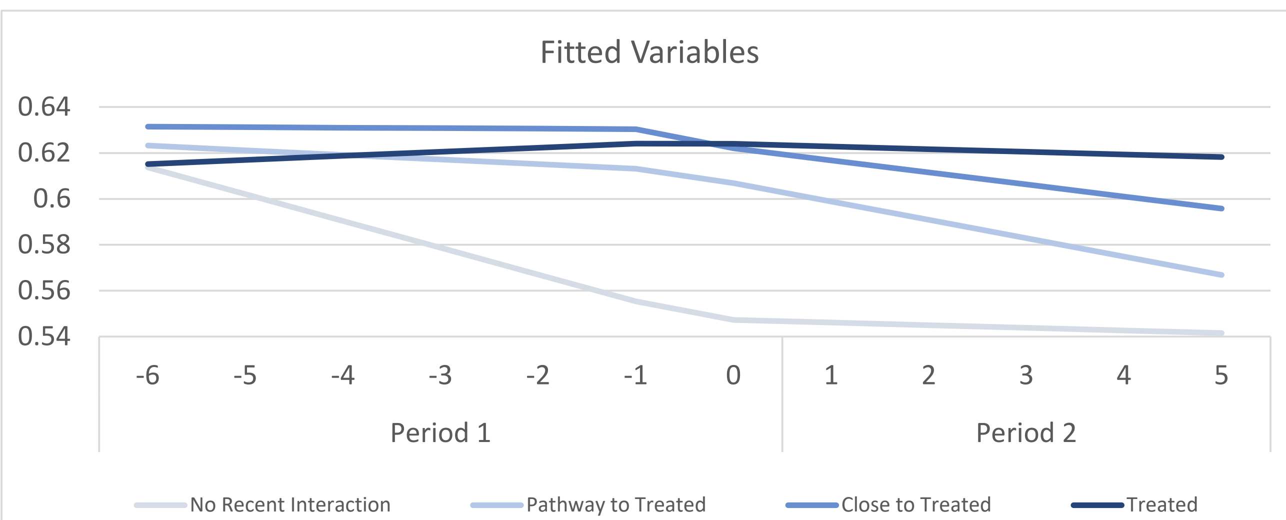


Figure 12

43 A fitted value is a statistical model's prediction of the mean response value when you input the values of the predictors, factor levels, or components into the model.

Reaffirming the points seen before, treated values have a positive slope in period 1, while the other statuses' values are all negative (with statuses further away from Treatment being more negative than those closer to Treatment). While in Period 2, The "Bottoming out" of No Recent Interaction is seen. This is coupled with Pathway to- and Close to Treated declining significantly, while treated declines less.

13 OPERATIONAL ANALYSIS

As these metrics were borne out of *Belmana (2019)*, their initial purposes were primarily as a way to assess the impact of NPL, given the wage and employment impacts treatment has on these firms. However, the way in which these firms impact NPL is also noteworthy. The number of invoices and revenue, given their proportion in our database is worthy of investigation, which the following graphs detail:

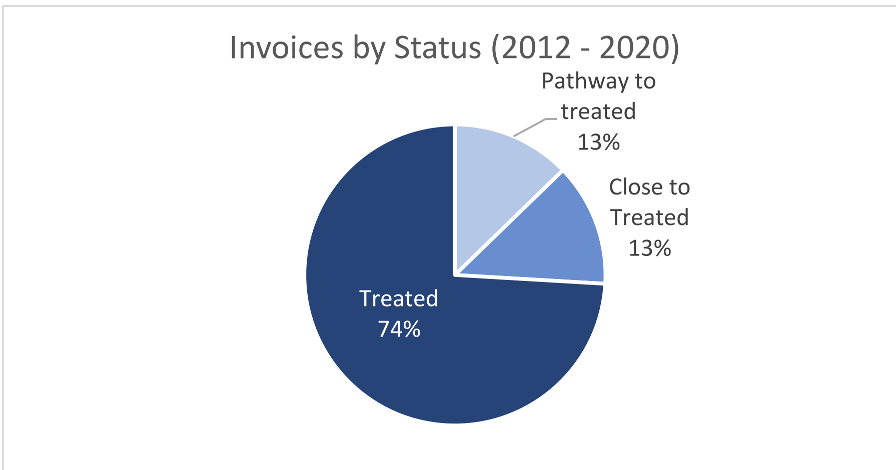


Figure 13

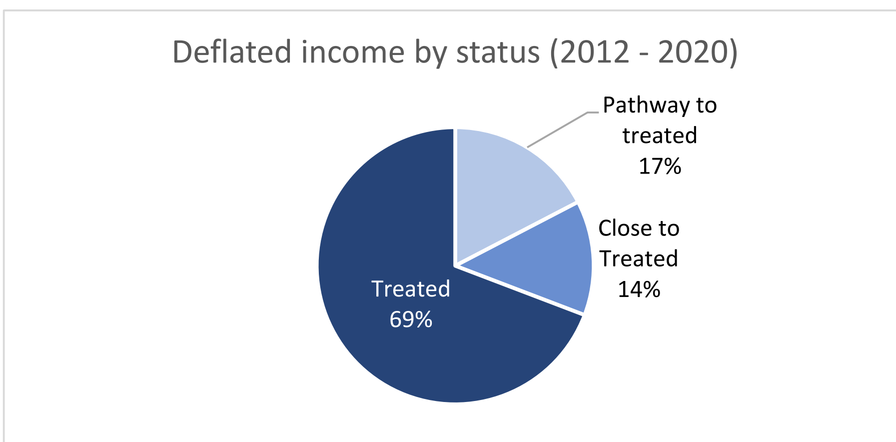


Figure 14

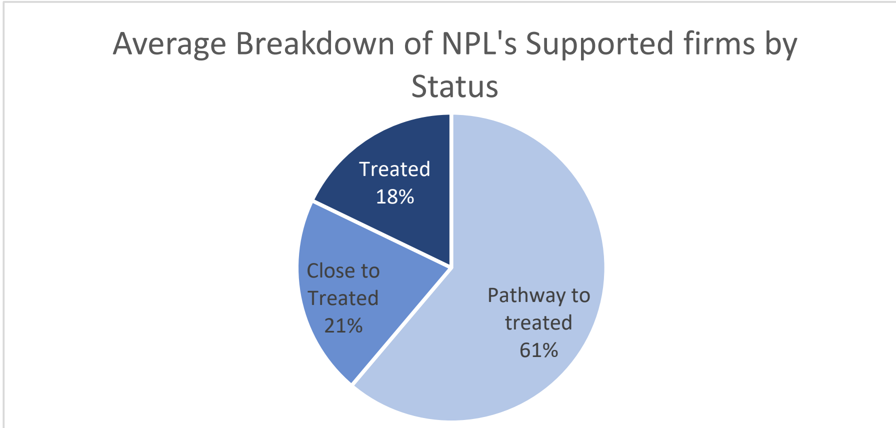


Figure 15

As can be seen by the following graphs, treated firms make up only 18% of NPL's supported firms each, yet they account for 69% and 74% of NPL's income and invoices respectively. This shows the value to NPL this group of firms hold when it comes to generating revenue through our work. As part of this, the headline metric of treated firms is a key indicator and likely corollary with NPL's private sector income in a given year. In annex 18.3, regressions were run, with income found to be significantly lower for all other statuses when compared to treated firms. This also includes control variables, moving towards a causal rather than associative relationship. The following pieces of analysis assess how NPL can use the indicators developed in this paper to assess how it does with regards to the flow of firms through the statuses, providing a benchmark to which NPL can assess its interventions with regards to the revenue and invoices received from the private sector.

13.1 MARKOV CHAIN ANALYSIS

This analysis is built on the Markov process, which details that predictions can be made regarding future outcomes based solely on its present state. What's notable about the Markov process is that such predictions are just as good as the ones that could be made knowing the process's full history. The application of the Markov process within the NPL context concerns the development of a Markov switching model, where data can be characterized as falling into different regimes/states, with a probability existing that any series within that data can be in a given regime and transition to a different regime. This model requires an assumed number of regimes in order to be developed. For each regime, there are probabilities for remaining within or transitioning between each respective one. These are known as transition probabilities and are the values attached to the arrows, as detailed by this simple example:

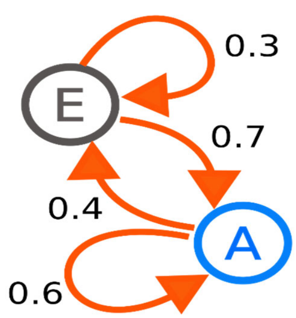


Figure 16

When assessing NPL, the Status of Supported firms' variables can be viewed as regimes, which allows for an assessment to be made with regards to the flows in and out of each variable. The use of the Markov chain allows for the first differences to be collected year-on-year, then averaged to assess the probabilities of flowing in and out of the system. This would allow for an assessment to be made on the current structure of the system, providing a benchmark to assess short-term changes to NPL.

On top of the aforementioned Status variables used in the analysis, there are two other variables that are required as part of this analysis. These capture the two unknowns aren't a part of the NPL's supported firms but capture two key outcomes and an input into NPL's statuses. As they are unknown, it is impossible to provide a value for them, though we do know the probability of a firm to fall into them. The two variables are:

1. Dead Firms – As detailed in section 9.1, this refers to firms that have ceased being active as detailed from the FAME database. A firm can "die" from any of the SSF variables and cannot return from that area.[44]

2. The Void – This refers to two groups of firms[45].
    1. Firms that have never worked with us before and can be defined as <u>brand new</u> when they enter the system (*Unknown firms*)
    2. Firms that haven't worked with NPL for over 8 years. these firms are deemed to have "fallen out" of the model and are referred to as <u>returning legacy firms</u> when they re-enter the system (*Fallen Firms*)

With these two variables, the model can be constructed as follows:

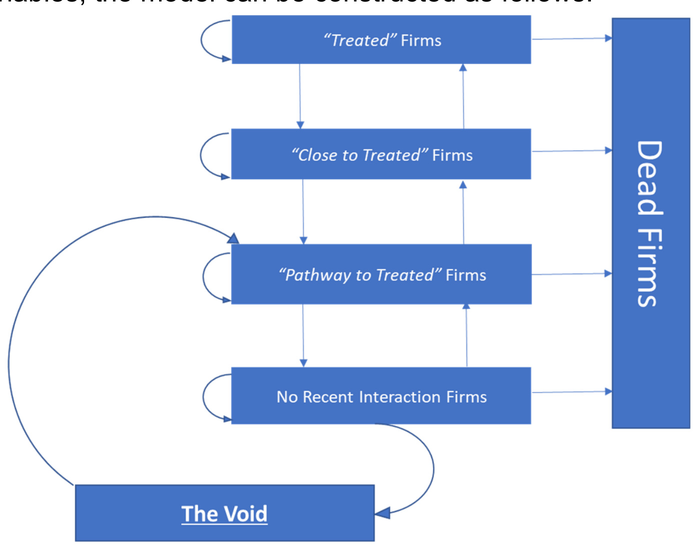


Figure 17

Here is the Markov Switching model for NPL. The main four statuses have been stacked by the amount of support they account for in a consecutive manner. As a firm can die out from any stage, arrows exist at each status. Every arrow has a respective probability attached to, denoting the probability a firm has to move along it. The arrows between the statuses are the probabilities of moving up or down them, the curved arrows along the side are the probability

44 It is assumed that the assets of dead firms are recycled through the economy, but this can't be captured within this simplistic model.

45 It may be possible to develop a model to capture the void, this would be in the ilk of a Mark and Recapture model. This will be detailed in section 15

of remaining within each status. The arrow from No Recent Interaction Firms to The Void are the firms who haven't worked with NPL for at least 8 years. The arrow from The Void to Pathway to Treated firms are the firms that are new to NPL (either Brand new or Returning Legacy). This arrow only has a number as we aren't sure how many firms are in the void at this point in time. The following flow chart details the process of constructing this model:

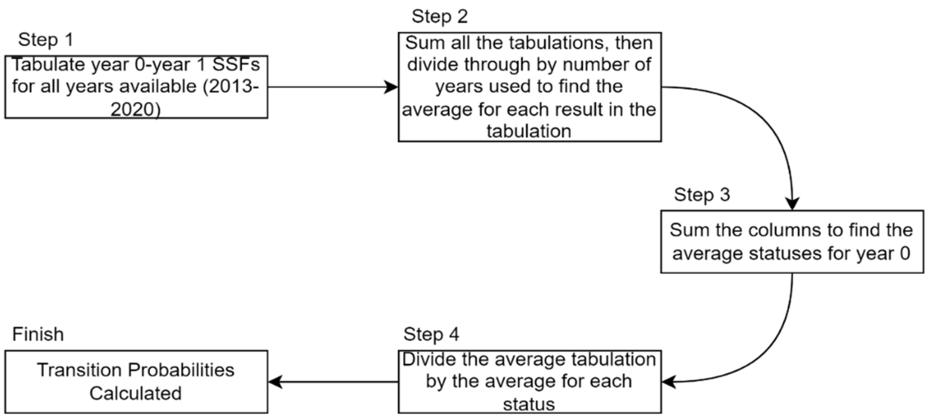
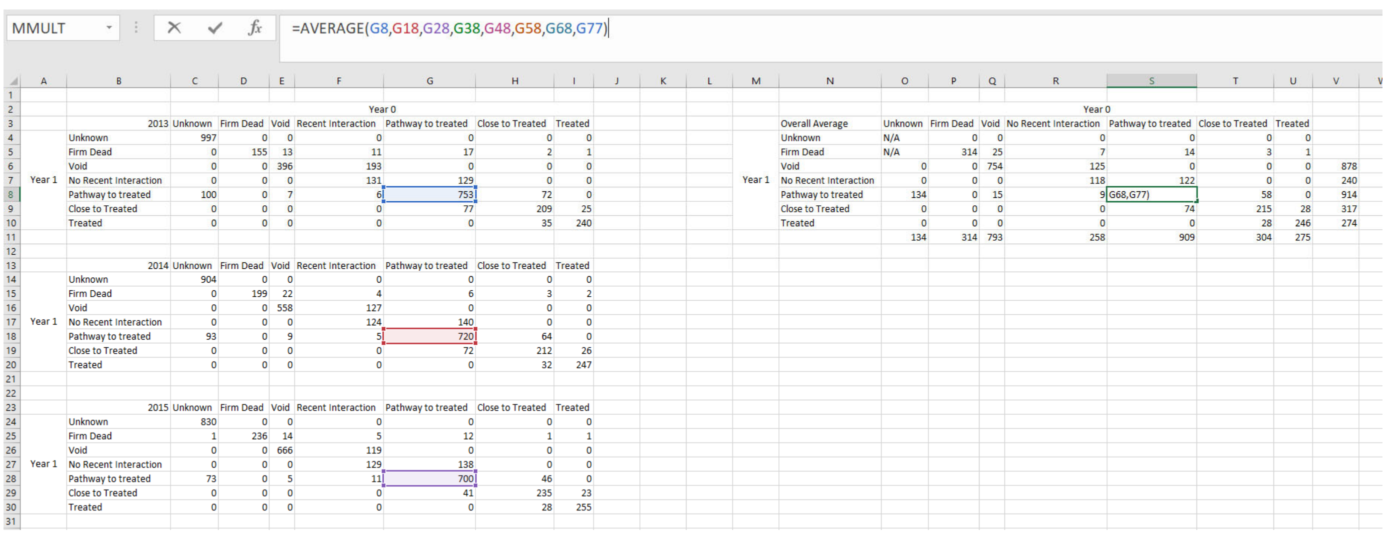


Figure 18

The excel sheet below is the method used in step 2 as detailed above. For each box of the tabulation, an average is taken of its equivalent box for each year of data, as seen by the code in the formula bar. The tabulations shown are from 2013 - 2015 but extends down for all years up to and including 2020. As the model requires a first difference, one year of data must be lost, which is why despite having nine years of data, only eight years of data can be reported.



MMULT =AVERAGE(G8,G18,G28,G38,G48,G58,G68,G77)

	2013	Unknown	Firm Dead	Void	Recent Interaction	Pathway to treated	Close to Treated	Treated
	Unknown	997	0	0	0	0	0	0
	Firm Dead	0	155	13	11	17	2	1
	Void	0	0	396	193	0	0	0
Year 1	No Recent Interaction	0	0	0	131	129	0	0
	Pathway to treated	100	0	7	6	753	72	0
	Close to Treated	0	0	0	0	77	209	25
	Treated	0	0	0	0	0	35	240

	2014	Unknown	Firm Dead	Void	Recent Interaction	Pathway to treated	Close to Treated	Treated
	Unknown	904	0	0	0	0	0	0
	Firm Dead	0	199	22	4	6	3	2
	Void	0	0	558	127	0	0	0
Year 1	No Recent Interaction	0	0	0	124	140	0	0
	Pathway to treated	93	0	9	5	720	64	0
	Close to Treated	0	0	0	0	72	212	26
	Treated	0	0	0	0	0	32	247

	2015	Unknown	Firm Dead	Void	Recent Interaction	Pathway to treated	Close to Treated	Treated
	Unknown	830	0	0	0	0	0	0
	Firm Dead	1	236	14	5	12	1	1
	Void	0	0	666	119	0	0	0
Year 1	No Recent Interaction	0	0	0	129	138	0	0
	Pathway to treated	73	0	5	11	700	46	0
	Close to Treated	0	0	0	0	41	235	23
	Treated	0	0	0	0	0	28	255

	Overall Average	Unknown	Firm Dead	Void	No Recent Interaction	Pathway to treated	Close to Treated	Treated	
	Unknown	N/A	0	0	0	0	0	0	
	Firm Dead	N/A	314	25	7	14	3	1	
	Void	0	0	754	125	0	0	0	878
Year 1	No Recent Interaction	0	0	0	118	122	0	0	240
	Pathway to treated	134	0	15	9	G68,G77)	58	0	914
	Close to Treated	0	0	0	0	74	215	28	317
	Treated	0	0	0	0	0	28	246	274
		134	314	793	258	909	304	275	

Figure 19

Following this process, the transition probabilities can be found, along with the average flow of firms in and out of each of the statuses. This allows for the following diagram to be constructed:

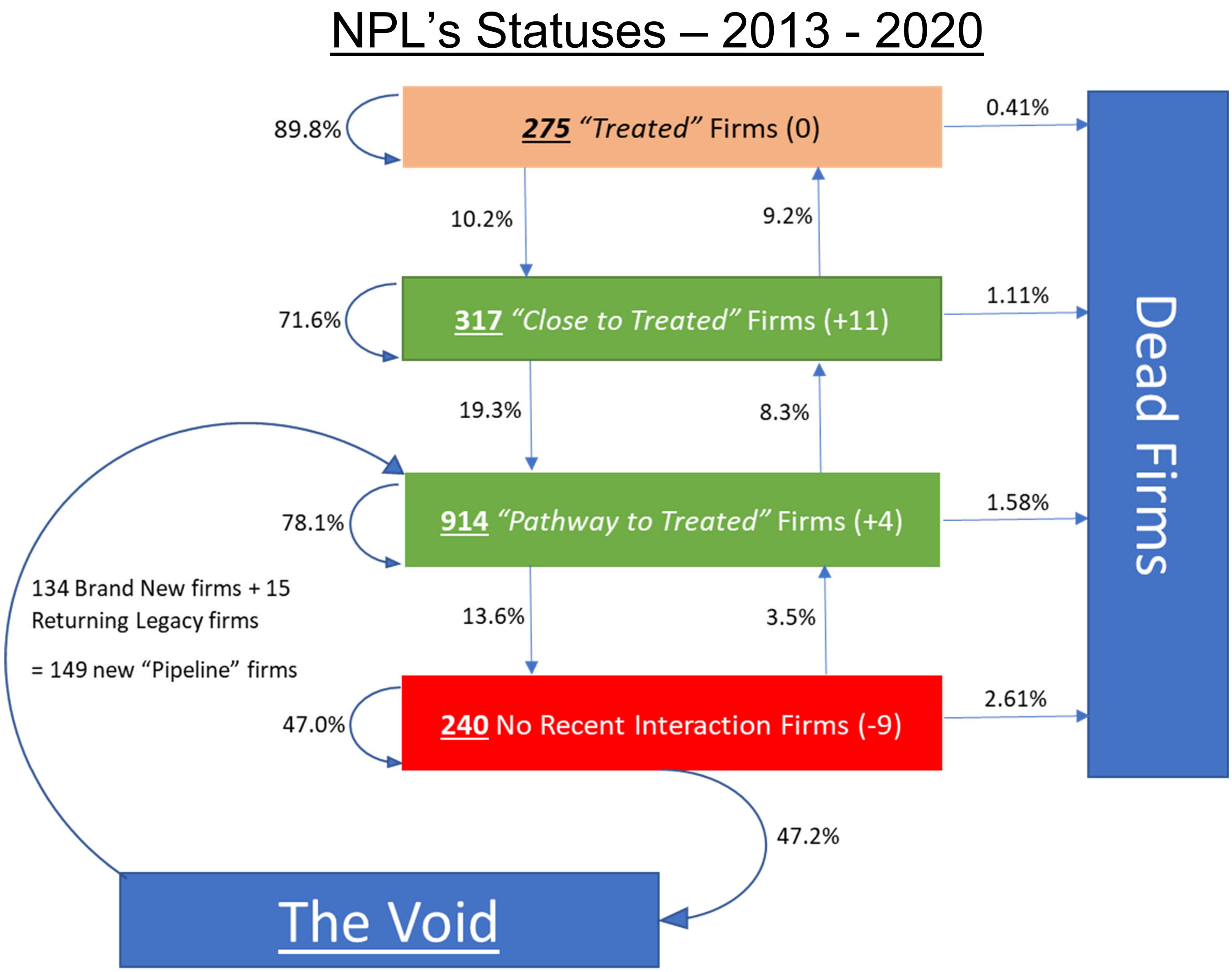


Figure 20

There are several interesting areas to note within the above diagram. From 2013 to 2020, NPL has seen its Treated firms remain fairly constant, while its pipeline has been increasing slowly year-on-year. It should be noted that flowing down the system (i.e., down levels of interactions) are more likely that flowing up. Another area of interest NPL's new "Pipeline" firms are broken down, 90% of them are Brand New firms. The final area of interest is probability of death, which also has an inverse relationship with level of support.

To extend and enrich the analysis, the dataset was divided into two periods, based on the analysis of NPL's treated firms in section 6, which saw an increase in treated firms until 2016, then a decline subsequently. Period 1 would be from 2013-2016 and Period 2 would be from 2017-2020, each consisting of four years as described in section 6. The following are the Markov models for each period:

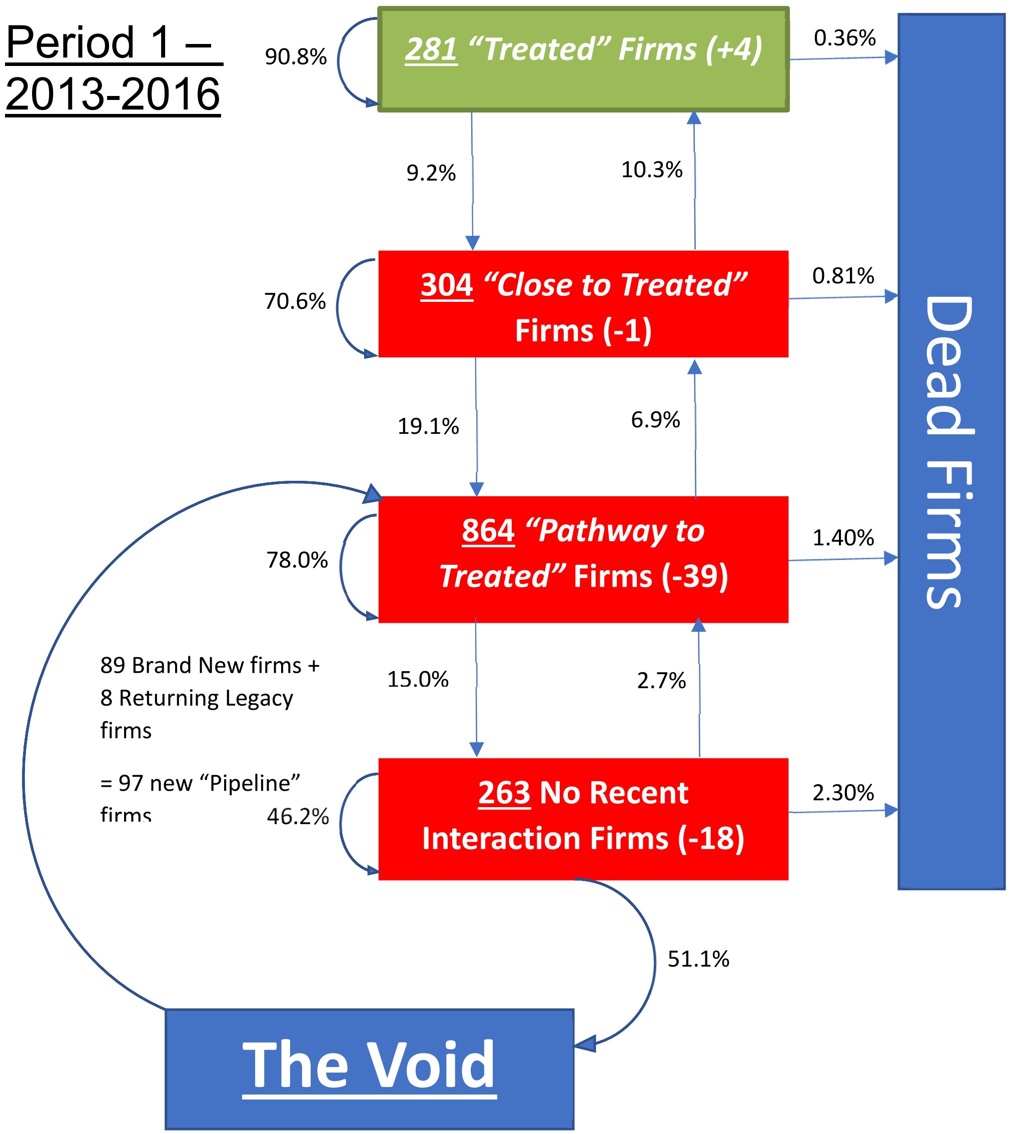


Figure 21

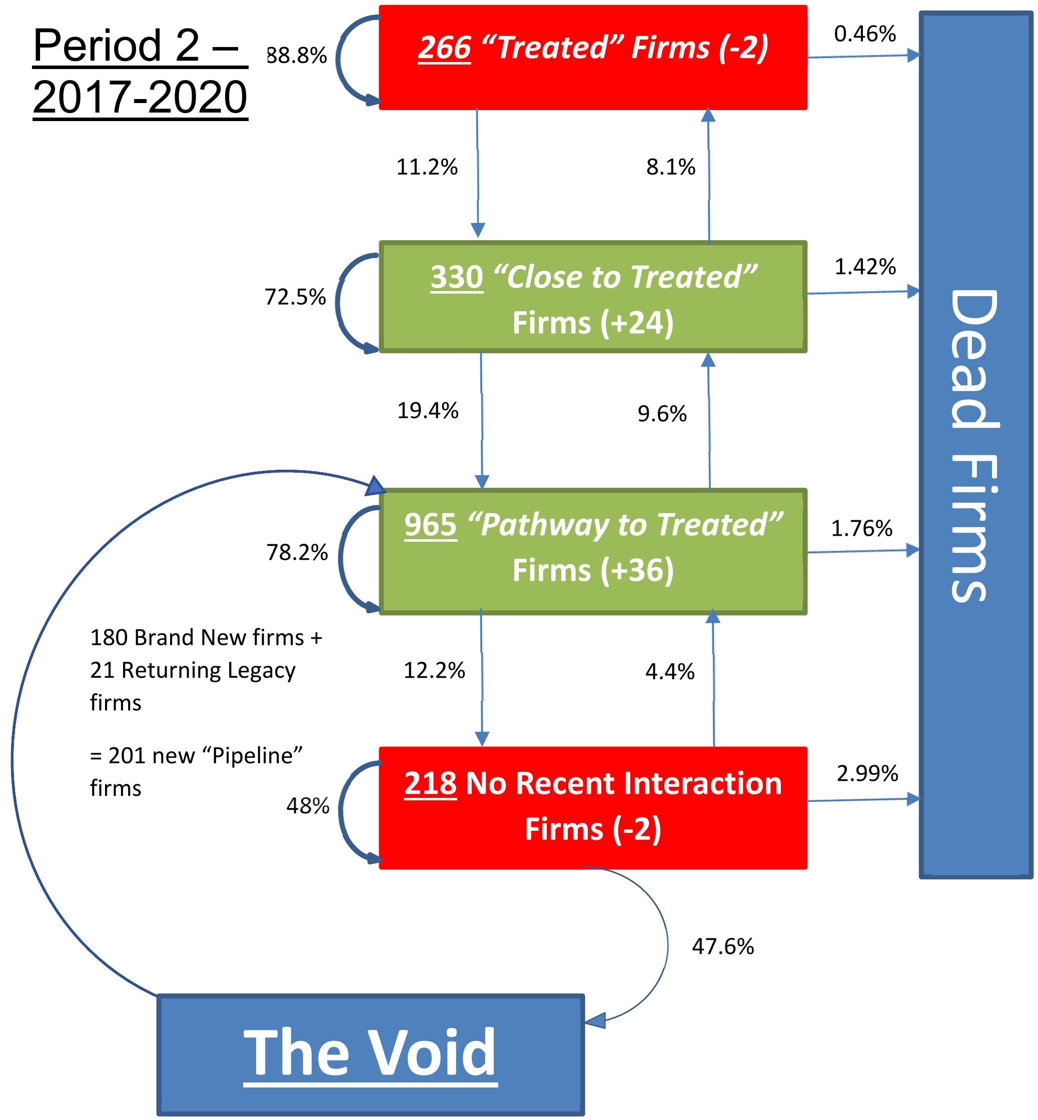


Figure 22

There are several notable differences between the two time periods. Firstly, there is double the amount of new “pipeline” firms in period 2 than in period 1. Annex 5 will provide more detail, but this is driven by a big uptick in firms in 2018, supplemented by the work done by A4I and its sister programmes. This in turn has helped flip the Pathway from a net decline to net growth between the two periods. As the Pathway feeds into Close to Treated, it also flips to net growth as well in comparison to the previous period. However, this net growth could be due to a flip to net decline in the treated firms in period 2. The net growth seen in period 1 was likely due to a push to commercialise within NPL, prioritising current, established customers over new ones. This “thinning of the base” can be seen in figure 21, where pathway firms had declined year-on-year up until 2017. This was arrested subsequently but came at the expense of the treated firms in recent years.

13.1.1 Forecasting

Returning to the logic sitting behind the Markov chain, it is assumed that the probability of an event occurring depends only on the state attained in the previous event. Within the NPL context, the status of the average firm in year 1 depends on the status of the average firm in year 0. Assuming this to be true, the transition probabilities developed in the Markov switching model above can be used to provide one-year projections on the breakdown of NPL’s supported firms by status. As 2021’s data (at time of writing) hasn’t been finalised, forecasts for this year can be made and tested using 2020’s data. Of the Diagrams above, two of their probabilities were used:

1. Overall NPL Markov Model (2013-2020) – Forecast 1
2. Period 2 NPL Markov Model (2017-2020) – Forecast 2

To generate the projections, a simple matrix multiplication was used, with the following matrices:

- A = 2020 status of firms
- B = Transition probabilities of the statuses from y0 to y1
- The multiplication is as follows: A . B = C,

Where C equals the forecast of 2021’s status of firms. Below are the results for each model, with the Delta shown in absolutes and percentages. It should be noted that the probabilities don’t account for the new firms working with NPL each year. Therefore, for each projection, the average number of new firms in a given year were added to their respective pathways, with 149 firms for the overall NPL Markov model and 200 firms for the period 2 NPL Markov model.

	2020	2021* (13-20)	Delta (13-20)	%Delta (13-20)	2021* (17-20)	Delta (17-20)	%Delta (17-20)
Treated	255	266	11	4%	259	4	2%
Close to Treated	421	407	-14	-3%	426	5	1%
Pathway to treated	1022	1021	-1	0%	1074	52	5%
No Recent Interaction	194	226	32	16%	213	19	10%

Table 4

What is seen are very differing outcomes for 2021’s breakdown of supported firms by status for each of the models. Forecast 1 sees growth in the treated firms, with the Pipeline declining, likely causing the increase in No Recent Interaction firms. This increase in No Recent Interaction firms is occurs for both models, suggesting NPL is consistently losing firms from its system which it likely won’t return given they are only 10% of NPL’s new pipeline firms. Forecast two sees the largest amount of growth in its pathway, with some growth in the other two statuses.

In my personal opinion, I believe that reality is somewhere between these two forecasts. The forecasts and transition probabilities are at their most representative when NPL's breakdown of supported firms is in a steady state, which means it struggles to pick up exogenous factors. If a "rock" is thrown at the system, it'll take a few years for the system to account for it. This "rock" was the growth of new firms in 2018, along with impact of A4I and its sister programmes. In subsequent years, this boosted the pathway, which has been accounted for now as this occurred a few years ago. But due to the sequential nature of the statuses, close to treated has only just experienced the effect of the "rock", with the first notable increase seen in 2020 as seen in figure 2. Therefore, the forecasts as they currently exist cannot foresee the increase in close to treated. In a few years, if this increase is sustained, it will be accounted for in future iterations of this analysis.

13.2 DYNAMIC ANALYSIS

The analysis in the previous section provides an assessment on how NPL's supported firms move from the range of statuses, detailing the probabilities as such. However, this analysis is very cross sectional, with no assessment on the journey each firm takes within NPL. Obviously every firm NPL works with is unique, with an individual working relationship with scientific and non-scientific staff alike. But there is merit in seeing how each status is comprised when looking before and after the year of assignment. This would allow for multi-year estimates be generated concerning an action in a given year, providing a baseline of how many firms should be expected to move up from one status to another (e.g., given i number of firms in Pathway to treated, what proportion would be expected to move into either close to treated or no recent interaction in t number of years).

This can be done using relative years, in the form of lag (known as l) and forwards (known as f) operators. This entails holding the year of assignment constant (year of assignment = s). By holding s constant, each cohort of firms can be stacked on top of each other when using lag and forward operators. As detailed before, this accentuates the statistical signal, showing the trends across NPL's users. The trends shown is how firms flow into each status from five years before assignment and where each firms goes, given their assigned status, five years into the future.

13.2.1 Method

```
tab s l5_s if e(sample)
tab s l4_s if e(sample)
tab s l3_s if e(sample)
tab s l2_s if e(sample)
tab s l1_s if e(sample)
tab s s if e(sample)
tab s f1_s if e(sample)
tab s f2_s if e(sample)
tab s f3_s if e(sample)
tab s f4_s if e(sample)
tab s f5_s if e(sample)
```

	l3_s						
s	Unknown	Void	No Recent	Pathway t	Close to	Treated	Total
No Recent Interaction	0	0	0	1,113	117	0	1,230
Pathway to treated	1,926	164	105	2,115	569	78	4,957
Close to Treated	217	19	15	570	608	312	1,741
Treated	0	0	0	86	319	1,115	1,520
Total	2,143	183	120	3,884	1,613	1,505	9,448

Figure 23

Like the Markov Switching analysis, this model also relies on the generation of a range of tabulations. The picture is the code used in order to generate all 11 tabulations for the analysis to work, with s being held constant and the operators used to look back and forward. The picture on the right shows an exemplar table, one of many that are constructed. The format of every table is the same, with four rows for each status, then a range of potential statuses/outcomes for the columns.

l5_s	Unknown	Void	No Recen	Pathway t	Close to T	Treated
No Recen	0	0	0	567	180	19
Pathway t	1,918	109	91	875	343	140
Close to T	353	28	17	319	279	205
Treated	32	3	1	161	186	611

l4_s	Unknown	Void	No Recen	Pathway t	Close to T	Treated
No Recen	0	0	0	784	211	0
Pathway t	1,987	140	104	1,372	463	134
Close to T	327	27	18	425	404	271
Treated	0	0	0	167	253	840

l3_s	Unknown	Void	No Recen	Pathway t	Close to T	Treated
No Recen	0	0	0	1,113	117	0
Pathway t	1,926	164	105	2,115	569	78
Close to T	217	19	15	570	608	312
Treated	0	0	0	86	319	1,115

l2_s	Unknown	Void	No Recen	Pathway t	Close to T	Treated
No Recen	0	0	0	1,462	0	0
Pathway t	1,672	162	100	3,178	646	0
Close to T	0	0	0	773	929	320
Treated	0	0	0	0	342	1,434

Treated Fi	Dead Firm	Unknown	Void	No Recen	Pathway t	Close to T	Treated	Total
-5	0	32	3	1	161	186	611	994
-4	0	0	0	0	167	253	840	1260
-3	0	0	0	0	86	319	1,115	1520
-2	0	0	0	0	0	342	1,434	1776
-1	0	0	0	0	0	208	1,816	2024
0	0	0	0	0	0	0	2,266	2266
1	2	0	0	0	0	200	1,839	2041
2	9	0	0	0	0	326	1,457	1792
3	15	0	0	0	83	311	1,128	1537
4	19	0	0	0	136	267	850	1272
5	21	0	0	22	137	206	620	1006

Figure 24

Using the tables, each row is taken and used to construct a table for each of the four statuses. The picture above shows the table being built for treated firms. The negative relative years match up to the lag operator, while the positive relative years match onto the forward operators, with the number next to the respective operators determining the position. Tables like these are generated for each status, with the following graphs produced when proportions are taken.

13.2.2 Results

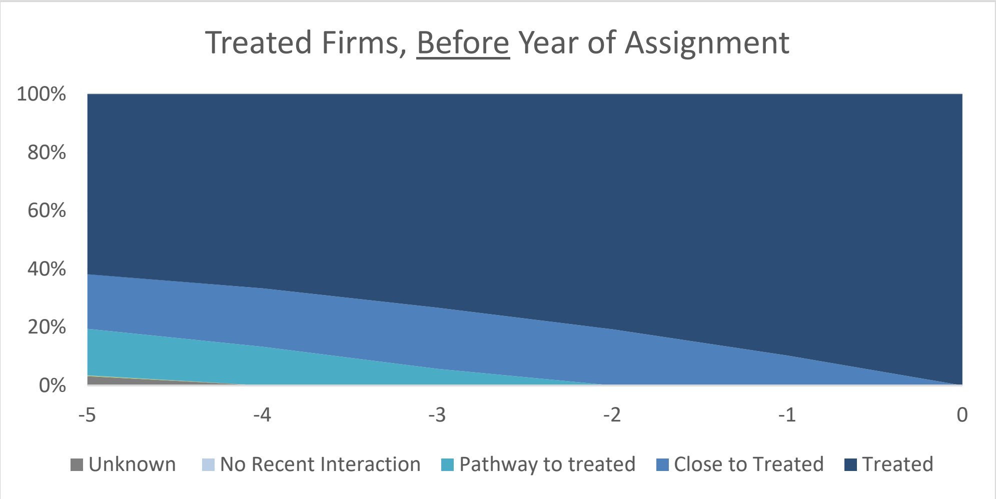


Figure 27

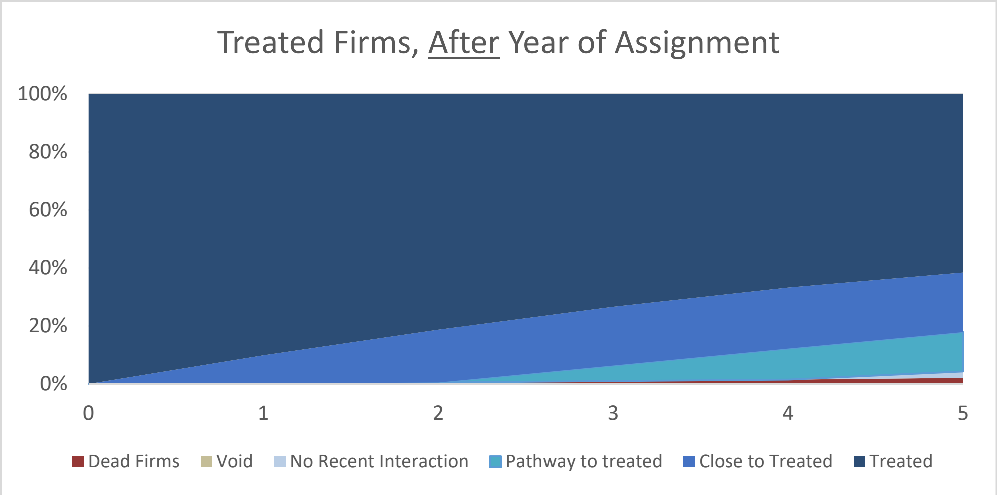


Figure 26

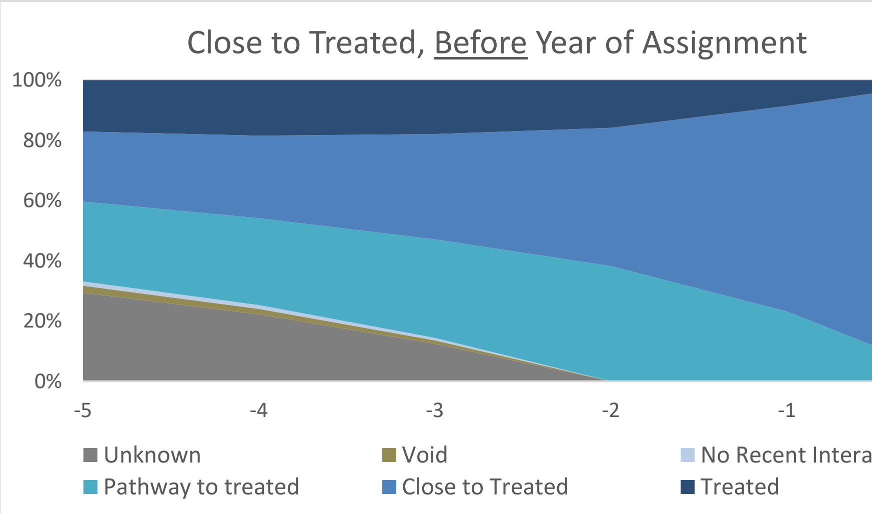


Figure 25

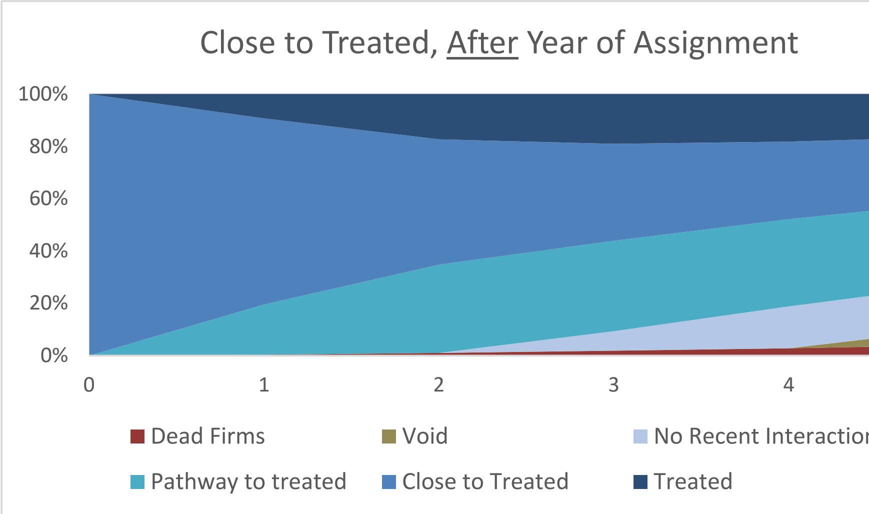


Figure 28

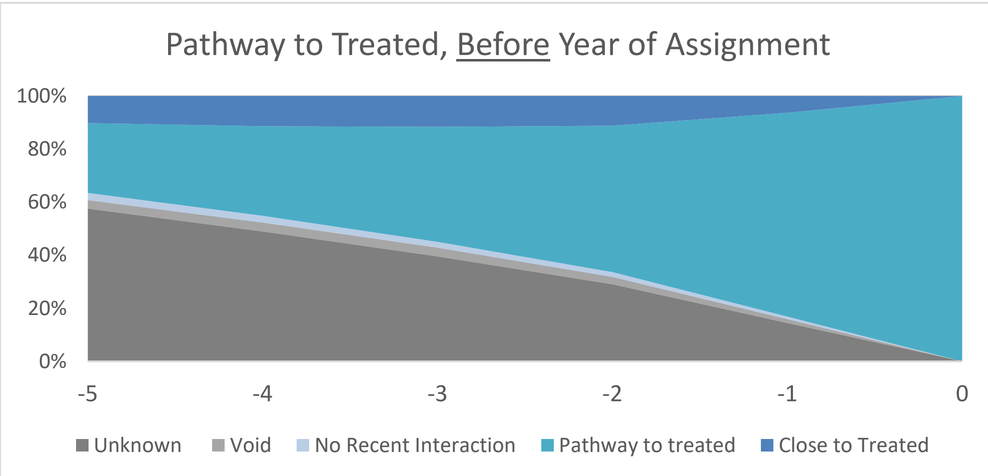


Figure 29

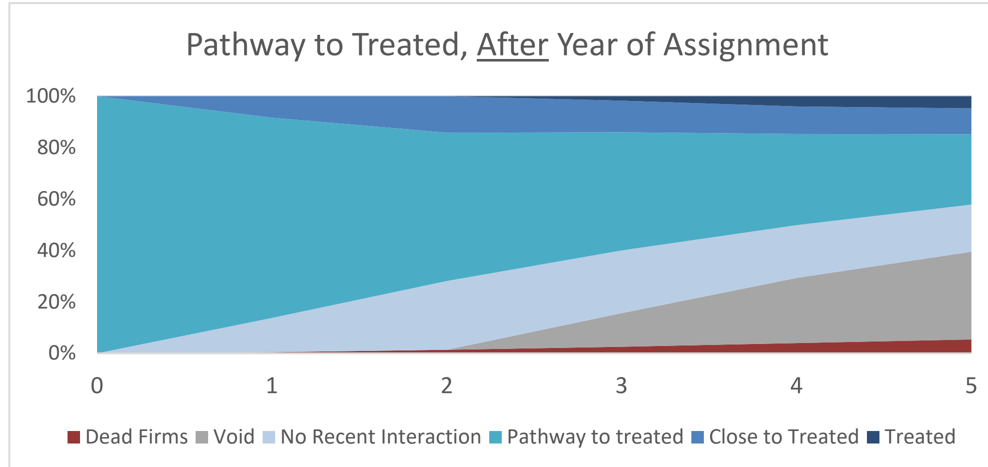


Figure 30

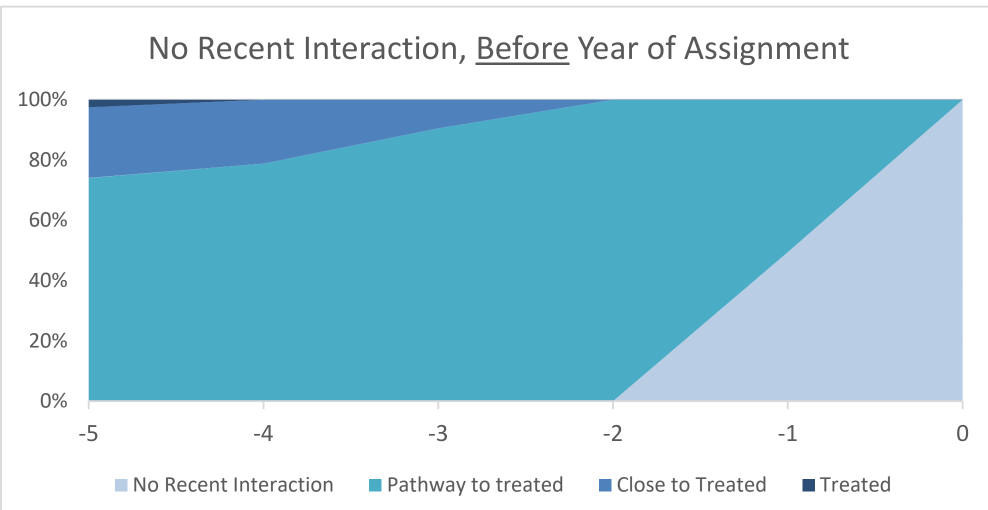


Figure 31

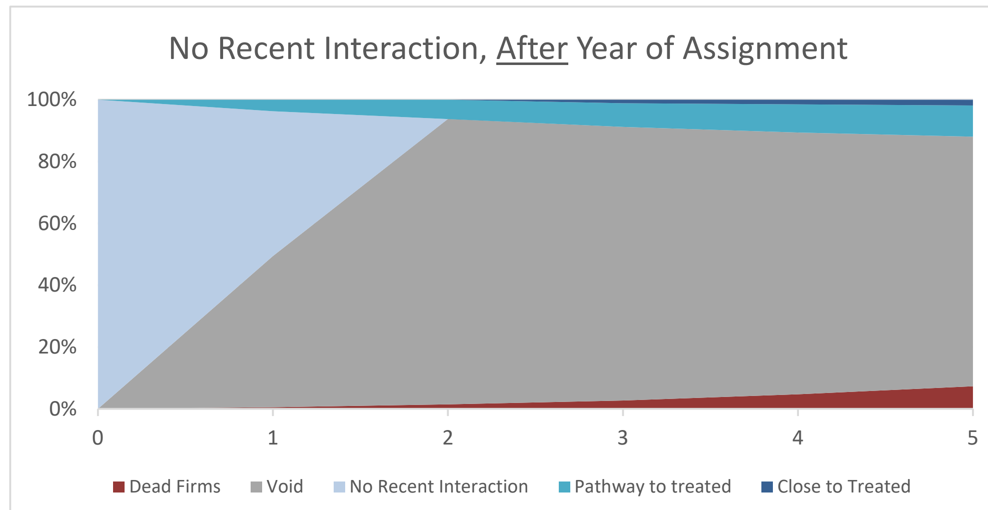


Figure 32

Concerning the treated and close to treated graphs, there is a symmetry to them, where both statuses have very similar proportions when looking five years before and after relative year 0. 60% of treated firms when assigned are still treated when looking back five years before their assignment. This suggests that firms when they become treated, tend to remain treated far more so than any other status. Close to treated is interesting as there is a very similar probability of being one of pathway to-, close to- or treated 5 years before and after being assign close to treated. This suggests that this category is the most “fluid” for firms who reside within it; the probability of firms moving up or down are very similar. This is notable as if they are able to be pushed in the treated category, as detailed before, there is a greater-than-50% probability that they would stay in treated, receiving the greatest impact from working with NPL.

The other two categories are far different with regards to symmetry. Concerning the pathway, over half of firms who were assigned so were brand new to NPL five years before, with some coming in from close to treated and very few from treated. This further shows the benefit of pushing firms up as they are likely to stay up for longer. Five years after assignment, over half of the firms aren’t interacting with NPL anymore, either within the No Recent Interaction group or into the void, though roughly 20% move into the higher categories once more. For No Recent Interaction, they generally come from the pathway when looking 5 years before assignment, with roughly 25 % coming from close to treated. The really interesting area is after assignment. What is seen after assignment is that some firms do move back to the pathway, but over 90% of the firms fall into the void or die. This shows how No Recent Interaction is a form of “cliff edge”, Once firms “jump”, they rarely ever come back from there, so identifying these firms before they move into this category is paramount in reducing the number of firms that fall into this category effect or increasing the probability of firms returning from No Recent Interaction.

14 SECTORAL ANALYSIS

So far, the analysis has aggregated at an NPL level in order to see how the organisation as a whole operates and is doing. However, as firms often work with specific parts of NPL, there is value in seeing how those subparts do. At NPL, there are 4 main “NPL sectors”, areas which comprise a range of scientific areas working towards a government challenge. They have their original name and challenge of focus. These are:

- Advanced Manufacturing (AM) - Prosperity
- Life Sciences & Health (LSH) - Health
- Energy & Environment (EE) - Environment
- Digital & Quantum Technologies (DQT) – Security

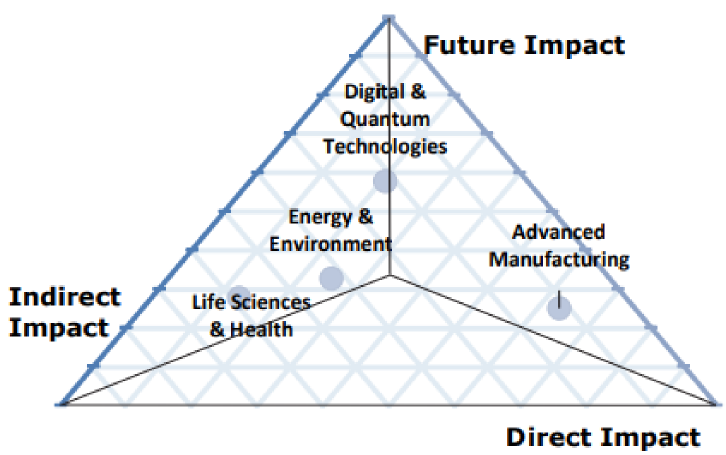


Figure 33

As seen in *Dias (2022)*, The sector each focus on different kinds of impact, as detailed by the graph above.[46] Advanced Manufacturing has prioritised direct impact over the last 20 years, Digital & Quantum has focused on future impact, while the remaining two have focused more on indirect impact. As the time period of analysis was 20 years, this is where the sectors have been in the past, which can be used as a form of baseline to see where they are heading towards.

Unlike the previous analysis, the sectoral data only goes back to 2015. This means that an assessment can only be made concerning each statuses' supported firms in 2020, without the other forms of analysis around it. However, at the start of 2023, sector-specific Markov models can be developed using 3 years of data (using 2020, 2021 and 2022's data). This would be preliminary as it would only have three years of data rather than four but would provide indicative transition probabilities.

Thanks to the work done by the A&E team, all the invoices and collaborations from 2015 onwards have been tagged to a group within NPL. These groups encompass a specific scientific area, such as Quantum or Materials research. These groups make up the sectors, with some groups being unique to each sector and some crossing over multiple sectors where necessary.[47] By working with a given group, a firm is in turn working with a sector (or sectors if working with a cross-over group). Therefore, a sector specific status can be generated at the firm-level, with strong segmentation.

status_firm	status_firm_am	status_firm_dqt	status_firm_lsh	status_firm_ee
.	.	.	.	.
Unknown	Unknown	Unknown	Unknown	Unknown
Pathway to treated	Pathway to treated	Unknown	Unknown	Unknown
Pathway to treated	Pathway to treated	Unknown	Pathway to treated	Unknown
Close to Treated	Close to Treated	Unknown	Pathway to treated	Unknown
Close to Treated	Close to Treated	Unknown	Pathway to treated	Unknown
Close to Treated	Close to Treated	Unknown	Pathway to treated	Unknown
Treated	Treated	Unknown	Close to Treated	Unknown
Treated	Treated	Unknown	Close to Treated	Unknown
Close to Treated	Close to Treated	Unknown	Pathway to treated	Unknown

Figure 34

Above is an example of a firm's statuses. The first column is the status of that firm with regards to NPL as a whole, which will default to the highest status of any of the sectors. The remaining four statuses are constructed in the same way, but a focus on made on the tagging of the invoice and collaboration with regards to sector. As part of this, if a sector has never worked a given firm, that firm is deemed as unknown to the sector even though they may have worked with other parts of NPL. Also, if a firm has stopped working with a sector for eight years but still works with the rest of NPL, the firm would be determined to have

46

Future Impact – Where work NPL conducts has the potential to produce benefit, often in the future with an uncertain probability of occurring.

Indirect Impact – Where the work NPL conducts producing impacts for third parties, who don't work with NPL directly but impact via positive externality effects.

Direct Impact– Where the work NPL conducts impact our customers and collaborators, along with their customers and collaborators.

47 See attached note "The User Database by Zahrah Qureshi" for more information.

fallen into that respective sector's void. If a firm worked with only one group that existed in two sectors, the status would be identical for the respective sectors.

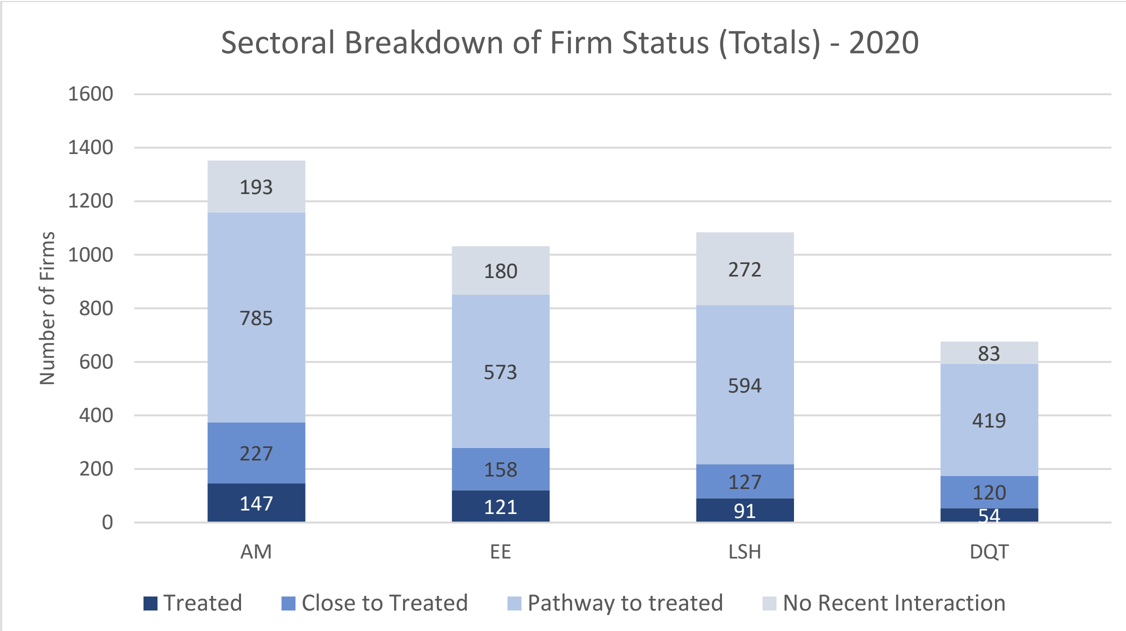


Figure 35

From the sectoral breakdown of the statuses, similar patterns to *Dias (2022)* are seen. Advanced Manufacturing's focus on direct impact has seen it work with the most private sector firms over the time period in question, followed by Energy & Environment and Life Sciences & Health, with Digital & Quantum with the least. This is expected due to the relative youth of DQT and the focus on future impact. It should be expected for these numbers to be increasing over time for DQT. The percentage breakdown for the sectors isn't significantly different, apart from a notably high percentage of No Recent Interaction firms for Life Sciences & Health.[48]

15 FURTHER WORK

Firstly, although, Belmana's report was finalised in 2019, the data used in the econometric analysis is somewhat older - straddling the period 2009-17. Moreover, the relevance of the results naturally diminishes over time, because of changes in the type of support being delivered, as well as changes in the population of firms that are being supported. (For example, in the period 2009-17, collaborative projects occurred less frequently than they do at the present time.) The analysis could also be amended with the untreated group broken down into the statuses below treated detailed in this report, assessing how different levels of support intensities lead to different outcomes. Also, the cohort method done here and within Fronter Economics (2014) could be implemented to assess more than one time period, enriching the dataset and reducing statistical noise. Furthermore, the data used in Belmana's analysis comes from the period before schemes such as A4I. Given the hypothesized role that A4I and its sister programs has had on NPL's supported firms, future econometric analysis may find that certain kinds of one-off interaction (e.g., support received through the A4I programme) have a positive effect on business outcomes, or that grant-funded collaborations are found to be a key channel through which new firms are encouraged to

48 See Annex 18.5 for the Percentage version of this graph.

seek regular support from NPL. Given the importance of the Belmana study to this report, a case can be made for a new version of that analysis, with some amendments as detailed above to enrich the results.

Another extension to the analysis would be possible once transition probabilities have been developed for each sector. This would allow for forecasts to be generated respectively, allow for assessments on a sectoral basis with regards to their own supported firms. This would involve the same method as detailed in section 13.1.1.

In its current guise, counting the number of "*treated*" firms, connects well to '*prosperity',* but isn't connected to other national challenges. Hence, further metrics should be introduced to assess NPL's contribution to some of the other national challenges. For example, some of the firms, that are classes as being "*treated"*, could be tagged to one of the national challenges based on their characteristics. (The firms could be tagged according to range of characteristics, such as, industry and region). This could be done by using input-output analysis (or IO analysis). IO analysis was developed by Wassily Leontief and is based on the interdependencies between different economic sectors or industries, assessing the ripple effects of positive or negative shocks in the economy. There are 3 main parts to this model:

- Inputs (Labour, Capital, Imports, Taxes)
- Intermediate Consumption (one sector's output feeds into another sector's production).
- Final Demand (Consumption, Investment, Exports)

The GVA growth, as detailed in annex 18.1, from treated firms is a form of input, while healthcare spend is a form of consumption. By using the matrices, an assessment can be made, given the siccodes of the firms NPL works with, into the total contribution made by measurement activity on healthcare. This is due to the face measurement has both a direct and indirect component. The direct input corresponds to a sector's own spending on labour and capital that's devoted to its own measurement activity, while the indirect input is embodied within measurement inputs from other sectors that are consumed during the production process.

A similar method can be adapted to assess the GHG emissions by firms NPL work with. The ONS provides emissions factors for each sector, the amount of *thousand tonnes* CO_2 *equivalent* emitted by each sector of the economy per £1 million of GVA, tagged by siccode. Given the average GVA growth for each firm, the amount of *thousand tonnes* CO_2 *equivalent* can be estimated year-on-year. It would be assumed that by increasing GVA, it is likely that firms would emit more into the atmosphere. But by working with NPL to reduce their emissions, the emissions factors would decline, leading to cleaner economic growth. The relationship between PSREs and emissions factors is an area of investigation which would be incredibly insightful for the broader public research community but is out of scope for NPL to do.

As part of the metrics NPL plan to publish yearly, a count of the supported firms' metrics would be published each year for NPL as a whole. There is also a plan to develop supported firm metrics to map onto NPL's internal Science & Engineering departments, assessing the impact at a departmental level.

Further developments of this analysis would include a determination on what leads to firms being one of the statuses, looking at a range of characteristic variables and see if that precludes them to a specific status. This would help to inform a potential study to find firms in databases such as FAME or Beauhurst who fit the profile of a firm who works with NPL, but don't at this point in time. This would help to expand NPL's private sector impact by potentially identifying firms that NPL could work with. Another extension of this analysis would be determining whether the types of firms that change status (e.g. from Regularly Supported to Close to Treated) were random or was there a causal relationship between characteristics of firms (size, siccode, location etc,.) and changing status. This would help to uncover reasons behind the changes in Regularly Supported firms we see, though would be difficult.

Another area of work that has spawned from this paper is the development of operational metrics. Given that most of NPL's revenue generation comes from Regularly Supported Firms, being able to assess how these firms transition between types of support is vitally important. Furthermore, there would also be an ability to forecast the changes in regularly supported firms, assuming no major outside influences. Examples of potential future measures include:

- the "retention rate" of regularly supported firms – percentage of regularly supported firms in year 0 (e.g., 2015) that remain so in year 1 (e.g., 2016)

- The "conversion rate" of regularly supported firms – percentage of close to treated firms that were one year away from being regularly supported in year 0 that did "convert" in year 1.

It should be noted that the development of these measures would have commercial applications, so other funding sources outside of the NMS should be considered to fund their creation and implementation.

Lastly, the approach to metrification found in this document would need to be tweaked if applied it to the public sector. Whilst metrics for the number of "*regularly supported*" hospitals and universities should be easy to determine, assessing the mechanisms through which an economic impact can be ascertained is required. The assumption concerning regular support is that those firms see employment and wage growth, leading to GVA growth. This won't hold for public sector firms and particularly hospitals. This requires other metrics for the public sector, such as, income from government departments, perhaps, tagged to one of the national challenges. And, to assess NPL's direct impact on greenhouse gas (GHG) emissions, it might be possible to track income from emissions monitoring services, such as, FEDS and DIAL. Finally, these impact metrics could be supplemented by a H-index for tracking the quality of science.

15.1 "MARK AND RECAPTURE" MODEL

Currently, there isn't a reliable estimate of the number of firms that have the requisite motivation and skillset to work with NPL. An estimation method from Ecology can be used in order to calculate the size of NPL's potential user base. This section details the theory, formula and assumptions surrounding this method, in particular the application of this ecological tool to NPL's potential user base.

The method used is a particular kind of "Mark and Recapture" model. In its simplest form, this model is used to estimate the population of rare animals in a given area when counting every animal is unfeasible. This would involve two visits to the area in question. The first visit would see the marking of animals captured; the second visit would just be focused on capturing animals. Following this, the following can be found:

- n = Number of animals marked on the first visit
- K = Number of animals captured on the second visit
- k = Number of recaptured animals that were marked

Given that the number of marked individuals within the second sample should be proportional to the number of marked individuals in the while population. an estimate of the total population size can be obtained by dividing the number of marked individuals by the proportion of marked individuals in the second sample. There are several different estimators that can be used. The estimator used here is the Lincoln-Petersen estimator, is as follows: [49]

$$N = \frac{nK}{k}$$

Where N = total population in the given area. To assess the number of NPL's potential user base, an "Overlapping Registers" version of the Mark and Recapture model can be used. This would entail comparing the "register of supported companies" in a given year with a "register of supported companies" in previous years, where:

- n = Number of firms supported in year t
- K = Number of firms supported in year t+1
- k = Number of firms supported in year t & t+1
- N = Size of NPL's potential userbase

This estimator requires a few assumptions to be made when applying it to the NPL context. It assumes that the population is closed, essentially that the two visits to the study area are close enough in time so that no individuals die, are born or move into or out of the study area between visits. Essentially, that N is a constant, over the short-term (e.g. 2-3 years). For this to be true, we assume the birth and death rate are at a replacement level, insofar that for every dead firm, a new one replaces it within N.

Using 2020 and 2021's data, a rough example can be done to show how the calculation is done. for this, the variables are as follows:

- n = Number of firms supported in 2020 = 958
- K = Number of firms supported in 2021 = 1,073
- k = Number of firms supported in year 2020 & 2021 = 686
- N = Size of NPL's potential userbase:

$$N = \frac{nK}{k} = \frac{958 \times 1073}{686} = {\sim}1{,}500 \text{ firms}$$

This calculation suggests that NPL's potential userbase could have up to 1,500 firms within it. This is a rough example with one year of data, but subsequent versions of the analysis could use a multi-year variation of the formula to estimate the number of firms more accurately within NPL's potential user base. However, this model assumes independence, that the probability of working with NPL in year t and year t+1 isn't related to one another. This assumption may hold at lower level of support, given that the definition of pathway to treated describes one instance of support in six years. But, for firms in the higher statuses, this independence won't hold, given the fact we know once firms move into Regular Support and Close to Treated, they likely won't move down. Using ecological terminology, this model works when assessing "wild" firms (pathway to treated firms), those that haven't working with us before. This allows for the aforementioned independence assumption to hold; given a "wild" firm has only worked with us once before, the probability of returning remains small. However, as firms keep returning to NPL, they undergo "domestication", where the probability of a firm returning increases with every instance of support. This in turn leads to

49 https://www.wikiwand.com/en/Mark_and_recapture#/overview

the probability of being resampled (returning to work with NPL in t+1, essentially $p_r = \frac{k}{n}$) being biased upwards as the “wild” and “domesticated” firms (Close to Treated and Regularly Supported) have been pushed together, despite their differences in p_r. Due to this limitation in the rough estimation above means that there is likely an underestimate of the size of NPL’s “wild” userbase, in turn meaning the 1,500 firms’ number is likely an underestimate. This would be one amendment to the model as it currently exists. Another amendment would include a multi-year assessment, looking at several years of data in order to estimate the potential size of NPL’s userbase, accounting for single year outliers.

This analysis would be the bedrock upon which a market analysis could be developed. This would entail an assessment into the breakdown of NPL’s potential userbase, assessing what kinds of firms make up NPL’s “ecosystem”, assessing regional and economic sectoral differences, both in terms of support intensity and types of support received from NPL.

16 IMPLICATIONS

The major implication of this analysis is that the type of relationship, that NPL has with its customers and collaborators, affects the scale of NPL’s impact on the private sector. The definition of “regular support” is based around having long-term relationships with customers, rather than one-off payments from a multitude of transient customers.

Nonetheless, a balance must be maintained between building relationships with new customers and developing the ongoing ones. Maintaining this balance is largely the responsibility of those tasked with Business Development (BD). To help grow NPL’s impact, BD could engage strongly with the 250-300 firms classed as being “*regularly supported*”, whilst also taking a keen interest in the 400 firms that are classed as being “*close to treatment”*. Ideally, any firms that are seen to drop out of “*regular support”* should be approached to determine why this has happened and what NPL could do to bring them back. Given the operational metrics, there is data concerning the probability of firms moving up and down the statuses in a given, along with the probability of how a firm may move in a multi-year period given its original status. These tools provide a benchmark to assess the effects of interventions by NPL’s staff in order to increase the number of firms in the higher statuses and entering on the pathway. Hypothetically, if the number of firms on the pathway is known, an assessment several years down the line can be made to see where those firms went, with the probabilities generated here to provide the “control group”, seeing the impact of NPL’s work to develop strong relationships with our customers.

Lastly, cultivating long-term relationships with firms requires a stable core of scientific and BD staff, working directly with the customers. As seen in 2016 following the portfolio rebalancing exercise, high churn in staff precipitates a loss in those long-term relationships which would take time to redevelop. A fundamental data issue at hand for the development of the support metric is that the collaborations data, collected in the esteem survey, isn’t as rigorous as the invoices. Managing NPL’s data on collaborations in a similar manner to the invoices would be beneficial to helping to main those long-term relationships with the private sector, as we would better understand how private sector firms work with NPL.

16.1 PRESENT VALUE OF NPL’S DIRECT BENEFITS CHANNELLED THROUGH THE PRIVATE SECTOR

Another major implication is that a yearly estimate of the present value (or PV) of NPL direct benefits channelled through the private sector can be found. NPL’s contribution to measurement-related productivity growth is channelled through the regularly supported/treated firms. As detailed in Belmana (2019), the innovation benefits led to an increase in productivity among this group of firms, evidenced by significant employment and wage growth when compared to a control group of matched firms[50] that has been observed.

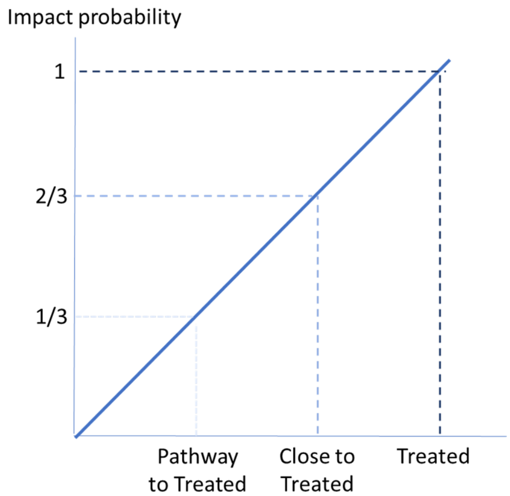
Persistently low levels of unemployment mean that HMT can't accept that the new jobs are truly net-additional to the UK – but what's important is that job switchers must be incentivised to change employers by the possibility of higher wages. That is, as wages typically track labour productivity, the increase in wages among job switchers represents underlying increases in productivity, that ultimately shows up as an increase in GDP. It should be noted that these productivity benefits are generated through innovations found while working on a project with NPL. These innovation benefits have specific lifetime though, (roughly six years, with a two-year delay), after which other competitor firms would be able to "catch up" to the regularly supported firms. As there are a flow of benefits over a six-year period, following a delay of two years, the impact must be discounted as the people tend to slightly discount the future relative to the present. As the discount rate is given by the Green Book, the discounted lifetime of an innovation can be found.

However, wages are only one of the three elements that comprise a firm's Gross Value Added (GVA), the other components being profits for the owners of capital and taxes paid to HMRC. There is evidence that the net-additional benefits to employees in the form of extra wages are matched by the benefits to employers (extra profit) and the government (extra tax revenue). Therefore, the innovation benefits are multiplied by three to account for this. Furthermore, following a study by Frontier Economics (2016), it was found that there is a 1:2 ratio of direct-to-indirect benefits. These benefits "spill over" from the direct benefits, meaning without the direct benefits, there won't be any indirect benefits. This collectively provides the gross benefits of NPL to the private sector

Once these calculations are complete, the social costs must be assessed, made up of private and public costs. The private costs are made up of the spend of NPL's users on our services, the leveraged spend of the users on R&D and opportunity cost of the R&D spend. Similar to the benefits, there are also a 1:2 ratio of direct-to-indirect costs to deal with as well. After dealing with the private costs, the public costs must be accounted for. This is found from the public funding for NPL, which comprises of the NMS and any other public programme (National Timing Centre and Quantum Test & Evaluation). As part of the analysis, only the NMS (minus the rent of NPL's facilities which is netted off of the funding given to NPL) is counted as the public cost as the employment and wage growth was done before these smaller programmes had begun. Once the social costs have been calculated, the net benefit of NPL's work can be calculated. The last addition to this is the profit generated by NPL. All firms who generate a profit would either re-invest the money or return it to the owner of the firm. As NPL is a private company owned by BEIS, this would mean that when NPL turns a profit, it would be paying BEIS (and in turn the society) a dividend. This dividend could be either paid to BEIS or invested in NPL, but its generation should be added onto the overall NPV. It also holds that if NPL was to make a loss, that loss would reduce the NPV of NPL.

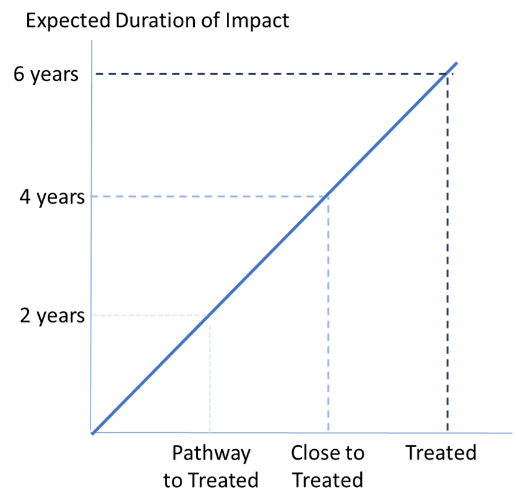
The use of the treated firm numbers to estimate GVA growth is a strict definition, but one that can be describe as "locked in" impact, irrefutable in nature. "Fuzzier" impact can be found by using the Close to Treated & Pathway to Treated numbers, using the Linear Dose Response model. Detailed in Belmana (2019), the Linear Dose Response (or LDR) model details an inference that can be made concerning the impact received by firms who work with NPL.

50 Individually, all firms are different. However, when aggregated together, two groups of firms can look similar to each other. A control group was created propensity score matching, which had the same characteristics as the regularly supported firms (such as R&D intensity, size, location, etc,.) in order for an "Apples-to-Apples" comparison can be made; The only difference between the two groups was NPL's support to the regularly supported firms.



As detailed in the small graph here, it is assumed that the probability of experiencing benefits from support from NPL increase as the support intensity increases. This has a linear relationship, with close to treated firms having a 2/3 probability of experiencing impact and pathway to treated firms only experiencing a 1/3 probability of experiencing impact. Therefore, when calculating the GVA numbers for firms with these categories, their job-years numbers are multiplied by their respective impact probabilities.

The other assumption that is made when using the LDR model is that the duration of impact also scales in the same manner as the probability of impact. From evidence in the UK innovation survey and the NMS customer survey, the benefits of NPL's support last for 6 years as an upper bound. We assume that this upper bound is only felt by the regularly supported firms, while Close to Treated and Pathway to Treated firms' duration of impact scales in a similar manner to the impact probability.



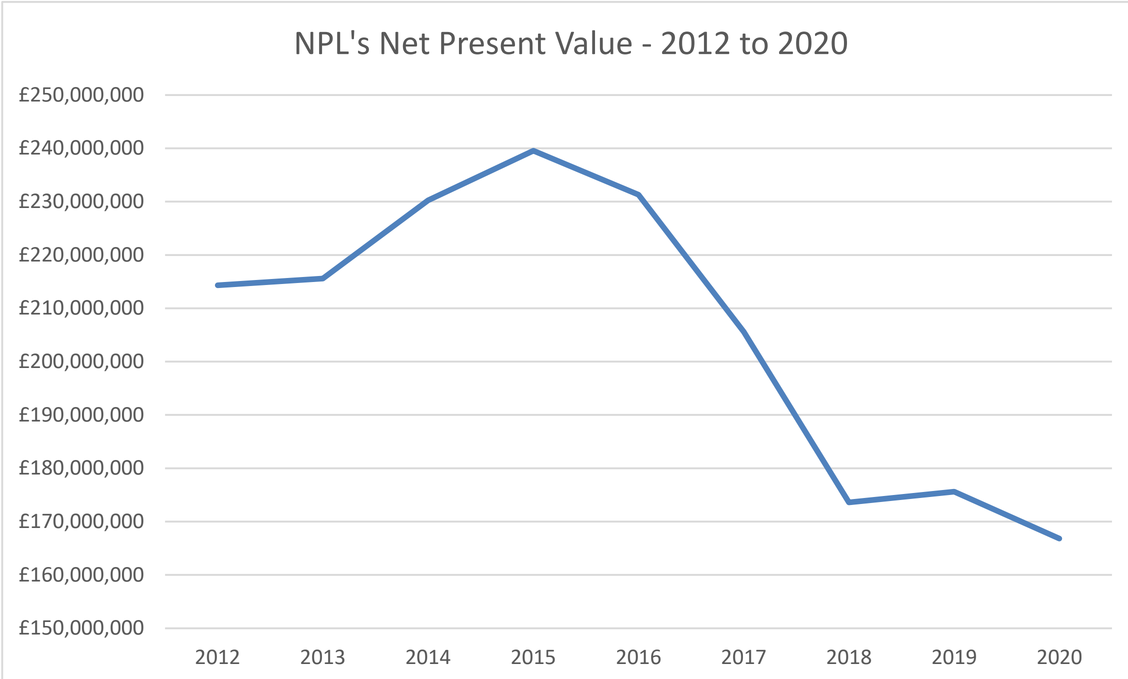
The wage boost doesn't scale in the same way. The wage paid to job-switchers to entice them to move roles (as employment is assumed to be full at a national level)[51] must be higher than their original wage. Therefore, all job switchers receive the same increase, with the subsequent benefit multiplied by three to account for the benefits felt by labour, owners of capital and government. However, as detailed before, this doesn't mean all forms of impact are equal. The benefits gained by the close to treated and pathway to treated firms are described as "fuzzy" and "very fuzzy" respectively. These are assumed to exist given the LDR model but haven't been identified empirically. The analysis produced the following graphs, with the first detailing the Net Present Value with the "locked in" benefits, calculated with the Treated Firms. The second details the Departmental Expenditure Limit – the total government funding NPL receives (including NMS, National Timing Centre and any other government funding).

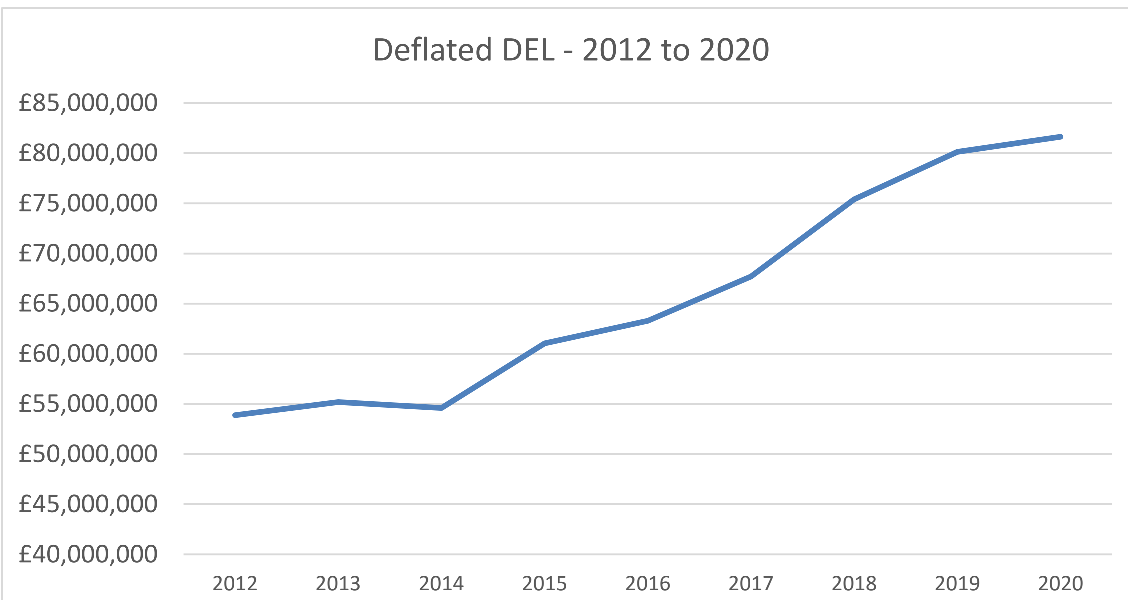
51 Full employment is defined as having a 75% employment rate.

https://commonslibrary.parliament.uk/full-employment-what-is-it-and-can-it-happen/

Currently, the The UK employment rate was estimated at 75.7%, 0.1 percentage points higher than the previous three-month period and 0.9 percentage points lower than before the coronavirus pandemic (December 2019 to February 2020).

https://www.ons.gov.uk/employmentandlabourmarket/peopleinwork/employmentandemployeetypes/bulletins/employmentintheuk/may2022





Further details of this analysis can be found in the attached document titled "Business Case Model".

17 CONCLUSION

To conclude, the implication of the econometric evidence is that NPL requires long-term relationships with its customers to generate impact, with a need for these relationships to be cultivated over time. This was the motivation for creating a time-series to track the number of firms in receipt of regular support from NPL (the "*treated*" firms).

The time-series for the number of "*regularly supported*" firms follow a random-walk, but with a systematic component to its movement. Up to 2016 there was a positive upward drift in the number of “*regularly supported*” firms. However, something happened, so that after 2016, there was a negative downwards drift in the number of “*regularly supported*” firms. It isn’t entirely clear what happened, but one factor could have been disruption to routines accompanying post-Serco reforms, perhaps, compounded by the COVID crisis in 2020. However, on a more positive note, a recovery can be seen in the health of NPL’s “*pipeline*”, with the number of firms on the “*pathway towards treatment*” increasing significantly in recent years, probably, due to the introduction of the *Analysis for Innovators* (A4I) programme.

The metrics can also be used analytically, with two main applications detailed in this analysis. The first analytical use is to assess the impact of the support the NPL provides to the private sector users. Although associative rather than causal, a relationship is identified between working with NPL and a growth in assets, along with better chances of survival. Although no control group has been used as part of this analysis, the direction the associative work is pointing in suggests that a causal assessment with a categorical treatment variable is warranted. The second analytical use is an operational application. As treated firms contribute the vast majority of NPL’s income and invoices, tracking the flows of firms through the statuses are very important for NPL’s private sector income. Probabilities can be attached on yearly and multi-year flows through the statuses, providing a benchmark to assess interventions to increase NPL’s treated firms.

The metrics can also be done at an NPL sector level, assessing the structure of the support firms for each sector. At the moment, the analysis can’t be done due to only having one cohort of data, but this can be developed in 2023 with three years of data. This will be preliminary but can be indicative of the structure and transition probabilities of the statuses of each sector.

Lastly, although, the metric is appropriate for impacts channelled through the private sector, impacts on the public sector aren’t accounted for. In part, this could be remedied by constructing metrics to count the number of regularly supported hospitals or universities, but other metrics are, no doubt, also required. This could include tracking the income from public institutions, such as, the NHS and government departments, with the possibility of NPL’s direct impact on the emission of greenhouse gases (GHG) being metricised using its income from sales of emissions monitoring services (e.g. FEDS).

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19 ANNEXES

19.1 CHANGE IN ASSET REGRESSIONS WITH CONTROLS

The analysis conducted in section 12.2 is purely associative but can be used to assess the probability of a firm seeing a growth in assets given a time period after being assigned a status. However, as the linear probability model is used as part of the analysis, it is fairly easy to introduce a range of controls. This has been done below, with the following equation and definitions to detail:

$$\mathbb{E}\left[I_{i,t+\tau}\right] = \beta_0 + \sum_{\kappa=1}^{4} \theta_\tau^\kappa . \mathbb{I}(S_{it} = \kappa) + \beta_i X_i + \varepsilon_{it}$$

The regression done here is very similar to the one done previously, with two exceptions:

- The constant is reintroduced here
- A range of control variables are used here, denoted by X_i, these include
    - Location
    - Sector
    - Beauhurst identifier
    - Knowledge-Intensive activities identifier
    - Manufacturing by R&D intensity
    - Size
    - Change in the natural log of fixed assets
    - R&D identifier

This analysis is produced a large regression table for 1 year after assignment (relative year = 1):

F.I	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
s						
No Recent Interaction	-.0454849	.0172469	-2.64	0.008	-.0792919	-.0116778
Pathway to treated	-.0271092	.0133142	-2.04	0.042	-.0532075	-.001011
Close to Treated	-.005135	.0159021	-0.32	0.747	-.0363061	.0260361
uk_region_2						
East of England	.0037872	.0222832	0.17	0.865	-.0398919	.0474663
London	-.0214467	.021903	-0.98	0.328	-.0643807	.0214872
North East (England)	.0162482	.0352043	0.46	0.644	-.0527588	.0852552
North West (England)	-.0228227	.0231423	-0.99	0.324	-.0681859	.0225405
Northern Ireland	.1694423	.0699948	2.42	0.016	.0322395	.306645
Scotland	-.0070634	.0259157	-0.27	0.785	-.057863	.0437361
South East (England)	-.0113178	.0198653	-0.57	0.569	-.0502576	.0276219
South West (England)	.0121454	.0246128	0.49	0.622	-.0361003	.0603912
Wales	-.0448908	.0291205	-1.54	0.123	-.1019723	.0121906
West Midlands (England)	-.0201883	.0229166	-0.88	0.378	-.065109	.0247324
Yorkshire and The Humber	.0278692	.0263414	1.06	0.290	-.0237649	.0795032
sic_sec						
Manufacturing	.0763763	.0428996	1.78	0.075	-.0077148	.1604675
Other Production	-.0089902	.0524439	-0.17	0.864	-.1117899	.0938095
Ret & Dist	.0478154	.0444361	1.08	0.282	-.0392875	.1349184
Info & Comms	.0438775	.0469382	0.93	0.350	-.0481301	.1358851
Other Services	.0045151	.0431688	0.10	0.917	-.0801038	.0891339
PSTAs	.0542635	.0422946	1.28	0.200	-.0286416	.1371686
3rd Sector	.1225064	.0595322	2.06	0.040	.0058124	.2392005
Unknown	-.1814551	.0521423	-3.48	0.001	-.2836635	-.0792467
1.beau_bin	-.0029998	.0099341	-0.30	0.763	-.0224723	.0164728
tech_lvl_manu						
low	-.0164259	.0212487	-0.77	0.440	-.0580773	.0252254
medium-low	-.0186084	.0189814	-0.98	0.327	-.0558154	.0185986
medium-high	-.0100115	.017217	-0.58	0.561	-.04376	.023737
high	0	(omitted)				
size_2						
Medium	-.0038271	.0136351	-0.28	0.779	-.0305545	.0229003
Small	-.0326404	.0157392	-2.07	0.038	-.0634922	-.0017886
Micro	-.0812897	.0143118	-5.68	0.000	-.1093435	-.0532359
No Employees	.0748963	.0839204	0.89	0.372	-.0896032	.2393958
N/A	-.0128705	.0547402	-0.24	0.814	-.1201714	.0944304
delta_ln_fix	.0456209	.0078426	5.82	0.000	.030248	.0609939
rd_bin	-.0169674	.0129388	-1.31	0.190	-.0423299	.0083951
_cons	.6189577	.0458493	13.50	0.000	.5290847	.7088307

The table above showed that one year after assignment, No Recent Interaction and Pathway to Treated firms had a significantly lower probability of surviving than Treated firms, even with all of the controls implemented. Close to treated firms aren't significantly different to

Treated firms one year after assignment, something that marries with what is seen in section 12.2. As many of the controls are insignificant, a follow-up regression model was developed which used binary controls, simplifying what was done above. The binaries used indicate the following:

- Lag of the Outcome variable to account for serial correlation found when regressing residuals on the lag of the residuals.
- Greater Southeast location – East of England, South-East and London
- Manufacturing as determined by SIC codes
- Tracked by Beauhurst – (find definition for Beauhurst firms)
- Deemed as Knowledge intensive by OECD definition (SIC codes)
- Large firm by employment (>250 employees)
- R&D, through R&D spend given by FAME

Treated firms were again held constant, with three regressions run:

- Regression with no controls
- Regression with the lagged outcome variable
- Regression with all the controls

For simplicity, Three stars next to the number = 1% significance; Two stars = 5% significance, One star = 10% significance. The three regressions produced the following coefficients:

	No controls		Lagged Outcome Variable		All controls	
	1 Year After Assignment	5 Years After Assignment	1 Year After Assignment	5 Years After Assignment	1 Year After Assignment	5 Years After Assignment
No Recent Interaction	-0.074***	-0.091***	-0.06***	-0.081***	-0.051***	-0.071***
Pathway to Treated	-0.041***	-0.065***	-0.034***	-0.058***	-0.027**	-0.055***
Close to Treated	-0.011	-0.054**	-0.0068	-0.051**	-0.006	-0.051**

Even with the control variables, the indicators are all significant in the same places as they were when no control variables were used. This starts to move away from mere association and towards a causal relationship between the status a firm holds, and the probability of growth being identified. This could be investigated in a follow-up version of the Belmana study. This would use the definition of treated firms found in the study, the extended variables developed here (close-to- and pathway-to-treated firms, coupled with No Recent Interaction) and the cohort technique used here and from the Frontier Economics analysis. Unlike the analysis in this report, the development of a control group would be required, likely using ONS data.

19.2 INCOME/INVOICES BY STATUS REGRESSIONS

The graphs detailed in section 13 show the value that treated firms have when compared to other firms who have a lower support intensity, with regards to invoices and income. The following regressions prove significance, with invoices and income are regressed on the statuses. Also, a set of controls are introduced to move away from just association and towards causality.

Although it is clearly likely that there is significance given the proportions seen in section 13, it is worth testing to guarantee that, while including controls assess if there is causality to be found. Invoices and Income tend to reveal similar things, but income tends to be skewed by larger firms in a way invoices aren't. This is due to the fact firms of all sizes tend to provide invoices, but larger firms can afford to pay more due to having greater assets. Both will be used here.

The regressions used are as follows:

$$R_{i,t} = \beta_1 + \sum_{\kappa=2}^{4} \eta_t^{\kappa} . \mathbb{I}(S_{it} = \kappa) + b_i X_i + \varepsilon_{it} \ or \ V_{i,t} = \beta_1 + \sum_{\kappa=2}^{4} \rho_t^{\kappa} . \mathbb{I}(S_{it} = \kappa) + \mathrm{B}_i X_i + \varepsilon_{it}$$

Where:

- t = Calendar year
- $R_{i,t}/V_{i,t}$= Deflated income/Invoices from firm i in year t
- β_1 = constant
- S_{it} = Status of firm i in year t where Sit $\in$ {Close to Treated, Pathway to Treated, No Recent Interaction}
- $\eta_t^{\kappa}/\rho_t^{\kappa}$= Income Coefficient given relative year and status
- X_i = A range of control variables
- ε_{it} = Error term

The controls used are the exact same as the ones used in Annex 18.2, with the regression presented in the same manner:

- Regression with no controls
- Regression with the lagged outcome variable (to account for serial correlation found when regressing residuals on the lag of the residuals for both income and invoices)
- Regression with all the controls

The table produced is as follows:

	Income			Invoices		
	No controls	Lagged Outcome Variable	All controls	No controls	Lagged Outcome Variable	All controls
No Recent Interaction	-16393.4***	-3555.83***	-3469.56***	-9.351253***	-6.326215***	-6.414524***
Pathway to Treated	-15191.32***	-2950.33***	-2839.83***	-8.881873***	-5.997414***	-6.07557***
Close to Treated	-13687.45***	-3115.51***	-3081.38***	-7.932865***	-5.4417***	-5.482098***

Even with the controls, the status variables clearly show significance. This moves beyond mere association, a causal relationship can be seen (though not proclaimed as further steps would need to be required to evidence this further) between both income and invoices and the treated firms, with all other statuses being significantly lower.

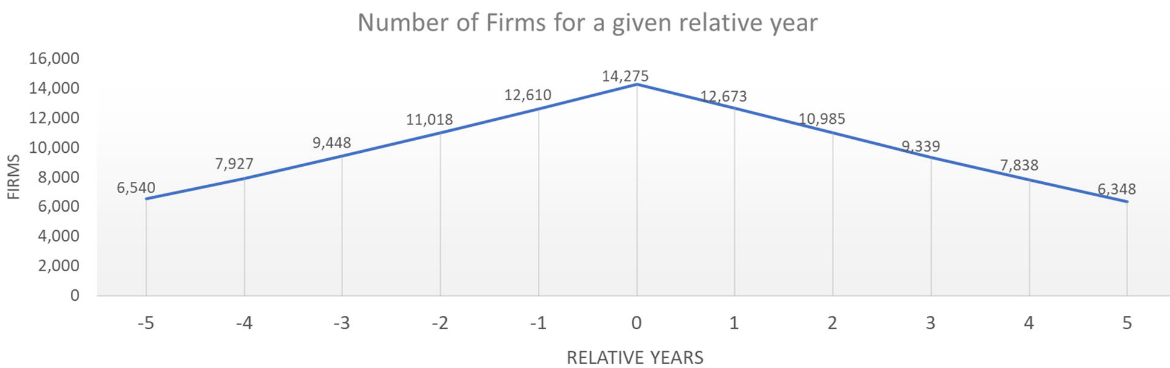
19.3 SAMPLE NUMBERS IN RELATIVE YEARS

	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020	Total Support during Cohort	Status
Cohort 1 (2007 to 2012)															4	Close to Treated
Cohort 2 (2008 to 2013)															5	Treated
Cohort 3 (2009 to 2014)															5	Treated
Cohort 4 (2010 to 2015)															5	Treated
Cohort 5 (2011 to 2016)															4	Close to Treated
Cohort 6 (2012 to 2017)															4	Close to Treated
Cohort 7 (2013 to 2018)															3	Close to Treated
Cohort 8 (2014 to 2019)															2	Pathway to Treated
Cohort 9 (2015 to 2020)															2	Pathway to Treated

Cohort Time Period Instance of Support

Returning to the example used in section 11.2, the structure of the cohorts can be seen here. These cohorts are stacked on each other, with the last year determining the calendar year detailed in the graphs. By stacking these, the number of observations increases dramatically, when compared to the raw observations. This is seen in the graph below:

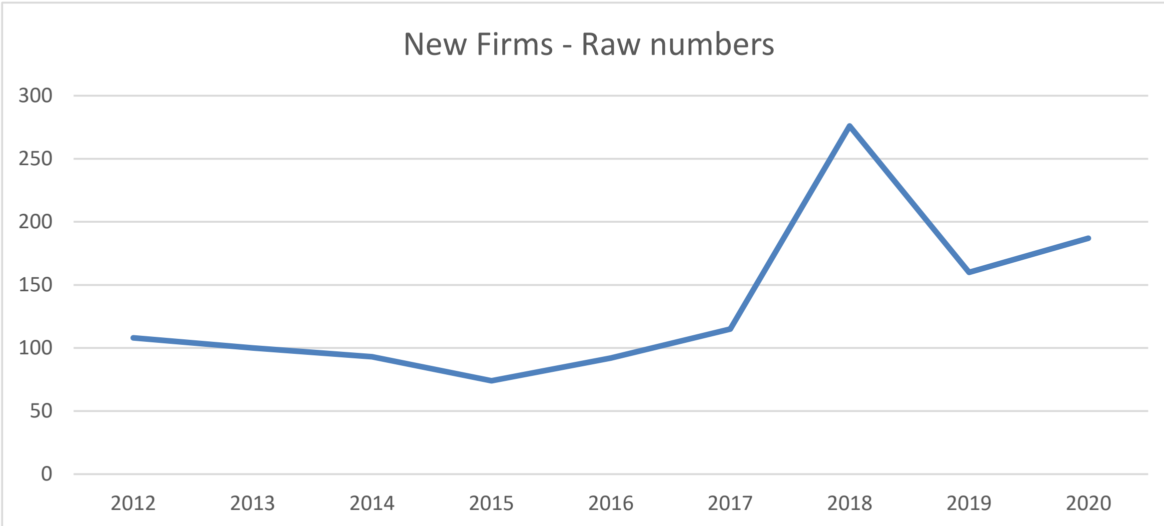
This graph shows the number of firms that can be identified at each relative year, looking five

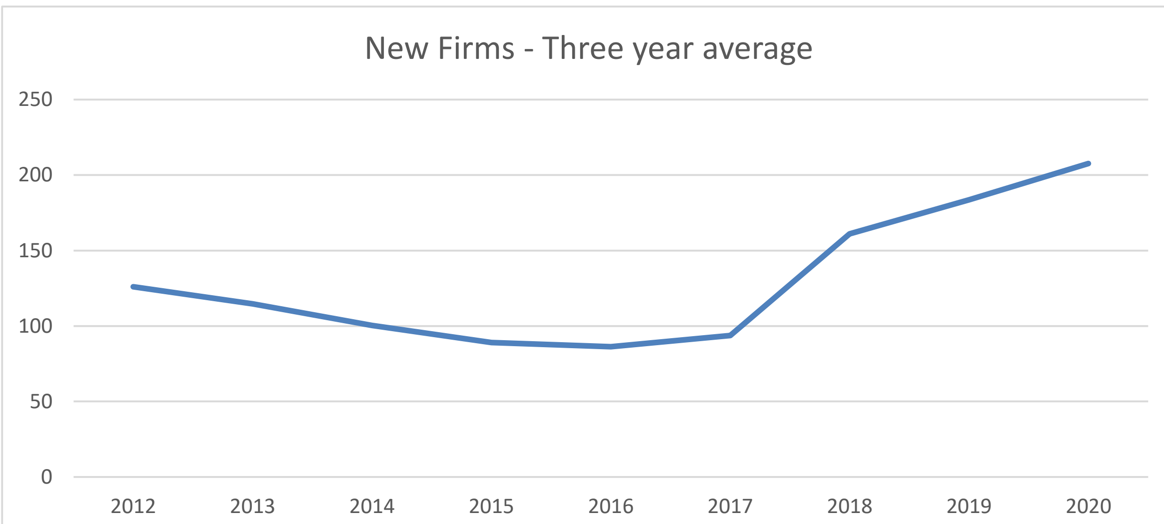


years away from the centre point (zero). As all firms within the data must be identifiable at relative year zero, as this is when they are assigned a status, the sample is largest here. However, not every firm will be tracked either five years forwards or five years backwards from relative year 0. Using an example, let's take a firm from Cohort nine (2015-2020). In Cohort 1, the past of that firm can be assessed for any year moving backwards. However, as the cohort is the last one developed for this work, it is impossible to go forwards. This issue is the same for every cohort; more and more firms drop out as it becomes impossible to track them over multiple years. This means that the further from relative year 0 is assessed, the higher the standard errors (SEs) are. This leads to greater uncertainty concerning the results, evidenced by higher SEs and therefore, confidence intervals.

19.4 NEW FIRMS BETWEEN 2012-2020

Here resides the numbers of new firms from 2012-2020. Below is the raw numbers and a three-year average of the totals:





What is seen is a decline in new firms from the start of the period up to 2015-2016, followed by a sharp increase in 2018, coupled with a general increase over the time period after 2016. The cause of the spike in 2018 is something that is unknown within the data at hand, but the increase in 2019 and 2020 is largely made up of firms from A4I and its sister programmes. It could be hypothesized that NPL's portfolio rebalancing exercise in 2016 likely led to the establishment of a sizeable "NPL Alumni" network, given 10% of staff were laid off. Therefore, these employees could then work with NPL in two ways:

1. Although these employees were made redundant in 2016, some of their projects at NPL were likely incomplete at the time. In order to complete these projects, they could have set up a nominal "company" and worked with NPL as a collaborator to finish their projects during 2017-2018.
2. The now-redundant former employees can be assumed to be now working for firms who could be viewed as potential users of NPL. These employees could influence their new firms, providing evidence of how NPL could provide significant impact for them, along with lasting working relationship with current NPL employees to assure ease-of-use for new users.

19.5 SECTORAL STATUSES (%)

Below is the Percentage version of the graph shown in section 14. As detailed there, there are only a few differences between the sectors, with the respective No Recent Interaction firms for Life Sciences and Health the only status that is significantly different to the other sectors.