

NPL REPORT IEA 5

**THE IMPACT OF THE NATIONAL MEASUREMENT SYSTEM
FUNDING ON THE UPTAKE OF NPL'S SERVICES**

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Abstract

This paper applies standard panel data analysis to study how NMS funding received by NPL affects the number of UK-based firms it can support. The data used consists of administrative information that NPL routinely collects to monitor the composition of the workforce, the evolution of income, as well as the number of paying customers of each of NPL's scientific groups which are specialised in different areas of metrology. The analysis finds that providing NPL with an additional million pounds per annum, enables it to directly support around 9 more UK companies.

The results of this study will, in time, be used to find the additional economic impact of NPL receiving extra public funding. To that end, it is necessary to know: (1) the effect of extra funding on the number of firms supported, and (2) the effect of such support on the growth of these companies. The scope of this report encompasses only the first of these two elements, whereas, the impact on supported companies is left to a separate study. Hence, this report does not provide an estimate of the impact generated by increased funding. In due course, this important question will be answered in a third study combining these two pieces of analysis.

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Preface

This paper has been prepared by NPL's Analysis and Evaluation team to support the evidence this organisation is submitting for the 2020 Comprehensive Spending Review. This document is addressed to NPL's government owner: The Department for Business, Energy & Industrial Strategy. Its objective is to support the case NPL is presenting to justify the benefits of its public funding.

NPL supports UK businesses by offering specialised services. This allows them to develop new products or processes. New products enable the company to increase its market power and command a price premium. On the other hand, new processes enhance productivity and competitiveness. This benefit carries over to society in the form of greater private profits of firms and better wages for their workers, as well as more value for consumers. These are direct economic benefits of public funding of NPL.

This report lays the foundations for an impact analysis that studies the effect that marginal shifts in the public funds received by NPL have on the direct benefits to UK companies. To that end, it is necessary to know: (1) how changes on the current level of public funding of NPL affect the number of companies it can support – the present study – and (2) the effect of such support on the growth of companies.

Lastly, it should be noted that this study only concerns to direct economic benefits. There are wider social economic benefits arising from knowledge spillovers to unsupported firms. Moreover, this report deals with support given to the private sector; hence no engagement with the NHS, government departments or academic institutions is within the scope of this work.

Executive Summary

NPL has analysed how NMS funding affects its capacity to support UK-based companies. To this end, two models have been developed to quantify the relationship between the level of NMS funding and both the number of scientists and engineers in NPL's workforce, as well as the number of companies supported in the UK.

NPL is organised into a number of scientific groups that specialise in different areas of expertise. The data used in this analysis consists of administrative information normally used for internal monitoring purposes and to report agreed metrics to BEIS. The data encompasses annual information from 2010 to 2017 for each of the 17 scientific groups¹ that compose NPL. This information includes:

- the level of funding received,
- the number of scientists and engineers in the workforce,
- and the number of UK-based firms supported.

The analysis finds that providing NPL with an additional £1 million per annum of resource funding, enables it to directly support around 9 more UK companies. These additional companies will either become NPL paying customers or will engage in collaborative R&D projects. This means an average cost of approximately £110,000 per company. For Innovate UK the average cost per incidence of support is around £155,000².

¹ The term *groups* used here is not entirely accurate. As mentioned, NPL is organised in scientific groups whose staff has varied over time in response to the allocation of funding across many different programmes. For that reason, in this analysis, NPL's groups have been aggregated into 17 *composite groups* based on their specialism. This ensures that each *composite group* retains its identity and character despite any organisational change. For the sake of simplicity, in this document we refer this *composite groups* as groups; hence the term is used somewhat loosely. More on this can be found in section 0.

² This average cost has been computed using Gov.uk (2019), which consists of a register of all Innovate UK funded projects since 2004. These include collaborative research and development (R&D), feasibility, smart and innovation voucher grants, and knowledge transfer partnerships between 2004 and 1 October 2019. Not all types of Innovate UK projects have been considered, as they are not comparable to those carried out by the NPL. In particular, *centres*, *BIS-Funded Programmes* and *Vouchers* have been excluded.

1 Introduction

1.1 The National Physical Laboratory

NPL is a government owned and funded national laboratory that specialises in measurement science. In particular, it conducts research into fundamental metrology and develops primary standards, as well as new instrumentation. NPL also supplies commercial calibration, testing, consultancy and training services to private businesses, hospitals, and universities. Lastly, NPL works with Innovate-UK to offer grant funded collaborative R&D projects, involving many firms and research organisations. One of the main channels to distribute these resources is the Analysis for Innovators (A4I) programme, which gives UK businesses access to cutting-edge R&D, expertise and facilities to help solve measurement challenges they face. The time of NPL's scientists and engineers is split between:

- maintaining NPL's capabilities by conducting international comparisons and doing research that generates articles in peer-reviewed scientific journals,
- delivering commercial measurement services (e.g. calibration services) or training,
- and working with other organisations on collaborative R&D projects.

The following figures give a clearer picture of NPL and its role within the UK productive economy³:

- 820 scientific and technical staff, as well as 280 administrative and managerial staff.
- A turnover of around £90m; £57m of that revenue in annual NMS⁴ funding.
- Around 350 articles in peer reviewed journals each year; also, its scientists perform around £30m of public research work each year⁵.
- £13m of revenue from sales of measurement services. The R&D performed by NPL supports the introduction of new and improved calibration services, whose benefits fan-out down the calibration chain.
- Around 7% of all business R&D (£1.7 billion) is directed at instrumentation. NPL works closely with instrument manufacturers to develop complementary calibration services.
- Sells services to around 500 UK-based firms each year. And, the lab's scientists collaborate on R&D projects with around 200 UK-based firms each year.

NPL seeks to fulfill its mandate of providing excellent metrology science to ultimately generate welfare for the UK. For that matter, it is essential for NPL to know the impact of its activity on the industrial fabric of the UK:

- NPL commissioned a survey asking its users about the sales of new products that they feel would not have been achieved without the support of NPL and the other NMS laboratories. This survey found that users of the NMS laboratories believe that without NPL's support, their total annual sales of new products would decrease by at least £470M. Furthermore, they believe that about £2bn worth of new products might be at risk without this support. The self-reported nature of these estimates may make the exact size of these benefits doubtful, but it still provides evidence that such benefits exist.
- An independent econometric study by Frontier Economics found that companies supported by NPL grow more rapidly than unsupported comparators - on average,

³ These figures are as of 2019. They differ to the ones used in this study which relates to the period 2010-2017.

⁴ The National Measurement System (NMS) is a network of national laboratories and processes that provide measurement standards and calibration testing facilities in the UK. It maintains the measurement infrastructure, represents the position of UK measurement internationally and influences the development of standards.

⁵ Based on tax credits claims information.

supported companies have around 20 additional employees 2-3 years after working with NPL, when compared to a matched control group of similar unsupported ones.

1.2 The public funding of NPL

The economic rationale for the existence of a publicly funded organisation like NPL is that measurement R&D is subject to market failure. Indeed, the private investment needed to generate innovative measurement capabilities, will always be below the socially optimal level. This occurs because the benefits that measurement R&D generates will always spill over to firms who did not contribute, and this creates a strong incentive to free-ride. The problem is particularly acute in the case of the R&D that the NPL undertakes, because advances in metrology tend to have applications across many sectors. It is this wide applicability that makes the development of these new tools and techniques particularly susceptible to free riding. Consequently, it is argued that measurement should really be seen as a public *infrastructure*, that is, a technology that provides tools and techniques which can be widely applied across a number of sectors to enable further innovation. In short, NPL and its partners' scientific work generates a pool of knowledge that can be accessed and used by any firm. This fact carries a strong incentive to free ride, and thus, there is a clear need for public funding to complement measurement R&D funded through private spending.

Another key argument for publicly supporting a specialist laboratory like NPL is that the kind of metrology research it conducts requires the setting up of large facilities. In such cases, the fixed costs could be so high that they exceed the private gains to any one company. Therefore, the facility would never be developed on the basis of individual private funds alone, despite the total benefits from the capability outweighing the cost.

Lastly, there is an efficiency justification that supports the idea of a publicly funded metrology laboratory like NPL. Indeed, the high cost and difficulty of maintaining primary standards makes the calibration chain very efficient. NPL supplies a costly high-level calibration service to a commercial laboratory, which then calibrates the instruments of a vast number of users without the need for the calibration laboratory to establish their own primary standard.

1.3 The rationale for subsidising NPL

Although NPL's portfolio is quite varied, roughly speaking it can be considered to offer one unique good: the time and the expertise of highly trained scientists and engineers. In that regard, NPL can be thought to operate much like a professional services firm which sells the time and the knowledge of its workforce. However, in other aspects NPL is far from resembling a typical professional services firm. In particular, there is a fundamental difference when comparing both business models – say between a law firm and NPL. For the former, its core business consists of one sole activity: representing its clients in court and providing them with legal advice. For NPL it is not as straightforward because NPL staff need to maintain the measurement capabilities required to deliver high-accuracy measurement services and engage in cutting-edge collaborative R&D projects. Hence, unlike a law firm, NPL must preserve a knowledge stock that depreciates over time in order to meet the requirements of its users. To do so, NPL's staff carry out a wide variety of activities. These include conducting international key comparisons, participating in proficiency testing schemes, maintaining UKAS accreditation for calibration and testing services, running audits, contributing to standards and protocols, and performing research that generates articles in peer-reviewed scientific journals. This knowledge base is then used to meet the needs of beneficiaries, whether they are users of measurement services or R&D collaborative partners. In this sense, NPL could be considered to resemble strongly an orchestra for which the day of the concert is only the tip of an iceberg of constant work over months and years of practice. The show would not be possible without the previous effort put into practice. Similarly, for NPL both activities (the maintenance of capabilities and the delivery of services) are deeply entwined.

More public funds allow NPL to hire more scientific staff, which leads to more UK companies receiving support. NPL's workforce help users to develop new products and processes. New products enable supported businesses to increase their market power and command a price premium. New processes enhance productivity and competitiveness. In any case, NPL's services lead to increased future earnings. In this sense, companies regard NPL's services as investment projects that generate profits over time. A rational consumer would prioritise projects with a higher payoff and, if no budget constraint is in place, would buy NPL's services to the point that the marginal benefit equals the marginal cost. This suggests a downward sloping aggregate demand curve for NPL's services: more profitable projects yield higher future earnings which makes customers more willing to pay for them. This situation is depicted in Figure 1. The horizontal axis shows NPL's number of scientific staff which is a proxy for the volume of services supplied. The vertical axis of Figure 1 (a) is the net present value of the investment projects supported by NPL, whereas in Figure 1 (b), the vertical axis is money measured in pounds:

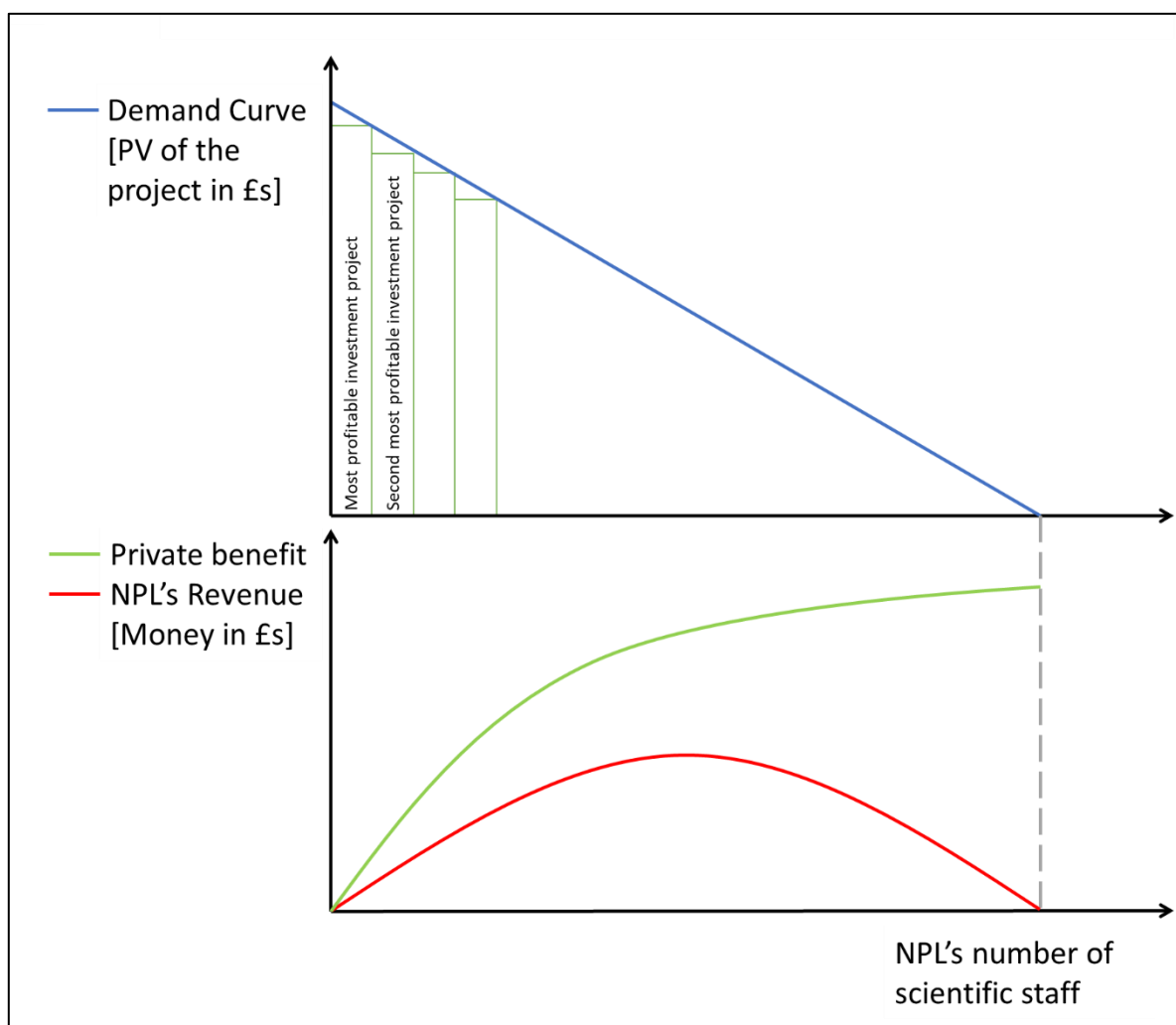


Figure 1: (a) Top: NPL's services demand curve. (b) Bottom: NPL's revenue and private benefit.

Figure 1 (a) considers the demand curve for NPL's services. Naturally, as any other normal good, as the price increases, the quantity demanded decreases. The negative slope of the demand curve reflects the fact that NPL holds a certain level of market power. This is consistent with NPL being a highly-specialised producer. As with any downward sloping demand, there is a point where NPL makes optimal use of its market power and maximises

its income. This leads to a bell-shaped curve for NPL's revenue which is outlined in Figure 1(b).

Figure 1(b) can lead to confusion if not interpreted correctly. It could be that the reader wonders how it is possible that NPL's revenue diminishes beyond a certain level of sales – even reaching a point where no income is generated. This might seem counterintuitive. However, it should be noted that NPL affects prices indirectly through the number of scientific staff it hires. That is, the more scientists and engineers working at NPL, the more services are provided to UK businesses, and thus, the lower the market clearing price. Hence, this could get to the point whereby the price is so low that it would not matter how much time it sells; income would be minimal (the limiting case being when the price is zero and therefore no income is generated)⁶.

On the other hand, from the customer's perspective, there must be a benefit associated with NPL's services. Moreover, we know this benefit should be greater than NPL's income; otherwise the transaction would not take place. However, we also know that any benefits that NPL's customers get must show some diminishing returns, since not all projects carry the same payoff, and in fact, the most profitable projects are prioritised. For that reason, the private benefit curve in the second chart consists of an increasing concave function. Indeed, the private benefit function plateaus at a certain level because there is a finite number of potential users within the UK's private sector.

Up to this point, we have addressed one side of the market, that is, the demand for NPL's services. In order to get a complete picture of the implications for welfare, the supply side must be analysed too. NPL incurs two types of costs. On the one hand, NPL has to cover fixed costs such as the rental of the facilities where it carries out its activity. On the other hand, NPL faces variable costs which are mainly the wages of its scientists and engineers. Hence, it is expected that the total cost is an increasing function of the number of scientific staff with a positive intercept at origin (F). Furthermore, this curve is likely to show some convexity because there is a limited pool of scientists and engineers with the specific knowledge required to work in NPL. The more NPL hires, the more it has to compete with other laboratories within the UK and in the rest of Europe. Therefore, costs (wages) tend to increase more than proportionally. Figure 2 adds the costs curve to the previous set up and focuses on the region of interest.

⁶ Formally, this can be seen by considering revenue generated. This is given by $R = P \cdot Q$. Now, if we consider a linear demand curve, price is given by $P = A - BQ$, where A and B are parameters. Hence, combining both expressions we get a quadratic expression for revenue: $R = (A - BQ)Q = AQ - BQ^2$. This parabola has two roots: $Q = 0$ and $Q = A/B$.

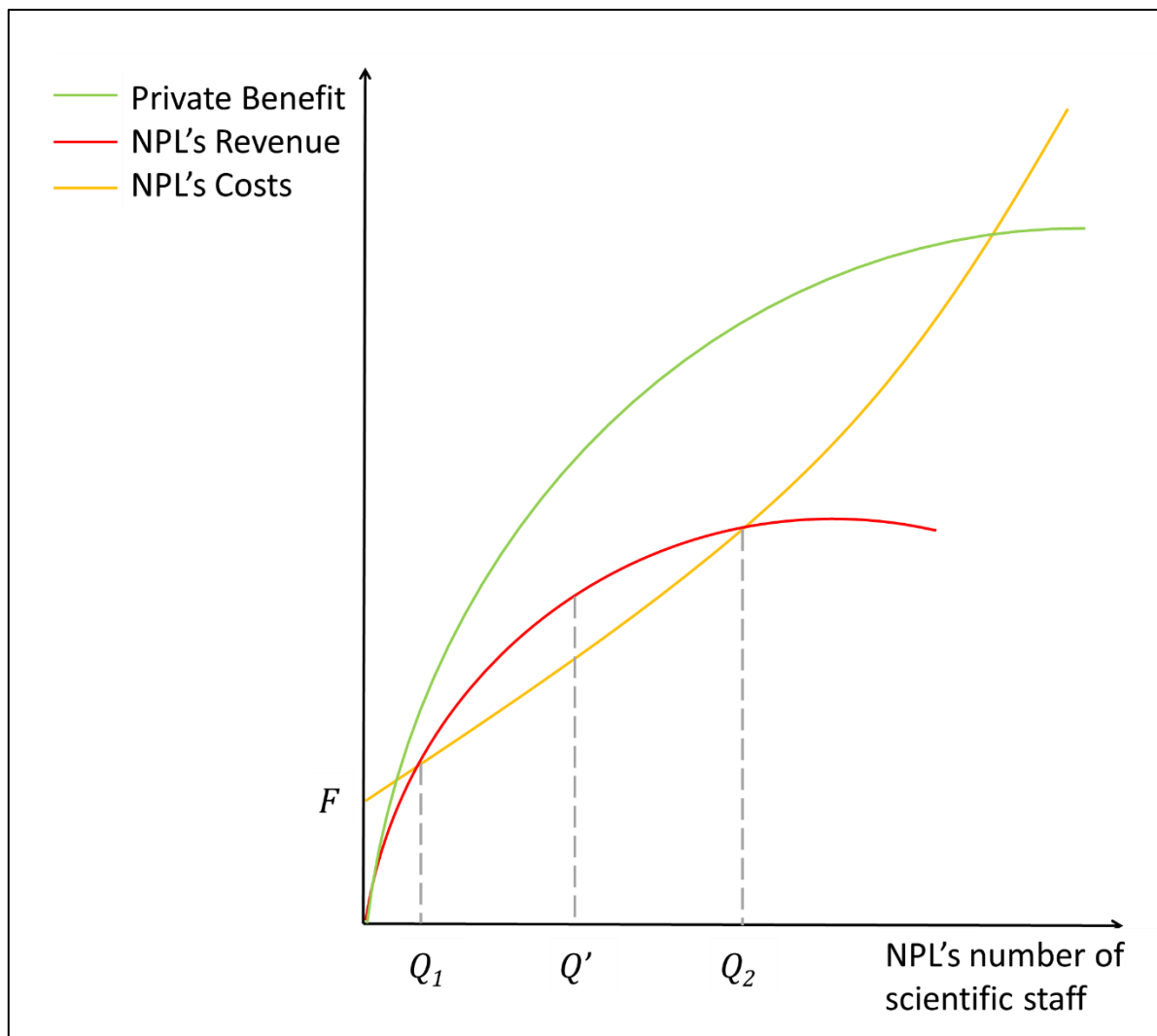


Figure 2: Private benefit and NPL's revenue and costs.

NPL's objective is to generate welfare for the UK (whilst being financially sustainable), rather than maximise its profit. Without public support, it could generate welfare up to the level where revenue equals costs. These are given by Q_1 and Q_2 . Q_1 represents the minimum scale that allows NPL to make a profit. Hence, NPL would always seek to expand its production beyond this point. If NPL were an organisation that seeks to maximise its profit, it would make use of its monopoly position by supplying Q' . However, since NPL pursues maximum social welfare, with no public support, it would supply Q_2 .

Everything depicted until this point refers to the monetary flows *within* the transaction; in other words, we have only addressed the value for both parties involved, that is, NPL and its customers. Nonetheless, as mentioned in section 1.2, there are wider social benefits from NPL's activity. This suggests that, even if NPL supplies the market with as many services as possible without incurring losses (Q_2), the socially optimal level of output is not achieved. In other words, public intervention is needed to get the maximum value from NPL's capabilities. In the context of Figure 2, this positive externality implies that there is a social benefit curve which is above the private benefit curve. Thus, social benefits consist of a private and a public component which combine to give the social benefit curve. The private component corresponds to the increase in profits by companies supported by NPL. The public component comes from firms that do not directly access NPL's services, but who benefit from NPL because of spillovers. In any case, the optimal level of output is achieved when the vertical

distance between the social benefit curve and NPL's cost is maximal (Q_3). To reach this point, a subsidy is needed. This subsidy would reduce NPL's marginal cost, effectively covering part of the wages of the scientific staff. Figure 3 shows the optimal scale of activity which accounts for public-sector intervention in the form of a subsidy.

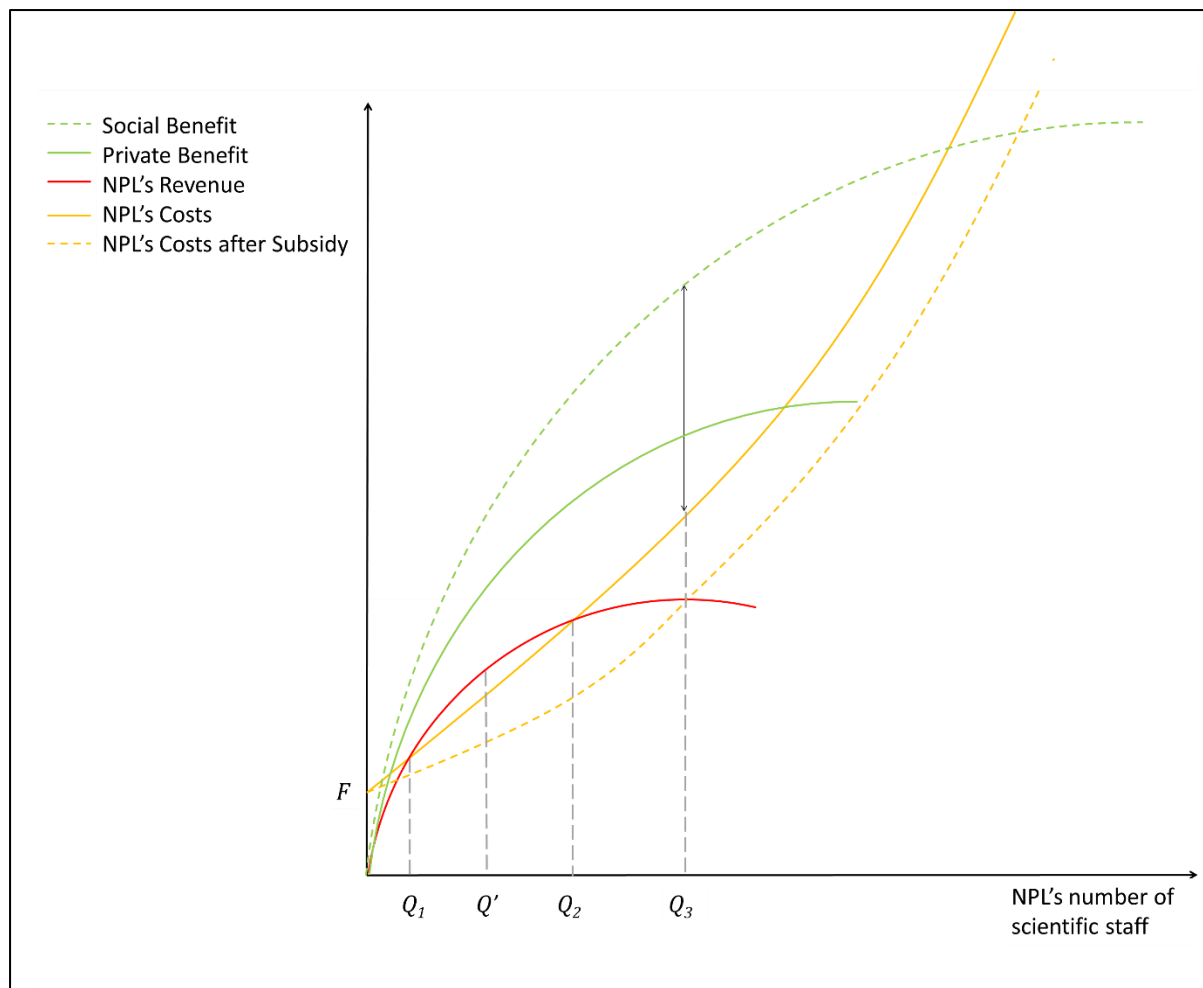


Figure 3: Socially-optimal production of NPL's services.

Therefore, the free market outcome does not reflect all the benefits of NPL's services. Public intervention is needed to internalise this positive effect. However, unsurprisingly, users are only willing to pay for the work pertaining to the services they receive. Hence, the way to secure these wider benefits is by subsidising NPL's services. Public funding pays for the maintenance of measurement capabilities that grow with the number of scientific staff. Therefore, NMS funding operates according to a cost-sharing formula that allows scientists to bill the NMS for work performed to maintain their measurement capabilities that are then drawn on to generate competitively won work. In fact, a substantial part of NMS funding is dedicated to this. Therefore, NMS funding is not used to pay for the work done to support private companies, nor it is given to R&D partners in the form of grants. NMS funding pays for the development and maintenance of measurement capabilities which are needed to support UK businesses. Maintenance activities contribute to retain customers but will not bring in new ones. Conversely, increasing a group's funding allows it to develop new measurement capabilities or to improve existing ones, which in turn helps to attract new customers.

The fact that NPL has commercial income indicates that it is generating value for its users. NPL's customers either pay for commercial services (the mean measurement invoice is around £3,800) or engage in collaborative R&D (typically with a several tens of thousands of

pounds private spending). However, although NPL generates revenue from both activities, the market failure that motivates its existence prevents it of being a self-financing organisation. In other words, although competitively won work creates revenue that helps to cover some of the cost of maintaining NPL's measurement capabilities, it is not generally sufficient to repay all of it. Therefore, NPL needs the cost-sharing agreement it has with the NMS to ensure that its scientists and engineers have the cutting-edge capabilities needed to serve its customers. Yet the NMS budget is fixed, which means this cost-sharing only operates up to a certain limit⁷. Beyond this point, it would be necessary for any additional scientific staff to bring in enough competitively won work to cover the full cost of their activities. Long experience has found that this is close to impossible in practice; which means the size of NPL is effectively set by the NMS resource, which in 2018 was over £56.8 million.

Figure 4 consists of a chart that shows all the sources of government money received by NPL on 2018.

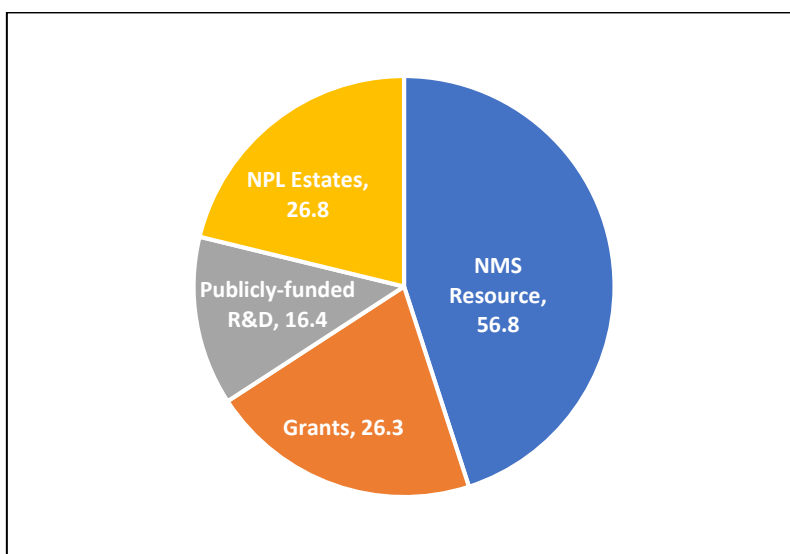


Figure 4: Money received from government by NPL in 2018 (£m).

However, not all of these sources of government money should be considered public funding, in the sense of being state aid. In the case of NPL Estates, this money is received to cover the maintenance and improvement of the facilities in which NPL carries out its activity. But since the government owns the premises, these funds follow from the rental agreement, for which NPL pays an annual rent. With regard to 'publicly funded R&D', this also should not be considered public funding. The reason being that, though this income is generated through research work that NPL performs for the government (defence and health), NPL is providing a service as it would for any business in the UK.

⁷ The kink point Q_3 in Figure 3 reflects the fact that NMS budget is fixed. Beyond this point, the marginal cost is the same as in the unsubsidised cost curve.

2 Data

In 2017, the last year included in the dataset, NPL was organised into 24 scientific groups that specialise in different areas of metrology such as *electrochemistry* or *advanced engineering materials*. The distribution of scientific staff across these groups has varied over time in response to the allocation of funds across many different programmes. In some instances, these changes have even led to groups being divided and brought back again. If the scientific groups were chosen as the unit of analysis, these organisational changes may undermine the results of this work. This is because the fundamental characteristics of the unit of analysis may change over time. From an econometric point of view, we would say that the *fixed effect* is not, in fact, fixed. For that reason, NPL's groups have been aggregated into 17 *composite groups* based on their specialism to come up with a more stable panel unit. This ensures that each *composite group* retains its identity and character despite any organisational change. For the sake of simplicity however, henceforth we will refer this *composite groups* as just *groups*. Although the term is used somewhat loosely because from an internal point of view this is not entirely accurate, it simplifies the nomenclature of the text.

Regardless of organisational aspects, it could be argued that the core of NPL is the expertise of its scientists and engineers. These act collectively as a knowledge bank which tends to grow over time. That is, although some scientist and engineers may leave or eventually retire, the labour force remains considerably stable, maintaining the existing measurement capabilities and developing new ones.

The internal data utilised in this analysis is routinely collected by NPL administrative and strategy functions to serve monitoring purposes and to support NPL management and board. The data consists of detailed information on workforce composition, finances (particularly income), and invoices issued to UK businesses by each scientific group. All paying customers names have been uploaded to the BVD FAME Database to identify its Company Reference Number and thus, obtain the number of unique UK businesses that engage with NPL.

The dataset constructed consists of a panel of 136 observations (17 groups and 8 years) containing the following information for a given group in a certain year:

- The number of UK-based firms supported; that is, customers who either paid for services or collaborated with NPL in R&D projects.
- The number of working scientists and engineers.
- The level of NMS funding.

Table 1 lists the variables used in this analysis.

Variable	Abbreviation
Number UK firms who paid for services or engaged in R&D projects	<i>USERS</i>
Total full-time-employment scientific workers	<i>STAFF</i>
NMS funding (£m constant prices)	<i>FUNDS</i>
Number of paying customers (<i>USERS</i>) per FTE scientific workers (<i>STAFF</i>)	<i>users</i>
NMS funding (<i>FUNDS</i>) per FTE scientific workers (<i>STAFF</i>)	<i>funds</i>

Table 1: Variables.

Throughout the rest of the document these variables will be referred by their respective abbreviations. Note that the variables in level are abbreviated in capital letters, whereas those normalised by FTE workers are lowercased. Table 2 below provides some basic descriptive statistics for these variables.

Variable	Variation	Mean	Std. Dev	Min	Max	Obs.
USERS	overall		33.3	0.0	136.0	N = 136
	between	38.4	33.6	1.0	125.3	n = 17
	within		6.2	16.5	55.9	T = 8
FUNDS	overall		1.2	0.3	7.7	N = 136
	between	2.5	1.1	0.9	5.4	n = 17
	within		0.5	1.2	4.8	T = 8
STAFF	overall		13.0	13.4	91.7	N = 136
	between	29.8	11.4	19.9	63.6	n = 17
	within		6.7	15.4	57.8	T = 8
users	overall		1.1	0.0	5.2	N = 136
	between	1.3	1.1	0.0	3.7	n = 17
	within		0.4	-0.1	2.8	T = 8
funds	overall		0.0	0.0	0.2	N = 136
	Between	0.1	0.0	0.0	0.1	n = 17
	Within		0.0	0.0	0.2	T = 8

Table 2: Descriptive statistics.

The main features of the dataset are:

- It is a fully balanced panel, that is, no observation is missing for any group and year. This means that:
 - Any analysis conducted over this dataset will not suffer from an efficiency loss due to missing information.
 - There is no unobserved characteristic that induces a selection bias issue.
- Although there is a non-trivial variation *within* group level variables, the dataset shows a more notable difference *between* the groups. The fundamental source of this *between* variation comes from the internal process through which NMS funds are split among the 17 scientific groups.
- Unfortunately, it is not possible to perform an individual analysis for each of the groups because the number of observations is not enough to produce robust results.

Once *USERS* and *FUNDS* are normalised by *STAFF*, the percentage of the *overall* variation coming from *between* the groups is reduced. This is because normalising by *STAFF* allows for comparisons to be made between groups of very different sizes.

3 Model

NPL is an organisation that acts as a vehicle to efficiently allocate the public funds needed to complement private spending in measurement R&D. Although, NPL has developed services that cover partly for its costs, it is not a completely self-financing company. Therefore, NPL's ability to support UK businesses depends to a considerable extent on the public funds received. Thus, strong relations between *FUNDS* and both *STAFF* and *USERS* are expected. This means that it is possible to find significant results despite the small scale of the panel (only 136 observations; 17 groups and 8 years).

The model below makes use of two mathematical relationships that are true by definition. These two expressions link the number of users (normalised by staff) and staff to funding. Given that NPL is subject to market failure, equations 3.1 and 3.2 below must hold. The next step is to combine both expressions through algebraic identities that come from fundamental rules of calculus to obtain the partial effect that public funds have on the number of users. Hence, the fundamental aspect of these setup is that there is no real economic modelling behind equation 3.3. We use two incontrovertible relationships linking funding to uptake and staff that are combined algebraically to come up with equation 3.3.

The analysis starts from the following linear relations for each of the scientific groups of NPL:

$$\frac{v}{u} = A_0 + B_0 \cdot \frac{w}{u} + \varepsilon_0 \quad (3.1)$$

$$u = A_1 + B_1 \cdot w + \varepsilon_1 \quad (3.2)$$

Where the variables have been represented as single letters for the sake of simplicity:

- $v(w, u(w))$ is the number of paying customers (*USERS*),
- $u(w)$ is the number of scientific workers (*STAFF*),
- w is the level of funding received (*FUNDS*),
- and $\varepsilon_i \sim N(0, \sigma_{\varepsilon_i})$ with $i = 0, 1$ is the error term in both expressions.

The error term in (1) is typically capturing macroeconomic shocks, *i.e.* technology and demand shocks, whereas in (2) it represents random changes in *STAFF* which cannot be explained by *FUNDS*, such as the retirement of senior scientists, long leaves of some employees and hiring decisions by the group leaders beyond the funding they receive.

Differentiating both sides of expression (1) and making use of the quotient rule, we get:

$$\Delta v \cdot u - v \cdot \Delta u = B_0 \cdot (\Delta w \cdot u - w \cdot \Delta u) \Leftrightarrow \frac{\Delta v}{\Delta w} = \frac{\Delta u}{\Delta w} \cdot \frac{v}{u} + B_0 \cdot \left(1 - \frac{\Delta u}{\Delta w} \cdot \frac{w}{u}\right)$$

Differentiating (2) we get:

$$\Delta u = B_1 \cdot \Delta w$$

Finally, combining these two previous expressions, the following result can be derived:

$$\frac{\Delta v}{\Delta w} = B_1 \cdot \frac{v}{u} + B_0 \cdot \left(1 - B_1 \cdot \frac{w}{u}\right) \quad (3.3)$$

Therefore, the effect of *FUNDS* in *USERS* can be split into two different components that depend on the slopes B_0 and B_1 . Equation (3) constitutes the central relationship to be tested throughout this work. To that end, parameters B_0 and B_1 have to be estimated.

4 Effect of funding per worker on the number of supported companies per worker

4.1 Variables

Figure 5 shows a box plot of the dependent variable *users* (i.e. the number of paying customers per FTE scientific workers). Its distribution shows a considerable positive skewness. This is because some of the groups have been traditionally more focused on growing its sales to the private sector, whereas others have put more effort in expanding its research and publications. Although both approaches constitute complementary ways of generating positive impact, the dependent variable *users* only measures the former, and hence the right-skewed nature of the distribution. The box plot also shows an outlier that may cause the regression results to vary considerably depending on whether it is considered or not. This is explored in section 4.3.2. Given the distribution of *users*, a group dummies OLS model is considered appropriate to analyse the relationship between *users* and *funds*.

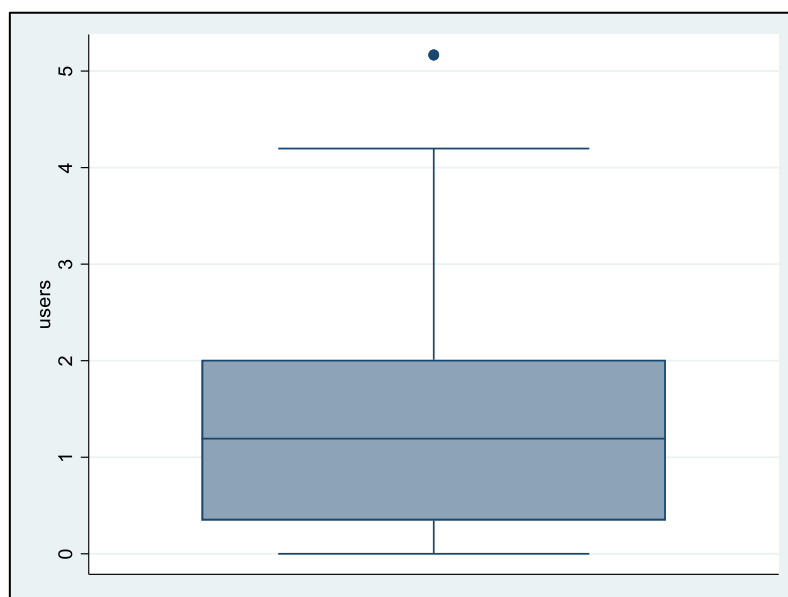


Figure 5: Box plot of *users*.

4.2 Econometric analysis

In order to estimate the effect of *funds* on *users* to compute B_0 , two key factors have to be taken into account:

- Independent of the number of scientific workers, NMS funding allows NPL to reach more companies by leveraging other financial resources and increasing its capital stock. Therefore, a positive relationship between the number of supported firms per worker and the level of NMS funding by worker is expected.
- Internal analysis has shown that approximately 60% of NPL's new customers decide to return the following year. This is either to continue with a support programme already initiated, or to demand new services. Therefore, NPL's customer base is somewhat stable. For that reason, a dynamic model is more appropriate. That is, the number of supported firms per scientist depends not just on funding per scientist, but on its own past values too.

Considering these two facts, the following equation details the linear relationship between *users* and *funds* to be tested:

$$\text{users}_{i,t} = \alpha_i + \beta_1 \text{users}_{i,t-1} + \beta_2 \text{funds}_{i,t} + u_{i,t} \quad (4.1)$$

Where $u_{i,t}$ is the idiosyncratic error term.

Note that the marginal effect⁸ of *funds* on *users* is given by β_2 which is equivalent to B_0 in the theoretical model outlined in section 3.

Equation (4) considers the existence of unobserved heterogeneity through a specific intercept α_i for each one of the groups. This heterogeneity is assumed to be related to specific characteristics of the group such as the innate ability of the group leader and senior scientists, or perhaps the fundamentals of the area of expertise of the group. In any case, any difference is assumed to be constant over time. All the models tested below include group dummies. This specification is numerically equivalent to a fixed-effects model in which the regressors are demeaned by the within transformation. The reason to choose the group dummies approach instead of a standard fixed-effects model, is to explicitly estimate each intercept as well as to check for its statistical significance. One of the groups is selected as base category to avoid perfect collinearity.

Table 3 summarises the estimation results⁹. Three different specifications are tested:

- Model 1 consists of a static specification that assumes no inertia. Hence, it does not include a lagged dependent variable as regressor. It includes time dummies to control for specific events that might have occurred during the period analysed; year 2010 is treated as the base year.
- Model 2 considers a dynamic structure by which the dependent variable depends on its first lag. Note that this means the observations for the first year (2010) are withdrawn; the second year (2011) is used as base category for the time dummies.
- Model 3 is a dynamic specification that does not include time dummies.

Note that models 2 and 3 do not account properly for the dynamics of the system and may suffer from dynamic panel bias. In principle, this dynamic panel bias should not be very significant because the two dimensions of our panel are quite comparable (17 groups and 8 years). However, we know that the coefficient estimates are somewhat biased. Unfortunately, we lack enough observations to implement any dynamic panel data analysis technique – in our case, ideally we would use the approach proposed by because the dependent variable behaves almost like random walk.

An alternative approach which is much less demanding on our dataset, is to compute the bias corrected LSDV estimator using the bias approximations in ; who builds on the original approach proposed by ¹⁰. Unfortunately, the Stata package that allows us to calculate this corrected estimator does not allow us to compute analytical weights. Hence why we use the uncorrected estimator.

⁸ The marginal effect is given by the derivative of the dependent variable with respect to the regressor:

$$\frac{d \text{users}_{i,t}}{d \text{funds}_{i,t}} = \beta_2$$

⁹ All Stata outputs can be found in Annex B. Observations 72 and 128 have high leverage; the coefficient estimates found if we drop those observations are very similar though. For the analysis, the results including both observations have been considered because there is no theoretical reason to drop them, and in any case, this is the most conservative estimate.

¹⁰ Annex B shows the Stata output for the bias corrected LSDV estimator. As seen, the bias correction does not impact significantly on the coefficient estimate.

The coefficient of *funds* shows how the ability to support UK firms per scientist changes with respect to the level of funding received per scientific staff. Note that this coefficient is equivalent to the coefficient B_0 in the theoretical model¹¹.

DV = <i>users</i> (t)	Model 1		Model 2		Model 3	
	Coeff.	P-value	Coeff.	P-value	Coeff.	P-value
<i>funds</i> (t)	6.24 (1.83)	0.001	5.63 (1.94)	0.005	5.80 (1.75)	0.001
<i>users</i> (t-1)	.	.	0.31 (0.13)	0.016	0.28 (0.13)	0.032
group dummies	Yes		yes		Yes	
F-stat	93.67		2.33		2.96	
P-value	0.00		0.01		0.00	
time dummies	Yes		yes		No	
F-stat	0.68		1.11		.	
P-value	0.69		0.36		.	
R-squared	0.90		0.91		0.91	
Number of obs.	135		118		118	

Table 3: Estimation results *users-funds*.

All three specification yield similar estimates. However, models 2 and 3 are considered more appropriate since the residuals of model 1 are serially correlated.

Table 4 shows the results of a link test¹² which has been run to check for misspecification of the dependent variable for the three models. The motivation behind the link test is to assess if a regression model is affected by the so-called *link error*, that is, that the dependent variable needs a transformation or *link* function to properly relate to the independent variables. To verify this is not the case, the link test regresses the dependent variable against the original regression's predicted values and the squared values of this prediction. If the squared prediction regressor in the test regression is significant, there is evidence that the model is misspecified; also it is expected that the coefficient for the prediction regressor is highly significant.

¹¹ We stick to the short-term effect. The long-term effect coefficient given by $\beta_2/(1 - \beta_1)$ is not considered.

¹² The test implemented here is based on an idea of (Tukey, 1949) which was further described by (Pregibon, 1980).

DV = <i>users(t)</i>	Model 1		Model 2		Model 3	
	Coeff.	P-value	Coeff.	P-value	Coeff.	P-value
<i>predicted values</i>	0.91 (0.08)	0.000	0.95 (0.08)	0.000	1.00 (0.08)	0.000
<i>squared prediction</i>	0.03 (0.02)	0.276	0.01 (0.02)	0.541	2.40E-04 (2.35E-02)	0.992
R-squared	0.90		0.91		0.91	
Number of obs.	135		118		118	

Table 4: Link test *users-funds*.

Given that the coefficient for the squared prediction regressor is not statistically significantly different than zero, we can be confident that the specification is appropriate. Moreover, the coefficient of the prediction regressor is highly significant and effectively equal to one; this provides greater assurance on the specification.

Based on the results of the link test, the preferred option is model 3.

In order to provide additional evidence of the correct specification of the model, the Ramsey Regression Equation Specification Error Test (RESET) is conducted. This technique tests whether the square and the cube of the fitted values have explanatory power over the dependent variable. The intuition behind this test is that if the second or the third power of any of the regressors, or any interaction term between them have any power in explaining the dependent variable, then the model omits relevant variables and may be better approximated by different functional form. Table 5 reports the results of the Ramsey RESET test for the three models considered.

Model 1		Model 2		Model 3	
F-stat	P-value	F-stat	P-value	F-stat	P-value
5.79	0.00	4.86	0.00	2.92	0.04

Table 5: Ramsey RESET test *users-funds*.

The test clearly rejects the null hypothesis of no omitted variables for all three models. This suggests we are missing either squared or cubic terms, or even more likely, interaction terms between *funds* and the group dummies. This issue is explored in Annex A.

Lastly, it should be noted that the residuals are heteroskedastic. This can be visually appreciated in Figure 6, which consists of a scatter plot of the square of the residuals against the predicted values of the regression. In order to obtain unbiased standard errors of the OLS coefficients, robust standard errors are computed using the sandwich estimator of the variance. This provides further assurance on the significance of the variable of interest.

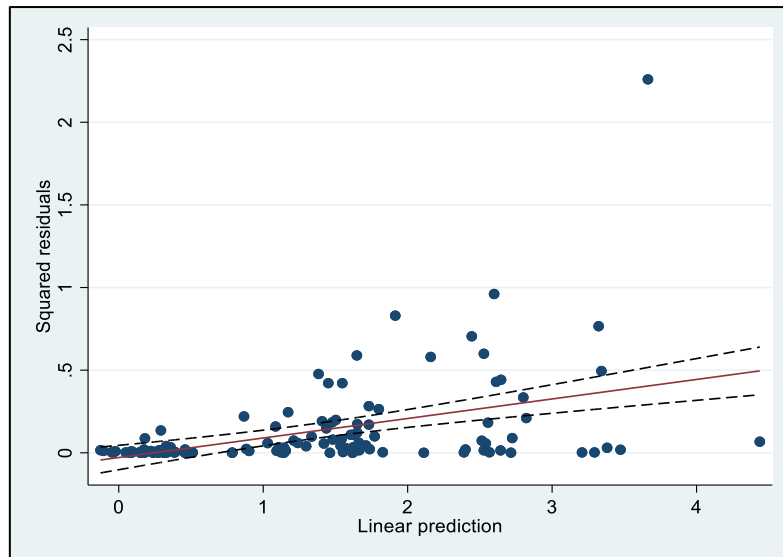


Figure 6: Linear prediction vs. residuals squared in Model 3.

5 Effect of funding on the number of scientific staff

5.1 Variables

Figure 7 shows a box plot of the dependent variable *STAFF* and Figure 8 its histogram. It should be noted that the variable is far from normal, with 12 observations outside the range defined by Tukey's fences. Moreover, it consists of a positive integer variable for which the bulk of observations lie within the first quarter of its range. Considering the distribution of the dependent variable, a count model is considered better for our purpose of modelling the effect of *FUNDS* on *STAFF*. This choice is tested in Annex A.

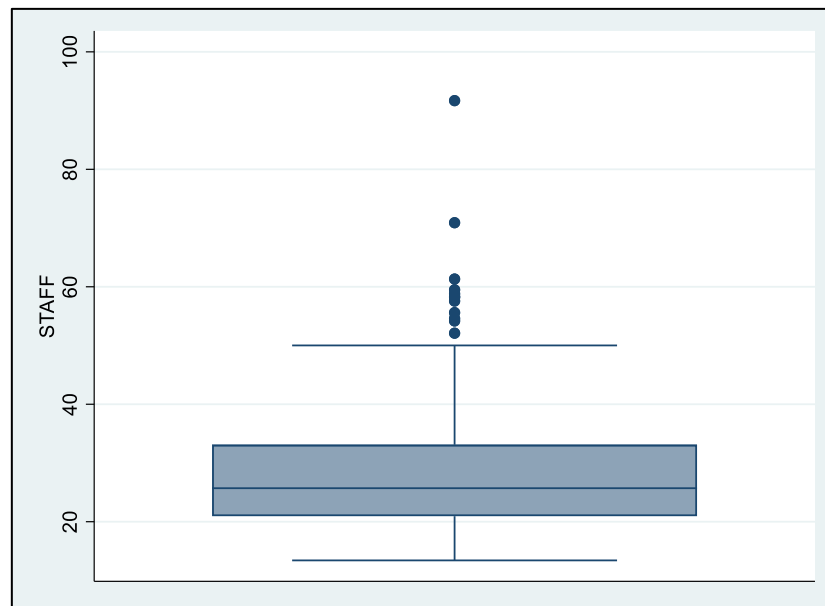


Figure 7: Box plot *STAFF*.

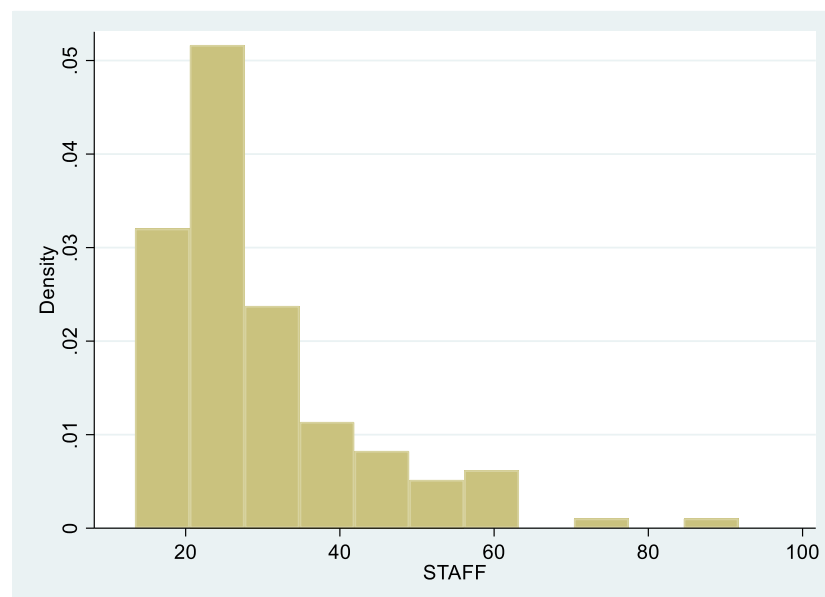


Figure 8: Histogram *STAFF*.

5.2 Econometric analysis

In order to estimate the effect of *FUNDS* on *STAFF* to compute B_1 , the following facts must be considered:

- Although NPL generates revenue, the market failure that motivates its existence also prevents it to be a self-financing organisation. This means that NPL cannot hire more staff to support more UK-based firms without more funding, because its costs exceed the commercial revenue it makes. Thus, a strong positive relationship between *STAFF* and *FUNDS* is expected.
- Within each group, scientists and engineers act collectively as a knowledge bank. Although some may leave or eventually retire, the labour force remains considerably stable. This stability is also a result of adjustment costs that any company faces when trying to shape its workforce to its short-term needs. Hence, a dynamic structure by which the number of scientific workers depends on its own past values seems appropriate.

Taking these facts into account, as well as the count nature of the dependent variable, the following equation details the exponential relationship between *STAFF* and *FUNDS* to be tested:

$$STAFF_{i,t} = \exp(\gamma_i + \theta_1 STAFF_{i,t-1} + \theta_2 FUNDS_{i,t} + v_{i,t}) \quad (5.1)$$

Where $v_{i,t}$ is the idiosyncratic error term, and γ_i allows for different intercepts for each of the groups.

Note that the marginal effect¹³ of *funds* on *users* is given by $\theta_2 \cdot STAFF_{i,t}$ which is equivalent to B_1 in the theoretical model outlined in section 3.

Table 6 summarises the estimation results¹⁴. As in section 4.2, three different specifications are tested¹⁵:

- Model 1 is a static specification where no lagged dependent variable regressor is considered and time dummies are included to control for specific events; 2010 is treated as the base year.
- Model 2 consists of a dynamic specification by which the dependent variable depends on its first lag. 2011 is used as base category for the time dummies, as the observations for 2010 are discarded.
- Model 3 is a dynamic specification that does not include time dummies.

DV = <i>STAFF</i> (t)	Model 1		Model 2		Model 3	
	Coeff.	P-value	Coeff.	P-value	Coeff.	P-value
<i>FUNDS</i> (t)	0.16 (0.03)	0.000	0.10 (0.03)	0.002	0.12 (0.03)	0.000

¹³ The marginal effect is given by the derivative of the dependent variable with respect to the regressor:

$$\frac{d STAFF_{i,t}}{d FUNDS_{i,t}} = \theta_2 \cdot STAFF_{i,t}$$

¹⁴ All outputs can be found in Annex B: Stata outputs. Observations 72 and 128 have high leverage; the coefficient estimates found if we drop those observations are very similar though. For the analysis, the results including both observations have been considered because there is no theoretical reason to drop them, and in any case this is the most conservative estimate.

¹⁵ As in section 4, models 2 and 3 do not account properly for the dynamics of the system, and may suffer from dynamic panel bias (Nickell, 1981). Annex B shows the Stata output for the bias corrected LSDV estimator. As seen, the bias correction does not impact significantly on the coefficient estimate. We stick to the Poisson regression including the lagged dependent variable because we believe this model captures better the nature of the distribution of the dependent variable. In any case, all estimates (Nickell bias corrected or uncorrected, OLS or Poisson) yield very similar results.

<i>STAFF</i> (t-1)	.	.	0.01 (0.00)	0.000	0.02 (0.00)	0.000
group dummies	Yes		yes		Yes	
Chi squared	537.91		65.57		72.29	
P-value	0.00		0.00		0.00	
time dummies	Yes		Yes		No	
Chi squared	16.02		5.33		.	
P-value	0.03		0.50		.	
Log likelihood	-402.76		-343.81		-345.11	
Number of obs.	136		119		119	

Table 6: Estimation results *STAFF-FUNDS*.

The coefficient for *FUNDS* shows the relative effect of additional funding per annum. For example, in Model 3, an additional million pounds per annum leads to a 12% increase in the scientific workforce. Currently, the average group has 48 scientists and engineers¹⁶, therefore each additional million would allow it to hire 5 or 6 scientists.

In order to test that a Poisson regression is appropriate, a goodness-of-fit test of the model is performed. In particular, both the deviance statistic and the Pearson statistic are reported; these statistics constitute a measure of how much unexplained variation there is in our Poisson regression model:

- The deviance statistic is a generalisation of the sum of squares of residuals in ordinary least squares to cases where model-fitting is achieved by maximum likelihood. It compares the difference in probability (log likelihood) between the predicted number of events and the actual number of events for each observation in our sample. It then sums these differences together to provide a measure of the total error in the model.
- The Pearson statistic consists of the sum of the squared differences between observed and expected outcome frequencies, divided by the expectation.

The resulting value of both statistics are then compared with a chi squared distribution to determine the goodness of fit. The results of the both tests are given for each of the models by Table 7.

Test	Model 1		Model 2		Model 3	
	Statistic	P-value	F-stat	P-value	F-stat	P-value
Deviance	103.48	0.68	71.55	0.96	74.14	0.98
Pearson	101.86	0.72	71.22	0.96	73.58	0.98

Table 7: Goodness-of-fit *STAFF-FUNDS*.

Models 2 and 3 show excellent goodness-of-fit. This suggests that the Poisson dynamic approach is indeed adequate.

¹⁶ 820 scientific staff in total split into 17 groups.

Lastly, a link test has been performed to check for misspecification. Table 8 reports the results of the test for the three models considered.

DV = <i>STAFF</i> (t)	Model 1		Model 2		Model 3	
	Coeff.	P-value	Coeff.	P-value	Coeff.	P-value
<i>predicted values</i>	1.39 (0.60)	0.02	1.44 (0.64)	0.02	1.26 (0.64)	0.05
<i>squared prediction</i>	-0.05 (0.08)	0.52	-0.06 (0.09)	0.49	-0.04 (0.09)	0.69
Log likelihood	-402.56		-343.57		-345.03	
Number of obs.	136		119		119	

Table 8: Link test *STAFF-FUNDS*.

The coefficient for the squared prediction regressor is not statistically significant, whereas the one for the predicted values is. This provides further assurance on the specification of the model.

Finally, given the better goodness-of-fit of the dynamic models plus the lack of significance of the time dummies, Model 3 is considered the best specification.

6 Results

From section 3 we know that the effect of NMS funding on the number of UK-based companies that pay for services or engage in collaborative R&D is given by (3):

$$\frac{\Delta v}{\Delta w} = B_1 \cdot \frac{v}{u} + B_0 \cdot \left(1 - B_1 \cdot \frac{w}{u}\right)$$

Where v is the number of paying customers (*USERS*), u is the number of scientific workers (*STAFF*), w is the level of funding received (*FUNDS*), and B_0 and B_1 are the slopes estimated in sections 4 and 5 respectively. Table 9 shows the scientific group means of the three variables for the period analysed. Table 10 contains the slopes estimated in sections 4 and 5.

Variable	Letter	Group Means
<i>USERS</i>	v	38.36 firms
<i>STAFF</i>	u	29.76 scientists
<i>FUNDS</i>	w	£2.49m

Table 9: Annualised values.

Parameter	Letter	Value
β_2	B_0	5.80 firms/£m
$\theta_2 \cdot \text{STAFF}$	B_1	3.44 scientists/£m

Table 10: Parameters.

Using these values in (3), we get¹⁷:

$$\frac{\Delta v}{\Delta w} = 3.44 \cdot \frac{38.36}{29.76} + 5.80 \cdot \left(1 - 3.44 \cdot \frac{2.49}{29.76}\right) = 8.53 \quad [\text{firms/£m}]$$

Therefore, providing NPL with an additional £1 million per annum of resource funding, enables it to directly support around 9 more UK companies. This additional funding is not used to pay for the work done to support these private companies, nor it is given as grants. Additional resource funding is used to maintain the measurement capabilities needed to support UK businesses.

This study relates to the period from 2010 to 2017. However, NPL has expanded substantially in recent years, and therefore, current figures are different from the annualised values used to get the previous result. Assuming that the relations found in sections 4 and 5 hold today, it is worth investigating whether this outcome is the same with the current figures. Table 11 shows the current values of the three variables of interest:

Variable	Letter	Value
<i>USERS</i>	v	41.18 firms
<i>STAFF</i>	u	48.24 scientists
<i>FUNDS</i>	w	£3.34m

¹⁷ Units are omitted for the sake of simplicity.

Table 11: Current figures.

Using these values in (3), we get:

$$\frac{\Delta v}{\Delta w} = 3.44 \cdot \frac{41.18}{48.24} + 5.80 \cdot \left(1 - 3.44 \cdot \frac{3.34}{48.24}\right) = 7.34 \quad [\text{firms}/\text{£m}]$$

The result of the analysis varies significantly when the current values of the variables are used instead of the annualised figures for the whole period. This is mainly due to the fact that although the average size of the groups has grown substantially (from around 30 scientists to almost 50), the average number of users has grown minimally (from 38 to 41). Yet there is an explanation to this decrease in productivity. In recent times, NPL has launched an expansive strategy that aims to respond to the great metrology challenges ahead for the UK. The objective of NPL's management is to extend the range of activities to which the laboratory provides excellent measurement science. Hence, NPL's vision is to support UK companies not just in traditional areas such as dimensional measurement or optics, but also contribute to novel technologies such as quantum and digital data. Therefore, NPL has recently increased its scientific staff in a substantial way, with the aim of developing the necessary capabilities that will enable it to play a distinct role in these emerging disciplines. Consequently, a significant proportion of the new incorporations into the workforce are focused on developing these new areas which are not yet commercially viable. Hence, the first result is considered to better reflect the long-term effect of increasing NMS funding.

7 Economic impact

NPL supports UK businesses by offering specialised services. These allow paying customers to develop new products and/or new processes. New products enable supported businesses to better meet the needs of their customers, which in turn increases their market power and grants them the possibility of commanding a price premium. On the other hand, new processes enhance productivity and competitiveness, normally through cost-saving improvements to the production process. Nevertheless, both cases imply an increased gross value added, namely greater profits for firms and better wages for their workers. These are direct benefits since they remain within the supported firm. However, there are wider social benefits arising from knowledge spillovers to unsupported firms. This section only addresses the former, because its objective is to show how the result found in the preceding section can be used to estimate the economic impact generated by NPL. Thus, this section does not aim to provide a comprehensive analysis of all types of impact derived from NPL's support to UK businesses.

A first question that arises from the previous analysis, is how comparable the cost of providing support to UK firms is, with respect to other organisations that carry out similar projects. As mentioned above, an additional £1 million per annum of resource funding enables NPL to support around 9 more UK businesses. This means an average cost of approximately £110,000 per company. For Innovate UK the average cost per incidence of support is around £155,000¹⁸. Therefore, it is observed how both costs lie in a similar range. Of course, this figure only gives us a partial view of the impact analysis. It only refers to the costs of NPL's engagement with the UK private sector; nothing tells us about the benefits generated (note that only direct benefits will be discussed here).

NPL has a long history of analysing the economic impact it generates for the UK. Frontier Economics analysed the impact of NPL's support on the performance of UK companies. This report found that NPL's support had a positive effect on survival rates and employment growth. This study was a first attempt to make use of econometric methods to assess the impact of the NMS. Based on firm-level data, it analysed the effect on survival and employment up to four years after the receipt of support. Currently, NPL is working with economists from Innovate UK and Belmana Consulting to take this analysis one step further by using person-level data from ASHE (Annual Survey of Hours and Earnings). The ASHE dataset is longitudinal and tracks a group of people - based on the last digit of their NI number - collecting annual data information from their employers on earning, hours worked, and job roles. The study is on-going but has found that workers' wages tend to increase when they join firms that had recently engaged with NPL. Furthermore, this increase in wages exceeds the one typically enjoyed by job switchers. The increase in wages for people joining a firm supported by NPL also exceeds that of people joining a control group of similar firms that do not work with NPL. Lastly, the study also finds that workers' wages tend to decrease slightly when they leave a firm supported by NPL, suggesting that their skills are not fully transferable. This joint work between NPL, Innovate UK and Belmana Consulting is in the final stages of its development, having gone through a peer-review process by external academics.

As these studies are empirical, there is not yet a settled understanding of what causes this increase (decrease) in wages that occurs when a worker joins (leaves) a firm that engages with NPL. There are several plausible explanations for this:

¹⁸ This average cost has been computed using Gov.uk (2019), which consists of a register of all Innovate UK funded projects since 2004. These include collaborative research and development (R&D), feasibility, smart and innovation voucher grants, and knowledge transfer partnerships between 2004 and 1 October 2019. Not all types of Innovate UK projects have been considered, as they are not comparable to those carried out by the NPL. In particular, *centres*, *BIS-Funded Programmes* and *Vouchers* have been excluded.

1. Some people possess certain technical skills which are highly prized by employers recruiting for certain specific jobs. However, there may be a limited demand for such skills, and so sometimes people with such skills occupy jobs for which a more generic skill-set is sufficient. Although these workers tend to earn reasonable wages, they are nonetheless underemployed; in other words, they could be more productive in other roles because they are not using their full abilities. Thus, support from NPL may enable certain firms to expand and, in so doing, help to create jobs that require the specific technical skills that this group of people possess. In short, NPL may be helping to create roles that allow certain types of human capital to be properly employed.
2. UK businesses that engage with NPL operate in highly globalised markets where competition for talent transcends national boundaries. UK companies in the high-tech manufacturing and services industries compete with firms in the rest of Europe to attract highly qualified employees. The collaboration with NPL involves the expansion of supported companies, which might translate into more ambitious projects that allow the creation of new jobs occupied by workers who come from the rest of the continent to the UK. Hence, these workers generate value in the UK rather than in other countries.
3. During recessions, private investment is dominated by uncertainty and negative perspectives on the evolution of the economic activity. However, companies that work with the NPL show greater employment resilience and survival rates. NPL support might enable those businesses to invest in profitable opportunities and expand their market share (typically in a global context). Therefore, NPL may contribute to safeguard jobs during the downward part of the business cycle.

NPL is currently developing several studies to assess the relevance of those channels for impact generation. However, regardless of which of the causes listed above is more relevant, the result of this work is essential in order to estimate the impact generated by NPL's support to UK businesses. The resources received by NPL lead to additional (1) or safeguarded (2) job-years, or a wage premium (3) earned by workers given the higher productivity of supported firms. In that sense, whatever the benefit may be, it must be evaluated in the context that £ 1 million of resource funding is needed for every 9 firms supported. Therefore, the net present value of the direct benefit for these companies has to be compared with the cost of generating such impact. Thus, the role of this paper is fundamental to produce any cost-benefit analysis which evaluates the public financing of NPL.

8 Conclusion

Our study quantifies the relation between NMS funding received by NPL and the level of support that it can deliver to UK businesses. This finding provides empirical support to the rationale that NPL acts as an efficient channel to allocate public funds which are needed to complement private spending in measurement. Although no impact is discussed in this report, its result constitutes the first necessary step of any further analysis that aims to measure the additional economic impact of NPL receiving extra public funding.

We use NPL internal administrative data to quantify the effect of NMS funding on the number of supported firms through changes in scientific staff. To do so, we make use of two panel data models. The first model assesses the effect of funding per worker in the number of supported companies per worker. The second model estimates the effect of NMS funding on staff. Since NPL's costs exceed its commercial revenue, it requires public funds to provide the current level of support to UK companies. For that reason, strong and significant relationships are found for both models. Finally, both results are combined to estimate that providing NPL with an additional £1 million per annum of resource funding, enables it to directly support around 9 more UK businesses.

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Annex A: Econometric issues

Sources of bias

To ensure that the estimate we get are close to the real parameter, any potential source of bias needs to be accounted for. These include omitted variables, measurement errors in the data, simultaneity issues and weighting corrections.

Regarding a potential omitted variables bias, our specifications assume that any time-varying omitted effect are completely random. Consequently, the idiosyncratic error term is uncorrelated with the regressors leading to unbiased coefficient estimates. The logic behind this assumption is that any systematic difference between the groups is fairly constant over time. Thus, these fixed effects are captured by the group dummies.

Errors-in-variables is another potential source of bias. If some of the independent variables have been measured with errors, the OLS regression is inconsistent leading to underestimate the coefficient (attenuation bias). However, this source of bias is considered to be negligible in this analysis because the data used comes from internal records which are constantly monitored. In principal, the number of UK-based firms NPL supports is the variable that could incorporate a greater measurement error, since the number of employees and the funds received are recorded constantly with precision. The main reason why USERS may differ from its real value is because some considerable jobs are paid fractionally in different years. Hence, this would artificially inflate the number of companies supported. However, this effect is judged to be minimal, because invoice splitting occurs very rarely, and when it does, it is often for recurrent customers who would have been accounted in different periods anyway.

Probably the most relevant source of bias that could affect the analysis is due to simultaneity issues when assessing the relation between *users* and *funds*. Clearly, the number of UK firms supported by a group depends on its funding. However, this relationship is also expected to work the other way around. The more businesses a group supports, the more funds it is expected to get. Hence, endogeneity could lead to a simultaneity bias by which the explanatory variable is correlated with the error term. However, it should be acknowledged that resource allocation within NPL is a highly complex process involving the top management, the scientific group leaders and external expert oversight. Funds are assigned after a thorough consideration of the fundamental trade-off between immediate anticipated demand and long-term strategic opportunities. Although commercial growth is a main strategic objective, NPL primarily focuses on foreseeing measurement challenges for future key technologies. This is achieved by constantly developing new capabilities thanks to cutting-edge research and the recruitment of talented scientists and engineers. Moreover, even if the goal is to allocate part of the resources based on anticipated demand, uncertainty towards the future conditions of the market makes this very difficult to achieve. Therefore, NPL's long-term approach as well as policy response imperfections due to uncertainty, introduce enough exogeneity in the analysis, so any source of simultaneity bias is assumed to be negligible.

Lastly, with regard to the weighting of the observations it should be noted that since the variables in the model are *observed means*, that is, both *users* and *funds* consist of its respective level variables normalised by *STAFF*, the regression has been weighted to account for the different sizes of each group. This technique is often used in macroeconometrics where it is customary to work with panel data of countries. Observations for each country cannot be treated equivalently because countries differ in population. Weighting each observation is required to obtain precise results. Hence, in this analysis an equivalent procedure has been adopted, although its impact on the results is negligible.

Effect of outliers on the users-funds model

As shown by Figure 5 in section 4.1 there is an observation that may influence substantially the estimation results (this observation belongs to the Mass and Dimensional group). To check for the effect of this observation, model 3 has been tested including the outlier. Table 12 compares the results of the original regression and the same model including the outlier (the original model is renamed as Model 3A and the one including the outlier is named Model 3B):

DV = <i>users</i> (t)	Model 3A		Model 3B	
	Coeff.	P-value	Coeff.	P-value
<i>funds</i> (t)	5.80 (1.75)	0.001	7.33 (2.53)	0.005
<i>users</i> (t-1)	0.28 (0.13)	0.032	0.24 (0.13)	0.072
group dummies	Yes		yes	
F-stat	2.96		2.97	
P-value	0.00		0.00	
time dummies	No		no	
F-stat	.		.	
P-value	.		.	
R-squared	0.91		0.90	
Number of obs.	118		119	

Table 12: Effect of the outlier *users-funds*.

The outlier impacts notably the coefficient estimate. It increases the effect of *funds* on *users* by more than a 25%. For the rest of the analysis the results without the outlier have been considered because of two reasons. Firstly, because the observation is likely to be due to a temporary random event that explains why is so different from the rest of the dataset. And secondly, because the goal of this paper is to estimate the impact of NMS funding on NPL's ability to support UK private businesses; thus, a conservative bound seems more appropriate.

Ramsey RESET test for users-funds

The Ramsey RESET test clearly rejects the null hypothesis of no omitted variables for all three models. This is likely due to the different nature of scientific groups¹⁹.

Ideally, we would consider a different slope for each group – i.e. we would interact *funds* with all group dummies. However, we lack the data to get meaningful results to do so – we simply do not have enough data points, and hence enough variation, to find precise estimates. A compromise solution consists of introducing an interaction term for only one group at a time and checking the results for the Ramsey RESET test. The test still rejects the null hypothesis of no omitted variables for almost every interaction term. However, when we introduce an

¹⁹ Squared and cubic terms of *funds* have been tested; the test keeps reject the null hypothesis.

interaction term between *funds* and the Earth Observation group (group label 2) the F statistic is quite low, and the test cannot reject the null hypothesis of no omitted variables²⁰. This means that the results found probably do not apply to this group. In any case, given that the lack of enough data and the fact that the marginal effect for the average group does not change drastically, we stick to the parameter estimates found in the model with no interaction terms.

Influence of each group on the marginal effect for the average

Both specifications in sections 4 and 5 assume that the marginal effect of the regressor of interest on the dependent variable is equivalent for all scientific groups in our dataset; we can think of these marginal effect as the *marginal effect for the average group*. Indeed, any differences between the groups is supposed to be captured by the group dummies – i.e. the different nature of each group is modelled by a fixed effect that is assumed to be constant over time. However, it may well be the case that these differences do not only affect the intercept, but slope as well; that is, it is not unreasonable, almost highly probable, that the marginal effect is different by group. The way to account for this effect is by including an interaction term between the regressor of interest in each model, and the group dummies. However, we lack the data to get meaningful results if we include interaction terms with all group dummies – we simply do not have enough data points, and hence enough variation, to find precise estimates.

A compromise solution for not considering a specific marginal effect for each group in our model, is to check that if removing those groups with a different slope from the sample alters the marginal effect for the average group. This can be easily done by introducing an interaction term for only one group at a time, and for those that this term's parameter estimate is statistically different from zero, repeat the original regression excluding that specific group and then comparing the parameter estimates. The rest of this subsection carries this robustness test for both specifications in sections 4 and 5.

users-funds

The following equation details the linear relationship between *users* and *funds* to be tested:

$$\text{users}_{i,t} = \alpha_i + \beta_1 \text{users}_{i,t-1} + \beta_2 \text{funds}_{i,t} + \beta_3 (\text{funds}_{i,t} \cdot \text{k.ID}) + u_{i,t} \quad (\text{A.1})$$

Where k.ID is a group dummy variable for which the index k takes a value between 1 and 17 at a time, and $u_{i,t}$ is the idiosyncratic error term. That is, in reality we are testing 17 different specifications, one for each one of the groups.

Now, after running all 17 OLS regressions, five groups showed different specific marginal effect (i.e. β_3 was statistically significant) – see Annex B Stata output for more detail²¹. For those groups, the original specification was tested, this time dropping the group from the dataset. The goal was to check if the exclusion of the group alters the marginal effect of *funds*.

²⁰ Annex B displays a table that summarises the findings for all 17 regressions. The table shows the coefficient estimates and significance levels for the lagged dependent variable, *funds* and the interaction term included, as well as the result of the Ramsey RESET test. The inclusion of the interaction term with the second group (Earth Observation) has a significant effect on the results of the test (p-value = 0.503)

²¹ Annex B displays a table that summarises the findings for all 17 regressions. The table shows (1) the marginal effect for the average group, (2) the coefficient estimate for the interaction term, and the marginal effect for the average group after excluding the group if the interaction term coefficient estimate was found significant. Standard errors and p-values are also shown in the table.

on *users* for the average group. As seen in the Stata output, there is no sign of any of those five groups having a significant effect on the marginal effect of the average group.

STAFF-FUNDS

The following equation details the linear relationship between *users* and *funds* to be tested:

$$\text{STAFF}_{i,t} = \exp(\gamma_i + \theta_1 \text{STAFF}_{i,t-1} + \theta_2 \text{FUNDS}_{i,t} + \theta_3 (\text{FUNDS}_{i,t} \cdot k. \text{ID}) + v_{i,t}) \quad (\text{A.2})$$

Where $k. \text{ID}$ is a group dummy variable for which the index k takes a value between 1 and 17 at a time, and $v_{i,t}$ is the idiosyncratic error term. That is, in reality we are testing 17 different specifications, one for each one of the groups.

Now, after running all 17 OLS regressions, four groups showed different specific marginal effect (i.e. θ_3 was statistically significant) – see Annex B Stata output for more detail²². For those groups, the original specification was tested, this time dropping the group from the dataset. The goal was to check if the exclusion of the group alters the marginal effect of *funds* on *users* for the average group. As seen in the Stata output, there is no sign of any of those four groups having a significant effect on the marginal effect of the average group.

Modelling the relationship between STAFF and FUNDS: Poisson vs. OLS

When modelling the relationship between *STAFF* and *FUNDS* the main concern revolves around the choice of using the Poisson regression approach. An alternative approach is to use a group dummies OLS regression. Table 13 summarises the estimation results for this approach.

DV = <i>STAFF</i> (t)	Group dummies OLS regression	
	Coeff.	P-value
<i>FUNDS</i> (t)	5.22 (1.40)	0.000
<i>STAFF</i> (t-1)	0.56 (0.12)	0.000
group dummies		Yes
F-stat		2.04
P-value		0.02
R-squared		0.88
Number of obs.		119

Table 13: Estimation results group dummies OLS regression *STAFF-FUNDS*.

Table 14 shows the results of the link test for this alternative approach.

²² Annex B displays a table that summarises the findings for all 17 regressions. The table shows (1) the marginal effect for the average group, (2) the coefficient estimate for the interaction term, and the marginal effect for the average group after excluding the group if the interaction term coefficient estimate was found significant. Standard errors and p-values are also shown in the table.

DV = <i>STAFF</i> (t)	Group dummies OLS regression	
	Coeff.	P-value
<i>predicted values</i>	0.66 0.15	0.000
<i>squared prediction</i>	4.29E-03 (1.81E-03)	0.019
R-squared	0.89	
Number of obs.	119	

Table 14: Link test group dummies OLS regression *STAFF-FUNDS*.

The coefficient for the squared prediction regressor is statistically significant. This shows that there is a misspecification issue with the alternative OLS regression with group dummies. Hence, the Poisson regression chosen seems more suitable.

In any case, it is worth comparing both estimation results. To do so, the Poisson regression coefficient has to be scaled by the mean of the dependent variable²³: $\theta_{Poisson} = 0.12 \cdot 29.76 = 3.44$. Comparing this result to the alternative OLS regression with group dummies, we see that they are not equivalent. This can be explained because the group dummies OLS regression is tilted positively because of two outstanding observations:

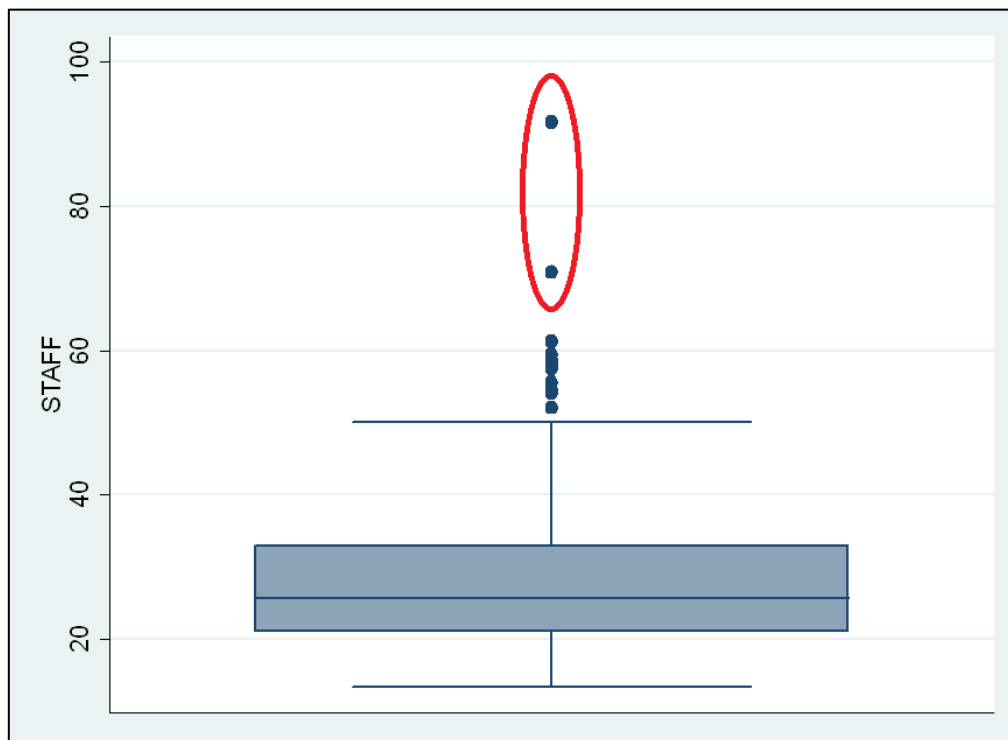


Figure 9: Outliers tilting positively the group dummies OLS regression.

The estimation results for both models without considering both outliers are given by Table 15:

²³ This is because the Poisson regression takes the form $y = e^{\alpha + \beta x}$. Hence, $\frac{dy}{dx} = \beta y$.

DV = <i>STAFF</i> (t)	Group dummies OLS regression		DV = <i>STAFF</i> (t)	Poisson regression	
	Coeff.	P-value		Coeff.	P-value
<i>FUNDS</i> (t)	4.077 (1.370)	0.004	<i>FUNDS</i> (t)	0.135 (0.041)	0.000
<i>STAFF</i> (t-1)	0.568 (0.119)	0.000	<i>STAFF</i> (t-1)	0.016 (0.003)	0.001
group dummies		yes	group dummies		yes
F-stat		2.06	Chi squared		73.04
P-value		0.016	P-value		0.000
R-squared		0.8496	Log likelihood		-338.33
Number of obs.		117	Number of obs.		117

Table 15: Estimation results for the group dummies OLS regression and Poisson regression without considering the two outstanding outliers.

When the same comparison is made dropping these two outliers, both results almost are identical ($\theta_{Poisson} = 0.135 \cdot 29.76 = 4.019$). This provides confidence that the coefficient estimated is accurate.

Leverage

The estimates found may be influenced by specific observations. We can run a diagnostic leverage-versus-residual-squared plot (a graph of leverage against the normalised residuals squared) to check if single data points are tilting the estimates significantly.

Users-funds

Figure 10 shows the leverage-versus-residual-squared plot for the *users-funds* preferred model:

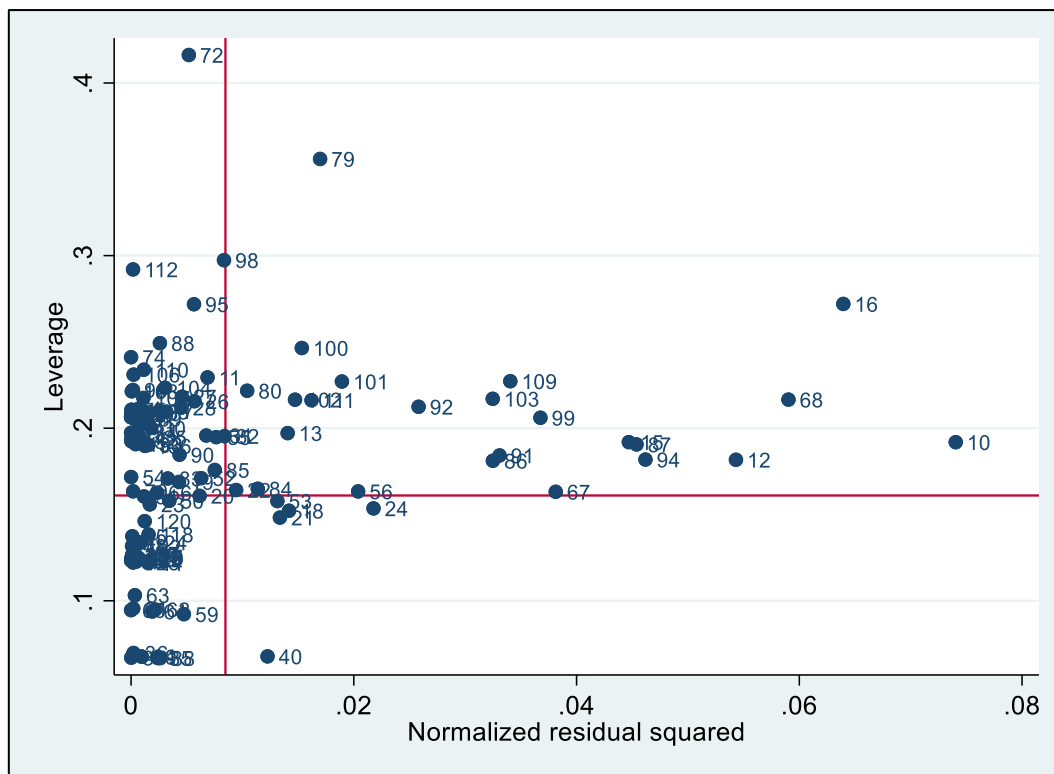


Figure 10: Leverage-versus-residual-squared plot for *users-funds*.

The red lines on the chart show the average values of leverage and the normalised residuals squared. Points above the horizontal line have higher-than-average leverage and points to the right of the vertical line have larger-than-average residuals. Observation 72 at the top of the graph has high leverage and a smaller-than-average residual; as in the previous outlier analysis, this observation also belongs to the Mass and Dimensional group. Table 16 compares the preferred model 3A against the same regression dropping observation 72 (model 3C).

DV = <i>users</i> (t)	Model 3A		Model 3C	
	Coeff.	P-value	Coeff.	P-value
<i>funds</i> (t)	5.80 (1.75)	0.001	6.96 (2.21)	0.002
<i>users</i> (t-1)	0.28 (0.13)	0.032	0.33 (0.13)	0.017
group dummies	yes		yes	
F-stat	2.96		2.62	
P-value	0.00		0.00	
time dummies	no		no	
F-stat	.		.	
P-value	.		.	

R-squared	0.91	0.90
Number of obs.	118	117

Table 16: Comparison between the preferred model and the same model excluding observation 72.

Observation 72 influences notably the coefficient estimate. It increases the effect of *funds* on *users* by around 20%. For the analysis the results including observation 72 have been considered because (1) there is no theoretical reason to drop this observation, and (2), as mentioned in the previous subsection, the goal of this paper is to estimate the impact of NMS funding on NPL's ability to support UK private businesses; thus, a conservative bound seems more appropriate.

STAFF-FUNDS

Figure 11 shows the leverage-versus-residual-squared plot for the *STAFF-FUNDS* preferred model:

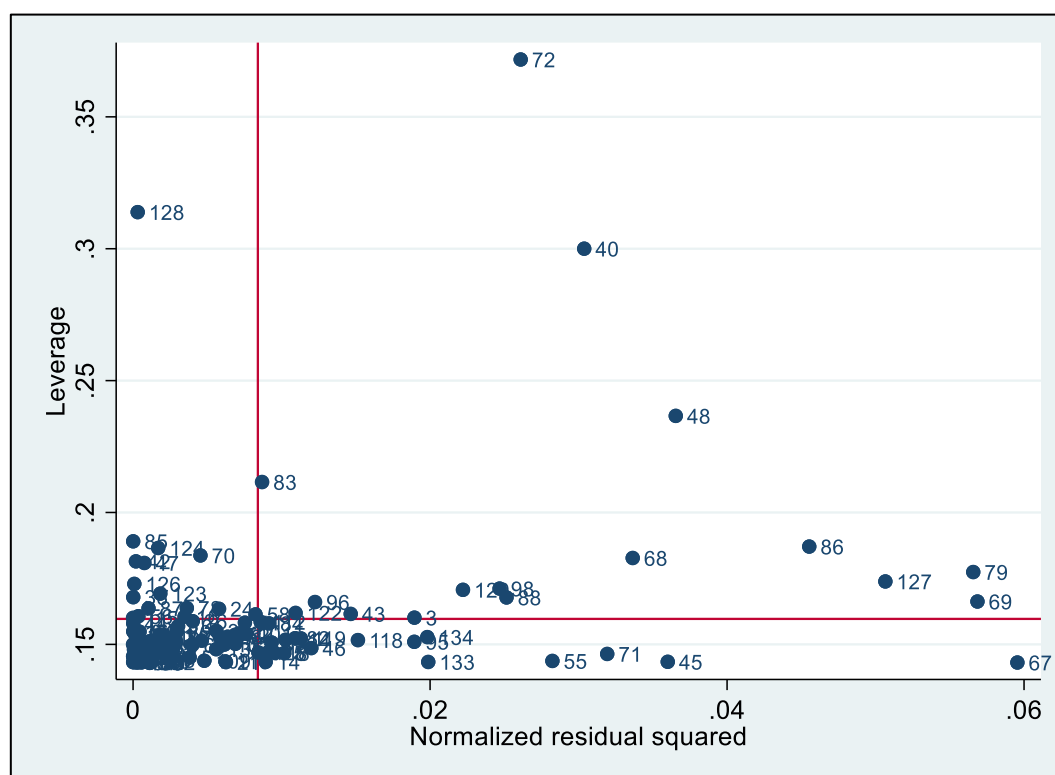


Figure 11: Leverage-versus-residual-squared plot for STAFF-FUNDS.

Observations 72 and 128 have high leverage; the coefficient estimates found if we drop those observations are very similar though²⁴. For the analysis, the results including both observations have been considered because there is no theoretical reason to drop them, and in any case, this is the most conservative estimate.

²⁴ For a detailed comparison of the estimation results after losing observations 72 and 128 see the Stata outputs in Annex B.

Annex B: Stata outputs

users-funds

Model 1

(sum of wgt is 4,012.19355392456)						
Linear regression						
			Number of obs	=	135	
			F(24, 110)	=	66.68	
			Prob > F	=	0.0000	
			R-squared	=	0.9009	
			Root MSE	=	.36017	
users	Coef.	Robust Std. Err.	t	P> t	[95% Conf. Interval]	
funds	6.244944	1.828992	3.41	0.001	2.620311	9.869578
ID						
2	2.153117	.2953627	7.29	0.000	1.567777	2.738456
3	1.672496	.1785567	9.37	0.000	1.318638	2.026353
4	.7689389	.095814	8.03	0.000	.5790581	.9588198
5	.8646536	.0738985	11.70	0.000	.7182043	1.011103
6	.1829581	.0649045	2.82	0.006	.0543327	.3115835
7	1.469209	.101664	14.45	0.000	1.267734	1.670683
8	1.593473	.131709	12.10	0.000	1.332457	1.854489
9	3.050631	.1917642	15.91	0.000	2.6706	3.430663
10	.1399347	.1307549	1.07	0.287	-.1191909	.3990602
11	1.277298	.208094	6.14	0.000	.8649049	1.689692
12	2.144348	.1775069	12.08	0.000	1.792571	2.496125
13	1.215842	.1933197	6.29	0.000	.8327279	1.598956
14	2.217532	.1722074	12.88	0.000	1.876257	2.558807
15	-.3565708	.0947088	-3.76	0.000	-.5442615	-.16888
16	-.2354087	.0662587	-3.55	0.001	-.3667178	-.1040996
17	.183598	.0675042	2.72	0.008	.0498206	.3173755
YEAR						
2011	.0357017	.1234071	0.29	0.773	-.2088622	.2802657
2012	.0748804	.1300474	0.58	0.566	-.182843	.3326039
2013	.0584048	.1281979	0.46	0.650	-.1956534	.312463
2014	-.0499963	.1149343	-0.43	0.664	-.277769	.1777765
2015	-.0196122	.1287084	-0.15	0.879	-.2746821	.2354577
2016	-.0185958	.1382736	-0.13	0.893	-.2926216	.25543
2017	-.154381	.1367763	-1.13	0.261	-.4254395	.1166775
_cons	-.2742918	.1829834	-1.50	0.137	-.636922	.0883384

(sum of wgt is 4,012.19355392456)

Source	SS	df	MS	Number of obs	=	135
Model	129.903926	2	64.9519628	F(2, 132)	=	606.30
Residual	14.1409584	132	.107128473	Prob > F	=	0.0000
				R-squared	=	0.9018
				Adj R-squared	=	0.9003
Total	144.044884	134	1.07496182	Root MSE	=	.3273

users	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]	
_hat	.9147111	.0830307	11.02	0.000	.7504681	1.078954
_hatsq	.0276458	.0252512	1.09	0.276	-.0223035	.0775952
_cons	.0375389	.0579481	0.65	0.518	-.0770883	.152166

Ramsey RESET test using powers of the fitted values of users
 Ho: model has no omitted variables
 F(3, 107) = 5.79
 Prob > F = 0.0010

Model 2

(sum of wgt is 3,577.3977689743)

Linear regression

Number of obs = 118
 F(24, 93) = 75.00
 Prob > F = 0.0000
 R-squared = 0.9127
 Root MSE = .33758

users	Coef.	Robust Std. Err.	t	P> t	[95% Conf. Interval]	
users						
L1.	.3102884	.1265593	2.45	0.016	.0589668	.56161
funds	5.634386	1.942732	2.90	0.005	1.776506	9.492267
ID						
2	1.229886	.4105242	3.00	0.004	.414666	2.045105
3	1.127127	.2690658	4.19	0.000	.5928156	1.661438
4	.4313453	.1343766	3.21	0.002	.1645	.6981906
5	.5336056	.1462012	3.65	0.000	.2432789	.8239322
6	.1008515	.0881802	1.14	0.256	-.0742569	.2759599
7	.9231165	.2279719	4.05	0.000	.4704096	1.375823
8	.9561903	.218159	4.38	0.000	.5229699	1.389411
9	1.980162	.5635315	3.51	0.001	.8610999	3.099224
10	.0062214	.1257949	0.05	0.961	-.2435824	.2560252
11	.8129655	.2290991	3.55	0.001	.3580201	1.267911
12	1.349875	.3420511	3.95	0.000	.6706292	2.02912
13	.8630392	.2588626	3.33	0.001	.3489893	1.377089
14	1.55241	.3133147	4.95	0.000	.9302287	2.17459
15	-.2963747	.1187841	-2.50	0.014	-.5322564	-.0604929
16	-.1703248	.0868021	-1.96	0.053	-.3426967	.002047
17	.1118758	.0798419	1.40	0.164	-.0466743	.270426
YEAR						
2012	.0110882	.118349	0.09	0.926	-.2239296	.2461059
2013	.0024048	.1282276	0.02	0.985	-.2522297	.2570394
2014	-.0934031	.0929726	-1.00	0.318	-.2780284	.0912221
2015	-.0386504	.1007662	-0.38	0.702	-.2387522	.1614514
2016	-.0577754	.1063916	-0.54	0.588	-.2690481	.1534973
2017	-.2132228	.1007569	-2.12	0.037	-.413306	-.0131396
_cons	-.2135096	.1573353	-1.36	0.178	-.5259463	.098927

(sum of wgt is 3,577.3977689743)

Source	SS	df	MS	Number of obs	=	118
Model	110.781688	2	55.3908441	F(2, 115)	=	603.02
Residual	10.5634594	115	.091856168	Prob > F	=	0.0000
				R-squared	=	0.9129
				Adj R-squared	=	0.9114
Total	121.345148	117	1.03713801	Root MSE	=	.30308

users	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]	
_hat	.9541052	.0801633	11.90	0.000	.7953172	1.112893
_hatsq	.0147613	.0240619	0.61	0.541	-.0329006	.0624233
_cons	.0204555	.0564582	0.36	0.718	-.0913773	.1322883

Ramsey RESET test using powers of the fitted values of users
 Ho: model has no omitted variables
 F(3, 90) = 4.86
 Prob > F = 0.0035

Model 3

(sum of wgt is 3,506.26085281372)

Linear regression

Number of obs = 118
 F(18, 99) = 106.32
 Prob > F = 0.0000
 R-squared = 0.9090
 Root MSE = .34068

users	Coef.	Robust Std. Err.	t	P> t	[95% Conf. Interval]	
users						
L1.	.2787721	.1284696	2.17	0.032	.0238606	.5336836
funds	5.799541	1.746955	3.32	0.001	2.333203	9.26588
ID						
2	1.414831	.450905	3.14	0.002	.5201377	2.309525
3	1.226444	.2592047	4.73	0.000	.7121254	1.740762
4	.4795186	.1343731	3.57	0.001	.2128932	.7461441
5	.5915928	.1545503	3.83	0.000	.2849315	.8982541
6	.0915015	.0631186	1.45	0.150	-.0337394	.2167424
7	.9880451	.2349697	4.20	0.000	.5218143	1.454276
8	1.01753	.2190784	4.64	0.000	.5828312	1.452229
9	2.141213	.5589257	3.83	0.000	1.032184	3.250243
10	.0171496	.1074726	0.16	0.874	-.1960993	.2303986
11	.949541	.2481119	3.83	0.000	.4572332	1.441849
12	1.454534	.3437054	4.23	0.000	.7725479	2.13652
13	.9288116	.2537627	3.66	0.000	.4252914	1.432332
14	1.646158	.3233329	5.09	0.000	1.004596	2.287721
15	-.3225888	.0880226	-3.66	0.000	-.4972448	-.1479329
16	-.1999997	.0616437	-3.24	0.002	-.3223143	-.0776852
17	.131154	.0744855	1.76	0.081	-.0166414	.2789495
_cons	-.2834129	.1368119	-2.07	0.041	-.5548775	-.0119484

(sum of wgt is 3,506.26085281372)

Source	SS	df	MS	Number of obs	=	118
Model	114.74644	2	57.3732199	F(2, 115)	=	574.24
Residual	11.4898797	115	.099911997	Prob > F	=	0.0000
				R-squared	=	0.9090
				Adj R-squared	=	0.9074
Total	126.236319	117	1.0789429	Root MSE	=	.31609

users	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]	
_hat	.9992282	.0810839	12.32	0.000	.8386165	1.15984
_hatsq	.0002403	.0235099	0.01	0.992	-.0463283	.0468088
_cons	.0003617	.0595104	0.01	0.995	-.1175168	.1182403

Ramsey RESET test using powers of the fitted values of users
 Ho: model has no omitted variables
 F(3, 96) = 2.92
 Prob > F = 0.0379

Bias corrected LSDV dynamic panel data estimator

Bias correction initialized by Anderson and Hsiao estimator

LSDV dynamic regression

users	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
users L1.	.2994721	.0891267	3.36	0.001	.1247871	.4741572
funds	5.581447	1.781583	3.13	0.002	2.089609	9.073284

note: Bias correction up to order $O(1/T)$

LSDVC dynamic regression
 (bootstrapped SE)

users	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
users L1.	.6069528	.1466775	4.14	0.000	.3194701	.8944355
funds	5.281633	2.632438	2.01	0.045	.12215	10.44112

Ramsey RESET test including an interaction term for each group

	c1	c2	c3	c4	c5
b_LDV	.27882236	.17406232	.2788739	.27308647	.27881476
pval_LDV	.03340131	.12650087	.03320652	.03750083	.033783
b_funds	5.795497	5.0293301	5.8157648	5.4874856	5.7984395
pval_funds	.00153181	.00100845	.00132363	.00246092	.00141188
b_interac	.3146899	34.859568	-1.2551187	7.4749052	.25487013
pval_interac	.95736553	.00490855	.95109917	.02300368	.98011464
pval_F	.03798758	.50299398	.03603318	.03068062	.03919235
	c6	c7	c8	c9	c10
b_LDV	.27925433	.27754142	.28121111	.26775139	.27235727
pval_LDV	.03362488	.03434278	.03554432	.06016517	.03764118
b_funds	5.7687684	5.9092407	5.76329	5.2070099	6.7553827
pval_funds	.00201935	.0016022	.00163421	.00661784	.00067213
b_interac	.89617887	-2.2168377	4.2708126	2.0340145	-7.0006099
pval_interac	.7138618	.78662598	.59961097	.6827229	.00346934
pval_F	.03756	.02811127	.03996393	.0007083	.06105567
	c11	c12	c13	c14	c15
b_LDV	.27830866	.27919983	.26368203	.27162184	.27507276
pval_LDV	.04092967	.03789806	.04576857	.03978482	.03593237
b_funds	5.8094788	5.784466	6.4667391	5.459274	6.1523772
pval_funds	.00201234	.00261008	.00087551	.00250172	.0016434
b_interac	-.17374832	.23915765	-8.4860283	6.4619842	-5.5511855
pval_interac	.98353626	.96562415	.0562546	.29535147	.00729562
pval_F	.03479599	.02991363	.0157139	.04289196	.05091225
	c16	c17			
b_LDV	.27745673	.27780594			
pval_LDV	.03415979	.03405356			
b_funds	6.0070166	5.8923479			
pval_funds	.00161647	.00157827			
b_interac	-4.81782	-3.3427187			
pval_interac	.01419109	.44604507			
pval_F	.04352214	.04196795			

Leverage (drop observation 72)

Linear regression		Number of obs = 117				
		F(18, 98) = 94.85				
		Prob > F = 0.0000				
		R-squared = 0.9025				
		Root MSE = .34032				
users	Coef.	Robust Std. Err.	t	P> t	[95% Conf. Interval]	
users						
L1.	.3270978	.1342001	2.44	0.017	.0607821	.5934135
funds	6.95692	2.214595	3.14	0.002	2.562128	11.35171
ID						
2	1.287981	.452343	2.85	0.005	.3903209	2.185641
3	1.207312	.2561032	4.71	0.000	.6990837	1.715541
4	.4300228	.1380192	3.12	0.002	.1561281	.7039175
5	.5363836	.1635012	3.28	0.001	.2119209	.8608464
6	.0701638	.0687193	1.02	0.310	-.0662074	.206535
7	.9070864	.2435009	3.73	0.000	.4238668	1.390306
8	.9503965	.2245647	4.23	0.000	.5047551	1.396038
9	2.016002	.5397358	3.74	0.000	.9449134	3.08709
10	-.0183705	.1188655	-0.15	0.877	-.2542552	.2175142
11	.8887083	.2516289	3.53	0.001	.3893589	1.388058
12	1.298671	.3667152	3.54	0.001	.5709364	2.026405
13	.8832889	.2617895	3.37	0.001	.3637762	1.402802
14	1.490079	.3575177	4.17	0.000	.780597	2.199561
15	-.3513793	.0993806	-3.54	0.001	-.5485969	-.1541617
16	-.2025621	.0663554	-3.05	0.003	-.3342423	-.070882
17	.1408489	.0784369	1.80	0.076	-.0148066	.2965044
_cons	-.3820365	.1778438	-2.15	0.034	-.7349618	-.0291112

Interaction terms estimates

	c1	c2	c3	c4	c5
b_funds	5.795497	5.0293301	5.8157648	5.4874856	5.7984395
se_funds	1.7776694	1.4835738	1.7591951	1.7652773	1.7647191
pval_funds	.00153181	.00100845	.00132363	.00246092	.00141188
b_interact~m	.3146899	34.859568	-1.2551187	7.4749052	.25487013
se_interac~m	5.8714328	12.111142	20.413828	3.2363203	10.199341
pval_inter~m	.95736553	.00490855	.95109917	.02300368	.98011464
b_funds_noID	.	5.1112976	.	5.4871434	.
se_funds_n~D	.	1.4726358	.	1.7595408	.
pval_funds~D	.	.0007886	.	.00241973	.
	c6	c7	c8	c9	c10
b_funds	5.7687684	5.9092407	5.76329	5.2070099	6.7553827
se_funds	1.8184238	1.8204654	1.7789269	1.8766232	1.9230013
pval_funds	.00201935	.0016022	.00163421	.00661784	.00067213
b_interact~m	.89617887	-2.2168377	4.2708126	2.0340145	-7.0006099
se_interac~m	2.4370052	8.1670457	8.1090449	4.9613759	2.337006
pval_inter~m	.7138618	.78662598	.59961097	.6827229	.00346934
b_funds_noID	.	.	.	.	6.7545621
se_funds_n~D	.	.	.	.	1.9151954
pval_funds~D	.	.	.	.	.0006552
	c11	c12	c13	c14	c15
b_funds	5.8094788	5.784466	6.4667391	5.459274	6.1523772
se_funds	1.8306132	1.872357	1.8836062	1.7592278	1.9000639
pval_funds	.00201234	.00261008	.00087551	.00250172	.0016434
b_interact~m	-.17374832	.23915765	-8.4860283	6.4619842	-5.5511855
se_interac~m	8.3983302	5.5351135	4.3924818	6.1421208	2.0257798
pval_inter~m	.98353626	.96562415	.0562546	.29535147	.00729562
b_funds_noID	.	.	.	.	6.1516337
se_funds_n~D	.	.	.	.	1.8920565
pval_funds~D	.	.	.	.	.00160073
	c16	c17			
b_funds	6.0070166	5.8923479			
se_funds	1.8521845	1.81261			
pval_funds	.00161647	.00157827			
b_interact~m	-4.81782	-3.3427187			
se_interac~m	1.9294232	4.3689426			
pval_inter~m	.01419109	.44604507			
b_funds_noID	6.0063901	.			
se_funds_n~D	1.8443873	.			
pval_funds~D	.00157426	.			

STAFF-FUNDS

Model 1

Iteration 0:		log pseudolikelihood =		-403.4579		
Iteration 1:		log pseudolikelihood =		-402.76491		
Iteration 2:		log pseudolikelihood =		-402.76448		
Iteration 3:		log pseudolikelihood =		-402.76448		
Poisson regression				Number of obs	=	136
				Wald chi2(24)	=	2206.18
				Prob > chi2	=	0.0000
Log pseudolikelihood = -402.76448				Pseudo R2	=	0.4081
STAFF	Coef.	Robust Std. Err.	z	P> z	[95% Conf. Interval]	
FUNDS	.164367	.0312379	5.26	0.000	.1031418	.2255922
ID						
2	.0827113	.0913636	0.91	0.365	-.0963579	.2617806
3	.4423759	.0774482	5.71	0.000	.2905803	.5941716
4	.019246	.095943	0.20	0.841	-.1687988	.2072907
5	.476056	.1374657	3.46	0.001	.2066282	.7454838
6	.2949004	.1082683	2.72	0.006	.0826984	.5071025
7	.1721526	.0847593	2.03	0.042	.0060275	.3382778
8	.5365956	.0829934	6.47	0.000	.3739315	.6992597
9	.1341858	.130874	1.03	0.305	-.1223225	.3906941
10	-.0640156	.089127	-0.72	0.473	-.2387012	.11067
11	.1676188	.0972943	1.72	0.085	-.0230746	.3583121
12	-.048871	.0766599	-0.64	0.524	-.1991216	.1013797
13	.01493	.0727855	0.21	0.837	-.1277269	.1575869
14	-.1457187	.0844819	-1.72	0.085	-.3113002	.0198627
15	.1758683	.1046667	1.68	0.093	-.0292747	.3810113
16	.278963	.0999063	2.79	0.005	.0831503	.4747757
17	.1102863	.0759579	1.45	0.147	-.0385885	.2591611
YEAR						
2011	.0468095	.0519235	0.90	0.367	-.0549587	.1485778
2012	.0734769	.0526514	1.40	0.163	-.029718	.1766717
2013	.119319	.046742	2.55	0.011	.0277062	.2109317
2014	.0935862	.0532641	1.76	0.079	-.0108096	.1979819
2015	.1260272	.0479855	2.63	0.009	.0319772	.2200771
2016	.1018849	.0594185	1.71	0.086	-.0145732	.2183431
2017	.2027418	.0607634	3.34	0.001	.0836477	.3218359
_cons	2.671194	.0863412	30.94	0.000	2.501969	2.84042

```

Deviance goodness-of-fit = 103.4818
Prob > chi2(111)         = 0.6813

Pearson goodness-of-fit = 101.8565
Prob > chi2(111)         = 0.7212

```

```

Iteration 0: log likelihood = -407.03562
Iteration 1: log likelihood = -402.55794
Iteration 2: log likelihood = -402.55563
Iteration 3: log likelihood = -402.55563

```

Poisson regression

```

Number of obs   =      136
LR chi2(2)      =    555.73
Prob > chi2     =    0.0000
Pseudo R2      =    0.4084

```

Log likelihood = -402.55563

STAFF	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
_hat	1.385759	.6003349	2.31	0.021	.2091238	2.562393
_hatsq	-.0533922	.0829338	-0.64	0.520	-.2159394	.109155
_cons	-.6874971	1.076472	-0.64	0.523	-2.797344	1.42235


```

Deviance goodness-of-fit = 71.54751
Prob > chi2(94)          = 0.9591

Pearson goodness-of-fit = 71.22249
Prob > chi2(94)          = 0.9615

```

```

Iteration 0:  log likelihood = -347.02875
Iteration 1:  log likelihood = -343.5752
Iteration 2:  log likelihood = -343.57082
Iteration 3:  log likelihood = -343.57082

```

```

Poisson regression                                Number of obs   =      119
                                                  LR chi2(2)      =    526.67
                                                  Prob > chi2     =    0.0000
Log likelihood = -343.57082                    Pseudo R2      =    0.4339

```

STAFF	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
_hat	1.443347	.6374686	2.26	0.024	.1939316	2.692762
_hatsq	-.0611268	.0877366	-0.70	0.486	-.2330873	.1108337
_cons	-.7928243	1.14658	-0.69	0.489	-3.04008	1.454432

Model 3

Iteration 0: log pseudolikelihood = -345.70838						
Iteration 1: log pseudolikelihood = -345.11245						
Iteration 2: log pseudolikelihood = -345.1121						
Iteration 3: log pseudolikelihood = -345.1121						
Poisson regression						
				Number of obs	=	119
				Wald chi2(18)	=	1844.03
				Prob > chi2	=	0.0000
Log pseudolikelihood = -345.1121				Pseudo R2	=	0.4314
STAFF	Coef.	Robust Std. Err.	z	P> z	[95% Conf. Interval]	
STAFF L1.	.0158323	.0029717	5.33	0.000	.0100079	.0216567
FUNDS	.115723	.028142	4.11	0.000	.0605657	.1708803
ID						
2	.112309	.088925	1.26	0.207	-.0619808	.2865987
3	.2953316	.0932484	3.17	0.002	.112568	.4780951
4	.0729235	.0970838	0.75	0.453	-.1173573	.2632043
5	.059821	.1272507	0.47	0.638	-.1895857	.3092277
6	.2262856	.1020182	2.22	0.027	.0263335	.4262376
7	.0982863	.0897928	1.09	0.274	-.0777043	.2742769
8	.2420145	.1026237	2.36	0.018	.0408757	.4431532
9	-.006542	.1327619	-0.05	0.961	-.2667506	.2536666
10	-.0674936	.0984569	-0.69	0.493	-.2604657	.1254785
11	.1145623	.1139915	1.01	0.315	-.1088569	.3379816
12	-.0387441	.0886173	-0.44	0.662	-.2124307	.1349425
13	.0055825	.0902251	0.06	0.951	-.1712556	.1824205
14	-.1148841	.0833708	-1.38	0.168	-.2782878	.0485196
15	.0816639	.1032926	0.79	0.429	-.1207859	.2841137
16	.1803295	.100317	1.80	0.072	-.0162883	.3769473
17	.0776477	.094891	0.82	0.413	-.1083352	.2636306
_cons	2.519767	.0847684	29.73	0.000	2.353624	2.68591

Deviance goodness-of-fit = 74.14083
 Prob > chi2(100) = 0.9754

Pearson goodness-of-fit = 73.58247
 Prob > chi2(100) = 0.9781

Iteration 0: log likelihood = -348.39043
 Iteration 1: log likelihood = -345.03417
 Iteration 2: log likelihood = -345.02926
 Iteration 3: log likelihood = -345.02926

Poisson regression

Number of obs = 119
 LR chi2(2) = 523.75
 Prob > chi2 = 0.0000
 Pseudo R2 = 0.4315

Log likelihood = -345.02926

STAFF	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
_hat	1.260884	.6435707	1.96	0.050	-.0004916	2.522259
_hatsq	-.0360243	.0886995	-0.41	0.685	-.2098721	.1378234
_cons	-.4658845	1.156003	-0.40	0.687	-2.731608	1.799839

Bias corrected LSDV dynamic panel data estimator

Bias correction initialized by Anderson and Hsiao estimator
 LSDV dynamic regression

STAFF	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
STAFF L1.	.5628256	.098092	5.74	0.000	.3705688	.7550824
FUNDS	5.215055	.9897002	5.27	0.000	3.275278	7.154831

note: Bias correction up to order $O(1/T)$

LSDVC dynamic regression
 (bootstrapped SE)

STAFF	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
STAFF L1.	.5654833	.1308077	4.32	0.000	.3091049	.8218617
FUNDS	5.418305	2.15139	2.52	0.012	1.201659	9.634951

Leverage (drop observation 128)

note: you are responsible for interpretation of noncount dep. variable						
Iteration 0: log pseudolikelihood = -342.6572						
Iteration 1: log pseudolikelihood = -342.00241						
Iteration 2: log pseudolikelihood = -342.00199						
Iteration 3: log pseudolikelihood = -342.00199						
Poisson regression						
			Number of obs	=	118	
			Wald chi2(18)	=	1675.55	
			Prob > chi2	=	0.0000	
Log pseudolikelihood = -342.00199			Pseudo R2	=	0.4262	
STAFF	Coef.	Robust Std. Err.	z	P> z	[95% Conf. Interval]	
STAFF						
L1.	.0169269	.0036257	4.67	0.000	.0098206	.0240332
FUNDS	.1142389	.0279808	4.08	0.000	.0593976	.1690803
ID						
2	.1091277	.0887574	1.23	0.219	-.0648335	.2830889
3	.285702	.095626	2.99	0.003	.0982786	.4731255
4	.0723224	.0964279	0.75	0.453	-.1166727	.2613175
5	.0215268	.1507406	0.14	0.886	-.2739193	.3169729
6	.214159	.1054128	2.03	0.042	.0075538	.4207643
7	.0908556	.0914975	0.99	0.321	-.0884761	.2701873
8	.2165152	.1169861	1.85	0.064	-.0127733	.4458037
9	-.0211858	.1376186	-0.15	0.878	-.2909133	.2485417
10	-.0676844	.09914	-0.68	0.495	-.2619952	.1266263
11	.1074783	.1157425	0.93	0.353	-.1193729	.3343295
12	-.0407526	.0892554	-0.46	0.648	-.2156899	.1341848
13	.0047423	.090709	0.05	0.958	-.173044	.1825286
14	-.1141293	.0833682	-1.37	0.171	-.277528	.0492695
15	.0706089	.1061419	0.67	0.506	-.1374255	.2786432
16	.1908517	.1025696	1.86	0.063	-.010181	.3918845
17	.0752038	.0957807	0.79	0.432	-.1125229	.2629306
_cons	2.500045	.0933479	26.78	0.000	2.317087	2.683004

Leverage (drop observation 72)

Iteration 0: log pseudolikelihood = -342.29189						
Iteration 1: log pseudolikelihood = -341.62702						
Iteration 2: log pseudolikelihood = -341.62658						
Iteration 3: log pseudolikelihood = -341.62658						
Poisson regression						
					Number of obs	= 118
					Wald chi2(18)	= 1556.92
					Prob > chi2	= 0.0000
Log pseudolikelihood = -341.62658					Pseudo R2	= 0.4346
STAFF	Coef.	Robust Std. Err.	z	P> z	[95% Conf. Interval]	
STAFF L1.	.0136274	.0031714	4.30	0.000	.0074115	.0198433
FUNDS	.137929	.0308263	4.47	0.000	.0775105	.1983474
ID						
2	.1076233	.0891618	1.21	0.227	-.0671306	.2823772
3	.3251353	.0924666	3.52	0.000	.1439041	.5063664
4	.0677171	.0973958	0.70	0.487	-.1231751	.2586092
5	.0575388	.1293149	0.44	0.656	-.1959138	.3109914
6	.2197672	.1015119	2.16	0.030	.0208074	.4187269
7	.1003814	.0892211	1.13	0.261	-.0744887	.2752515
8	.2602766	.1027979	2.53	0.011	.0587965	.4617567
9	.0154621	.134456	0.11	0.908	-.2480669	.278991
10	-.077578	.0975499	-0.80	0.426	-.2687722	.1136163
11	.1189039	.1104702	1.08	0.282	-.0976136	.3354214
12	-.056103	.0883407	-0.64	0.525	-.2292477	.1170417
13	.0101657	.0892334	0.11	0.909	-.1647286	.1850599
14	-.1294329	.0831611	-1.56	0.120	-.2924256	.0335598
15	.0617209	.1048061	0.59	0.556	-.1436954	.2671372
16	.1748848	.0997265	1.75	0.079	-.0205756	.3703452
17	.085024	.0932067	0.91	0.362	-.0976577	.2677058
_cons	2.529907	.0851932	29.70	0.000	2.362931	2.696882

Interaction terms estimates

	c1	c2	c3	c4	c5
b_FUNDS	.11329891	.11555555	.11335665	.11540361	.13877565
se_FUNDS	.02772271	.02806576	.02809616	.02804762	.04134788
pval_FUNDS	.00004372	.00003833	.0000547	.00003879	.00078995
b_interact~m	.56264113	.23099941	.11823878	.20266791	-.0517286
se_interac~m	.17143438	.17761968	.12873012	.19264025	.03577591
pval_inter~m	.00103087	.19341997	.35835649	.29277485	.14820363
b_FUNDS_noID	.11091288	.	.	.	.
se_FUNDS_n~D	.02758014	.	.	.	.
pval_FUNDS~D	.00005783	.	.	.	.
	c6	c7	c8	c9	c10
b_FUNDS	.10972158	.118309	.11715106	.14585849	.1209941
se_FUNDS	.02697814	.02894675	.02875716	.03186009	.02925184
pval_FUNDS	.00004761	.00004367	.00004625	4.692e-06	.0000353
b_interact~m	.15737369	-.14381505	-.06182701	-.1849219	-.12006857
se_interac~m	.05296179	.129952	.08521902	.06937567	.13302737
pval_inter~m	.0029639	.26843308	.46814095	.00768705	.36674594
b_FUNDS_noID	.10826863	.	.	.13599205	.
se_FUNDS_n~D	.02712596	.	.	.03237665	.
pval_FUNDS~D	.0000657	.	.	.00002665	.
	c11	c12	c13	c14	c15
b_FUNDS	.10518264	.1190986	.1173174	.11892559	.11314691
se_FUNDS	.02564589	.02920489	.02874762	.02883155	.0283513
pval_FUNDS	.00004108	.00004542	.00004485	.0000371	.00006583
b_interact~m	.22048518	-.120337	-.05185612	-.3361452	.07536727
se_interac~m	.13989615	.0821284	.10742047	.05180632	.13991481
pval_inter~m	.11501122	.14285817	.62928063	8.670e-11	.59011776
b_FUNDS_noID	.	.	.	.11883176	.
se_FUNDS_n~D	.	.	.	.02884082	.
pval_FUNDS~D	.	.	.	.00003784	.
	c16	c17			
b_FUNDS	.10845692	.11674099			
se_FUNDS	.02621289	.02840023			
pval_FUNDS	.0000351	.00003947			
b_interact~m	.09915371	-.20274468			
se_interac~m	.07164747	.18964581			
pval_inter~m	.16638573	.28503805			
b_FUNDS_noID	.	.			
se_FUNDS_n~D	.	.			
pval_FUNDS~D	.	.			

Alternative group dummies OLS regression

Linear regression			Number of obs = 119			
			F(18, 100) = 49.78			
			Prob > F = 0.0000			
			R-squared = 0.8821			
			Root MSE = 4.9612			
STAFF	Coef.	Robust Std. Err.	t	P> t	[95% Conf. Interval]	
STAFF L1.	.5628256	.1220577	4.61	0.000	.3206666	.8049846
FUNDS	5.215054	1.395297	3.74	0.000	2.446825	7.983284
ID						
2	.4101062	2.030915	0.20	0.840	-3.619171	4.439383
3	7.055131	2.592483	2.72	0.008	1.911718	12.19854
4	.6215813	2.050879	0.30	0.762	-3.447304	4.690467
5	1.745974	5.324847	0.33	0.744	-8.818371	12.31032
6	2.600637	3.261745	0.80	0.427	-3.870572	9.071845
7	-.8236107	2.396035	-0.34	0.732	-5.577275	3.930053
8	3.712805	3.666431	1.01	0.314	-3.56129	10.9869
9	-7.446801	5.045555	-1.48	0.143	-17.45704	2.563436
10	-2.960348	2.526685	-1.17	0.244	-7.973219	2.052523
11	.5388901	3.005381	0.18	0.858	-5.423701	6.501481
12	-4.58991	2.541371	-1.81	0.074	-9.631919	.4520987
13	.5374428	2.252606	0.24	0.812	-3.931663	5.006548
14	-4.480102	2.023866	-2.21	0.029	-8.495394	-.464809
15	-4.147158	3.667564	-1.13	0.261	-11.4235	3.129184
16	1.195034	3.055027	0.39	0.697	-4.866053	7.256122
17	1.459047	2.348699	0.62	0.536	-3.200705	6.1188
_cons	1.253889	2.68221	0.47	0.641	-4.06754	6.575318

Source	SS	df	MS	Number of obs = 119		
Model	18532.368	2	9266.184	F(2, 116) = 457.93		
Residual	2347.24494	116	20.2348702	Prob > F = 0.0000		
				R-squared = 0.8876		
				Adj R-squared = 0.8856		
Total	20879.6129	118	176.945872	Root MSE = 4.4983		
STAFF	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]	
_hat	.6553333	.1488608	4.40	0.000	.3604957	.9501708
_hatsq	.0042908	.0018067	2.37	0.019	.0007125	.0078692
_cons	5.836836	2.686303	2.17	0.032	.5162738	11.1574

More information

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