Master Thesis U.S.E.

Valorise or Perish?

An Altmetric Approach to Measure the Societal Contributions of Dutch Economists

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Abstract

Western governments are increasingly interested in the social impact of publicly financed research. At the same time, there are structural concerns about the social relevance of economic research. Social impact is hard to quantify and measure, especially for social sciences. Recently, altmetric approaches have been introduced within scientometrics to quantify social impact using non-traditional quantitative data. In this paper, I use an altmetric approach to interpret the relationship between the societal contribution and the scientific performance of Dutch economists. To do so, I use publications in the journal *Economisch Statistische Berichten* as a proxy for social contribution and the Economentop 40 as a measure for scientific performance. Using a negative binomial regression model, this research shows that there is a significant, positive relationship between scientific performance and ESB publications. The empirical findings are robust to different model specifications and estimation methods. The findings suggest that even though there are legitimate concerns about the social relevance of economic research, the scientific success of economists is not unrelated to their societal contribution efforts.

Code

C23, A12, A3.

Keywords

Altmetrics, Dutch economists, Scientometrics, Social impact, Valorisation.

"The ideas of economists ... are more powerful than is commonly understood. Indeed the world is ruled by little else." –John Maynard Keynes[1]

[1] Cited in: Stephen Weymouth & J. Muir Macpherson (2012). The Social Construction of Policy Reform: Economists and Trade Liberalization Around the World, *International Interactions*, 38:5, 670-702.

Content

1. Introduction

1.1 Social impact of scientific research

Recently, governments of western countries became increasingly concerned with the societal relevancy of publicly funded academic research. Governmental funding has traditionally been the primary beneficiary of scientific research. In 1945, Vannevar Bush, at the time science advisor to President Franklin D. Roosevelt, established the rationale for the public funding of academic research (Jong, Smit, & Drooge, 2016). In his report "Science, the endless frontier" he pointed out the huge societal contributions of scientific research; such as the sharp increase of medical knowledge and military advantages (Bush, 1945). He advised the US President to set up an agency to distribute funding to scientific researchers and research projects. According to his philosophy, public health, welfare, and security would eventually benefit from the new knowledge and techniques brought about by independent academic research (Bush, 1945). Throughout the last months of World War II and during the Cold War, an increasing amount of money was spent on academic research. Initially, nuclear physicians benefited most, but gradually, other fields with a less salient military or economic potential also saw an increase of funding (Bornmann, 2012).

In most countries, scientific research still depends heavily on public funding as its major beneficiary. However, the growth of the scientific community, and thereby the number of applications for funding, outpaced the public resources available (Bornmann, 2012). As the government bodies providing funding were forced to differentiate between applications, decision mechanisms had to be put in place. These funding bodies did not only consider the scientific relevancy of the research but increasingly also its societal relevance, labelling it as 'the third mission' (UK) or 'valorisation' (NL). From the 1990s onwards, Western governments started to implement social impact criteria into the allocation procedures of funding councils (Jong, Smit, & Drooge, 2016). In the 2000s, these criteria were formalised in regulations and laws. For example, social impact is an important criterion for research projects to receive funding from the European Horizon 2020 programme (Europese Commissie, 2014). The UK Research Excellence Framework (REF) dedicates 20% of its evaluation to social impact (2011) and the Dutch government made social impact of research on the three main ambitions of its official research policy (OCW, 2014).

So, the social impact of academic research is clearly on the agenda of public funding agencies. However, this poses difficult questions upon these agencies: what is social impact, and how can you measure this for scientific research? According to the European Commission, social impact involves the social, cultural, environmental and economic returns of a publicly funded research project (European Commission, 2010). In the Netherlands, the government has put increased connectedness between academic science on the one hand, and society and businesses on the other, high on its agenda. Maximizing the 'social impact' of Dutch science is one of the three core elements of the national research policy (OCW, 2014). However, what exactly is meant with social impact remains unclear. According to Lutz Bormann (2016), a scientist studying the social impact of academia, social returns, or benefits include all contributions to the 'social capital' of a nation. Such contributions are, for example, the introduction of new approaches to social and economic issues, informing public and political debates and supporting policy making.

Besides the definition problem, there is also the problem of measurement. Studying the impact of scientific research, also referred to as 'sciencometrics', is not new. So-called 'bibliometric' designs, mostly based on citation indexes, became an established method to assess and rank the scientific impact of academic research (Bornmann, 2016). Though there are well-established methods to quantify scientific impact using citation indexes, there is no clear consensus on how to measure its social equivalent. This is a problem since governments increasingly ask their funding agencies to assess the social impact of potential research projects as a criterion to receive funding. Recently, however, several scholars have tried to establish methods to assess the social impact of academia as well. Thereby, they are setting up a new branch of sciencometric science, moving away from dominant bibliometric approaches.

Most prominent in this new branch are the so-called 'altmetric approaches' (Priem, Taraborelli, Groth, & Neylon, 2010). Initiated by Priem et al. in 2010, altmetrics is a collective of new approaches that use large, non-traditional datasets to track impact 'outside academia'. Potential sources of data could be Twitter, Wikipedia or Mendeley. Similar to traditional bibliometric approaches, altmetrics makes use of (citation) indexes. The key difference is that they apply these tools outside the pool of peer-reviewed academic journals. This particular branch of research is still very much in its childhood stages and the body of literature using altmetrics remains little (Priem, Taraborelli, Groth, & Neylon, 2010). However, it does indicate that researchers are actively looking for ways to measure social impact.

So, though there is definitely a tendency in scientometrics to move away from traditional approaches, an established method to measure or indicate societal impact has not been presented yet.

1.2 Social impact of Dutch economists

Growing concerns about the social impact of researchers also apply to economists. It is not hard to argue that some economists such as John Keynes or Adam Smith had an impact on society or public policy. When it comes to contemporary economists, this impact becomes less clear. In the 1990s, critiques on the economic discipline were issued in public media sources. Economists were accused of not having attention for issues that were of actual importance for society (Davis, 2007). Similar critiques gained momentum during recent economic crises, accusing economists of doing research that is "theoretical drivel, mathematically elegant but not about anything real" (Gorga, 2009, p. 53). Even some economists themselves are uncertain about the spillover benefits of their research for society or government policy makers (Davis, 2007).

So, there are some clear concerns about societal involvement of economists. However, in their daily practice, researchers and universities remain very much obsessed with scientific impact scores, rather than social impact. Similar to many other academic fields, an economists' tenure is basically a direct result of his or her success in publishing (Rond & Miller, 2005). Even though some researchers would argue that: "research that is highly cited or published in top journals may be good for the academic discipline but not for society" (Nightingale & Scott, 2014, p. 547). A good example of such a bibliometric index for scientific success is the Dutch *Economentop 40* (E40), an index listing the 40 'best performing economists'. The index is calculated each year and measures the annual amount of publications of Dutch economic researchers weighted by the impact score of the journal in which it was published and the number of co-authors (Lukkezen, 2019).

At the same time, the Dutch government is increasingly concerned with social impact, as 'valorisation' became a key element of their research policy. The Dutch government defines valorisation as the process of value creation from knowledge by making this knowledge available for and to economic or societal utilization (Nederland Ondernemend Innovatieland, 2009). So, rather than focusing on the impact itself, this definition proposes a focus on the process. Considering the epistemological problem of measuring societal impact, it is more fruitful to measure the output instead of the outcome of societal impact; i.e. how can researchers have an impact *beyond* the scientific community? Using data from the E40, this research sets out to analyse the relationship between the scientific performance of Dutch economists and their societal contribution. The main research question of this project is: What is the relationship between the scientific performance of Dutch economists as measured by the *Economentop 40* and their societal contribution?

The E40 is a clear example of a traditional bibliometric approach to measure the scientific impact of researchers. I will compare the scientific performance of these researchers as measured by the index score of the E40, with data from the journal *Economisch Statistische Berichten* (ESB). ESB is a Dutch language, non-academic journal which publishes articles written by scientists or economic policy officers. It presents itself as a communication platform where economic scientist and policy officers can exchange information, theories and findings (ESB, 2020). By placing itself on the intersection of economic science and policy, it has a clear societal focus. Publishing in ESB does not contribute to a researcher's scientific impact score. Considering the scope and target audience of the journal (policy officers and economists), I take a publication in the journal as a proxy for the author's societal involvement. A negative binomial regression model is used to estimate the empirical relationship between economists' scientific impact as measured by the E40 index with their societal involvement of which publishing in ESB.

Using new data, this research gives insight into some of the fundamental questions that governments are now dealing with. For example: how can we map the impact of scientific research beyond academia. By giving an insight into the relationship between the scientific performance and the societal involvement of professional researchers, this research contributes to an understanding of the interactions between academia and society. Do high ranking scientists also contribute to society at large? At the same time, as this introduces a new way to measure societal contribution using quantitative data, it contributes to the ongoing scientific debate dealing with questions relating to the development of methods to measure the social impact of scientific research.

2. Literature review & theoretical framework

2.1 Scientometrics

Attempts to measure the impact of scientific research are not new. Researchers and policy makers have been trying to quantify the scientific impact of researchers for more than 50 years. The study of the impact of academic research, often referred to as 'scientometrics', became a research field in its own rights, with a rich body of literature and its own academic journals (Bornmann, 2016).[2] Citation measurements became the dominant methods of scientometrics. Coined as 'bibliometrics', such approaches rank scientific publications. Both journals and scientists received impact scores, quantifying their scientific performance. In 2005, Jorge E. Hirsch introduced the *h-index*, which is a measurement of the number of times a researcher's publication is cited in other academic publications (Bornmann & Daniel, 2005). Although the index received substantial critiques over time, it remains the most prevailing measure of a researcher's scientific success. It is common use that a research institute judges its employees on their h-index score. In universities, a faculty member's tenure is therefore basically a direct result of his or her success in publishing. A practice that is commonly (and ironically) referred to as 'publish or perish' (Rond & Miller, 2005).

Though there are some critiques on the widespread use of the h-index and its implications for academic practice, bibliometric methods such as citations measurements are, when used properly, widely accepted to give a good impression of the impact a publication has on the scientific community. Partly driven by the above-mentioned policy changes, researchers have recently started to explore the possibilities of quantifying societal impact in a similar manner (Bornmann, 2016). An early example of such an approach is Van der Meulen and Rip's (2000) assessment of the 'societal quality' of research in the Netherlands. For Van der Meulen and Rip, societal quality includes the usability of research (for policy or industry); contributing to the understanding of (or the development of a solution for) societal problems; and cultural importance. Social impact, they argue, must not be confused with relevance. As relevance is intrinsic to the research, impact must be mediated through channels. According to them, a researcher has to differentiate between indications and indicators of societal impact. Indications can be measured ex ante, indicators ex post. Van der Meulen and Rip state that the best way to assess societal quality is to build frameworks of indicators and indications specifically designed

[2] See for example *Scientometrics*: *An International Journal for all Quantitative Aspects of the Science of Science, Communication in Science and Science Policy.* Retrieved from https://www-springer-com.proxy-ub.rug.nl/journal/11192 (27-03-2020).

to each research (sub)group. Ex ante evaluation of societal quality based on indicators should then contribute to improve the frameworks (Meulen & Rip, 2000).

Several other researchers have developed similar ‘payback’ frameworks. These frameworks are mainly a retrospective tool to assess the societal impact of research. It is based mostly on case studies, focussing on individual research projects. Methods that are used include interviews, questionnaires, and the analysis of (policy) documents and patents (Samuel & Derrick, 2015). According to Samuel and Derrick (2015), these payback framework approaches are broadly assessing societal quality based on five categories: knowledge production, research targeting, capacity building, informing policy, health benefits and economic benefits. They then argue that these ‘narrative case studies’ can be considered as best practices to assess ‘non-academic’ impact (Samuel & Derrick, 2015).

These ‘framework’ or ‘payback’ approaches have predominantly been used to assess medical and natural sciences (Samuel & Derrick, 2015). Pedersen, Gronvad and Hvidtfeldt (2020) point out that for social sciences and humanities, such approaches do not always pay off as impact cannot be measured as easily. After studying many different approaches that were used since the early 2000s, they find that especially with regard to social sciences, impact simply means different things to different funding agencies and policy makers. What kind of approach is chosen, or fits best, depends on the definition of social impact that is used.

2.2 **Altmetrics**

It is clear that in the last two decades, there is a tendency within scientometrics to examine the possibilities of measuring or assessing the social impact of research. However, no unified approach has emerged so far. Especially for the humanities and social sciences, several different methods coexist (Pedersen, Gronvad, & Hvidtfeldt, 2020). One approach that recently has gained some attention is ‘altmetrics’. Altmetric (short for ‘alternative metrics’) was launched as a ‘manifesto’ in 2010 by Priem et al. Altmetrics aims to use quantitative approaches that consider non-traditional metrics. Instead of peer-reviewed journals, altmetrics proposes to study data such as the number of page views, downloads, posts and views on social media, tweets, etc. as a proxy for social impact (Tahamtan & Bornmann, 2020). Altmetrics does not propose a single method or index, but it is a collective for approaches that use large quantitative data sets to assess ‘non-scientific’ indicators of impact. A wide variety of potential data sources can be considered as long as they ‘track’ activity around academics or academic products (Priem, Groth, & Taraborelli, 2012). Since its launch in 2010, most researchers using altmetrics approaches studied internet-based sources, such as Facebook, Twitter, or Mendeley (Tahamtan & Bornmann, 2020).

According to Björn Hammerfelt, altmetrics are especially useful for research fields where impact is not as easily identifiable, such as the humanities and social sciences (Hammerfelt, 2014). According to him, altmetrics is promising for four main reasons: its speed, diversity of methods and sources, the openness of methods and its capability to reach 'beyond' scientific impact. One of the most used sources of data in altmetric studies so far is Twitter. Holmberg and Thelwall (2013) analysed a large data set of tweets posted by academics. They found that Twitter is an important tool for scholarly communication, but that it is barely used for sharing academic publications. Furthermore, they found profound differences between disciplines. Scholars in (digital) humanities use Twitter to communicate with peers, while economists mostly use Twitter to share links (Holmberg & Thelwall, 2013). Another source that is often used for altmetric studies is Mendeley. Mendeley is a 'social reference manager' with more than 2 million users. Altmetric studies have been performed analysing correlations between the number of citations and readership density (Li, Thellwall, & Guistini, 2012). Mohammadi and Thelwall (2013) found that the correlation between Mendeley readership and number of citations is stronger for beta disciplines than for the humanities or social sciences. This could indicate that indication indexes are more suitable as impact measures for beta disciplines than for the humanities or social sciences.

Overall, altmetrics is still very much a new and developing movement within scientometrics. However, it has the potential to offer solutions for the limitations of traditional bibliometric methods, and to open up ways to systematically and quantitatively study the impact of academics beyond the scientific community. Furthermore, it offers a solution to the lack of impact indicators for social sciences and humanities.

2.3 Social impact

As mentioned before, there is no clear consensus among scholars or policy makers about the definition of 'social impact'. Pedersen et al. (2020) argue that there are as many definitions of social impact as there are researchers and policy makers. Ben Martin (2007) identifies four main problems for defining and assessing social impact. First of all, there is a causality problem as it is usually hard to identify the causes of societal phenomena. Secondly, there is an attribution question because social impact can be diffuse as it might not be clear what outcomes can be attributed to which cause. Thirdly, the high level of internationalisation of contemporary academics makes attribution even more complicated. Finally, timescale problems arise as some effects might take a long time to reach their full potential while others might be visible immediately (Martin, 2007). Problems like these make societal impact harder to measure than scientific impact. In addition, there are probably no indicators of societal impact that are valid for all academic disciplines (Bornmann, 2012).

According to Bornmann (2012), all social impact studies essentially try to measure the social, cultural, environmental or economic returns of research, including both products as well as ideas. For Bornmann, social impact can be broadly divided into 'societal benefits', 'cultural benefits', 'environmental benefits' and 'economic benefits'. Societal benefits include contributions to social capital, finding new approaches to social questions and informing public debate and policy making (Bornmann, 2012). So according to this definition, contributing to public debates and enabling informed policy making is a way for academics to contribute to the social capital of the nation. Following this reasoning, a publication in ESB would qualify as a societal contribution. Therefore, publishing in ESB is a way for Dutch economist to valorise their research. So, instead of quantifying the societal impact of scientists, this research focuses on their output, i.e. societal contribution.

When it comes to the quantity and quality of economists' societal contribution, there is no consensus among commentators nor economists themselves. Davis (2007) notes how economists have been criticised in the media and by the lay public for the profession's 'obsession' with abstract reasoning and mathematical models that are allegedly of little interest for society. According to Davis, critics would argue there is a tendency to study esoteric topics instead of economic issues that are important for society. Such criticism comes from outside as well as from within the discipline. A survey held among 900 economists living in the USA and Canada gives insights into how economists themselves feel about the social impact of their research. Of the surveyed economists, more than 65% disagrees with the statement that economists are effective in communicating their research to laypersons. Furthermore, only 35% believes that publishing articles in scientific journals entail spillover benefits for society, while less than 30% thinks that these journals are useful for policy makers (Davis, 2007).

So, there is a sense that economics as a discipline is more concerned with scientific relevancy than it is with social impact. Akerlof (2020) supports this view and argues that there is a structural tendency within the economic discipline to comply with a certain tradition. According to Akerlof there is a strong bias towards so-called 'hard' research. Following Comte's classification of sciences into hard and soft, Akerlof argues that there is a hierarchy that favours the 'hard' empirical work over 'soft' economics. For economics, research is ‘harder’ when it uses quantitative methods, preferably in combination with complicated mathematical models (Akerlof, 2020). This bias is sustained and reinforced through the organisation of the discipline, in which a lot of emphasis is placed on publishing in academic journals. The evaluation boards of these journals are filled with scientists who made a career in hard economics. In order to be published, research has to comply with the board’s expectations. And as publishing in these journals is of crucial importance for scientists’ careers, they tend to do research which has the highest chance of being published. This dominance of a select group of academic journals within the economic discipline was recently reconfirmed by Ductor et al. (2020). They find that the influence of top scientific journals is substantially larger in economics than in other scientific disciplines (Ductor, Goyal, Leij, & Paez, 2020). According to Akerlof, this led to the current state of the profession in which there is an excessive demand for “compliance in favour of the hard relative to the important” (Akerlof, 2020, p. 409). Akerlof states that this leads to a dismissal of research topics that are actually relevant for society, which is, for example, why economics failed to predict the Financial Crisis (Akerlof, 2020).

The literature suggests that there is a clear tendency within the economic discipline to publish a certain type of work. This is further enhanced by the influence of a small selection of top journals that dominate the discipline. Publishing in these peer-reviewed academic journals is a major concern for scientific economists and has an impact on what topics they decide to study. Considering that a publication in ESB does not contribute in any way to scientific performance scores, it seems that it is not directly beneficiary for scientists to devote their time and effort to it. Furthermore, as ESB has a clear societal scope, it does not necessarily cover the same topics as the ones relevant for peer-reviewed academic journals. Therefore, there is no reason to assume that economists who perform well scientifically, also tend to valorise their work through channels such as ESB, as this is simply not in their interest. This leads to the first hypothesis that will be considered in this research:

H1. There is no significant relationship between the scientific performance and the societal contribution of Dutch economists.

Assuming that the topics that are covered by ESB differ from the ones that are of interest for scientific journals, one could expect that researchers either devote their time to these publishable topics, or more socially relevant topics. This would involve that researchers either invest in their scientific careers, or in societal relevance, which leads the second hypothesis:

H2. ESB authors are not among the highest-ranked Dutch scientific economists

3. **Empirical strategy**

3.1 Data

For this research, I use data from ESB and from the E40 for the period 2010-2019. The data is used to build two indexes: one on scientific performance (E40 score) and one on societal contribution (ESB index) for the years 2015 – 2019.

ESB

Economisch Statistisch Berichten is a Dutch language economic journal. It was founded in 1916 as a periodical journal for economic literature. Since then it has changed publisher and ownership several times. Since 2015 it is part of the FD Mediagroup, which also publishes *Het Financieel Dagblad* (Molle, 2016). Its core business is to enable discussion on economic and societal issues. Thereby it aims to inform- and contribute to public debate and policy making (Molle, 2016). Most of the journal's content is only available to subscription holders who pay a yearly fee. In addition, ESB also publishes several thematical releases each year in collaboration with a sponsor.

ESB presents itself as the communication platform for economic scientist and policy officers to discuss public policy and economic issues in a broad sense (ESB, 2020). It publishes articles written by external authors. These authors can be economic scientists, but also policy officers or other professionals working in a related field. The articles have to fit the core activity of ESB, which is informing the public debate and policy making. The journal publication guidelines state that every contribution has to meet the following five criteria: (1) it needs to approach a topic or problem from an economic perspective; (2) the topic has to be relevant for the Netherlands; (3) the article has to be based on new research or research results; (4) it has to contribute to the scientific or public debate and (5) it has to be well structured and written (ESB, 2020). Authors do not get paid for their contribution, nor do they have any contractual or institutional ties to ESB (2020). Besides articles, which are published online and in print, ESB also accepts other contributions such as blogs and columns (ESB, 2020).

ESB is not a peer reviewed scientific journal. Its main goal is to inform public debate and policy making. Publishing in ESB does not contribute to any scientific performance indicators such as the H-index or the Economentop40. Thus, a publication in ESB does not directly contribute to an economist's scientific career or tenure. Considering the scope of the journal, publishing in ESB is a way for scientists to *valorize* their research by making it available to society and by using it to inform the public debate and policy making. Therefore, I take a publication in ESB as a proxy for societal contribution.

The ESB dataset contains all publications ever made in the journal. This includes all articles in printed editions, but also online publications, blogs and editorial comments. Each publication has a unique id number. For each publication, the dataset contains the names of the author(s), date of publication, in which section it was published and the full title of the publication. For each publication, I extracted all author names. Then, I summed the total number of contributions per individual author per year. All types of contributions are included except for editorial pieces. This gives me a list of number of publications in ESB per author per year. Extreme outliers are excluded and the score is capped at 10 publications per year (so an author with >10 publications in one year will receive an ESB score of 10 for that year). Because the identifier is the author name, data cleaning was necessary to control for the fact that names can be documented in different ways.

Economentop 40

The *Economentop 40* is a score based on publications made in peer-reviewed economic journals. It is a bibliometric method that quantifies the scientific performance of individual scientists by making use of large datasets and citation scores. The E40 is made by the Erasmus University of Rotterdam and published each year in ESB. The E40 score considers the 5 years prior to the current year (so for the E40 of 2019, the period 2014 – 2018 is considered). The index is a sum of the weighted scores for each publication the economists has made during the period under consideration. A list of publications per author is retrieved from the Clarivate Analytics Web of Science (2020) website. The index considers all publications made in journals listed on either the Tinbergen Journal List (2020) or the ERIM Journal List[3] (2020) with at least one author connected to a Dutch research institution (Phlippen, 2014). The score for each publication is based on the 5-year average Article Influence Score[4] (AIS) of the journal in which it was published and corrected for the number of co-authors. The formula to calculate the score for each publication *i* is as follows:

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[3] Only categories P* and P

[4] Article Influence Score indicates the average influence of articles published in a journal over the first five years after publication. The score is calculated as follows:

$$\frac{0.01 * EigenFactor\ Score}{X}$$

Where x is the 5-year Journal Article Count divided by the 5-year Article Count from all journals (Clarivate Analytics, 2020). See also: http://help.incites.clarivate.com/incitesLiveJCR/glossaryAZgroup/g4/7790-TRS.html

$$P_i = \frac{2}{1 + (Number\ of\ authors)} * AIS_{Journal\ in\ which\ i\ is\ published}$$

The total E40 score is the sum of the scientists' publications in the previous 5 years. When a scientist has published more than 15 articles in this period, only the 15 best-performing articles are considered (Phlippen, 2014). A list with the 40 highest-ranking economists is published in ESB each year in the December edition. This gives for each year (2015-2019) a list with all Dutch economists that qualify the requirement of having at least one publication in a scientific journal in the previous 5 years. The name of the author is the identifier so data cleaning was necessary to control for the fact that names can be documented in different years.

After the cleaning, the two datasets were merged into one list. To do so, data cleaning was again necessary to control for the fact that the same author could be listed differently on each list. Units of observation in the dataset are individual economists. Every economist that is included meets the requirement of having at least one publication in ESB or a scientific journal in the considered time period. Economists in the dataset that did not publish in any scientific journal in the previous 5 years will receive an E40 score of 0. Similarly, an economist that did not publish in ESB during a given year will receive an ESB score of 0. Per year I can calculate how many publications the economist has made in ESB in the previous 5 years. By doing so, each economist in the dataset receives an ESB index score which considers the same period as the E40 score. The ESB index is defined as the sum of the number of publications in ESB during the previous 5 years.

3.2 Descriptive statistics

The final dataset has a total of 44,026 observations from 8,806 individual economists. Each observation has a value for the E40 score and one for the ESB index. All missing values are valued as 0. The ESB index is a count variable that ranges between 0 and 47, with a median value of 0, a mean of 0.34 and a standard deviation of 1.49. The distribution is bell-shaped and right-skewed. The E40 score ranges between the values 0 and 34.80, it has a median value of 0.09, a mean value of 0.80 with a standard deviation of 1.88. The distribution of E40 score is also bell-shaped and right-skewed.

For the purpose of analysis, the dataset is divided into three subgroups. First of all, a distinction is made between scientific economists and non-scientific economists. A scientific economist is defined as an economist who has made at least one contribution to a peer-reviewed scientific journal in the previous 5 years. This implies that it has an E40 score which is larger than 0 (i.e. E40 score > 0). The second subgroup under consideration is referred to as ESB authors. This group includes all authors who have made at least one contribution to ESB in the previous 5 years (i.e. ESB index > 0). The final subgroup considers only scientific ESB authors (i.e. ESB index > 0 and E40 score > 0). The scientific authors group has 22,307 observations (7,703 unique economists), the ESB authors subgroup has 6,608 observations (2,064 unique economists), and the scientific ESB authors subgroup has only 2,278 observations (736 unique economists). For all descriptive statistics for each subgroup see table 1. Finally, the subgroup scientific authors has been subdivided in quintiles based on their E40 score. This way I can check whether the effect differs between the best performing scientists and those who get a lower E40 score. For all descriptive statistics for each quintile, see table 2.

Descriptive statistics in tables 1 and 2 indicate that the data is highly dispersed. The median value for ESB index in most sample specifications is 0. Furthermore, the mean value is low compared to the maximum value. This indicates an extreme spike in the distribution around the values 0 and 1, with a very narrow, long right skew. Another indication of a highly dispersed distribution is when the mean value is smaller than the variance. This is the case for both variables in the dataset, and for all sample specifications.

Table 1. Descriptive statistics ESB index and E40 score

	Total sample	Scientific authors	ESB authors	Scientific ESB authors
ESB index				
Min.	0	0	1	1
Max.	47	47	47	47
Median	0	0	1	2
Mean	0.34	0.32	2.25	3.10
Std. Dev	1.49	1.70	3.23	4.44
Variance	2.21	2.90	10.41	19.72
E40 score				
Min.	0	0.01	0	0.046
Max.	34.80	34.80	34.80	34.80
Median	0.09	0.71	0	1.34
Mean	0.80	1.59	1.00	2.90
Std. Dev.	1.88	2.41	2.62	3.79
Variance	3.56	5.80	6.85	14.36
Number of Observations	**44,026**	**22,307**	**6,608**	**2,278**
Unique ID	**8,806**	**7,203**	**2,064**	**736**

Table 2. Descriptive statistics by quintiles

	Q1	Q2	Q3	Q4	Q5
ESB index					
Min.	0	0	0	0	0
Max.	31	24	19	31	47
Median	0	0	0	0	0
Mean	0.23	0.14	0.15	0.30	0.77
Std. Dev	1.39	0.80	0.77	1.39	3.02
Variance	1.93	0.65	0.59	1.93	9.13
E40 score					
Min.	0.010	0.32	0.55	0.98	2.13
Max.	0.32	0.54	0.98	2.13	34.80
Median	0.23	0.43	0.71	1.38	3.85
Mean	0.22	0.43	0.73	1.44	5.12
Std. Dev.	0.074	0.062	0.13	0.33	3.52
Variance	0.0055	0.0038	0.016	0.11	12.39
Number of Observations	**4,472**	**4,482**	**4,437**	**4,455**	**4,461**

3.3 Data analysis

The constructed ESB index will be the main dependent variable of the empirical analysis. The E40 index will serve as the main explanatory variable. The first step of the empirical analysis will be to check for the correlation between the dependent variable and the explanatory variable in the full sample and the different subgroups. The preferred estimation method is a negative binomial regression model. Robustness checks are included to check whether the empirical findings are consistent with different model specification and estimation methods.

Negative binominal regression

The ESB index is a count data variable. This implies that the dependent variable is a nonnegative integer, which is why a linear regression model may not be the most appropriate model for estimating the empirical relationship between E40 score and the ESB index (Ver Hoef & Boveng, 2007). For the analysis of count data, Poisson regression is more appropriate. One condition for using Poission regression is that the data follows a Poission distribution where the variance is equal to the mean. When the variance exceeds the mean, there is a clear indication that the data is 'overdispersed', and the Poisson restriction is violated (Ver Hoef & Boveng, 2007). As becomes clear from the previous section and tables 1 and 2, the variance for the variable ESB index exceeds the mean for the full sample as well as every subgroup. This is a strong indication that the data might be 'overdispersed'. This is probably due to the fact that the distribution shows an extreme spike at the left-hand side of the distribution for the values 0 and 1, while it continues up to the value 47.

A negative binomial model can be applied to overdispersed count data. The negative binomial regression model is an adaption of the Poisson regression where the condition E(Y) = Var(Y) no longer has to hold (Green, 2008). Like the Poission regression model, a negative binomial model estimates maximum log-likelihood. A log-transformed parameter (ln(alpha)) is included in the model to correct for over-dispersion. The model estimates the following equation:

$$Log(ESB\ Index)_{i,t} = \alpha_i + \beta_1 E40\ Score_{i,t} + \varepsilon_{i,t}$$

Robustness checks are included to test whether the findings are robust to other specifications and estimation methods. These include a pooled OLS regression, a random effects negative binomial regression and different model specifications using a lagged dependent variable and a linear probability model with a dummy for ESB author as dependent variable.

4. Results

4.1 Main findings

The first step of the empirical analysis is to check for the correlations between the variables ESB index and E40 score. Table 3 shows that there is a positive correlation between the two variables. This means that a higher E40 score is associated with a higher ESB index. The direction of the correlation is the same for all the different subgroups. However, the size of the correlation differs. For the full sample the correlation is 0.110, for the scientific authors it is 0.157, for ESB authors 0.191 and for scientific ESB authors it is 0.131.

Table 3. Correlations

Total sample

Variables	ESB index	E40 score
ESB index	1.000	
E40 score	0.110	1.000

Scientific authors

Variables	ESB index	E40 score
ESB index	1.000	
E40 score	0.157	1.000

ESB authors

Variables	ESB index	E40 score
ESB index	1.000	
E40 score	0.191	1.000

Scientific ESB authors

Variables	ESB index	E40 score
ESB index	1.000	
E40 score	0.131	1.000

Main model

The preferred estimation method is a negative binomial regression model. This model estimates the dispersion parameter alpha. When alpha is significantly larger than 0, the data is overdispersed and a negative binomial regression is preferred over a Poisson regression. For all sample specifications, the estimated alpha is significantly larger than 0, i.e. 0 lies outside the 95% confidence interval (see table 4). For most specifications, the estimated alpha is extremely large, which is a strong indication that the date is overdispersed and that it follows a negative binomial distribution. Therefore, negative binomial regression is the most appropriate model for this dataset.

The estimated regression coefficients are reported in table 4 for all sample specifications. The estimates for the effect of E40 score on ESB index are positive and significant at the 1% significance level for all 4 sample specifications. The size of the estimated regression coefficients indicates a substantial relationship between both variables. For the full sample the estimated coefficient is 0.145, this indicates that a 1 point increase of the E40 score is associated with a 15.6% increase of the ESB index.[5] The estimated coefficient for the scientific authors subgroup is substantially larger. For this group a 1 point increase of the E40 score is associated with a 27.3% increase of the ESB index.[6] The estimated coefficient for ESB authors is smaller compared to the full sample. For ESB authors, an increase of 1 point of the E40 score is associated with an 8.98% increase of the ESB index.[7] A possible explanation for the lower effect size is that this subsample only includes observations for which ESB index already has a value of 1 or higher. The estimated coefficients for the full sample and the scientific authors might be higher due to the fact that they capture the effect of becoming an ESB author (i.e. from ESB index 0 to 1). Most ESB authors only publish 1 article as the median value for ESB index is 1.

Subdividing the scientific authors in quintiles based on their E40 score shows that the empirical relation between E40 score and ESB index differs between the quintiles. For the first quintile, the estimated coefficient is negative and significant at the 1% level. For the second and third quintile, the regression coefficients do not differ significantly from 0. For the fourth quintile, the estimated coefficient is positive and significant at the 5% level. For the highest quintile, the estimated coefficient is substantially smaller than for the fourth quintile, but again positive and significant at the 1% level.

The estimated regression coefficient for the lowest quintile suggests that for this quintile an increase of 1 point of the E40 score is associated with 99.5% decrease of the ESB index.[8] An increase of 1 point for the E40 is a relatively large increase, considering that the E40 scores for this quintile vary between 0.010 and 0.32. It does indicate that in the bottom 20% of the E40 score distribution, an increase of scientific performance is negatively associated with the ESB index. The estimated coefficient does not differ significantly from 0 for the second and third quintiles. The effect is significant again and positive for the fourth and fifth quintile.

[5] $100 * (e^{0.145} - 1) \approx 15.6$
[6] $100 * (e^{0.241} - 1) \approx 27.3$
[7] $100 * (e^{0.0860} - 1) \approx 8.98$
[8] $100 * (e^{-5.356} - 1) \approx -99.5$

To understand the model better, predicted counts for ESB index at intervals of E40 score are reported in table 5. The estimated marginal effects indicate that the average predicted ESB index for an economist with an E40 score of 1 is 0.330. For an economist with an E40 score of 5, the average predicted ESB index is 0.590. The predicted ESB index value increases with E40 score, a high ranked economist with an E40 score of 31 has an expected ESB index of more than 25. Although all estimates differ significantly from zero at the 1% level, some caution is needed when interpreting the results. The 95% confidence interval shows that the estimates are less precise when the E40 score increases. This is probably due to several extreme values in the right skew of the distributions of both the ESB index and the E40 score. However, the 95% confidence intervals still show that the ESB index steadily increases with E40 score.

A negative binomial regression model does not have an R-squared. Therefore, researchers came up with a pseudo R2 which has a similar interpretation. The pseudo R2 values are listed in table 4 and indicate that the explanatory value of the model is low. This is probably because the dataset contains a lot of observations that have the value 0 for either ESB index or E40 score.

Table 4. Negative binomial regression

	1. Full sample	2. Scientific authors	3. ESB authors	4. Scientific ESB authors	5. Q1	6. Q2	7. Q3	8. Q4	9. Q5
VARIABLES	ESB index	ESB index	ESB index	ESB index	ESB index	ESB index	ESB index	ESB index	ESB index
E40 score	0.145***	0.241***	0.0860***	0.0499***	-5.356***	1.481	-0.220	0.541**	0.135***
	(0.00982)	(0.0139)	(0.00791)	(0.00855)	(1.218)	(1.644)	(0.596)	(0.211)	(0.0164)
Constant	-1.254***	-1.720***	0.700***	0.971***	-0.352	-2.625***	-1.739***	-2.007***	-1.050***
	(0.0207)	(0.0450)	(0.0162)	(0.0331)	(0.277)	(0.747)	(0.453)	(0.301)	(0.107)
Alpha	7.873***	14.892***	0.413***	0.604***	21.980***	23.810***	17.451***	14.112***	9.649***
	(0.196)	(0.519)	(0.0232)	(0.0348)	(1.773)	(2.351)	(1.596)	(0.986)	(0.493)
Observations	44,026	22,307	6,608	2,278	4,472	4,482	4,437	4,455	4,461
Pseudo R2	0.0081	0.0195	0.0175	0.0082	0.0054	0.0005	0.0000	0.0017	0.0091

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 5. Average predicted value for ESB index at interval values of E40 score

N = 44,026

	Margin	Std.Err.	z	P>z	[95%Conf.	Interval]
_at						
1 E40 score = 1	0.330	0.006	51.330	0.000	0.317	0.342
2 E40 score = 3	0.441	0.013	34.180	0.000	0.416	0.466
3 E40 score = 5	0.590	0.027	21.810	0.000	0.537	0.642
4 E40 score = 7	0.788	0.051	15.580	0.000	0.689	0.887
5 E40 score = 9	1.054	0.088	12.030	0.000	0.882	1.225
6 E40 score = 11	1.408	0.144	9.770	0.000	1.126	1.691
7 E40 score = 13	1.883	0.229	8.220	0.000	1.434	2.332
8 E40 score = 15	2.517	0.355	7.090	0.000	1.821	3.213
9 E40 score = 17	3.365	0.540	6.230	0.000	2.306	4.424
10 E40 score = 19	4.499	0.810	5.550	0.000	2.911	6.086
11 E40 score = 21	6.014	1.200	5.010	0.000	3.662	8.367
12 E40 score = 23	8.040	1.762	4.560	0.000	4.587	11.493
13 E40 score = 25	10.749	2.566	4.190	0.000	5.720	15.777
14 E40 score = 27	14.369	3.711	3.870	0.000	7.096	21.643
15 E40 score = 29	19.210	5.337	3.600	0.000	8.749	29.671
16 E40 score = 31	25.681	7.638	3.360	0.001	10.710	40.652
17 E40 score = 33	34.332	10.884	3.150	0.002	13.000	55.664
18 E40 score = 35	45.897	15.450	2.970	0.003	15.616	76.178

4.2 Robustness checks

Several robustness checks have been performed to check whether the empirical results hold when the model is specified differently or estimated differently.

Linear regression

The first robustness check is an estimate of the same model specification using a pooled OLS regression instead of a negative binomial regression. The results are listed in appendix 7.1. The Pooled OLS estimates show similar results as the negative binomial regression. The estimated regression coefficients are positive and statistically significant for all 4 sample specifications. The estimated effect is significant at the 1% level for the full sample, scientific authors and ESB authors. For scientific ESB authors, the effect is significant at the 5% level. The similarity also holds for the quintiles of scientific authors. The first quintile has a negative regression coefficient that is significant at the 1% level. For the second and the third quintile, the estimated effect does not differ significantly from zero. For the fourth and fifth quintile the effect is statistically significant again (respectively at the 10% and the 1% level) and positive.

The one notable difference between the pooled OLS estimates and the negative binomial regression estimates is the size of the regression coefficients. Contrary to the negative binomial model, the size of the regression coefficient for the ESB authors sample is larger than the one for the full sample and the scientific authors sample. However, pooled OLS does not control for the overdispersion in the data. The estimates are therefore influenced by the large amount of 0s in the dataset which could lead to over- or underestimations of the regression coefficients. Therefore, the size of the regression coefficient cannot be interpreted.

Lagged dependent variable

The second robustness check is to estimate the negative binomial regression using a one-year lag of the ESB index. The new dependent variable ESB index_lag is measured one year later than the E40 score. So, for example, where the E40 index for 2015 is calculated over 2010-2014, the ESB index_lag is calculated over 2011-2015. So far, I have only tested for the contemporary relationship between ESB index and E40 score. If there is a causal relationship between the two variables, it would be possible that it takes some time to reach its full effect.

The results are listed in appendix 7.2. The estimates are very similar to the estimates of the contemporary model. The significance levels, direction and size of estimated effects are almost equal to the contemporary model. Therefore, there is no reason to assume that the estimates of the contemporary model are biased due to lagged effects. Since both the ESB index and the E40 score already consider a 5-year period, the main model could already be capturing some lagged effects.

Random effects

Because the of the panel structure of the data, a random effects estimation can be performed to test whether the results hold when author specific tests are controlled for. The estimates of a random effects negative binomial regression are reported in appendix 7.3. The log likelihood ratio test gives a P-value < 0.01 which is a strong indication that random author-specific effects are statistically related to the ESB index. The size of the estimated regression coefficients for E40 score are smaller, but still significant at the 1% level for both the full sample and the subsample of ESB authors. The random effects estimates indicate that at least part of the statistical relationship between ESB index and E40 score can be explained by author-specific effects. However, even when controlling for these effects, the estimated regression coefficients for the E40 score are still positive and significant at the 1% level.

A fixed effects estimator has not been performed because such a model is not appropriate for this dataset for two main reasons. First of all, it is not likely that author specific effects are constant over time. Secondly, using a fixed effects estimator substantially lowers the amount observations.

Linear probability model

Finally, a linear probability model is used to estimate the relationship between economists' scientific performance and the probability they will publish in ESB. The dependent variable is the dummy variable ESB author. It has the value 0 if the economist has not published in ESB in the previous five years (i.e. ESB index = 0) and the value 1 of the economist has (i.e. ESB index > 0). The model is only estimated for the subgroup scientific authors, so it estimates the probability that a scientific author will publish in ESB. The results are listed in appendix 7.4.

The estimated regression coefficients are in line with the main model. It indicates a positive, statistically significant relationship between E40 score and becoming an ESB author.

The estimated regression coefficient suggests that a 1-point increase of E40 score increases the likelihood that an economist publishes in ESB with 2.32%. The estimated coefficient for the lowest quintile is negative and statistically significant at the 1% level. The coefficient suggests that for this quintile, the likelihood of becoming an ESB author decreases by 25.6% with an increase of 1 point for E40. The size of the estimate is large, but this is probably due to the fact that E40 score for this quintile varies between 0.010 and 0.32. An increase of one standard deviation (0.074) would be associated with a 1.89% decrease of the likelihood that the economist publishes in ESB. The estimated effects are insignificant for the second, third and fourth quintile. The effect is positive and significant for the fifth quintile. For this quintile, a one standard deviation (3.52) increase of E40 score is associated with a 6.79% increase of the likelihood that the economist will publish in ESB in the same period. Again, there is no indication that the main model biased or insufficient.

4.3 Discussion

The empirical evidence strongly suggests that there is a positive relationship between scientific performance as measured by the E40 score and societal contribution for which the number of ESB publications is used as a proxy. For all sample specifications, the relation is positive and highly significant. The empirical findings are robust to different estimation methods and model specifications. Effect sizes differ between the different sample specifications. However, these differences can be largely explained by the spike of observations around the values 0 and 1 for both the ESB index and the E40 score. That the estimated size of the relationship is weaker for ESB authors and scientific ESB authors is probably due to the fact that the jump from the value 0 to 1 for ESB index is filtered out in these samples.

These findings provide strong evidence against the hypothesis (H1) that there is no significant relationship between scientific performance and societal contribution. Contrary to what the literature would suggest, there is a clear indication that scientifically successful economists are more likely to publish in ESB. As ESB serves as a proxy for societal contribution, these findings suggest that scientific success and valorisation are positively correlated. There is also no evidence that supports the notion that researchers either devote their time to publishing in academic journals (i.e. their academic career) or to more socially relevant topics. There is also no evidence for the second hypothesis (H2) that scientifically successful economists are not among the most prominent ESB authors. For the subgroups ESB authors and scientific ESB authors, the size of the relationship is significant and positive. So even among ESB authors, those who are scientifically more successful tend to publish more in ESB.

One remarkable finding is that the direction and the size of the relationship differ between the quintiles of scientific economists. For the 20% lowest-scoring economists, there is a negative relationship between scientific performance and ESB publications. For the second and third quintiles, the relationship is not statistically significant. Only for the highest-scoring 40%, there is a statistically significant positive relation between E40 score and the number of ESB publications. This finding suggests that there are career effects at work: more successful economists are more likely to publish in ESB. Two potential explanations can be thought of:

(1) Researchers with established careers find it easier to get their work published in ESB. They have already built a reputation for themselves and their research as their high E40 score indicates that they have published in leading journals. It could be the case that they want to valorise their successful research. Or there could be unobserved network effects at work. The ESB editorial board regularly requests articles from authors on certain topics they find relevant (Kleinknecht, 2020). It is likely that successful scientists have a higher chance to be asked because they are either considered to be an expert in a certain field, or they hold important positions at universities or research institutes which makes them more visible.

(2) Those researchers with already established academic careers might devote more of their time to societal contributions. As they have already proven themselves in academia, there is less need for them to publish in the top journals. In that sense, they would have more time to pursue socially relevant research topics. For the lowest quintile, the estimated relationship between scientific performance is negative. A possible explanation for this finding could be that starting researchers or researcher without established academic careers devote most of their time to their academic careers and research topics that are publishable in peer-reviewed journals.

Limitations

As mentioned before, a causal interpretation of the relationship between scientific performance and societal contribution is not possible based on this research. Any interpretation is limited to the direction and significance of the empirical relationship. So, it is not possible to conclude that scientific success *causes* an economist to publish in ESB. There could be other, unobserved variables that determine whether or not an economist decides to publish in ESB. Furthermore, it is not clear in what direction the two variables affect each other. This could be tested through a Granger Causality test. With the limited amount of time periods available in this dataset, such a statistical test is not possible (Wooldridge, 2014). Finally, there are other channels through which economists can valorise their work. It is possible that results would be different if additional proxies for societal contribution are included.

Due to time and data constraints, it was not within the scope of this research to include more explanatory variables. Further research could include more time periods and more explanatory variables such as gender, institution affiliation, age and academic position to increase the explanatory power of the model. Furthermore, alternative ways for economists to valorise their work could be included to have a more complete understanding of societal contributions. Potential other sources through which economists can valorise their work are online platforms such as Twitter, media performances or (opinionated) publications in journals and newspapers. Such sources lend themselves well for an altmetric research approach to measure the societal contribution efforts of scientists.

5. Conclusion

This research uses new data to analyse the relationship between scientific performance and societal contribution of Dutch economists. The empirical findings of this research indicate a significant, positive relationship between the two variables. This suggests that on average, researchers who are scientifically successful are more likely to valorise their work through ESB. The estimated relationship seems to be driven mainly by the highest-ranking economic scientists. For the 60% lowest-scoring scientists, the estimated relationship is either insignificant or negative. The findings are robust to different model specifications and estimation techniques. So, even though there are legitimate concerns in the literature about the social relevance of economic research, this research suggests that economic scientists are, at least to some extent, concerned with the valorisation of their work. The causal mechanism and intrinsic motivations behind these findings remain unclear, but there is a clear indication that scientific success is not separate from societal contribution.

This research is the first quantitative analysis of the societal contribution efforts of Dutch economists. Future research is needed to further analyse the quantitative relationship between academic performance and societal contribution. One possible way to do so is by including more channels through which scientists can valorise their work. This type of research is particularly valuable to policy makers who are increasingly concerned with the valorisation of publicly financed research. Empirical research can provide policy makers with insights into the actual valorisation practices of researchers and enables them to make informed policy decisions. This research also contributes to the academic debate on measuring the social impact of scientific research. It suggests that altmetric methods are useful to move away from payback framework analyses, which have big methodological implications for humanities and social sciences. As it is hard to measure social impact, a focus on output channels for the valorisation of research could serve as an alternative for future studies into the social impact of social sciences and humanities.

6. Bibliography

Akerlof, G. A. (2020). Sins of Omission and the Practice of Economics. *Journal of Economic Literature*, *58*(2), 405-418.

Bornmann, L. (2012). Measuring the Societal Impact of Research. *EMBO reports, 13*, 673-676.

Bornmann, L. (2016). Scientific Revolution in Scientometrics: The Broadening of Impact from Citation. In C. R. Sugmito, *Theories of Informetrics and Scholarly Communication* (pp. 347-359). Berlin: De Gruyter.

Bornmann, L., & Daniel, H.-D. (2005). Does the h-index for ranking of scientists really work? *Scientometrics, 65*(3), 391-392.

Bush, V. (1945). *Science, The Endless Fronteir.* Arlington, VA: National Science Foundation.

Clarivate Analytics. (2020). *Journal Citation Reports*. Retrieved 06 22, 2020, from InCites: http://help.incites.clarivate.com/incitesLiveJCR/glossaryAZgroup/g4/7790-TRS.html

Clarivate Analytics. (2020). Retrieved 06 22, 2020, from Web of Science: http://apps.webofknowledge.com.proxy.library.uu.nl/WOS_GeneralSearch_input.do?product=WOS&search_mode=GeneralSearch&SID=F6vUEwR69RIgMPWH7rI&preferencesSaved=

Davis, W. L. (2007). Reflections and Self-Reflections on the Economics Profession: Economists' Opinions of Economists' Work. *American Journal of Economics and Sociology*, 267-288.

Ductor, L., Goyal, S., Leij, M. v., & Paez, G. (2020). On the Influence of Top Journals. *Tinbergen Institute Discussion Paper*.

ERIM. (2020). *ERIM Journals List (EJL)*. Retrieved 06 22, 2020, from Erasmus Institute of Management: https://www.erim.eur.nl/about-erim/erim-journals-list-ejl/

ESB. (2020). *Over ESB*. Retrieved 03 26, 2020, from ESB: https://esb-nu.proxy.library.uu.nl/service/overesb#het-vakblad-voor-economen

ESB. (2020). *Publiceren*. Retrieved 06 26, 2020, from esb.nu: https://esb-nu.proxy.library.uu.nl/service/publiceren#artikelen

European Commission. (2010). *Assessing Europe's university-based research. Expert group on assessment of university-based research.* Brussels: Publication Office of the European Union.

Europese Commissie. (2014). *Hirzon 2020 in het kort: het kaderprogramma van de EU voor onderzoek en innovatie.* Luxemburg: Bureau voor publicaties van de Europese Unie.

Gorga, C. (2009). Concordian Economics: Tools to Return Relevance to Economics. *Forum of Social Economics*, 53-69.

Green, W. H. (2008). Accounting for Excess Zeros and Sample Selection in Poisson and Negatvie Binomial Regression Models. *NYU Working Paper No. EC 94 - 10*, 1 - 37.

Hammerfelt, B. (2014). Using altmetrics for assessing research impact in the humanities. *scientometrics*, 1419-1430.

Holmberg, K., & Thelwall, M. (2013). Disciplinary differences in Twitter scholarly communication. In J. Gorraiz, E. Schieber, C. Gumpenberger, M. Hörlesberger, & H. Moed, *Proceedings of ISSI 2013* (pp. 567-582). Vienna: Austrian Institute of Technology GmbH.

Jong, S. P., Smit, J., & Drooge, L. v. (2016). Scientists' Response to Societal Impact Policies: A Policy Paradox. *Science and Public Policy, 43*(1), 102-114.

Kleinknecht, R. (2020, 6 11). Interview with Robert Kleinknecht, Senior Editor ESB. (T. Stuart, Interviewer). Full record available upon request.

Li, X., Thellwall, M., & Guistini, D. (2012). Validating Online Reference Managers for Scholarly Impact Measrument. *scientometrics, 91*(2), 337-354.

Lukkezen, J. (2019). Economentop 40 2019. *Economisch Statistische Berichten, 104*, 581-583.

Martin, B. (2007). Assessing the Impact of Basic Research on Society and the Economy. *FWF-ESF International Conference on Science Impact: Rethinking the Impact of Basic Research on Society and Economy.* Vienna: FWF-ESF.

Meulen, B. v., & Rip, A. (2000). Evaluation of societal quality of public sector research in the Netherlands. *Research Evaluation*, 11-25.

Mohammadi, E., & Thelwall, M. (2013). Assessing the Mendeley Readership of Social Science and Humanities Research. In J. Gorraiz, E. Schiebel, C. Gumpenberger, M. H:orlesberger, & H. Moed, *Proceedings of ISSI 2013* (pp. 200-214). Vienna: Austrian Institute of Technology GmbH.

Molle, W. (2016). *ESB 100 jaar in bedrijf: Behoud van het doel; verandering van de vorm.* Amsterdam: Economisch Statistisch Berichten.

Nederland Ondernemend Innovatieland. (2009). *Van voornemens naar voorsprong: Kennis moet circuleren. Voorstel voor een Nederlandse valorisatieagenda.* Den Haag: Interdepartementale Programmadirectie Kennis en Inovatie.

Nightingale, P., & Scott, A. (2014). Peer review and the relevance gap: ten suggestions for policy-makers. *Science and Public Policy*, *34*(8), 543-553.

OCW. (2014). *Wetenschapsvisie 2025: keuzes voor de toekomst.* Den Haag: Ministerie van Onderwijs, Cultuur en Wetenschap.

Pedersen, D. B., Gronvad, J. F., & Hvidtfeldt, R. (2020). Methods for mapping the impact of social sciences and humanities - A literature review. *Research Evaluation*, 4-21.

Research Excellence Framework. (2011). *Assessment framework and guidance on submissions.* Bristol: REF.

Phlippen, S. (2014). De Economentop 2014. *Economisch Statistische Berichten*, *99*, 786-788.

Priem, J., Groth, P., & Taraborelli, D. (2012). The Altmetrics Collection. *Plos One*, 1-2.

Priem, J., Taraborelli, D., Groth, P., & Neylon, C. (2010, 10 26). *Altmetrics: A manifesto*. Retrieved from Altmetrics: http://altmetrics.org/manifesto/

Rond, M. d., & Miller, A. N. (2005). Publish or Perish: Bane or Boon of Academic Life? *Journal of Management Inquiry*, 321-329.

Samuel, G. N., & Derrick, G. E. (2015). Societal impact evaluation: Exploring evaluator perceptions of the characterization of impact under the REF2014. *Research Evaluation*, 229-241.

Tahamtan, I., & Bornmann, L. (2020). Altmetrics and societal impact measurements: Match or mismatch? A literature review. *El profesional de la información*.

Tinbergen. (2020). *The TI Journal List*. Retrieved 06 22, 2020, from Tinbergen: https://www.tinbergen.nl/media/research/ti_jrn_list_update-november-2016.pdf

Ver Hoef, J. M., & Boveng, P. L. (2007). Quasi-Poisson vs. Negative Binomial Regression: How Should We Model Overdispersed Count Data? *Ecological Society of America, 88*(11), 2766 - 2772.

Weymouth, S., & Macpherson, J. M. (2012). The Social Construction of Policy Reform: Economists and Trade Liberalization Around the World. *International Interactions, 38*(5), 670-702.

Wooldridge, J. M. (2014). *Introduction to Econometrics.* Mason, OH: Cengage Learning EMEA.

7. Appendix

7.1 Pooled OLS

	Full sample	Scientific authors	ESB authors	Scientific ESB authors	Quintile 1	Quintile 2	Quintile 3	Quintile 4	Quintile 5
VARIABLES	ESB index	ESB index	ESB index	ESB index	ESB index	ESB index	ESB index	ESB index	ESB index
E40 score	0.0865***	0.111***	0.235***	0.154**	-0.954**	0.216	-0.0320	0.161*	0.0926***
	(0.0188)	(0.0207)	(0.0581)	(0.0613)	(0.440)	(0.253)	(0.106)	(0.0889)	(0.0279)
Constant	0.269***	0.141***	2.019***	2.658***	0.441***	0.0446	0.173**	0.0658	0.292**
	(0.0145)	(0.0253)	(0.0708)	(0.186)	(0.125)	(0.112)	(0.0815)	(0.113)	(0.124)
Observations	44,026	22,307	6,608	2,278	4,472	4,482	4,437	4,455	4,461
R-squared	0.012	0.025	0.036	0.017	0.003	0.000	0.000	0.001	0.012

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

7.2 Negative binomial regression with one-period lagged dependent variable

VARIABLES	Full sample ESB index_lag	Scientific authors ESB index_lag	ESB authors ESB index_lag	Scientific ESB authors ESB index_lag	Q1 ESB index_lag	Q2 ESB index_lag	Q3 ESB index_lag	Q4 ESB index_lag	Q5 ESB index_lag
E40 score	0.136***	0.240***	0.0916***	0.0518***	-4.567***	2.845*	-0.249	0.485**	0.134***
	(0.00987)	(0.0140)	(0.00861)	(0.00936)	(1.221)	(1.625)	(0.628)	(0.200)	(0.0169)
Constant	-1.220***	-1.734***	0.623***	0.911***	-0.533*	-3.214***	-1.720***	-1.948***	-1.062***
	(0.0197)	(0.0442)	(0.0175)	(0.0348)	(0.273)	(0.738)	(0.479)	(0.285)	(0.108)
Alpha	7.487***	15.220***	0.588***	0.783***	21.744***	23.592***	18.319***	14.314***	10.077***
	(0.181)	(0.520)	(0.0281)	(0.0427)	(1.787)	(2.262)	(1.644)	(0.967)	(0.519)
Observations	44,026	22,307	6,608	2,278	4,472	4,482	4,437	4,455	4,461
Pseudo R2	0.0072	0.0191	0.0154	0.0072	0.0041	0.0016	0.0001	0.0014	0.0087

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

7.3 Random effects

	Full sample	ESB authors
VARIABLES	ESB index	ESB index
E40 score	0.0572***	0.0625***
	(0.00758)	(0.00563)
Constant	20.66	5.083***
	(12.82)	(0.617)
r	2.78e+08	206.1947***
	(3.57e+09)	(123.02)
s	.0925***	2.357403***
	(.00256)	(.0992572)
Observations	44,026	6,608
Number of authors	8,806	2,064

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

7.4 Linear probability model

	Scientific authors	Q1	Q2	Q3	Q4	Q5
VARIABLES	ESB_auteur	ESB_auteur	ESB_auteur	ESB_auteur	ESB_auteur	ESB_auteur
E40 score	0.0232***	-0.256***	0.0986	0.0329	0.0290	0.0193***
	(0.00240)	(0.0801)	(0.0740)	(0.0425)	(0.0180)	(0.00364)
Constant	0.0654***	0.133***	0.0167	0.0470	0.0678***	0.0946***
	(0.00442)	(0.0204)	(0.0317)	(0.0312)	(0.0263)	(0.0187)
Observations	22,307	4,472	4,482	4,437	4,455	4,461
R-squared	0.034	0.005	0.001	0.000	0.001	0.029

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1