Outerfactor and the indirect journal impact

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Abstract

In this paper, we use research chains across the citation graph as the basis for journal impact analysis. While some existing measures take into account research chains that end in a given journal, we calculate the proportion of research chains that *include* a journal, obtaining a new index of journal impact, Outerfactor, that is directly related to Pagerank (Brin and Page, 1998), Eigenfactor (Bergstrom, 2007) and the Invariant Method (Pinsky and Narin, 1976). In this way, the Outerfactor score obtained by each journal is independent on its own citation pattern and its article share. To our knowledge, this is the first measure that satisfifes these invariance properties whilst accounting for both direct and indirect impact. Based on research chains that connect two journals, we also construct new measures for analyzing cross-impact. This cross-impact analysis results in a two-fold view of Outerfactor in terms of a journal's influence (impact) on other journals, or a journal's contribution to all journals' impact scores. Finally, we provide an illustration with 60 economics journals, showing how Outerfactor performs compared to other measures: apart from its cardinal invariance, Outerfactor behaves more robustly to ordinal manipulation than other eigenvector-based measures.

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1 Introduction

Citation analysis is an area of increasing interest that has become an important tool for research quantification and analysis. Although it is an imperfect measure of research impact, the fact that researchers make references to those papers they have found useful, implies that citation patterns include partial information about the significance of research papers or journals. In this paper, we provide a theoretical framework that is able to accommodate several journal impact measures, we construct a new index of journal impact and we provide an illustration of our results by to a subset of sixty economics journals.

Measures of journal impact assign different scores to journals depending on their position in a citation graph where journals are represented by nodes and references by links between those journals. The most direct way of quantifying this influence is by counting how many citations a journal receives. Ceteris paribus, a journal receiving more citations is more influential, since each citation can be regarded as a "vote" for that journal. This is the idea behind Impact Factor (Garfield, 1955), a measure reported by the Journal Citation Reports since its creation. A journal's Impact Factor is the average number of citations per article that this journal receives.

However, information in the citation graph can be used in a more extensive way. Direct citation count is only one of many measures that produce information about the importance of nodes in a given citation graph. Other measures weight differently citations received from different articles or journals, so that the impact of a journal depends on its citations as well as on the impact of its citing journals. Therefore, these measures take into account both direct and indirect impact. Traditional examples are shortest-path centrality, closeness, betweenness (Freeman, 1979), eigenvector centrality (Bonacich, 1987) and the Katz centrality measure (Katz, 1953).

A more recent influential measure of this type is Pagerank (Brin and Page, 1998). In the context of journal citations, Pagerank assigns to each journal the stationary probability of a Markov chain where a random surfer travels across the citation graph, jumping to a random journal with a fixed probability. Pagerank is the founding algorithm used by Google to sort its search results. Several measures that rely on Pagerank have been specifically used for journal ranking. For instance, the Invariant Method (Pinsky and Narin, 1976; Palacios-Huerta and Volij, 2004) is closely related to Pagerank, Scopus also assesses journal impact by using Pagerank (González-Pereira et al., 2009). Finally, Eigenfactor (Bergstrom, 2007) uses Pagerank in order to assign different weights to each journal, and then it counts citations of each journal weighting them by the Pagerank of the source. Eigenfactor is the first eigenvector-based measure that has been included in the Journal Citation Reports.

In this paper, we propose a new measure of journal impact that also takes into account both direct and indirect influence. The model relies on the basic concept of a *research chain*, which is a finite sequence (or pile) of journals (or papers) connected through references. Intuitively, in this research chain model a researcher starts reading a given article, and then she starts reading another article from the reference list, and so on. At some point, the researcher stops this process, resulting in a chain (pile) of articles. The measure that we propose −Outerfactor−, is roughly the proportion of research chains in which a given journal is included, *i.e.,* the probability that a paper from this journal *appears at least once* in the typical research chain. In this sense, the Outerfactor score of a journal can be regarded as a measure of its *impact* on other journals. This framework will also allow us to provide cross-journal statistics to measure how a given journal will influence (or contribute to the impact of) any other journal. As we will show, cross-journal analysis will allow for an added interpretation of Outerfactor as a measure of *contribution* to all journals' Eigenfactor impact.

An interesting feature of Outerfactor is that the score of each journal depends only on other journals' citation patterns. Therefore, our measure is completely independent of own citation patterns and journal i will not be able to increase its score by promoting citations to the journals that often cite journal i directly or indirectly (or to itself). To our knowledge, no measure taking into account indirect impact has this property. For instance, as we will show, Pagerank, Eigenfactor and the Invariant Method can be interpreted as probabilities of a researcher ending his research chain in a given journal[1]. Thus, under these measures, a journal is able to increase its score if it generates *cycles* that return to it, and this is possible even when the indirect-impact measure ignores (removes) self-citations before calculations are carried out. computation takes place[2]. However, once a researcher has arrived to a given journal for her first time, it is irrelevant to Outerfactor whether she returns to this journal again during the research process. This is the simple reason why the Outerfactor score assigned to a journal i is independent of the structure of citations made by journal i.

Another related property is that a journal's Outerfactor is invariant to this journal's article share. In other words, journal i's Outerfactor will be robust to journal i "trying" to increase its score by producing more articles and, hence, increasing the probability that the researcher starts a chain at journal i. This property is also the result of a very intuitive fact: in order to assess a journal's Outerfactor, no research chain is allowed to start at that journal.

Our contribution possesses four inter-related dimensions. *First*, we use a simple framework, the *research chain model*, that relates Pagerank, the Invariant Method, Eigenfactor and Outerfactor in the same setting,

[1] An equivalent interpretation of these measures is the average number of times that journal i will appear in a research chain.

[2] Self-citations are cycles of length one. Meassures of indirect impact typically include longer cycles, for instance of length two, when the researcher visits journal i, then j, and then returns to i.

allowing us to easily interpret and compare all these measures as well-defined probabilities. The research chain model is identical to the Markov model used in Pagerank, it only differs in its interpretation. In Pagerank's Markov model, a random surfer starts a random walk at a journal (or article) chosen at random from the whole set of journals (or articles). Then the researcher follows citations in the research graph, but with probability $1-\alpha \in (0,1)$ she starts a new research chain by jumping to a new randomly selected journal (or article). This results in a Markov chain, an infinite walk where every journal will be visited with a stationary probability, its Pagerank score. However, in the research chain model, we focus on the typical (average) research chain which has finite length almost surely, that is, on any research chain formed between these random jumps. In this framework, it is easy to frame and compare all these eigenvector-based measures. More specifically the Pagerank and Eigenfactor scores for a journal i are probabilities of ending at journal i in a research chain[3]. Similarly, journal i's Outerfactor is the probability of using (at least once) any article from journal i in the typical research chain. We point out that the research chain model (and the set of measures we propose) is still valid when the researcher is assumed to perform more than one but a *finite* number of research chains.[4] The model enables us to provide a closed-form formula for our measure as a function of Pagerank and Eigenfactor.

Second, to our knowledge Outerfactor is the first impact score that takes into account both direct and indirect citations, whilst preserving the invariance to own-citation patterns and to article shares. Impact factor (when self-citations are removed) is invariant to own-citation patterns but it does not take into account indirect citations. Pagerank, Eigenfactor and the Invariant Method take into account indirect citations but they do depend on own-citation patterns (even when self-citations are removed). The increasing importance of impact measures in research evaluation makes these properties specially pertinent. Several scientometric measures are often used by research evaluation committees and institutions as a tool to obtain partial information about a candidate's research performance. Moreover, journal impact is also used by libraries when deciding which journals they will subscribe. Therefore it is important to evaluate this impact with measures that are as robust to manipulation by journals/authors as possible.

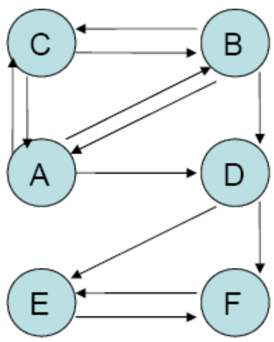
As the vast majority of measures of journal impact, Outerfactor is cardinal in nature. In our model, cardinal comparisons of Pagerank, Eigenfactor or Outerfactor have a straightforward meaning: journal i receives twice the score of journal j if i is twice as used as j.[5]

[3] The Invariant Method will be the same probability when the typical research chain has length that grows to infinity, that is, when α tends to 1.

[4] To see this, note that if OF_i is the Outerfactor score of journal i, and the researcher follows K different research chains, then its adjusted Outerfactor for K trials would be $1-(1-OF_i)^K$. This is increasing in OF_i, so that the ranking of journals will be the same.

[5] We also believe that Outerfactor is somehow related to actual journal revenue. In fact, most journals offer subscription

An interesting consequence of the invariance properties of Outerfactor is that if we have two journals that receive exactly the same citations from the same set of journals, Outerfactor assigns a higher score to the journal which cites relatively less this set of reference sources. Why? Because the less citing journal obtains indirect impact from the more citing journal. On the contrary, Eigenfactor, Impact Factor and the Invariant Method will give the same score to both journals. We illustrate this fact in Figure 1:



	OF	IF	EF	IM
A	0.215	2	0.059	0
B	0.215	2	0.059	0
C	0.167	2	0.050	0
D	0.260	2	0.050	0
E	0.894	2	0.391	0.5
F	0.894	2	0.391	0.5

Figure 1: Outerfactor (IM), Impact Factor (IF), Eigenfactor (EF) and Invariant Measure (IM) for a set of 6 journals with 10 articles each. Each link represents 10 citations.

Each node represents a journal. All journals have 10 articles. Each link represents citations from journal to journal, and for simplicity we suppose that every link represents 10 citations. Thus, 50% of journal C's citations go to journal B and 50% to journal A. An instance of a research chain could be (A,B,D,E), or (C,B,C) where the latter chain starts with an article from C, citing an article from B, citing an article from C, and finally the research chain ends. Therefore, the chain (C,B,C) occurs with probability $\frac{1}{6}\alpha^2(1-\alpha)$ in the research chain model. All journals receive 2 edges (20 citations), therefore they are scored equally by Impact Factor (IF). Outerfactor (OF) and Eigenfactor (EF) take into account both direct and indirect impact by weighting differently citations from different journals. They assign the highest score to E and F. Nevertheless, they value journals C and D in a different way. In particular, EF assigns the same score to C and D because they receive the same citations from the same set journals. However, OF ranks D over C, because it does not take into account own citation patterns so that the value received by D through A and B is increased by indirect impact of C, while there is no indirect impact from D to C through A and B.

Third, the research chain framework allows for the measurement of cross-effects between any two journals. Cross-effects are an extension of cross-citations to include both direct and indirect impact. We divide these

fees to institutions. These institutions generally decide whether to subscribe or not depending on mere usage (for instance, by establishing a minimum threshold of journal usage in order to make the subscription decision).

cross-effects into two classes of measures: cross-influences and cross-contributions. On the one hand, cross-influence of journal i on journal j refers to how often articles from journal i are used in research chains that started at journal j, that is, how journal j cites directly or indirectly journal i. In simple words, cross-influence is accounting for the impact of one journal on another. In this paper, we introduce two measures of cross-influence: Eigen-influence and Outer-influence. On the other hand, cross-contribution of journal i to journal j's impact refers to how much of j's impact score (measured by Eigenfactor) is due to journal i, i.e., how often citations made to journal j make direct or indirect use of journal i. In other words, our coefficients of cross-contribution measure how much journal i is responsible for journal j's impact score. We introduce closed-form expressions for all cross-effects as functions of the Pagerank (or Eigenfactor) of journals i and j.

More importantly, measuring these cross-effects will allow us to provide an important two-fold interpretation of Outerfactor: a journal's Outerfactor can be seen as its average impact (*influence*) on other journals, or as its *contribution* to the all journals' impact scores (measured by their Eigenfactor).

Finally, we illustrate all measures for a subsample of 60 economics journals. We compute Outerfactor and compare it with Impact Factor, Eigenfactor Pagerank and the Invariant Method. Results show that the rankings provided by Outerfactor are very similar to those by Eigenfactor, but both scores have cardinal differences that become evident when we normalize them by the number of articles in each journal.[6] Moreover, we show that our measure displays a higher resistance to ordinal manipulation in several aspects, like the strategic deletion/addition of references or articles. Additionally, we show that the ranking obtained by Outerfactor is very robust to the existence of self-citations, meaning that Outerfactor is already controlling for the possible undesirable effects of self-citations and that they need not be artificially excluded from the data. We finally compute all of cross-effects for this subset of journals.[7]

2 The model

2.1 Research chains

Our model relies on the notion of *research chain*, which we use as the basic tool for measuring journal impact. A research chain is a finite sequence of journals[8] (for instance, a pile of articles) that a researcher uses during

[6] When we divide Eigenfactor by the share of articles we obtain Article Influence, which is the main eigenvector-based measure provided by JCR that can be compared to Impact Factor.

[7] Differences in the Impact Factor that we report with respect to JCR are mainly due to the fact that we present a simple illustration with a subset of 60 economics journals, while JCR uses all citation data from social sciences.

[8] We perform our analysis on journals, as in the Journal Citation Reports, Palacios-Huerta and Volij (2004), Vergstrom (2007) and Fersht (2009), although the analysis could be carried out at the article level when data is available.

her research process.

Let J be a finite *set of journals* and $s_i > 0$ the number of articles published by journal i. Let $\mathbf{a}$ the vector of *article shares*, that is, $a_i = s_i / \sum_{j \in J} s_j > 0$. Citation patterns are summarized through the $|J| \times |J|$ *citation matrix* $\mathbf{C}$, where each entry c_{ij} denotes the number of citations from journal j to journal i in a specific period of time. Let $c_i = \sum_j c_{ji}$ be the number of citations made by journal i.

We remove self-citations by making the entries in the diagonal equal to zero. Hence, it is assumed that $c_{ii} = 0$ for all $i \in J$.[9]

In order to describe the research chain process, let us define the matrix $\mathbf{H}$, where

$$h_{ij} = \begin{cases} c_{ij}/c_j & \text{if} \quad c_j > 0 \\ 0 & \text{if} \quad c_j = 0 \end{cases}$$

Each entry h_{ij} represents the proportion of citations made by j that are pointing to i. We say that a journal i is a *dangling node* if it makes no citations to other journals, that is, $c_i = 0$. We assume that there are no dangling nodes, that is, every journal cites at least once some other journal. This assumption is reasonable for the vast majority of scientific journals. Thus $\sum_i h_{ij} = 1$ for every journal j, i.e., $\mathbf{H}$ is column stochastic.[10] We define $\mathbf{H}_i$ as the $i-th$ row vector of $\mathbf{H}$.

A research chain is generated as follows. The researcher starts the chain in a randomly selected article, *i.e.,* journal k will be selected with probability a_k. At each moment in time when she is at journal j, with probability $0 \leq \alpha < 1$ she will follow the reference list to read a new journal cited by j; and with probability $1 - \alpha$ the research chain will terminate. In case of continuation, the researcher will step from j to i with probability given by h_{ij}. The matrix $\mathbf{H}$ defines the transition probabilities between journals in this process.

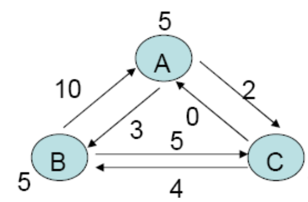
More formally a *research chain* in $\mathbf{H}$ is a finite sequence of journals $\psi = (j_0, j_1, \ldots, j_m)$ such that $h_{j_{l+1} j_l} > 0$ for $0 \leq l < m$. In this random process, journal j_o is initially chosen with probability a_{j_0}. At any moment in time, when the research process is at journal j, it will continue to journal i with probability αh_{ij},

[9] This is inessential to our theoretical contribution. We perform this step in our data in order to fairly compare Pagerank (Brin and Page, 1998), Eigenfactor (Bergstrom, 2007) and Outerfactor in the same citation setting, since the computation of Eigenfactor removes self-citations from the matrix $\mathbf{C}$. However, the invariance properties of our measure (Outerfactor), and specifically the independence of the score with respect to own cittation pattern, also hold when self-citations are not deleted from the citation graph. Moreover, as we show in our examples with 60 economics journals, Outerfactor is very robust to the consideration of self-citations as part of the citation patterns.

[10] A typical scientific journal includes citations to other journals. However, dangling nodes can be incorporated into the model in order to consider journals that are out of the sample. If it is the case, dangling nodes can be treated as in Eigenfactor: defining $h_{ij} = a_i$ when $c_j = 0$, this implies that a dangling node will be forced to point to all other journals according to their article shares given by the vector $\mathbf{a}$. In other words, when a research chain arrives to a dangling journal, it will jump to a random journal.

and it will terminate with probability $1-\alpha$. The *length* of a particular research chain like $(j_0, j_1, \ldots, j_m)$ is m. The length of the typical research chain, that is, the expected amount of journals visited by the researcher in this random process, is given by $l(\alpha) = \alpha/(1-\alpha)$. We adopt a value of $\alpha = 0.85$, which corresponds to a process where our random researcher follows chains of an average length of $l(\alpha) = 6$ journals, *i.e.,* the size of the typical research pile is 6 articles.[11]

As an example, consider the following case with three journals $J = \{A, B, C\}$, where A has 10 articles, B has 6 and **C** has 4. Their mutual citations are



Example 1

Then, the corresponding matrices are

$$\mathbf{s} = \left\{ \begin{array}{c} 10 \\ 6 \\ 4 \end{array} \right\}, \mathbf{a} = \left\{ \begin{array}{c} 0.5 \\ 0.3 \\ 0.2 \end{array} \right\}$$

$$\mathbf{C} = \left\{ \begin{array}{ccc} 5 & 10 & 0 \\ 3 & 5 & 4 \\ 2 & 5 & 1 \end{array} \right\}, \mathbf{H} = \left\{ \begin{array}{ccc} 0 & 0.67 & 0 \\ 0.6 & 0 & 1 \\ 0.4 & 0.33 & 0 \end{array} \right\}$$

2.2 Impact Factor, Invariant Method, Pagerank and Eigenfactor

We now describe some of the existing measures in the literature and we also settle them in the research chain framework.

Definition 1 *The Impact Factor of journal i is*

$$IF_i = \frac{\sum_j c_{ij}}{s_i}$$

[11] The value $\alpha = 0.85$ was proposed by Brin and Page when implementing Pagerank in Google. It is the value usually adopted in the literature. We note that this value could be personalized for different scientific disciplines.

Impact Factor is reported for a sample of 8000 journals by the Journal Citation Reports. It assigns to each journal the number of citations that point to it, divided by citable items in the journal.

Definition 2 *The Invariant Method score of journal i is*

$$IM_i = \frac{\mu_i}{s_i},$$

where μ is the principal eigenvector of $\mathbf{H}$.[12]

In their influential article, Palacios-Huerta and Volij (2004) showed that the Invariant Method can be characterized as the unique ranking method that meets four properties.

For $0 < \alpha < 1$, let

$$\mathbf{Q} = \alpha \mathbf{H} + (1 - \alpha)\, \mathbf{a} \cdot \mathbf{e}^{\top}$$

where $\mathbf{e}$ is a vector of ones.

The Pagerank vector $\mathbf{q}$ (Brin and Page, 1998) of journals is defined as the principal (probability) eigenvector of $\mathbf{Q}$, and it is a function of α, $\mathbf{H}$ and $\mathbf{a}$. Pagerank is the centrality measure used by Google in order to assess the significance of webpages. It is the stationary probability of a Markov chain on the matrix $\mathbf{Q}$. The following straightforward result frames Pagerank in the setting of the typical research chain of finite length that we defined.

Lemma 1 *The probability that a typical research chain terminates at journal i is given by q_i.*

[12] The Invariant Method assumes that the matrix $\mathbf{H}$ is irreducible and this results in a well-defined unique principal eigenvector of $\mathbf{H}$.

According to Palacios-Huerta and Volij (2004), the Invariant Method is the vector $\mathbf{v}$ that solves

$$\mathbf{A}^{-1}\mathbf{C}\mathbf{D}_{\mathbf{C}}^{-1}\mathbf{A}\mathbf{v} = \mathbf{v},$$

that is, $\mathbf{v}$ is the principal eigenvector of

$$\mathbf{A}^{-1}\mathbf{C}\mathbf{D}_{\mathbf{C}}^{-1}\mathbf{A}.$$

In our notation,

$$\mathbf{H} = \mathbf{C}\mathbf{D}_{\mathbf{C}}^{-1}$$

Moreover, $\mathbf{A}$ is a positive diagonal matrix such that its entry a_{ii} is the number of articles of journal i, s_i in our notation.

The principal eigenvector of $\mathbf{H}$ is the vector μ that solves

$$\mathbf{H}\mu = \mu,$$

and therefore

$$\mu = \mathbf{A}\mathbf{v}.$$

Eigenfactor is a successful measure of journal impact (Bergstrom, 2007; Fersht, 2009), which has been included in the Journal Citation Reports since its 2008 Edition. It is a linear transformation of Pagerank.

Definition 3 *The Eigenfactor score (Bergstrom 2007) of journal i is the probability vector*[13]

$$EF_i = \mathbf{H}_i \cdot \mathbf{q}. \tag{1}$$

Since Impact Factor counts citations and Eigenfactor (and Pagerank) weights them by impact of the citing journal, they have been interpreted as measures of "popularity" and "prestige", respectively. One of the main advantages of Eigenfactor, the Invariant Method and Pagerank with respect to Impact Factor is that Impact Factor only accounts for direct impact by counting references. However, Eigenfactor, the Invariant Method and Pagerank take into account both direct and indirect impact of journals, by assigning more weight to citations coming from more relevant journals.

In the research chain model, Eigenfactor also has a straightforward interpretation as summarized in the following lemma.

Lemma 2 *The probability that a typical research chain of length ≥ 1 terminates at journal i is given by EF_i.*

Lemmas 1 and 2 deliver a new neat probabilistic relationship between Pagerank and Eigenfactor that is not feasible if we restrict to the Markov chain interpretation. Both Pagerank and Eigenfactor are measuring a journal's impact by the probability of terminating at that journal in a research chain. The only difference between them is that the EF assumes that at least one citation has been followed by the researcher. This is a reasonable adjustment with respect to Pagerank when analyzing journal impact since journals with a high article share are receiving a high Pagerank score. In particular, it is clear that $q_i \geq (1-\alpha)\, a_i$, where this bound corresponds to the Pagerank of an non-cited journal when the research chain has length zero. On the contrary, Eigenfactor's conditioned probability is bounded below by zero. In fact, if a journal receives no citations its Eigenfactor score will be zero.

The following result relates both Pagerank and Eigenfactor in the opposite direction to (1) through a simple closed-form expression:

[13] The Eigenfactor measure is in fact defined by its creators as:

$$EF_i = \frac{\mathbf{H}_i \cdot \mathbf{q}'}{\sum_{j \in J} \mathbf{H}_j \cdot \mathbf{q}'}$$

where $\mathbf{q}'$ is the Pagerank of an adjusted matrix $\mathbf{H}'$ that deals with dangling nodes assuming that they cite all journals according to their article share, *i.e,* if j is a dangling node then $h'_{ij} = a_i$ for all i. Since we are assuming that there are no dangling journals, then $\mathbf{H}' = \mathbf{H}$. Consequently $\mathbf{q}' = \mathbf{q}$ and $\sum_{j \in J} \mathbf{H}'_j \cdot \mathbf{q}' = \sum_{j \in J} \mathbf{H}_j \cdot \mathbf{q} = 1$ because $\mathbf{H}$ is column-stochastic and $\sum_{i \in J} q_i = 1$. Thus, $EF_i = \mathbf{H}_i \cdot \mathbf{q}$

Lemma 3 *Pagerank and Eigenfactor are related as follows*

$$q_i = \alpha EF_i + (1 - \alpha)\, a_i.$$

The interpretation of lemma 3 is simple. The Pagerank of journal i is an average between its article share a_i (the score that i obtains when the research chain has length zero) and its Eigenfactor score EF_i (the corresponding score when the research chain has positive length).

Remark 1 *Both q_i and EF_i are functions of α, $\mathbf{H}$ and $\mathbf{a}$. In particular, q_i and EF_i can vary with citations $(h_{ji})_{j\in J}$ made by journal i, and with i's article share a_i. Also, the Invariant Method score assigned to journal i, IM_i, is not independent of $(h_{ji})_{j\in J}$ or a_i.*

In Appendix I, we illustrate with an example how a journal can change its Eigenfactor, Invariant Method and Pagerank scores by modifying its citation pattern or its article share.

2.3 Outerfactor

Let $\mathbf{R}$ be the matrix

$$\mathbf{R} = (1 - \alpha)\,(\mathbf{I} - \alpha\mathbf{H})^{-1}$$

Each entry r_{ij} of $\mathbf{R}$ is the probability that a research chain starting from journal j will terminate at node i (see Appendix).[14]

We introduce a new measure −Outerfactor− that complements Eigenfactor naturally in the analysis of journal impact. It is the probability that a journal is used (at least once) in a research chain. We now provide a closed-form formula for Outerfactor as a function of Pagerank (or Eigenfactor, by lemma 3).

Definition 4 *The Outerfactor (OF) of journal i is defined as*

$$OF_i = \frac{\frac{q_i}{r_{ii}} - a_i}{\alpha\,(1 - a_i)}.$$

As before, the research chain model accommodates Outerfactor easily.

Proposition 1 *OF_i is the probability that a research chain of length ≥ 1 that does not start from journal i uses journal i.*

[14] The inverse is well-defined because $\mathbf{H}$ is a non-negative matrix and $|\alpha| < 1$. Moreover, $\mathbf{R}$ is a column-stochastic matrix, that is, $r_{ij} \geq 0$ and $\sum_i r_{ij} = 1$.

Outerfactor divides Pagerank q_i of the journal i by its corresponding diagonal entry in $\mathbf{R}$. The entry r_{ii} of $\mathbf{R}$ is the probability that a research chain that starts from journal i will also terminate at i. In the Appendix, we compute the score obtained by the journals in Example 1 with different impact measures.

There are two important differences between Eigenfactor and Outerfactor. The main difference is that EF measures the chance of *terminating* at a journal in a research chain, while OF accounts for the likelihood of *using* that journal in a research chain. Thus, once journal i is reached for the first time in the chain, OF_i does not account for subsequent uses of journal i in the research chain. This subtle difference in the definition of probabilities has deeper implications in the manipulability of the scores as we will show in the next paragraphs. A second difference is that OF_i only considers chains that do not start from journal i, while EF_i considers all journals as potential starting points. This adjustment is done as a normalization since the (Outerfactor) probability of using journal i would be bounded below by a_i otherwise, which would correspond to the case where a research chain starts at journal i and then this journal would be trivially used.

Measures that take into account indirect impact typically improve information, since they assign higher values to those journals cited by more relevant journals, which are usually assumed to reference to high quality research. This notion is also behind the success of Google Pagerank algorithm when assessing the importance of webpages.

Remark 2 *Invariant Method, Pagerank, Eigenfactor and Outerfactor take into account indirect impact, while Impact factor does not.*

The parameter α controls the average length of the research chain. Brin and Page (1998) initially proposed $\alpha = 0.85$ for Pagerank, which has become a standard value. In our framework, a lower value of α implies to give a higher value to shorter research chains, and a higher value of α implies to give more weight to longer chains. When $\alpha \to 1$, Pagerank and Eigenfactor tend to the infinite stationary Markov process on $\mathbf{H}$, the Invariant Method.

When $\alpha \to 0$, q_i is just the probability a_i, while Outerfactor and Eigenfactor are closely related[15]: both measures report the share of other journals' citations that point to a given journal. In this case, only research chains of length 1 matter, and then the concepts of a research chain *terminating* or *using* a journal are equivalent. The only difference comes from the fact that Outerfactor accounts for research chains that do not start from the journal, while this possibility is included in Eigenfactor. To summarize, when $\alpha \to 0$

[15] See the Appendix for detailed proofs.

Eigenfactor and Outerfactor are related as follows

$$\lim_{\alpha \to 0} OF_i = \lim_{\alpha \to 0} \frac{EF_i}{1 - a_i} = \frac{\sum_{j \in J} a_j h_{ij}}{1 - a_i}$$

which is imply the probability of arriving to journal i in exactly one step when the research chain does not start at i.

In our first main result, we highlight one important dissimilarity between OF and the other measures: the chance of using journal i in a research chain is independent of the citation pattern of i, as opposed to remark 1.

Theorem 1 *OF_i is invariant with respect to i's citation pattern $(h_{ji})_{j \in J}$.*

This result is a direct consequence of the probabilistic interpretation of Outerfactor in the research chain model given in Proposition 1. Since OF_i measures the proportion of chains that use journal i, it does not depend on the citations made by i. This is the case because once journal i is reached in a research chain, OF_i will not account for future appearances of journal i in that chain. This is in contrast with Eigenfactor or Pagerank: under these scores, journal i could increase the likelihood that a chain terminates at i by referencing journals that point to i directly or indirectly. Even when self-references are removed from the citation matrix $\mathbf{C}$, this does not prevent Eigenfactor or Pagerank from being manipulated in this manner. In Appendix I, we show how a journal can manipulate its own Eigenfactor or Invariant Method by changing its citation pattern, while Theorem 1 shows that this is not the case with Outerfactor.

This has immediate implications when the actual rankings are obtained with EF and OF. With Eigenfactor manipulation can occur if journal i starts citing journals that have cited it, because this generates cycles that can increase journal i's EF score. As a consequence, journals forming small and closed groups are usually benefited from the existence of these cycles in the citation graph. This is not the case with OF which basically considers the mere use of journals: once a journal is visited by a research chain for the first time, Outerfactor will not consider subsequent visits to this journal in order to assess its impact.

The most basic form of Impact Factor uses total cites received by a journal, including self-citations. Manipulability of Impact Factor can be easily addressed, by deleting self-references. This measure is known as the Impact factor without self-references. Nevertheless, it only takes into account direct impact. Eigenfactor and Pagerank also include indirect impact but this inclusion triggers undesirable manipulability issues. Outerfactor is a first step towards reconciling the inclusion of indirect impact with the robustness to manipulation, because it does not take into account the effect of i's citations on i's score.

It is important to remark that a journal can not vary its own Outerfactor, but it may affect its ranking position. This is because Outerfactor of the other journals generally depend on citations made of this journal, and therefore it could potentially decrease Outerfactor of other journals in order to increase its own relative position. However, in our illustration with 60 economics journals, we will show how Outerfactor performs very well against ordinal manipulation.

An additional property of Outerfactor is that a journal's score is independent of its article share. Once again, this invariance property is a consequence of Proposition 1: If research chains considered in OF_i cannot start at journal i then the probability of using journal i does no longer depend on i's article share, given that article shares only determine where the research chain starts. This property is unique to Outerfactor and it is summarized in the following result.

Proposition 2 *OF_i is invariant to a_i.*

Finally, we note that Pagerank, Eigenfactor and Outerfactor are measures of *global impact*, that is, they are not computed in a per-article basis. We think that a measure of global impact should be independent of the article share, and this is what Outerfactor does. In particular, if a journal produces new non-cited articles (without changes in the matrix $\mathbf{H}$) its Outerfactor will not change as a measure of global impact. Nevertheless, as we mentioned before, this invariance to own article share constitutes a pure normalization of the measure. However, it is always convenient to normalize by the share of articles in order to assess the true average impact of a journal.

Impact Factor measures impact per article by dividing the measure of global impact of the journal (the total amount of citations received in the period) by the number of articles. Invariant Method also reports impact per article. Eigenfactor considers per-article impact by dividing a journal's impact by its share of articles, which is known as the Article Influence (AI) of that journal and is also included in the Journal Citation Reports:

$$AI_i = \frac{EF_i}{a_i}$$

Following this line, we analyze impact per article in our framework by dividing Outerfactor by the article share, resulting in a new measure of per-article impact, Article-Outerfactor (AO):

$$AO_i = \frac{OF_i}{a_i}$$

The following corollary is a direct consequence of proposition 2, and it states that if a journal increases its number articles while keeping the citations it receives ($\mathbf{H}$ constant), then it will decrease its per-article Outerfactor score.

Corollary 1 *AO_i is a decreasing function of a_i.*

This property is also satisfied by Impact Factor, but not by Article Influence: a new article by journal i has a direct negative effect on AI_i by increasing the denominator and an indirect effect by changing EF_i that can be positive or negative.[16]

2.3.1 Other Impact Measures

There have been proposed different ways of quantifying journal impact and a number of these approaches take into account both direct and indirect impact. Although self-references are usually deleted in order to alleviate the problem of manipulation, none of these measures circumvents the problem of manipulation when indirect impact is considered, which is precisely the main feature of Outerfactor.

The Liebowitz-Palmer measure (Liebowitz and Palmer, 1984) also considers both direct and indirect impact. However, it can also be manipulated if a journal increases the number of its citations pointing to journals that cite it. Note that this strategy can be used by deleting self-citations. A successful measure of impact is the H-Index (Hirsch, 2004), which is the maximal number h of articles of journal i such that each one is cited at least h times.[17] This notion can avoid manipulation just by not using self-citations, but as in the case of Impact Factor, it does not take into account indirect impact.

Kóckzy and Strobel (2010) address the problem of manipulability providing a ranking score which is non manipulable through addition of new references. They compare two journals by mutual references, and assign to each journal the amount of times that it gets more citations than its rival. This kind of rankings are known as "tournaments", and the ranking they propose is similar to the one typically used in sports leagues. This measure can be manipulated by decreasing the number of references that a journal makes to other journals, but Kóckzy and Strobel reasonably argue that this behavior would not be accepted in the research publication process.[18]

2.4 Cross-Effects

In this section, we take advantage of the research chain framework in order to address the problem of analyzing cross-effects between pairs of journals. We do so by studying the interactions between any pair of

[16] Eigenfactor can be adjusted in order to make it invariant to own article shares. The formula

$$\widetilde{EF}_i = \frac{q_i - a_i r_{ii}}{\alpha\,(1-a_i)} = r_{ii} OF_i$$

is the probability that a research chain not starting at journal i will terminate at i, which does not depend on a_i by definition.

[17] Although H-Index was initially proposed for ranking scientists, it is also used for journals.

[18] Kóckzy and Strobel meassure does not take into account indirect impact. However, it can be easily incorporated in their meassure, by comparing indirect mutual impact among journals, instead of direct mutual references. Our meassure of Cross-Influence could be used for such a comparison.

journals in the same research chain. We propose different ways of measuring these cross-effects that allow us to understand the interplay of journals in determining journal impact, taking into account both direct and indirect relationships. These measures of cross-effects can be understood as assessments of how a journal is influenced or impacted by others (cross-influence), or how large is the contribution of a journal to the impact score of others (cross-contribution). Propositions 4 and 6 provide a *double interpretation* for Outerfactor: it can be understood as an average influence of a journal on other journals, or as its average contribution to all journal's impact. Proposition 3 also gives an interpretation of Eigenfactor as the average influence of a journal on all journals.

2.4.1 Cross-Influence

Cross-influence of journal i on j refers to the relevance of journal i to another journal j, by analyzing the pattern of direct and indirect citations from journal j to journal i. In simple words, it refers to the impact that journal i has on j. In the simplest case of direct impact, cross-influence is the proportion of direct citations from journal j to journal i and this proportion shows how influent is journal i on journal j. We extend this intuition in order to incorporate indirect impact in the research chain model. We introduce two new probabilities that incorporate this idea: Eigen-influence of journal i in journal j (EI_{ij}), which is the proportion of research chains starting from j that terminate at i; and Outer-influence of journal i in journal j (OI_{ij}), which is the proportion of research chains starting from j that include (use) journal i. Therefore, these two probabilities capture how relevant is journal i for the research published in journal j. Note that both probabilities converge to the simple case of direct impact if we account only for research chains of length 1, which occurs when $\alpha \to 0$.

Definition 5 *The Eigen-influence of journal i in j is.*

$$EI_{ij} = \frac{r_{ij}}{\alpha},$$

and for $i = j$

$$EI_{jj} = \frac{r_{jj} - (1 - \alpha)}{\alpha}.$$

In the research chain model, EI_{ij} is the probability that a research chain of length ≥ 1 that starts at journal j will terminate at node i.[19] Consequently, $\sum_i EI_{ij} = 1$ for all $j \in J$. The following result is straightforward by using the Bayes rule

[19] All cross-effects expressions and their interpretation as probabilities in the research chain model are relagated to the Appendix.

Proposition 3 *The Eigen-influence EI_{ij} is the probability that a research chain of length ≥ 1 that starts at journal j will terminate at node i. Moreover, journal i's Eigenfactor is the weighted average of its eigen-influence on all journals:*

$$EF_i = \sum_j a_j EI_{ij}.$$

We note that EI_{ij} is independent of $\mathbf{a}$, but not of citations made by journal i's.

Definition 6 *The Outer-influence of journal i in j is*

$$OI_{ij} = \frac{EI_{ij}}{r_{ii}},$$

and for $i = j$

$$OI_{ii} = 1.$$

OI_{ij} is the probability that a research chain of length ≥ 1 that starts at journal j will use journal i.

Proposition 4 *The Outer-influence OI_{ij} is the probability that a research chain of length ≥ 1 that starts at journal j will use journal i. Moreover, the Outerfactor of journal i can be expressed as the weighted average of its outer-influence on other journals:*

$$OF_i = \sum_{j \neq i} \frac{a_j}{1 - a_i} OI_{ij}.$$

Interestingly, OI_{ij} is independent of both journal i's citation pattern and a_i.

2.4.2 Cross-Contribution

The idea of cross-contribution refers to how a journal i contributes to the impact of journal j. This notion is different from cross-influence where we study how often i is cited by j; now we study the chance that i appears in chains that increase j's impact (where j is cited). Once again, we propose two usable measures that are equivalent when we restrict to direct citations ($\alpha \to 0$).

Definition 7 *The Eigen-contribution of journal i to journal j's impact is, for $i \neq j$,*

$$EC_{ij} = \frac{a_i r_{ji}}{\alpha EF_j},$$

and for $i = j$

$$EC_{jj} = \frac{a_j \left[r_{jj} - (1 - \alpha) \right]}{\alpha EF_j}.$$

In the research chain model, EC_{ij} is the probability that a research chain of length ≥ 1 that terminates at journal j started at journal i. Clearly, $\sum_i EC_{ij} = 1$. More importantly, from this interpretation we derive that EC_{ij} is a measure of the contribution of journal i to journal j's Eigenfactor EF_j. For instance, if $EC_{ij} = 0.2$, it means that journal i contributes to 20% of journal j's eigenfactor because journal i is the starting journal in 20% of all chains terminating at j. EC_{ij} depends on citations made by i and on a_i, since i is the starting point of all chains accounted for by this measure.

Proposition 5 *The Eigen-contribution OC_{ij} is the probability that a research chain of length ≥ 1 that terminates at journal j started at journal i. Moreover,*

$$\sum_j EF_j EC_{ij} = a_i.$$

Definition 8 *The Outer-contribution of journal i to to journal j's impact is, for $i \neq j$,*

$$OC_{ij} = \frac{1}{\alpha} \frac{r_{ji}}{r_{ii}} \frac{q_i}{EF_j}.$$

and for $i = j$

$$OC_{ii} = 1.$$

As we show below, OC_{ij} is the probability that a research chain of length ≥ 1 that terminates at journal j uses journal i. The Outer-contribution score captures the contribution of a journal to other journals' impact measured by Eigenfactor, because it restricts precisely to chains of positive length that end at journals, that is, those chains that form the Eigenfactor score. Note that, $\sum_i OC_{ij} \geq 1$ since using one journal in a chain does not exclude the possibility of using another journal. OC_{ij} is capturing the contribution of journal i to journal j's eigenfactor EF_j in a different way than EC_{ij} does: when $OC_{ij} = 0.2$, journal i contributes to 20% of journal j's eigenfactor because journal i is used at least once in 20% of all chains terminating at j. Now, we provide an expression of the Outerfactor of a journal as the average contribution to other journals impact measured by Eigenfactor: the Outerfactor of journal i is its average contribution to all journals' Eigenfactor scores.

Proposition 6 *The Outer-contribution OC_{ij} is the probability that a research chain of length ≥ 1 that terminates at journal j uses journal i. Moreover, journal i's Outerfactor can be expressed as the weighted average of its outer-contribution to other journals' impact:*

$$OF_i = \sum_j EF_j \frac{OC_{ij} - a_i}{1 - a_i}.$$

The averaging weights are given by EF. The ratio $(OC_{ij} - a_i) / (1 - a_i)$ is just the same contribution probability as OC_{ij} conditioned on the initial node of the research chain not being journal i. This ratio is an affine transformation on OC_{ij} and it is independent of a_i and it is essential in relating Outerfactor and Outer-contribution since OF_i is conditioned on the initial journal not being i. Finally, we note that OC_{ij} is *not* independent of i's citation pattern even when it is accounting for chains that use i. This is so because we analyze research chains that arrive at j after crossing i. Therefore, these research chains go through i's references and are sensitive to i's citation structure. Similarly, OC_{ij} is not independent of i's article share because a higher proportion of research chains pointing to j start in (and therefore includes) journal i when this journal increases its article share.

All these measures of cross-influence can be used for analyzing mutual impact of journals, as well as a basis for building new rankings. Other rankings of journals take as the basic notion of influence the number of direct citations among journals. Our measures of cross-influence are extensions of citations in order to include also indirect impact, and therefore, they contain richer information than direct citations. For instance, Kockzy and Strobel (2010) propose a tournament to rank journals, by comparing their cross-citations two by two, and assigning points to the journal with the highest number of citations in each comparison. The same procedure can be developed using our measures of cross-influence instead of direct citations, with the additional advantage is that our measures incorporate both direct and indirect impact. Another possible application of this approach would be to construct a ranking based in the H-index, where citations can be substituted by direct and indirect research chains with an appropriate normalization.

3 Evaluating impact of economics journals

3.1 A comparison

We computed rankings and scores for a citation graph with 60 economics journals[20]. We have obtained the citation data from the *JCR* 2009. Citation data for each journal i are the citations made by journal i in 2009 to articles published between 2004 and 2008[21]. In all relevant cases, we use $\alpha = 0.85$ corresponding to an average chain length of 6.

In Table 1 we show the different *non-normalized* impact measures (that is, not normalized by article shares) for the Top 10 journals according to Outerfactor (OF), as well as total share of citations (C),

[20] We take the 60 economics journals from the JCR with the highest Article Influence score (AI). Recall that $AI_i = EF_i/a_i$.

[21] We have considered a ciation window of 5 years, which is the one that uses Eigenfactor in its computation. The JCR reports also the impact factor for each journal with a 5 year window appart from the standard 2 year window version.

Eigenfactor (EF) and the non-normalized Invariant Method (that is, $\mu_i = a_i IM_i$). We also show the rankings that result from all these measures. For the sake of comparability, we have deleted all self-citations from the citation matrix $\mathbf{C}$ before computing these measures.

	OF	C	R_C	EF	R_{EF}	μ	R_{IM}
AER	0.5184	0.1192	*1*	0.1303	*1*	0.1364	*1*
QJE	0.3415	0.0640	*2*	0.0698	*2*	0.0726	*2*
ECO	0.3125	0.0557	*3*	0.0638	*3*	0.0668	*3*
JPE	0.2812	0.0465	*4*	0.0541	*4*	0.0575	*4*
RES	0.2752	0.0455	*5*	0.0526	*5*	0.0560	*5*
JME	0.2120	0.0399	*6*	0.0390	*6*	0.0413	*6*
JET	0.1966	0.0261	*13*	0.0361	*7*	0.0381	*7*
RE&S	0.1882	0.0334	*9*	0.0330	*9*	0.0337	*9*
JE	0.1826	0.0366	*8*	0.0352	*8*	0.0358	*8*
EJ	0.1725	0.0368	*7*	0.0293	*10*	0.0274	*12*

Table 1. non-normalized measures. Columns OF, C, EF and μ report scores of each journal and R_C, R_{EC} and R_{IM} are ranking positions. The table for the whole set of 60 journals appears in the Appendic.

American Economic Review is ranked as the journal with highest impact according to all non-normalized measures. Although it receives 11.92% of all citations, the proportion of all direct and indirect citations that point to it is higher, 13.03% in the case of Eigenfactor and 13.64% with the Invariant Method. The top 5 journals increase their shares by considering indirect impact. Outerfactor reveals that any of these top 5 journals is present in more than 27% of all research chains, being the American Economic Review in 51.84% of all research chains. The six highest ranked journals coincide in all rankings; and very similar orderings are obtained for the three non-normalized measures of indirect impact (Outerfactor, Eigenfactor and the non-normalized Invariant Method). When only direct citations are used (C), the Journal of Economic Theory gets a much lower score that when any type of indirect impact is used. As opposed to other measures, OF ranks the Review of Economics and Statistics over the Journal of Econometrics.

Abstracting from these subtle ordinal differences, there are important cardinal differences that arise when the Outerfactor score is computed. This will trigger substantial changes in rankings when we normalize by article shares later. For instance, the American Economic Review has more than twice the score of Econometrica when using direct citations, Eigenfactor or the Invariant Method (the score of AER is, respectively, 114.00%, 104.23% and 104.19% higher than ECO). However, this is not the case with Outerfactor, where AER gets a probability of use 65.89% higher than ECO. These differences in the score are due to the fact that Outerfactor focuses on the event of using (at least once) a journal, whilst all other indirect measures take into account *all* visits to a journal during the research process.

Table 2 shows all measures *normalized* by share of articles: Article Outerfactor (AO), Impact Factor (IF), Article Influence (AI) and the Invariant Method (IM).

	AO	IF	R_{IF}	AI	R_{AI}	IM	R_{IM}
JPE	31.37	5.19	*1*	6.03	*1*	6.41	1
QJE	27.47	5.15	*2*	5.62	*2*	5.84	2
BPEA	24.21	2.86	*6*	3.75	*3*	4.00	3
RES	19.04	3.15	*5*	3.64	*4*	3.87	4
JEL	18.56	3.16	*4*	3.00	*6*	2.98	6
ECO	17.72	3.16	*3*	3.62	*5*	3.79	5
RJE	14.64	2.36	*7*	2.55	*7*	2.60	7
JLE	13.93	2.15	*9*	2.24	*10*	2.31	11
JEP	13.59	2.36	*8*	2.33	*8*	2.37	10
REDC	13.08	1.66	*13*	2.15	*11*	2.40	8

Table 2. Measures normalized by article shares. IF is computed as C/a_i.

Appendix B reports the table for the 60 journals.

As we see in Table 2, when we adjust by the size of the journal, we find more differences in rankings. The differences in rankings of IF with respect to AO, AI or IM are due to the indirect nature of the latter measures, that is, to differences in the quality of the citing journals: a journal may improve its classification under an indirect measure compared to IF because citations to this journal come from high-impact journals. This is the case of Brooking Papers on Economic Activity, which goes up from the sixth position in the IF ranking to the third position in AO, AI and IM rankings. Ordinal differences in rankings under AO, AI and IM arise from the cardinal differences shown in Table 1. For instance, Journal of Labour Economics improves two positions under AO with respect to AI, or three positions with respect to IM. In fact, JLE obtains a relatively higher OF score in Table 1 due to the fact that this journal has a relatively higher indirect impact on other journals through the citations made *by others*, which is the main feature underlying Outerfactor. On the contrary, AER decreases 4 positions with respect to other indirect measures, reflecting that a relatively important part of its impact is due to the citations it makes. In our sample, AER is in the 9th position under AI and IM, and in the 10th position under citations, but it falls to the 13th position under Article Outerfactor.

3.2 Including self-citations

The popularity and wide use of Impact Factor has been argued as the motivation of journals in order to inflate their impact through self-citations (Smith, 1997). The JCR reports Impact Factor as well as the Impact Factor without self-references. The Eigenfactor score used in JCR is also computed by discarding self-citations. This methodology is used in order to alleviate the problem derived from the incentives of journals to increase their citations, although it implies to put apart relevant citation information. In order to analyze these differences, we have computed new scores when self-citations are included. Table 3 reports the Top 6 ranking for our impact measures per journal. Remember, as Table 1 shows, that the four ranking methods coincide in their Top 6 ranking after deleting self-citations, while now it is not the case:

	OF	C	R_C	EF	R_{EF}	IM	R_{IM}
AER	0.4300	0.1036	*1*	0.1267	*1*	0.1392	1
QJE	0.2717	0.0526	*2*	0.0632	*3*	0.0692	3
ECO	0.2476	0.0485	*3*	0.06488	*2*	0.0734	2
JPE	0.2188	0.0361	*8*	0.0437	*4*	0.0483	4
RES	0.2139	0.0362	*7*	0.0431	*6*	0.0478	5
JME	0.1655	0.0399	4	0.0387	8	0.0425	8

Table 3. Rankings including self-citations

Once we include self-citations, the ranking by Outerfactor is the one that remains with less variations[22]. Although self-citations do not affect the own Outerfactor score of each journal, they affect Outerfactor of other journals, and therefore, have an effect on rankings. In our sample, the ranking obtained by Outerfactor changes with the inclusion of self-citations for 16 of the 60 journals, with a maximum increase of two positions and a maximum decrease of two positions. Table 4 shows some descriptive statistics about the changes that inclusion of self-ctiations generates in the different rankings.

[22] Although we do not show the variations in rankings under the normalized versions of the measures, our robustness results remain in those cases.

	Effects of inclusion of Self-Citations			
	OF	*C*	*EF*	*IM*
Maximal Increase	2	36	31	12
Maximal Decrease	2	10	7	6
# of journals better off	8	24	20	18
# of journals worse off	8	32	31	28
Average positions when up	1.13	6.54	5.8	3.17
Average positions when down	1.13	4.92	3.74	2.04
Spearman's Rank correlation	0.9994	0.9058	0.9405	0.9868

Table 4. All numbers are ranking positions.

As shown in Table 4, the inclusion of self-citations affects the ranking by any measure, with Outerfactor been the least affected with a rank correlation of 0.9994. Thus, Outerfactor generates very similar rankings even when we use the full information about citation for its calculation. In this regard, Outerfactor is very robust to the consideration of self-citations, and in fact it is not strictly necessary to remove self-citations from the data in order to compute Outerfactor.

3.3 Rank manipulation

Since measures of indirect impact are not extensively used yet, it is unlikely that they have generated already incentives to manipulate them. However, in this section we simulate how sensitive each measure is to manipulation in our sample of economics journals. We assumed four different ways in which a journal could manipulate the citation graph: by increasing or decreasing its citations, or by increasing or decreasing its article share.

Simulations have been performed as follows. In the case of increasing citations, we assume that journal i duplicates its citations, pointing all new citations to one journal so as to maximize the increase in its Outerfactor ranking position. Then, journal i's new position in the ranking is compared to the original one. This procedure is repeated for each journal. In the case of decreasing citations, we assume that journal i deletes all its citations to one journal so as to maximize the increase in its Outerfactor ranking position. Finally, rankings have been also computed by duplicating or dividing by two the article share of each journal. Table 5 summarizes this information:

	Adding citations				*Deleting citations*			
	OF	C	EF	$IM(\mu)$	OF	C	EF	IM
Maximal Increase	2	0	9	7	*1*	*1*	*1*	*1*
Average Maximum Increase	0.200	0	0.983	0.917	*0.20*	*0.183*	*0.25*	*0.25*
Journals that improve	11	0	29	28	*12*	*11*	*15*	*15*

	Adding articles				*Deleting articles*			
	OF	C	EF	IM	OF	C	EF	IM
Maximal Increase	0	0	1	0	*1*	*0*	*1*	*0*
Average Maximum Increase	0	0	0.1	0	*0.033*	*0*	*0.033*	*0*
Journals that improve	0	0	6	0	*2*	*0*	*2*	*0*

Table 5. Maximal Increase is the maximum number of positions that a journal improves in each different ranking.

In our simulation, Outerfactor is significantly more robust than Eigenfactor or the Invariant Method to an increase in citations. Finally, by changing its article share, a journal is not able to change its C ranking or its μ ranking, since these measures do not depend on the article share. By changing its article share, a journal is not able to change its Outerfactor score, but may change other journals' Outerfactor. This generates a potential ranking manipulation that is nevertheless negligible in our simulations.

3.4 Cross-Effects

Now we illustrate cross-effect measures for the case of the American Economic Review. We show the journals that are the more related to AER through cross-influence or cross-contribution.

3.4.1 Cross-Influence

Table 6 reports the six journals with highest impact on AER:

Influence in American Economic Review		
Direct Influence	**Eigen-influence**	**Outer-influence**
QJE, 0.1671	AER 0.1206	AER 1
JPE, 0.0962	QJE, 0.0849	QJE, 0.4150
JME, 0.0532	ECO, 0.0635	JPE, 0.3281
RES, 0.0532	JPE, 0.0632	ECO, 0.3108
JET, 0.0456	RES, 0.0555	RES, 0.2904
REStat, 0.0456	JME, 0.0424	JME, 0.2309

Table 6. The six journals with the highest influence on AER. Note that AER's direct influence on AER is zero given that self-citations have been excluded. QJE has a direct influence of 0.1671, that is, 16.71% of references made by AER point to QJE. ECO has an Eigen-influence of 0.0635, that is, more than 6% of research chains that start in AER terminate at to ECO.JPE has an Outer-influence of 0.328, meaning that more than 32.8% of all research chains that start in AER include JPE.

After removing self-citations, the Quarterly Journal of Economics is the journal with highest influence on AER, since 16.71% of AER direct references go to QJE. However, its indirect impact is smaller when we analyze Eigen-influence: in this case 8.5% of the research chains that start in AER point to QJE. As for Outer-influence, 41.5% of the research chains that start in AER include QJE. Note here that the relative values of Eigen-influence and Outer-influence are quite similar (for instance, the Eigen-influence of QJE on AER is 34.5% higher than the influence of JPE; and 26.5% when we compute Outer-influence), while these two measures are different in relative terms to Direct influence (QJE's direct influence on AER is 73.7% higher than JPE's). Although Econometrica is the seventh more cited journal by American Economic Review, it becomes more important when indirect impact is taken into account. On the other hand, JME has a more direct than indirect impact on the American Economic Review. In general, OI shows a smoother influence of journals on AER.

In Table 7 we show the six journals which are the most influenced by AER:

Influence of American Economic Review		
Direct Influence	**Eigen-influence**	**Outer-influence**
JPE, 0.2636	JPE, 0.1532	JPE, 0.6066
JRiskU, 0.2576	JRiskU, 0.1520	JRiskU, 0.6019
RES, 0.2500	JME, 0.1513	JME, 0.5988
JME, 0.2353	RES, 0.1511	RES, 0.5982
QJE, 0.2339	QJE, 0.1509	QJE, 0.5974
Energy J, 0.2143	JEPersp, 0.1461	JEPersp, 0.5784

Table 7. The six journals with highest influence by AER: AER has a direct influence of 0.2636 in JPE, that is, 26.36% of references made by JPE point to AER. JRiskU has an Eigen-influence of AER of 0.1518, meaning that 15.18% of the research chains that start in JRiskU point to AER (but up to 25.7% of references). JME obtains an Outer-influence by AER of 0.5988: almost 60% of all research chains that start in JME include AER.

Three of the journals in our sample have more than 25% of its citations pointing to AER, while the highest proportion of indirect research chains is 15% for Eigen-influence and 60% for Outer-influence. The Journal of Political Economy and Journal of Risk and Uncertainty are the two journals most influenced by AER, independently of the measure used.

By Proposition 3, the AER's Eigenfactor score of 0.1303 is the a weighted average of AER's Eigen-influences on all journals reported in Table 7. And proposition 4 stated that AER's Outerfactor (0.5184) is the average of its Outer-Influences on other journals.

3.4.2 Cross-Contribution

Table 8 reports the six journals which contribute more to the impact of AER: [23]

[23] Cross-Contribution for all journals is available upon request

Contribution to American Economic Review's value		
Direct contribution	**Eigen-contribution**	**Outer-contribution**
JME, 0.0741	AER, 0.0524	AER, 1
JET, 0.0509	JEBO, 0.0506	QJE, 0.3464
JPublicE, 0.0498	VH, 0.0438	ECO, 0.2966
QJE, 0.0463	WD, 0.0434	JPE, 0.2891
RES, 0.0451	GEB, 0.0417	RES, 0.2841
JEBO & JEL, 0.0428	JET, 0.0363	JME, 0.2329

Table 8. The six journals with the highest contribution to AER's impact: QJE creates 7.47% of the references that point to AER. 5.06% of the research chains that terminate at the AER started in JEBO. And while 28.91% of the research chains that terminate at AER used ECO.

There are significant differences among the three columns. Journals with many articles tend to have a higher Eigen-contribution and Direct contribution because they only account for journals where citations originate (which are usually bigger journals). On the other hand, Outer-contribution extends this to journals usage at any step of the research chain.

Table 9 reports the highest contributions of AER to other journals' impact.

Contribution of American Economic Review		
Direct Contribution	**Eigen-contribution**	**Outer-contribution**
BPEA, 0.20	BPEA, 0.0765	AER, 1
QJE, 0.1422	QJE, 0.0689	BPEA, 0.6368
JLEO, 0.1333	Energy J, 0.0677	QJE, 0.5746
JPE, 0.1128	GEB, 0.0666	Energy J, 0.5643
GEB, 0.1118	JLEO, 0.0662	GEB, 0.5554
Energy J, 0.1	JPE, 0.0662	JLEO, 0.5519

Table 9. The six journals to which AER contributes more: 20% of the references in our sample that point to Brooking Papers on Economic Activities are in articles of AER. In the Eigen-contribution column, 6.89% of the research chains that point to QJE start in AER, while 56.43% of the research chains that point to Energy Journal use AER.

References made by AER constitute more than 10% of all references. In particular, 20% of direct references to BPEA and more than 14% of direct references to QJE come from AER. However, AER's indirect Eigen-contribution is less significant: 7.65% of research chains that point to BPEA start in AER. By applying Proposition 6, we can average the Outer-contribution column of AER to obtain its Outerfactor score (0.5184).

4 Discussion

Measures of journal impact are increasingly being used for many purposes related to research evaluation, affecting incentives to manipulation. We propose a new measure of journal impact –Outerfactor– that addresses this problem while preserving information about both direct and indirect influence. We note, however, that Outerfactor is not completely immune to some strategic considerations. For instance, although a journal can not change its score, it may change score of competitors and modify its position in the ranking. Nevertheless, simulations show that Outerfactor behaves well in this respect compared to other measures. In addition to this, even though the Outerfactor score is invariant to individual strategies, a set of journals may modify their scores by agreeing on their citing strategies.

Computational considerations also deserve a special attention. In the case of Outerfactor, it is required to compute the diagonal of an inverse matrix of size N, or the full inverse in the case of computing all cross-effects. This can be costly in computational terms if N is large. For cases where N is in the order of 10^4, as in the case of scientific journals, all our computations can be done in a regular computer in seconds.

References

[1] Bergstrom, C. T. (2007): "Eigenfactor: Measuring the value and prestige of scholarly journals", *C&RL News* 68(5)

[2] Bonacich, P. (1987): "Power and Centrality: A Family of Measures," *American Journal of Sociology*, 92, 1170-1182.

[3] Brin, S., and L. Page (1998): "The Anatomy of a Large-Scale Hypertextual Web Search Engine," *Computer Networks and ISDN Systems*, 30(1,2),107-117.

[4] Fersht, A. (2009): "The most influential journals: Impact Factor and Eigenfactor," *Proceedings of the National Academy of Sciences*, 106 (17): 6883

[5] Freeman, L. C. (1979): "Centrality in Social Networks: Conceptual Clarification.", *Social Networks* 1:2 15-39.

[6] Garfield, E. (1955): "Citation Indexes to Science: A New Dimension in Documentation through Association of Ideas," *Science*, 122(3159), 108-111.

[7] González-Pereira, B., V.P. Guerrero-Bote and F. Moya-Anegón (2009): "The SJR indicator: A new indicator of journals' scientific prestige",. arXiv:0912.4141v1.

[8] Hirsch, J. E. (2004): "An Index to Quantify an Individual's Scientific Research Output," *Proceedings of the National Academy of Sciences*, 102(46), 16569-16572.

[9] Katz, L. (1953): "A New Status Index Derived from Sociometric Analysis." *Psychometrika* 18:39-43

[10] Kóczy, L. A., and M. Strobel. (2010): "The World Cup of Economics Journals: A Ranking by a Tournament Method," Working Paper Series 1011, Óbuda University, Keleti Faculty of Economics

[11] Liebowitz, S. J., and J. C. Palmer (1984): "Assessing the Relative Impacts of Economics Journals," *Journal of Economic Literature*, 22(1), 77-88.

[12] Pinski, G., and F. Narin (1976): "Citation Influence for Journal Aggregates of Scientific Publications: Theory, with Application to the Literature of Physics," *Information Processing & Management*, 12(5), 297-312.

[13] Palacios-Huerta, I., and O. Volij (2004): "The Measurement of Intellectual Influence," *Econometrica*, 72(3), 963-977.

[14] Smith, R. (1997): "Journal accused of manipulating impact factor,", *British Medical Journal*, 314, 461.

5 Appendix

5.1 Appendix I

The following example illustrates Remark 1, showing how a journal may vary its Pagerank and Eigenfactor by varying its citation pattern and/or its article share. Consider a set of 3 journals $J = \{A, B, C, D\}$ whose citations and article shares are given by

$$\mathbf{H} = \begin{pmatrix} 0 & 0.6 & 0.1 & 0.1 \\ 0.6 & 0 & 0.1 & 0.1 \\ 0.2 & 0.2 & 0 & 0.8 \\ 0.2 & 0.2 & 0.8 & 0 \end{pmatrix}, \mathbf{a} = \begin{pmatrix} 0.25 \\ 0.25 \\ 0.25 \\ 0.25 \end{pmatrix}$$

We use $\alpha = 0.85$. Journals A and B cite each other and this is also the case between C and D. Pagerank and Eigenfactor of A and B are $q_A = q_B = 0.23$ and $EF_A = EF_B = 0.2265$. Note that A can increase its score by increasing its relative citations to B as follows:

$$\mathbf{H}' = \begin{pmatrix} 0 & 0.6 & 0.1 & 0.1 \\ 0.8 & 0 & 0.1 & 0.1 \\ 0.1 & 0.2 & 0 & 0.8 \\ 0.1 & 0.2 & 0.8 & 0 \end{pmatrix}, \mathbf{a}' = \mathbf{a}$$

Now, Pagerank and Eigenfactor scores for journal A become $q'_A = 0.2364$ and $EF'_A = 0.234$. This happens because, by increasing its citations to journal B, journal A generates a higher Pagerank and Eigenfactor in B which will be partially transmitted to A.

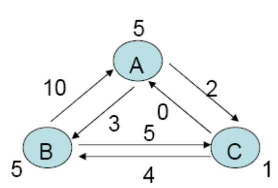
This type of manipulation is also feasible by changing articles shares. For instance,

$$\mathbf{H}'' = \mathbf{H}, \mathbf{a}'' = \begin{pmatrix} 0.4 \\ 0.2 \\ 0.2 \\ 0.2 \end{pmatrix}$$

Now we have that Pagerank and Eigenfactor of A are $q''_A = 0.2533$ and $EF''_A = 0.2292$. By increasing its articles share, journal A is able to increase its own Pagerank and Eigenfactor.

5.2 Appendix II

We compute impact measures for Example I. The citation graph in Example 1 is given by



A is cited by A (5 times), B (10 times) and not by C. B is cited by A (3 times), B (5 times) and C (4 times). C is cited by A (twice) and B (5) and C (once) with 10, 6 and 4 articles respectively. We use $\alpha = 0.85$ for OF and EF. The following table summarizes the results:

	OF_i	IF_i	EF_i	μ_i
A	0.7165	5	0.2855	0.2941
B	0.9975	15	0.4486	0.4412
C	0.8223	4	0.2660	0.2647

In order to make the measures comparable, we have computed the unnormalized version of Impact Factor (that is, total number of citations) and Invariant Method ($\mu_i = a_i IM_i$), excluding self-citations in all cases. Remarkably, OF ranks C over A, while IF, EF and IM do not.

5.3 Appendix III

Let us define the following events in the research chain model:

$$\begin{aligned} i \rightarrow &: \text{ The research chain starts in journal i} \\ i \nrightarrow &: \text{ The research chain does not start in journal i} \\ \rightarrow i &: \text{ The research chain ends in journal i} \\ \rightarrow i \rightarrow &: \text{ The research chain includes journal i} \\ + &: \text{ The research chain has positive length} \end{aligned}$$

Proof of Lemma 1. This is simply the result of re-interpreting the eigenvector $\mathbf{q}$ of $\mathbf{Q}$ as the unique solution to the linear system:

$$\mathbf{q} = (1 - \alpha)\,\mathbf{a} + \alpha \mathbf{H}\mathbf{q},$$

from which $\mathbf{q} = (1 - \alpha)\,(\mathbf{I} - \alpha\mathbf{H})^{-1}\,\mathbf{q}$. Note that this system defines q_i as $P\,(\rightarrow i)$ for all i: with probability $(1 - \alpha)$ the research chain has length zero and the probability is a_i; and with probability α the chain continues to i's neighbors in the matrix $\mathbf{H}$. *QED.*

Accordingly, the entry r_{ij} of the matrix $\mathbf{R}$ is the probability of ending in journal i conditional on having started the research chain from journal j:

$$P\,(\rightarrow i | j \rightarrow) = r_{ij}.$$

This is so because $\mathbf{R}$ is the unique matrix that solves:

$$\mathbf{R} = (1 - \alpha)\,\mathbf{I} + \alpha \mathbf{H}\mathbf{R}.$$

Proof of lemma 2. The probability that a research chain of length longer than 1 ends at i is

$$P(\to i,+) = \sum_{j\in J} P(\to j)\cdot h_{ij} = \sum_{j\in J} q_j \cdot h_{ij} = \mathbf{H}_i \cdot \mathbf{q} = EF_i.$$

QED.

Lemma 4 *The Pagerank score of journal i is*

$$q_i = P(\to i \to)\, r_{ii}.$$

Proof. First, note that $P(\to i \to)$ is the probability of reaching journal i for the first time in a research chain. Then, the probability of ending at a journal i is the probability of journal i being reached for the first time, times the probability of returning to journal i. ■

Proof of Proposition 1. We show that the probability of using journal i is OF_i:

$$\begin{aligned} P(\to i \to | i \not\to, +) &= \frac{P(\to i \to, i \not\to, +)}{P(i \not\to, +)} = \frac{P(\to i \to, i \not\to)}{P(i \not\to, +)} = \\ &= \frac{P(\to i \to) - P(\to i \to, i \to)}{P(i \not\to, +)} = \frac{\frac{q_i}{r_{ii}} - P(i \to)}{P(+)\cdot P(i \not\to)} = \\ &= \frac{\frac{q_i}{r_{ii}} - a_i}{\alpha \cdot (1-a_i)} = OF_i. \end{aligned}$$

QED.

When $\alpha \to 0$,

$$\begin{aligned} \lim_{\alpha\to 0} q_i &= \lim_{\alpha\to 0} \left[(1-\alpha)\, a_i + \alpha \mathbf{H}_i \mathbf{q}\right] \\ &= a_i \end{aligned}$$

and therefore

$$\lim_{\alpha\to 0} \frac{EF_i}{1-a_i} = \lim_{\alpha\to 0} \frac{\mathbf{H}_i \mathbf{q}}{1-a_i} = \frac{\sum_{j\in J} h_{ij} a_j}{1-a_i} = \frac{\sum_{j\in J, j\neq i} a_j h_{ij}}{1-a_i}$$

Define now $h_{ij}^{H^k}$ as the ij–entry of the matrix H^k. Then

$$\begin{aligned} \lim_{\alpha\to 0} OF_i &= \lim_{\alpha\to 0} \frac{\frac{q_i}{r_{ii}} - a_i}{\alpha\cdot(1-a_i)} = \lim_{\alpha\to 0} \frac{\frac{\sum_{j\in J} a_j r_{ij}}{r_{ii}} - a_i}{\alpha\cdot(1-a_i)} = \lim_{\alpha\to 0} \frac{\frac{\sum_{j\in J, j\neq i} a_j r_{ij}}{r_{ii}} + \frac{a_i r_{ii}}{r_{ii}} - a_i}{\alpha\cdot(1-a_i)} = \\ &= \lim_{\alpha\to 0} \frac{\frac{\sum_{j\in J, j\neq i} a_j (1-\alpha)\left(\alpha h_{ij} + \alpha^2 h_{ij}^{H^2} + \ldots\right)}{(1-\alpha)\left(1+\alpha h_{ii} + \alpha^2 h_{ii}^{H^2} + \ldots\right)}}{\alpha\cdot(1-a_i)} = \lim_{\alpha\to 0} \frac{\frac{\sum_{j\in J, j\neq i} a_j (1-\alpha)\alpha h_{ij}}{(1-\alpha)(1+\alpha h_{ii})}}{\alpha\cdot(1-a_i)} = \\ &= \lim_{\alpha\to 0} \frac{\alpha \frac{(1-\alpha)\sum_{j\in J, j\neq i} a_j h_{ij}}{(1-\alpha)(1+\alpha h_{ii})}}{\alpha\cdot(1-a_i)} = \lim_{\alpha\to 0} \frac{\frac{\sum_{j\in J, j\neq i} a_j h_{ij}}{(1+\alpha h_{ii})}}{(1-a_i)} = \frac{\sum_{j\in J, j\neq i} a_j h_{ij}}{(1-a_i)} \end{aligned}$$

Proof of Proposition 3. For $i \neq j$:

$$P(\to i|j \to, +) = \frac{P(\to i, +|j \to)}{P(+|j \to)} = \frac{P(\to i|j \to)}{P(+)} = \frac{r_{ij}}{\alpha} = EI_{ij}.$$

And for $i = j$:

$$\begin{aligned} P(\to i|i \to, +) &= 1 - \sum_{j \neq i} P(\to j|i \to, +) = 1 - \sum_{j \neq i} \frac{r_{ji}}{\alpha} \\ &= 1 - \frac{1 - r_{ii}}{\alpha} = \frac{r_{ii} - (1 - \alpha)}{\alpha}. \end{aligned}$$

Finally,

$$\begin{aligned} EF_i &= P(\to i|+) = \sum_j P(j \to |+) P(\to i|j \to, +) \\ &= \sum_j P(j \to |+) P(\to i|j \to, +) \\ &= \sum_j P(j \to) P(\to i|j \to, +) \\ & \sum_j a_j EI_{ij}. \end{aligned}$$

QED.

Proof of Proposition 4. For $i \neq j$:

$$P(\to i \to |j \to, +) = \frac{P(\to i|j \to, +)}{P(\to i|i \to)} = \frac{EI_{ji}}{r_{ii}}$$

For $i = j$:

$$P(\to i \to |i \to, +) = 1.$$

Finally,

$$\begin{aligned} OF_i &= P(\to i \to |i \nrightarrow, +) \\ &= \frac{1}{P(i \nrightarrow |+)} \sum_{j \neq i} P(j \to |+) P(\to i \to |j \to, +) \\ &= \frac{1}{P(i \nrightarrow)} \sum_{j \neq i} P(j \to) OI_{ij} \\ &= \frac{1}{1 - a_i} \sum_{j \neq i} a_j OI_{ij}. \end{aligned}$$

QED.

Proof of Proposition 5. For $i \neq j$:

$$\begin{aligned} P(i \to | \to j, +) &= \frac{P(i \to, \to j, +)}{P(\to j, +)} = \frac{P(\to j, + | i \to) \cdot P(i \to)}{P(\to j | +) \cdot P(+)} = \\ &= \frac{P(\to j | i \to) \cdot P(i \to)}{P(\to j | +) \cdot P(+)} = \frac{r_{ji} \cdot a_i}{EF_j \cdot \alpha} = EC_{ji} \end{aligned}$$

For $i = j$:

$$\begin{aligned} P(i \to | \to i, +) &= \frac{P(\to i, i \to, +)}{P(\to i, +)} = \frac{P(\to i, + | i \to) \cdot P(i \to)}{P(\to i, +)} = \\ &= \frac{(r_{ii} - (1-\alpha)) \cdot a_i}{EF_i} = EC_{ii}. \end{aligned}$$

Also,

$$\begin{aligned} \sum_j EF_j EC_{ij} &= \sum_j P(\to j | +) P(i \to | \to j, +) \\ &= \sum_j P(i \to, \to j | +) = P(i \to | +) \\ &= P(i \to) = a_i. \end{aligned}$$

QED.

Proof of Proposition 6. For $j \neq i$

$$\begin{aligned} P(\to i \to | \to j, +) &= \frac{P(\to i \to, \to j | +)}{P(\to j | +)} = \frac{P(\to i \to, \to j, +)/P(+)}{EF_j} \underset{i \neq j}{=} \\ &= \frac{P(\to i \to, \to j)}{\alpha EF_j} = \frac{\frac{q_i}{r_{ii}} r_{ji}}{\alpha EF_j}. \end{aligned}$$

When $i = j$ it is clear that $P(\to i \to | \to i, +) = 1$.

5.4 Appendix A

Unnormalized measures for the 60 journals:

	OF	q	EF	IM (unnorm)	C
AM ECON REV	0.51842	0.11926	0.13031	0.13643	0.11922
Q J ECON	0.34151	0.06122	0.06983	0.07263	0.06403
ECONOMETRICA	0.31248	0.05689	0.06382	0.06679	0.05575
J POLIT ECON	0.28118	0.04733	0.05410	0.05746	0.04650
REV ECON STUD	0.27521	0.04687	0.05258	0.05591	0.04554
J MONETARY ECON	0.21201	0.03685	0.03896	0.04132	0.03988
J ECON THEORY	0.19657	0.03556	0.03613	0.03807	0.02608
REV ECON STAT	0.18821	0.03057	0.03295	0.03373	0.03339
J ECONOMETRICS	0.18255	0.03425	0.03525	0.03583	0.03657
ECON J	0.17242	0.02862	0.02934	0.02736	0.03684
J ECON PERSPECT	0.16114	0.02520	0.02756	0.02809	0.02801
J PUBLIC ECON	0.14557	0.02525	0.02445	0.02402	0.02746
RAND J ECON	0.14386	0.02280	0.02508	0.02559	0.02318
J FINANC ECON	0.13968	0.02830	0.02855	0.02777	0.03215
GAME ECON BEHAV	0.12991	0.02512	0.02266	0.02374	0.02097
J INT ECON	0.12349	0.02049	0.02043	0.01981	0.02594
INT ECON REV	0.10339	0.01634	0.01693	0.01788	0.01614
J MONEY CREDIT BANK	0.10330	0.01839	0.01720	0.01837	0.01766
REV ECON DYNAM	0.10208	0.01547	0.01682	0.01877	0.01297
J DEV ECON	0.09966	0.01733	0.01621	0.01484	0.02277
J ECON LIT	0.09660	0.01405	0.01561	0.01551	0.01642
EUR ECON REV	0.09401	0.01576	0.01518	0.01506	0.01890
J ECON BEHAV ORGAN	0.08448	0.01902	0.01370	0.01359	0.01421
J LABOR ECON	0.08056	0.01189	0.01297	0.01336	0.01242
J HEALTH ECON	0.08022	0.01664	0.01494	0.00719	0.01532
J HUM RESOUR	0.07516	0.01174	0.01192	0.01103	0.01325
EXP ECON	0.07212	0.01115	0.01168	0.01120	0.01518
INT J IND ORGAN	0.06950	0.01264	0.01140	0.01133	0.01118
HEALTH ECON	0.06820	0.01557	0.01291	0.00292	0.01959
ECONOMET THEOR	0.06279	0.01253	0.01106	0.01192	0.00787
J BUS ECON STAT	0.05884	0.00969	0.00951	0.00973	0.00828
J URBAN ECON	0.05213	0.00900	0.00819	0.00817	0.01021
J IND ECON	0.04514	0.00776	0.00724	0.00731	0.00593
J FINANC QUANT ANAL	0.04451	0.00927	0.00815	0.00781	0.00580
J ECON GROWTH	0.03842	0.00558	0.00595	0.00647	0.00524
LABOUR ECON	0.03760	0.00779	0.00585	0.00573	0.00676
BROOKINGS PAP ECO AC	0.03500	0.00482	0.00541	0.00579	0.00414
OXFORD B ECON STAT	0.03147	0.00574	0.00482	0.00402	0.00676
J LAW ECON	0.02916	0.00520	0.00449	0.00462	0.00414
J ECON MANAGE STRAT	0.02726	0.00521	0.00424	0.00375	0.00511
WORLD BANK ECON REV	0.02581	0.00429	0.00398	0.00270	0.00745
J ACCOUNT ECON	0.02576	0.00506	0.00447	0.00423	0.00386
ECON DEV CULT CHANGE	0.02533	0.00438	0.00388	0.00276	0.00676
J ENVIRON ECON MANAG	0.02454	0.00530	0.00374	0.00320	0.00483
ENERG J	0.02398	0.00499	0.00367	0.00402	0.00276
J RISK UNCERTAINTY	0.02308	0.00418	0.00354	0.00321	0.00345
WORLD DEV	0.02129	0.00955	0.00338	0.00287	0.00649
OXFORD ECON PAP	0.02014	0.00455	0.00306	0.00256	0.00442
SCAND J ECON	0.01998	0.00414	0.00304	0.00281	0.00455
ECON POLICY	0.01827	0.00306	0.00279	0.00254	0.00455
J LAW ECON ORGAN	0.01603	0.00304	0.00246	0.00253	0.00207
J ECON SURV	0.01291	0.00308	0.00194	0.00134	0.00331
J POLICY ANAL MANAG	0.01098	0.00254	0.00166	0.00169	0.00179
J ECON GEOGR	0.00764	0.00251	0.00117	0.00111	0.00166
WORLD BANK RES OBSER	0.00494	0.00107	0.00075	0.00040	0.00152
MATH FINANC	0.00454	0.00184	0.00069	0.00075	0.00041
IND CORP CHANGE	0.00440	0.00247	0.00066	0.00018	0.00097
ECON SOC	0.00201	0.00143	0.00030	0.00012	0.00097
VALUE HEALTH	0.00174	0.00862	0.00045	0.00008	0.00041
REV ENV ECON POLICY	0.00000	0.00074	0.00000	0.00000	0.00000

5.5 Appendix B

Normalized measures for the 60 journals.

	AO	q/a	AI	IM	IF
J POLIT ECON	31.3744	5.2808	6.0362	6.4113	5.1887
Q J ECON	27.4717	4.9247	5.6173	5.8423	5.1504
BROOKINGS PAP ECO AC	24.2103	3.3334	3.7452	4.0043	2.8638
REV ECON STUD	19.0392	3.2421	3.6378	3.8678	3.1502
J ECON LIT	18.5639	2.7004	3.0005	2.9799	3.1555
ECONOMETRICA	17.7194	3.2261	3.6189	3.7871	3.1611
RAND J ECON	14.6360	2.3192	2.5520	2.6038	2.3584
J LABOR ECON	13.9336	2.0564	2.2428	2.3098	2.1479
J ECON PERSPECT	13.5948	2.1263	2.3251	2.3702	2.3632
REV ECON DYNAM	13.0781	1.9816	2.1548	2.4049	1.6617
J ECON GROWTH	11.0734	1.6082	1.7156	1.8636	1.5115
REV ECON STAT	11.0344	1.7920	1.9318	1.9776	1.9577
AM ECON REV	9.1490	2.1047	2.2996	2.4078	2.1040
EXP ECON	8.9098	1.3769	1.4434	1.3834	1.8751
J MONETARY ECON	8.5273	1.4821	1.5671	1.6617	1.6040
INT ECON REV	7.9475	1.2563	1.3016	1.3740	1.2410
J HUM RESOUR	7.0265	1.0971	1.1142	1.0309	1.2384
ECON J	7.0164	1.1648	1.1939	1.1134	1.4993
J ECONOMETRICS	6.3784	1.1967	1.2314	1.2518	1.2776
J ECON THEORY	6.0707	1.0983	1.1157	1.1757	0.8054
J INT ECON	5.9329	0.9842	0.9814	0.9515	1.2463
J BUS ECON STAT	5.5003	0.9059	0.8892	0.9097	0.7740
J FINANC ECON	5.1953	1.0527	1.0620	1.0330	1.1958
EUR ECON REV	4.9271	0.8261	0.7955	0.7892	0.9908
J PUBLIC ECON	4.8887	0.8479	0.8211	0.8068	0.9222
WORLD BANK ECON REV	4.2513	0.7069	0.6552	0.4441	1.2273
J IND ECON	4.2204	0.7250	0.6765	0.6829	0.5547
J DEV ECON	4.2039	0.7310	0.6836	0.6259	0.9604
J MONEY CREDIT BANK	4.1072	0.7313	0.6839	0.7303	0.7022
ECON POLICY	3.9500	0.6622	0.6026	0.5492	0.9844
J URBAN ECON	3.8364	0.6624	0.6028	0.6010	0.7515
INT J IND ORGAN	3.5351	0.6430	0.5800	0.5763	0.5685
ECON DEV CULT CHANGE	3.5044	0.6063	0.5368	0.3824	0.9355
GAME ECON BEHAV	3.3285	0.6436	0.5807	0.6082	0.5374
J LAW ECON	3.1516	0.5625	0.4853	0.4993	0.4475
J ACCOUNT ECON	3.0727	0.6030	0.5329	0.5042	0.4608
J HEALTH ECON	3.0491	0.6327	0.5679	0.2732	0.5822
ECONOMET THEOR	3.0167	0.6018	0.5315	0.5727	0.3779
J RISK UNCERTAINTY	2.9564	0.5354	0.4534	0.4118	0.4419
OXFORD B ECON STAT	2.8646	0.5228	0.4385	0.3662	0.6155
J FINANC QUANT ANAL	2.8509	0.5938	0.5222	0.5005	0.3712
J ECON MANAGE STRAT	2.5482	0.4867	0.3961	0.3509	0.4773
J LAW ECON ORGAN	2.5207	0.4785	0.3865	0.3971	0.3254
HEALTH ECON	2.2256	0.5082	0.4214	0.0954	0.6394
LABOUR ECON	2.0009	0.4146	0.3113	0.3052	0.3598
ENERG J	1.9292	0.4011	0.2954	0.3233	0.2220
SCAND J ECON	1.9201	0.3980	0.2917	0.2696	0.4375
J ENVIRON ECON MANAG	1.7326	0.3745	0.2641	0.2262	0.3409
J ECON BEHAV ORGAN	1.7189	0.3870	0.2789	0.2765	0.2892
WORLD BANK RES OBSER	1.7102	0.3698	0.2586	0.1381	0.5250
OXFORD ECON PAP	1.5481	0.3497	0.2349	0.1968	0.3394
J POLICY ANAL MANAG	1.4604	0.3381	0.2213	0.2248	0.2387
J ECON SURV	1.3534	0.3230	0.2035	0.1409	0.3471
J ECON GEOGR	0.7546	0.2481	0.1154	0.1094	0.1636
MATH FINANC	0.5417	0.2196	0.0819	0.0896	0.0494
WORLD DEV	0.4781	0.2145	0.0759	0.0644	0.1457
IND CORP CHANGE	0.3458	0.1938	0.0516	0.0143	0.0759
ECON SOC	0.2570	0.1826	0.0384	0.0151	0.1237
VALUE HEALTH	0.0317	0.1570	0.0082	0.0015	0.0075
REV ENV ECON POLICY	0.0000	0.1500	0.0000	0.0000	0.0000