On the Nuisance of Control Variables in Regression Analysis

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This version: 2 October 2020
First version: 20 May 2020

Abstract:

Control variables are included in regression analyses to estimate the causal effect of a treatment on an outcome. In this note we argue that the estimated effect sizes of control variables are unlikely to have a causal interpretation themselves though. We therefore recommend to refrain from reporting marginal effects of controls in regression tables and instead to focus exclusively on the variables of interest in the results sections of empirical research papers.

Key words: Multivariate Regression; Research Methodology; Causal Inference; Econometrics
JEL classification: C18; C51

Introduction

Multivariate regression analysis is an important tool for empirical research in management, organization studies, and economics. These methods account for confounding influence factors between a treatment and an outcome by including a set of control variables in order to obtain unbiased causal effect estimates. Notwithstanding their importance for causal inference, in practice scholars often overstate the role of control variables in regressions. In this note we argue that, while essential for the identification

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of treatment effects, control variables generally have no structural interpretation themselves. This is because even *valid* controls are often correlated with other unobserved factors, which renders their marginal effects uninterpretable from a causal inference perspective (Westreich and Greenland, 2013; Keele *et al.*, 2020). Consequently, researchers need to be careful with attaching too much meaning to control variables and should consider to ignore them entirely when interpreting the results of their analysis.

Drawing substantive conclusions from control variables is common however in empirical research. Authors frequently make use of formulations such as: *"control variables have expected signs"* or *"it is worth noting the results of our control variables"*. Based on the volume of papers published in the last five years in *Strategic Management Journal* and *Organization Science*, we found that more than 47 percent of papers that made use of parametric regression models also explicitly discussed the estimated effects of controls.[1] This is inline with a previous observation made from top management journals in which 48 percent of papers were found to interpret and discuss the estimated effects of controls (Carlson and Wu, 2012).[2] Moreover, in our own experience as authors of empirical research papers, we encountered instances in which reviewers specifically asked us to provide an interpretation of control variable coefficients. The argument was that, although they were not the main focus of the analysis, the controls could still provide valuable information for other researchers in the field who are investigating related research questions. In the following, we will explain why this approach is potentially misleading and should therefore better be avoided.

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[1]We analyzed all research articles published in Strategic Management Journal between January 2015 and July 2020 and found that, out of a total number of 468 papers which included parametric regression models, 218 proceeded to explicitly interpret and draw substantive conclusions based on the marginal effects of control variables. Similarly, in Organization Science between January 2015 to June 2020, 122 out of 256 papers proceeded to interpret the marginal effects of control variables.

[2]Carlson and Wu (2012) analyzed all articles with empirical analyses including at least one control variable published in Academy of Management Journal, Journal of Applied Psychology and Strategic Management Journal in 2007.
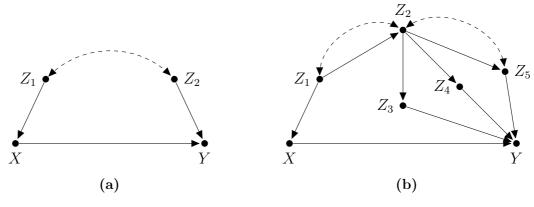
Figure 1.

The structural interpretation of control variables

The relationship between the main explanatory variables and the controls in a regression can be complex, therefore it is useful to explicitly depict them in a causal diagram (Pearl, 2000; Hünermund and Bareinboim, 2019). Durand and Vaara (2009) were the first to introduce causal graphs to the management literature and demonstrate their usefulness as a tool for empirical research. Figure 1a presents a simple model with a treatment variable X and an outcome variable Y. Both variables are connected by an arrow, denoting the direction of causal influence between them. In addition, there are two confounding variables, Z_1 and Z_2, that are affecting the treatment and the outcome. Z_1 and Z_2 are correlated, as a result of a common influence they share, which is denoted by the dashed bidirected arc in the graph. The fact that Z_1 and Z_2 are correlated creates what is known as a backdoor path between the treatment and the outcome (Pearl, 2000). X and Y are not only connected by the genuinely causal path $X \rightarrow Y$, but also by a second path, $X \leftarrow Z_1 \leftarrow ---\rightarrow Z_2 \rightarrow Y$, which creates a spurious, non-causal correlation between them.

The role of control variables in regression analysis is exactly to block such backdoor paths, in order to get at the uncontaminated causal effect of X on Y. For this purpose, it

is sufficient to control for any variable that lies on the open path.[3] Thus, in the example of Figure 1a, the researcher has the choice between either controlling for Z_1 or Z_2, since both would allow to identify the causal effect of interest. The choice between different admissible sets of control variables is thereby of high practical relevance. Researchers often have fairly detailed knowledge about the treatment assignment mechanism $Z_1 \to X$; e.g., because there are organizational or administrative rules that determine individual treatment status, which can be exploited for identification purposes (Angrist, 1990; Flammer and Bansal, 2017; Hünermund and Czarnitzki, 2019). At the same time, the set of variables Z_2 that are direct influence factors of Y will likely be quite large. Thus, in practical applications it might be much easier to control the treatment assignment mechanism than trying to include all the variables that have an effect on the outcome measure in a regression.

Nevertheless, although controlling for Z_1 is sufficient to obtain an unbiased estimate for X, its marginal effect will itself not correspond to any causal effect of Z_1 on Y. This is because Z_1 is correlated with Z_2 and will thus partially pick up an effect of Z_2 on Y too (Cinelli and Hazlett, 2020).[4] The danger of interpreting estimated effects of potentially endogenous control variables, such as Z_1, is referred to as *table 2 fallacy* in

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[3]Technical note: Requiring the path to be previously unblocked rules out that the variable which is adjusted for is a collider (Hünermund and Bareinboim, 2019). A discussion of collider variables in causal graphs goes beyond the scope of this note.

[4]To illustrate this phenomenon quantitatively, we parametrize the causal graph in Figure 1a in the following way:

$$z_1 \leftarrow u + \varepsilon_1,$$
$$z_2 \leftarrow u + \varepsilon_2,$$
$$x \leftarrow z_1 + \varepsilon_3,$$
$$y \leftarrow x + z_2 + \varepsilon_4,$$

with $N = 1000$, and u and ε_m being standard normal. We then run a regression of Y on X and Z_1, which gives us a consistent coefficient estimate for X ($= 0.970$, std. err. $= 0.052$; bootstrapped with 1000 replications), while the effect of Z_1 ($= 0.541$, std. err. $= 0.064$) turns out to be biased. By contrast, if we also include Z_2 in the regression, the coefficient of Z_1 drops to zero ($= -0.016$, std. err. $= 0.042$), which corresponds to its true causal effect on Y in this example.

epidemiology (Westreich and Greenland, 2013).[5] In a recent paper, Keele *et al.* (2020) discuss similar examples from the field of political science using causal graphs.

Figure 1b depicts a more complex setting, with several admissible sets of controls, each sufficient to identify the causal effect of X on Y (Textor and Liśkiewicz, 2011). One possibility in this situation is to simply control for Z_1, which is the only direct influence factor of X, and thus blocks all paths entering X through the backdoor. Similarly, controlling for the direct influence factors of Y (Z_3, Z_4, and Z_5) also blocks all backdoor paths. A third alternative is to control for the entire set of confounders (Z_1, Z_2, Z_3, Z_4, and Z_5), although this would be the most data-intensive identification strategy leading to less precise estimates, due to lower degrees of freedom. This example illustrates that the minimally sufficient set of controls (here: Z_1) for identifying the causal effect of X is often much smaller than the total number of confounding variables in a model. At the same time, the estimated marginal effects for the control variables only have a structural interpretation themselves if all the direct influence factors of Y (here: Z_3, Z_4, and Z_5) are accounted for in the regression. As we argued above, this is unlikely to be the case, since in many real-world settings the number of causal factors determining Y can be prohibitively large.

Implications for research practice

Attaching substantive meaning to the marginal effects of biased control variables is problematic, as researchers could develop false intuitions or draw erroneous managerial and policy conclusions based on them. Therefore it is advisable to not discuss the results obtained for control variables in empirical papers, unless the researcher can be sure that they have accounted for all relevant influence factors of the outcome in a regression (*all-causes regression*). Since in many practical settings this is unlikely to be the case, we

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[5]Epidemiologists usually present the results of multivariate regression analyses right after a table with descriptive statistics of the data, therefore the name *table 2 fallacy*.

recommend to treat controls as *nuisance parameters*, which are included in the analysis for identification purposes (and discussed as such) but their effects are not reported in the output tables (Liang and Zeger, 1995; Meehl, 1971). This corresponds to the way control variables are treated by non-parametric matching estimators (Heckman *et al.*, 1998) and modern machine learning techniques for high-dimensional settings (Belloni *et al.*, 2014). These methods similarly do not report estimation results related to controls, either because there are simply too many covariates in the analysis (which is the primary use-case for machine learning) or marginal effects of control variables are not even returned by the estimation protocol (as in the matching case).

Our recommendation thereby contradicts claims that have been made in prior literature along several important dimensions. Becker (2005, p. 286) advises to report all beta coefficients of control variables as well as their significance levels. Similarly, Spector and Brannick (2011, p. 297) advocate that controls should be given equal status with the main treatment variable in the analysis. Furthermore, Atinc *et al.* (2012) consider it to be best practice that the sign of the relationship between controls and the outcome should be predicted based on theory. While we agree with these authors that the inclusion of control variables in multivariate regressions needs to be carefully motivated given a causal model of the phenomenon under study (Bono and McNamara, 2011), on the basis of the preceding discussion we do not find it advisable to hypothesize about the signs of control variables and draw substantive conclusions based on their estimated effect sizes. The main reason for these differing recommendations is perhaps that we recognize that valid control variables do not need to be direct causes of the outcome (nor of the treatment), which renders the statistical correlations between them hard to interpret.[6]

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[6]Becker (2005) makes the additional argument that reporting coefficients of control variables facilitates meta-analyses and thus contributes to cumulative research. However, we see little benefit in including biased effect sizes in meta-analytic studies.

To conclude, there is no reason to be worried if the estimated coefficients of control variables do not have expected signs, since they are likely to be biased anyways in practical applications. Instead, researchers should rather focus on interpreting the marginal effects of the main variables of interest in their manuscripts. The estimation results obtained for controls, by contrast, have little substantive meaning and can therefore safely be omitted—or relegated to an appendix. This approach will not only prevent researchers from drawing wrong causal conclusions based on endogenous controls, but will also allow to streamline the discussion sections of empirical research papers and save on valuable journal space.

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Appendix

The following table lists the number of articles per volume and issue, published in *Strategic Management Journal* and *Organization Science* between January 2015 and July 2020 that were identified to include an explicit interpretation of the estimation results for control variables. *Total* refers to the total number of papers using parametric regression models in the respective issue. We counted articles that either explicitly discuss marginal effects of control variables (e.g., their sign and significance) with regards to to prior research findings or draw substantive conclusions based on them for policy and managerial practice.

Strategic Management Journal

Volume	Issue	Total	Count	Articles
41	7	7	2	Belderbos, Tong & Wu, 2020; Oh, Shapiro, Ho & Shin, 2020;
41	6	6	2	Chattopadhyay & Bercovitz, 2020; Smulowitz, Rousseau & Bromiley, 2020;
41	5	4	2	Sakakibara & Balasubramanian, 2020; Rocha & van Praag, 2020;
41	4	7	2	Aggarwal, 2020; Bonet, Capelli & Homari, 2020;
41	3	4	2	Arikan, Arikan & Shenkar, 2020; Agarwal, Braguinsky & Ohyama, 2020;
41	2	5	2	Ryu, Reuer & Brush, 2020; Jia, Gao & Julian, 2020;
41	1	5	0	-
40	13	7	1	Hsu, Kovács & Koçak, 2019;
40	12	6	4	Kim, 2019; Petrenko, Aime, Recendes & Chandler, 2019; Guldiken, Mallon, Fainshmidt, Judge & Clark, 2019; Shi, Conelly, Mackey & Gupta, 2019;
40	11	5	2	Woo, Canella & Mesquita, 2019; Zweiger, Stettler, Baldauf & Zamudio, 2019;
40	10	6	3	Ridge, Imgram, Abdurakhmonov & Hasija, 2019; Gómez–Solórzano, Tortoriello & Soda, 2019; Kavusan & Frankort, 2019;
40	9	5	0	-
40	8	6	1	Barlow, Verhaal & Angus, 2019;
40	7	5	2	Corsino, Mariani & Torrisi, 2019; Andrus, Withers, Courtright & Boivie, 2019;
40	6	5	2	Hiatt & Carlos, 2019; Piazzai & Wijnberg, 2019;

Volume	Issue	Total	Count	Articles
40	5	4	2	Hill, Recendes & Ridge, 2019; Yu, Minniti & Nason, 2019;
40	4	5	3	Paik, Kang & Seamans, 2019; Bruce, de Figueiredo & Silverman, 2019; Zheng, Ni & Crilly, 2019;
40	3	3	2	Chatterji, Delecourt, Hasan & Koning, 2019; Bigelow, Nickerson & Park, 2019;
40	2	5	3	Criscuolo, Alexy, Sharapov & Salter, 2019; Ren, Hu & Cui, 2019; Boone, Lokshin, Guenter & Belderbos, 2019;
40	1	7	4	Haans, 2019 (Appendix); Chatterji, Cunningham & Joseph, 2019; Westphal & Zhu, 2019; Belderbos, Tong & Wu, 2019;
39	13	5	1	Garg & Zhao, 2018;
39	12	5	4	Cui, Yang & Vertinsky, 2018 (Appendix); Ranganathan, Ghosh & Rosenkopf, 2018; Arslan, 2018; Asgari, Tandon, Singh & Mitchell, 2018;
39	11	8	5	Feldman, Gartenberg & Wulf, 2018; Claussen, Essling & Peukert, 2018; Burbano, Mamer & Snyder, 2018; Koch-Bayram & Wernicke, 2018; Mata & Alves, 2018;
39	10	8	4	Eberhardt & Eesley, 2018; Hornstein & Zhao, 2018; Kang & Zaheer, 2018; Albino-Pimentel, Dussauge & Shaver, 2018;
39	9	6	3	Khanna, Guler & Nerkar, 2018; Hawk & Pacheco-de-Almeida, 2018; Schepker & Barker, 2018;
39	8	5	4	Yayavaram, Srivastava & Sarkar, 2018; Gandal, Markovich & Riordan, 2018; Manning, Massini, Peeters & Lewin, 2018; Shi & Connelly, 2018;
39	7	8	4	Byun, Frake & Agarwal, 2018; Mawdsley & Somaya, 2018; Alvarez-Garrido & Guler, 2018; Gupta, Mortal & Guo, 2018;
39	6	0	0	-
39	5	9	5	Chen & Garg, 2018; Kaul, Nary & Singh, 2018; Flammer, 2018; Ramírez & Tarziján, 2018; Wiersema, Hishimure & Suzuki, 2018;

Volume	Issue	Total	Count	Articles
39	4	8	5	Hawn, Chatterji & Mitchell, 2018; Choudhury & Haas, 2018; Bode & Singh, 2018; Tarakci, Ateş, Floyd, Ahn & Wooldridge, 2018; Rhee & Leonardi, 2018;
39	3	0	0	-
39	2	6	4	Chen, Kale & Hoskisson, 2018; Choi & McNamara, 2018; Deichmann & Jensen, 2018; Pek, Oh & Rivera, 2018;
39	1	8	3	Furr & Kapoor, 2018; Vidal & Mitchell, 2018; Jiang, Xia, Canella & Xiao, 2018;
38	13	8	4	Chem, Qian & Narayanan, 2017; Rabier, 2017; Dorobantu & Odziemkowska, 2017; Li, Yi & Cui, 2017;
38	12	5	3	Lee & Puranam, 2017; Werner, 2017; Theeke & Lee, 2017;
38	11	8	4	Carnahan, 2017; Kölbel, Busch & Jancso, 2017; Bos, Faems & Noseleit, 2017; Li & Zhou, 2017;
38	10	8	4	Moeen, 2017; Raffiee, 2017; Jiang, Canella, Xia & Semadeni, 2017; Wei, Ouyang & Chen, 2017;
38	9	8	5	Souder, Zaheer, Sapienza & Ranucci, 2017; Caner, Cohen & Pil, 2017; Shan, Fu & Zheng, 2017; Wang, Zhao & Chen, 2017; Li, Xia & Lin, 2017;
38	8	9	5	Zhou & Wan, 2017; Kulchina, 2017; Kim & Steensma, 2017; Steinbach, Holcomb, Holmes, Devers & Canella, 2017; Makino & Chan, 2017;
38	7	10	3	Armanios, Eesley, Li & Eisenhardt, 2017; Ref & Shapira, 2017; McCann & Bahl, 2017;
38	6	7	3	Roy & Cohen, 2017; Dowell & Muthulingam, 2017; Vanacker, Collewaert & Zahra, 2017;
38	5	9	5	Stan & Puranam, 2017; Asgari, Singh & Mitchell, 2017; Kuusela, Keil & Maula, 2017; Girod & Whittington, 2017; Connelly, Tihanyi, Ketchen, Carnes & Ferrier, 2017;
38	4	8	1	Silverman & Ingram, 2017;
38	3	10	4	Bermiss, Hallen, McDonald & Pahnke, 2017; Chatterjee, 2017; Oh & Oetzel, 2017; Blake & Moschieri, 2017;

Volume	Issue	Total	Count	Articles
38	2	11	5	Flammer & Luo, 2017; Madsen & Walker, 2017; Mackey, Barney & Dotson, 2017; Fonti, Maoret & Whitbred, 2017; Deb, David & O'Brien, 2017;
38	1	0	0	-
37	13	6	2	Hawn & Ioannou, 2016; Stuart & Wang, 2016;
37	12	7	3	Wang, Zhao & He, 2016; Easley, Decelles & Lenox, 2016; Wu & Salomon, 2016;
37	11	10	7	Ghosh, Ranganathan & Rosenkopf, 2016; Kalnins, 2016; Chang, Kogut & Yang, 2016; Tsang & Yamanoi, 2016; Massimo, Colombo & Shafi, 2016; Chadwick, Guthrie & Xing, 2016; Park, Borah & Kotha, 2016;
37	10	8	2	Husted, Jamali & Saffar, 2016; Van Reenen & Pennings, 2016;
37	9	6	1	Gomulya & Boeker, 2016;
37	8	10	5	Fonti & Maoret, 2016; Rodríguez & Nietro, 2016; Zhu & Yoshikawa, 2016; Yu, Umashankar & Rao, 2016; Jain, 2016;
37	7	12	3	Bennet & Pierce, 2016; Anand, Mulotte & Ren, 2016; Geng, Yoshikawa & Colpan, 2016;
37	6	8	3	Smith & Chae, 2016; Klingebiel & Joseph, 2016; Karna, Richter & Riesenkampf, 2016;
37	5	5	4	Roy & Sarkar, 2016; Lungeanu, Stern & Zajac, 2016; Tyler & Caner, 2016; Brandes, Dharwadkar & Suh, 2016;
37	4	6	4	Adner & Kapoor, 2016; Maslach, 2016; Poppo, Zhou & Li, 2016; Eckhardt, 2016;
37	3	9	3	Feldman, Amit & Villalonga, 2016; Pe'er, Vertinsky & Keil, 2016; Barroso, Giarratana, Reis & Sorenson,2016;
37	2	8	3	Chen, Crossland & Huang, 2016; Desender, Aguilera, Lópezpuertas-Lamy & Crespi, 2016; Kang, 2016
37	1	6	2	Dezsö, Ross & Uribe, 2016; Ge, Huang & Png, 2016;
36	13	8	3	Joseph & Gaba, 2015; Macher & Mayo, 2015; Zhu & Chen, 2015;
36	12	7	3	Fuentelsaz, Garrido & Maicas, 2015; Malhotra, Zhu & Reus, 2015; Chen, 2015;

Volume	Issue	Total	Count	Articles
36	11	8	5	Zheng, Singh & Mitchell, 2015; Speckbacher, Neumann & Hoffmann, 2015; Skilton & Bernardes, 2015; Bermiss & Murmann, 2015; Fosfuri, Giarratana & Roca, 2015;
36	10	4	3	Kaplan & Vakili, 2015; Chen, Crossland & Luo, 2015; Ang, Benischke & Doh, 2015;
36	9	7	4	Chittoor, Kale & Puranam, 2015; Chang & Shim, 2015; Banalieva, Eddleston & Zellweger, 2015; Hashai, 2015;
36	8	8	4	Bidwell, Won, Barbulescu & Mollick, 2015; Steensma, Chari & Heidl, 2015; Durand & Vergne, 2015; Lange, Boivie & Westphal, 2015;
36	7	9	6	Elfenbein & Knott, 2015; Blettner, He, Hu & Bettis, 2015; Arrfelt, Wiseman, McNamara & Hult, 2015; Ioannou & Serafeim, 2015; Wowak, Mannor & Wowak, 2015; Pacheco & Dean, 2015;
36	6	7	3	Kim, 2015 (Appendix); Chizema, Liu, Lu & Gao, 2015; Miller, Xu & Mehrotra, 2015;
36	5	7	5	Bertrand & Capron, 2015; Ganco, Ziedonis & Agarwal, 2015; Younge, Tong & Fleming, 2015; Damaraju, Barney & Makhija, 2015; Madsen & Rodgers, 2015;
36	4	6	3	Greve & Seidel, 2015; Harmon, Kim & Mayer, 2015; Tortoriello, 2015;
36	3	4	3	Diestre, Rajagopalan & Dutta, 2015; Chadwick, Super & Kwon, 2015; Kapoor & Furr, 2015;
36	2	6	4	Pacheco-de-Almeida, Hawk & Yeung, 2015; Chown & Lui, 2015; Argyres, Bigelow & Nickerson, 2015; Tong, Reuer, Tyler & Zhang, 2015;
36	1	2	1	Cain, Moore & Haran, 2015;

Organization Science

Volume	Issue	Total	Count	Articles
31	3	9	5	Claes & Vissa, 2020; Younkin & Kaskooli, 2020; Tilleman, Russo & Nelson, 2020; Withers, Howard & Tihanyi, 2020; Aharonson, Bort & Woywode, 2020;
31	2	6	2	Chambers & Baker, 2020; Hallen, Cohen & Bingham, 2020;
31	1	5	2	Diestre & Santaló, 2020; Jacqueminet, 2020;
30	6	7	4	Rahmandad & Vakili, 2019; Bowers & Prato, 2019; Negro & Olzak, 2019; Rietveld, Schilling & Bellavitis, 2019;
30	5	5	3	Moore, Payne, Filatotchev & Zajac, 2019; Berchicci, Dutt & Mitchell, 2019; Furr, 2019;
30	4	8	2	Gaba & Greve, 2019; Bird, Short & Toffel, 2019;
30	3	6	2	Lee, 2019; Blevins, Sauerwald, Hoobler & Robertson, 2019;
30	2	8	3	Chatman, Greer, Sherman & Doerr, 2019; Furlan, Galeazzo, 2019; Eklund & Kapoor, 2019;
30	1	9	4	Knott & Turner, 2019; Zhang, 2019; Rockart & Wilson, 2019; Godart & Galunic, 2019;
29	6	8	1	Keum & Eggers, 2018;
29	5	9	4	Furlotti & Soda, 2018; Berry,2018; Albert, 2018; Ertug, Gargiulo, Galunic & Zou, 2018;
29	4	5	4	Zhao, Ishihara, Jennings & Lounsbury, 2018; Hiatt, Carlos & Sine, 2018; James & Vaaler, 2018; Madsen & Desai, 2018;
29	3	5	2	Lee, 2018; Blevins, Sauerwald, Hoobler &Robertson, 2018;
29	2	5	2	Maslach, Branzei, Rerup & Zbaracki, 2018: Rietveld & Eggers, 2018;
29	1	7	3	Conti, 2018; Durand & Georgallis, 2018; Hsu, Koçak & Kovács, 2018;
28	6	6	1	Greve & Yue, 2017;
28	5	6	4	Ditriadis, Lee, Ramarajan & Battilana, 2017; Tzabbar & Margolis, 2017; Lee & Kapoor, 2017; Ozmel, Yavuz, Reuer & Zenger, 2017;
28	4	5	3	Merluzzi, 2017; Keum & Kelly, 2017; Mannucci, 2017;

Volume	Issue	Total	Count	Articles
28	3	8	3	Laursen, Moreire, Reichstein & Leone, 2017; Kapoor & Agarwal, 2017; Reuer & Devarakonda, 2017;
28	2	7	2	Chattopadhyay & Choudhury, 2017; Bonet & Salvador, 2017;
28	1	8	7	Obloj & Zenger, 2017; Lee & Meyer-Doyle, 2017; Gartenberg & Wulf, 2017; Hoehn-Weiss, Karim & Lee, 2017; McEvily, Zaheer & Kamal, 2017; Ferguson & Carnabuci, 2017; Eberhart, Eesley & Eisenhardt, 2017;
27	6	8	4	Quintane & Carnabuci, 2016; Boone & Özcan, 2016; Mollick, 2016; Vanacker & Forbes, 2016;
27	5	11	7	Wang, Doucet, Waller, Sanders & Phillips, 2016; Sako, Chondrakis & Vaaler, 2016; Choi, Kumar & Zambuto, 2016; Souder, Reilly, Bromiley & Mitchell, 2016; Yang & Schwartz, 2016; Eesleym, 2016; Zhang, Marquis & Qiao, 2016;
27	4	8	6	Stenard & Sauermann, 2016; Hahl, 2016; Montauti & Wezel, 2016; Lin , 2016; Burbano, 2016; Bhaskarabhatla, 2016;
27	3	0	0	-
27	2	8	5	Szulanski, Ringov & Jensen, 2016; Zhang & Gimeno, 2016; Kilduff, Willer & Anderson, 2016; Khessina & Reis, 2016; Eesley, Li & Yang, 2016;
27	1	8	5	Adams, Fontana & Malerba, 2016; McDonell, 2016; Slavova, Fosfuri & De Castro, 2016; Cuypers, Koh & Wang, 2016; Kozhikode, 2016;
26	6	9	4	Hasan, Ferguson & Koning, 2015; Carnabuci, Operti & Kovács, 2015; Huang & Washington, 2015; Hiatt, Grandy, & Lee, 2015;
26	5	12	3	Cobb, 2015; Srivastava, 2015; Verhaal, Khessina & Dobrev, 2015;
26	4	10	5	Sosa, Gargiulo & Rowles, 2015; Marino, Aversa, Mesquita & Anand, 2015; Vidal & Mitchell, 2015; Brands, Menges &b Kilduff, 2015; Kleinbaum, Jordan & Aufia, 2015;

Volume	Issue	Total	Count	Articles
26	3	13	7	Sterling, 2015; Dobrajska, Billinger & Karim, 2015; Piazza & Perretti, 2015; O'Reilly, Robinson, Berdahl & Banki, 2015; Lee & Lounsbury, 2015; Jacobides &Yae, 2015; Yang, Li & Delios, 2015;
26	2	13	6	Williams & Polman, 2015; Rider & Tan, 2015; Casciaro & Lobo, 2015; Tortoriello, McEvily & Krackhardt, 2015; Gambardella, Ganco & Honoré, 2015; Evans, Hendron & Oldroyd, 2015;
26	1	14	7	Jensen & Kim, 2015; Smith & Hou, 2015; Lo & Kennedy, 2015; Almeida, Phene & Li, 2015; Aggarwal & Wu, 2015; Zhou, 2015; Lui & Wezel, 2015;