Does Output Influence Productivity? - A Meta-Regression Analysis

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The goal of this paper is to conduct a meta-regression analysis (MRA hereafter) regarding the effects of the Kaldor-Verdoorn effect – the relation between output/demand and productivity. The Kaldor-Verdoorn effect has been subject to many econometric studies and while the overwhelming majority of them finds a positive overall effect, there is no consensus on its size – the results vary quite a bit, especially according to the chosen econometric specification.

This MRA estimates a 'true value' of the Kaldor-Verdoorn effect without interference from potential publication selection bias via the use of multivariate MRA. A series of moderator variables is used to check for their effect of excess variation, including amongst others the year of publication, the sectors and the countries studied.

This MRA study uses available data from 22 published studies with 303 estimations of the Kaldor-Verdoorn effect. When examining the primary literature as a whole, there seems to be publication bias. While there seems to exist a genuine Kaldor-Verdoorn effect, its size varies considerably depending on the specification chosen.

KEYWORDS
Kaldor-Verdoorn effect, Productivity, Meta-regression analysis, Effective demand, Learning by doing

1 | INTRODUCTION

In 1929, P.J. Verdoorn published an article pointing at a potential link between the long-run rate of growth of labour productivity and the rate of growth of output. Verdoorn's conclusion was that the causation runs from the rate of growth of output to productivity growth. This finding was first referred to by Arrow (1962) and later on coined Verdoorn's Law by Kaldor (1966). Kaldor (1966) also presented the findings by Verdoorn (2002) in order to explain the by then slow rate of growth of the UK economy – the reason for which Verdoorn's law is also known as 'Kaldor's second law'.[1] While Kaldor (1966) and his use of Verdoorn's law created an intensive debate on its theoretical implications and empirical regularities, it is important to point out that Verdoorn himself never referred to his findings as a law-like relation. Indeed, in an exchange of letters with A. P. Thirlwall, Verdoorn explicitly forbid the publication by Thirlwall of an English translation of his own work, stating that, unlike at the time of the original publication, he was now convinced that this relationship was only stable at the steady state. Verdoorn restated in 1980 that *'(t)he "law" that has been given my name appears therefore to be much less generally valid than I was led to believe in 1929'* (Verdoorn, 1980, p.385).

While Verdoorn might have stopped believing in a law-like relationship, others did not. Since the 1950s there has been a plethora of studies trying to estimate a possible Kaldor-Verdoorn effect. While the overwhelming majority seems to find overall positive results (if statistically significant) for such a relation, there is no real consensus about its definite strength. In this paper, we conduct a more detailed literature survey using meta-regression analysis (abbreviated MRA from here on). MRA is a method for examining the scientific validity of empirical estimates, not only regarding one specific study but the complete field of research as a whole. Meta-regression analysis is relatively new in economics but an established standard in other domains such as medicine or psychology. For this study a new dataset consisting out of 22 studies has been created and is being tested for an underlying overall Kaldor-Verdoorn effect.

The remainder of this paper is organised as follows: section 2 explains the debate around the Kaldor-Verdoorn effect and its implications for industrial and development policy, as well as questions on long-term growth trajectories. Section 3 presents MRA as a useful tool for both a complete and detailed literature survey as well as a means to synthesise the different results into an overall result, explaining the difference in obtained results via the characteristics of the specific studies. The section then explains the methodology in detail using the FAT-PET-PEESE test as state-of-the-art in meta-regression analysis. The search process through the available literature and the structure of the newly created dataset is explained in detail in section 4. In section 5, we conduct a meta-regression analysis on the 22 aforementioned studies estimating a potential Kaldor-Verdoorn effect, using both linear and multiple estimation techniques. As far as we know, this is the first MRA ever conducted on the Kaldor-Verdoorn effect. Section 6 concludes.

2 | PUTTING THE KALDOR-VERDOORN EFFECT INTO CONTEXT

The reactions to Verdoorn's (2002) paper split up into three interpretations, of which two represent the currently most widely used.

The first interpretation of Verdoorn's law emphasises the importance of 'learning by doing' and the complementarity of capital and labour, which applies to both Verdoorn's early interpretation and the work by Arrow (1962). This interpretation makes use of 'the principle of the learning curve, applied to national accounts' (Arrow, 1962, p.156). One justification for this would be the so-called 'manufacturing progress function', where an increase in cumulative output enables a higher division of labour. Parts of this interpretation can be traced back up to Adam Smith's and Allyn Young's notions that the division of labour increases with the activity of the market.

The second interpretation has been put forward by Kaldor (1966) and has stressed the macroeconomic impact of

aggregate demand on growth. Here higher aggregate demand creates the need for rationalisation and more efficient production schemes, which in turn affects technical progress and productivity growth. This interpretation in microeconomic terms also emphasises the existence of increasing returns to scale, which challenged formerly dominating hypothesis of constant returns to scale in neo-classical economic theory.

The third interpretation used perfect substitutability of labour and capital via the use of a Cobb-Douglas production function. Neo-Classical theory in the 1950s and 60s had no complete growth model explaining technological change, assuming instead exogenous technological growth, full employment and steady state growth. Additionally, the dissatisfaction with the idea of constant returns to scale, the new availability of international consistent data led to the pursuit of different models. Finally, the presence of very different growth patterns around the world were at odds with the idea of the theory of the tendency of growth rates to converge as in the Solow-Swan model. Here, Arrow (1962) provided a stepping stone which later inspired the creation of the endogenous growth literature (Romer, 1988; Lucas, 1988) with increasing returns to scale and endogenous technological growth. This increased the need for a proper explanation concerning the relation between production and technology (and vice-versa).

The validity of the Verdoorn effect would imply more than just the importance of aggregate demand in the long-term evolution of the economic system. Its link to the potential existence of increasing returns to scale would lead to far-reaching conclusions for policy, especially for developing countries and infrastructure decisions. As the Kaldor-Verdoorn effect is supposed to be stronger in the manufacturing sector than in non-manufacturing sectors, de-industrialisation might have hampered long-term growth due to weaker productivity growth. Similarly, in a country with sustained higher growth, the respective country would not necessarily lose in competitiveness since the increase in output would induce higher productivity growth. Growth itself might be reinforcing. On the other hand, a sustained period of slow growth might put a country into a descending spiral of ever-deteriorating competitiveness.

Since Verdoorn's first publication, a lot of empirical studies have been conducted onb the overall validity of his 'law' (amongst many others Kaldor (1966); Rowthorn (1975); Stoneman (1979); McCombie (1982b); McCombie and de Ridder (1984); Bairam (1987); Targetti and Foti (1997); Leon-Ledesma (2002); McCombie et al. (2002); Storm and Naastepad (2012). The biggest part of those studies were published in the 1980s, with the 1990s showing less interest in the possible existence of the Verdoorn effect. Only in the recent decade there seems to be a renewed interest in this topic, which might have to do with the idea of a period of 'secular stagnation' (Hansen, 1938; Gordon, 2015; Storm, 2017). In such a period, innovation would have to play a key role and thus the determinants of technological change became increasingly important again. An attempt at summarising the available econometric literature on the Verdoorn effect has been made by McCombie et al. (2002), who surveyed the literature dating from Verdoorn's first publication on this topic in 1929 until 2001. The authors conclude that a one percentage increase in output (or demand, depending on the reader's interpretation) growth raises productivity growth between 0.3 and 0.6 percentage points. This relationship generally holds in sector-wide, single country or regional studies, and different forms of estimations like for example cross-section estimations or time series. Similarly, Hein (2014) extends this survey by several recent studies and finds similar conclusions.

The literature uses two different estimation techniques in order to estimate the Kaldor-Verdoorn coefficient. The straightforward method consists in estimating productivity growth $\hat{y}$ as a function of output growth $\hat{q}$, where α_1 is a constant and β_1 the coefficient of output/demand growth.

$$\hat{y}_i = \alpha_1 + \beta_1 \hat{q}_i + \epsilon_i \tag{1}$$

This is the method used by Verdoorn (2002) himself. Now the measurement of productivity itself is a tricky subject,

and one might want to evade having to explain the reasons as to why a certain measurement for it has been chosen despite all the implied problems discussed during the Cambridge capital controversies (Robinson, 1953; Samuelson, 1966; Sraffa, 1975). Another objection consists in the possible spurious correlation inherent in equation 1, emphasised by Rowthorn (1975). Thus, a second method for estimating the effect has been established by him, using the fact that productivity growth $\hat{y}$ is by definition the difference between output growth $\hat{q}$ and employment growth $\hat{e}$ ($\hat{y} \overset{!}{=} \hat{q} - \hat{e}$).

$$\hat{e}_i = -\alpha_1 + (1 - \beta_1)\hat{q}_i + \epsilon_i \tag{2}$$

Equation 2 is the interpretation by Kaldor (1966). Following Rowthorn (1975), it can can also be written as

$$\hat{q}_i = \alpha_2 + \beta_2 \hat{e}_i + \epsilon_i \tag{3}$$

or

$$\hat{q} = \frac{\alpha_1}{1 - \beta_1} + \frac{R^2}{1 - \beta_1}\hat{e} + \epsilon_i \tag{4}$$

under the condition that the statistical fits are exact ($R^2 = 1$). In this case, $(1 - \alpha_1) = \frac{1}{\alpha_2}$ because $(1 - \beta_1)\alpha_4 = R^2$. This is the definition of Verdoorn's law commonly know as 'Rowthorn's specification'. It implies that if R^2 is less than 1, $(1 - \beta_1) < \frac{1}{\alpha_4}$ and the resulting estimate will be in favour of constant returns to scale rather than increasing ones.

The main critique of Rowthorn (1975) was that, in Verdoorn's specification, there is an issue of simultaneous equation bias. Employment growth $\hat{e_i}$ is correlated with wage growth, which in turn is correlated with productivity growth $\hat{y_i}$. Running regressions like equation 2 is therefore not the correct specification.

It has to be said that there exists a series of misunderstandings concerning the names of the different specifications used. Rowthorn (1975) himself did not use equation 3 as the subsequent literature assumes, but rather the following specification, explaining productivity growth $\hat{y}$ via employment growth $\hat{e}$.

$$\hat{q} = \frac{\alpha_1}{1 - \beta_1} + \frac{R^2}{1 - \beta_1}\hat{e} + \epsilon_i \tag{5}$$

or

$$\hat{y}_i = \frac{\alpha_1}{a - \beta_1} + \frac{\beta_1}{1 - \beta_1}\hat{e} + \epsilon_i \tag{6}$$

In his study, Rowthorn (1975) always used equation 6 for estimation purposes, even though, in a fleeting manner, he mentions equation 3 as well. Apparently it was John McCombie that coined the term 'Rowthorn's specification' for equation 3 in a series of studies (McCombie, 1982b,a; McCombie and de Ridder, 1984; McCombie, 1986), while one could argue that the 'true' specification according to Rowthorn (1975) would be the other one. Unluckily, the misunderstandings do not stop here, since Rowthorn (1975) calls the term $\frac{\beta_1}{1-\beta_1}\hat{e}$ in equation 6 'Kaldor's implicit estimator' Rowthorn (1975)[p.16]. Kaldor (1966) never used this term, as he favoured equation 2 over 6. Indeed, in a reply to Rowthorn (1975), Kaldor (1975) explains that his choice of specification is related to his conviction that the

economy as a whole is demand-constrained, rather that supply-constrained.

> *The important implication of these assumptions is that economic growth is demand-induced, and not resource-constrained - i.e. that it is to be explained by the growth of demand which is exogenous to the industrial sector' and not by the (exogenously given) growth rates of the factors of production, labour and capital, combined with some (exogenously given) technical progress over time.(Kaldor, 1975, p.895)*

The overall result has thus to be differentiated by the estimation technique used. If one believes that output growth is demand-constrained rather than supply-constrained, then equation 2 would be the correct interpretation rather than Rowthorn's (1975) formulation, represented by equation 3.

Another open question is whether or not to include the capital stock as a control variable. Again, Kaldor (1968) argued that the stock of capital should not be included in the estimation, as 'capital accumulation is a symptom rather than cause of growth'(p.390). Another opportunity lies in using total factor inputs as proxies, because the stock of capital is already implicitly taken into account this way.

There is disagreement over the way the Kaldor-Verdoorn law is supposed to work as well. For example, the question whether the law affects the firm, industrial, sectorial or macro level has direct consequences on the type of data that should be used. In a similar vein, one might argue that wage growth should be included as a control variable to take into account the so-called 'Webb effect', whereby an increase in wages is pressuring capitalists to invest into labour-saving machinery, thus increasing productivity growth (Hein, 2014; Storm and Naastepad, 2011, 2012, 2017)[2].

Figure 1 summarises the distribution of estimates over the different estimation models. Even though most of the available studies hint at the presence of such an effect as Verdoorn (2002) described, the size of the reported overall effect is not clear.

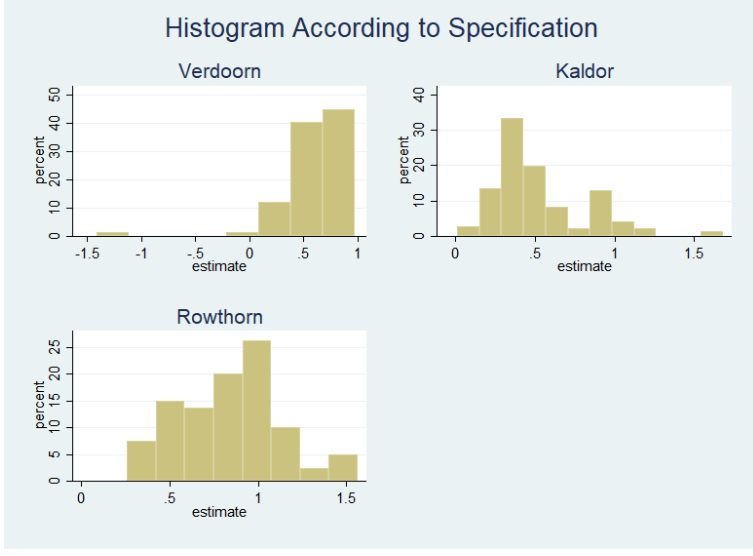

FIGURE 1 Histogram of the different estimation specifications

McCombie et al. (2002) gives a historical overview of of Verdoorn's (2002) work and in particular its impact on the

work of Nicholas Kaldor. It also discusses several methodological issues as well as the different interpretations of this law-like relationship and its application to several growth models. McCombie et al. (2002) also includes a thorough literature review of studies estimating the overall effect from 1929 until 2001, finding that

> *'On the whole, the law appears to be largely substantiated in these studies, although, as is the case for most statistical economic relationships, the estimates sometimes need to be qualified. Indeed, in certain circumstances, the law still needs further work to solve a number of econometric problems. However, it is fair to say that Verdoorn's Law should be regarded as something more than just a 'stylised fact''(McCombie et al., 2002, p.1).*

How can we explain this heterogeneity? And how can we even believe to find an underlying effect under all of this 'white noise' generated by the difference in estimation techniques and results?

3 | META-REGRESSION ANALYSIS (MRA) AS A QUANTITATIVE LITERATURE SURVEY

3.1 | The Specification Problem

Meta-Regression Analysis (MRA hereafter) builds upon a technique commonly known as 'meta analysis' in other fields like psychological and educational research, medicine and the social sciences (Stanley and Jarrell, 2005). Meta analysis tries to summarise and integrate the existing empirical literature about a common parameter. As such, it presents a systematic review of all scientific knowledge currently available and explains the given findings in all its vast variety in a comprehensive way (Stanley and Doucouliagos, 2012).

Traditional literature surveys are often not able to present an all-encompassing survey of already existing studies, one of the obvious reasons being the word limit imposed by academic journals. But there is more to it. As Stanley and Jarrell (2005) argue,

> *'The reviewer often impressionistically chooses which studies to include in his review, what weights to attach to the results of these studies, how to interpret those results, and which factors are responsible for the differences among those results. Traditionally, economists have not formally adopted any systematic or objective policy for dealing with the critical issues which surround literature surveys As a result, reviews are rarely persuasive to those who do not already number among the converted.' (Stanley and Jarrell, 2005, p. 300)*

Meta analysis can thus be of great help when it comes to examining a certain effect on which a lot of empirical studies have been published – it enables the researcher to see the bigger picture. Additionally, MRA offers the tools to estimate the effect of different model specifications on the overall results and their significance. This way the researcher can distinguish true economic effects from disturbances caused by wrong model specification more easily.

Another reason for the use of MRA is the file drawer problem: as the standard deviation of the estimated correlations are becoming smaller with an increase in the number of observations, studies using a dataset with a comparatively small amount of observations face higher difficulties to obtain significant results. This might become important insofar as peer-reviewed journals may prefer publishing only studies that offer significant results, even though from a methodological point of view the publication of not significant results would be equally important for the progress of economics. Such strict publication policies might incentivise researchers to alter their estimation model successively

until significant results have been obtained (publication selection bias). In the worst case scenario, the researcher(s) might not publish their findings at all – the study stays in the file drawer.

Meta analysis has been increasingly used in the economics literature during the past decades. The most commonly quoted studies include Rose and Stanley (2005) on the effect of common currencies on international trade, Doucouliagos (2005) on the link between freedom and economic growth, Nijkamp and Poot (2005) on the unemployment elasticity of wages, Weichselbaumer and Winter-Ebmer (2005) on the gender wage gap, Knell and Stix (2005) on the income elasticity of money demand and Doucouliagos and Stanley (2009) on the effect of minimum wages on employment.

While MRA has become a well-accepted approach in other scientific fields, its appearance in economics is as of yet a comparatively rare sight. Nevertheless, a guideline for a more standardised use of MRA in economics has been proposed by the Meta-Analysis of Economics Research Network (MAER) in order to improve both the transparency and the quality of future Meta analysis.

To conduct a MRA, several steps have to be followed. First, the researcher is collecting all available studies on a specific effect she or he wants to study. Whether those studies are published in peer-reviewed journals or not should *a priori* not play any role. Indeed, one is even encouraged to include non-published studies, as those studies not being published might not necessarily indicate unscientific methods or a lower quality with respect to the used methods, but rather point at potential publication selection bias, as was explained in the former section.

In a second step, the reported estimates in these gathered studies are being treated as individual entries in a new dataset. For a study to be included in the dataset, the researcher has to code at least the estimate, and the corresponding t-value (or its standard deviation). If those two variables can be obtained, then the estimate can be included in the dataset. Furthermore, the researcher might be interested in adding several characteristic elements of the specific study that might be worth considering in the form of dummies, such as the sources of the datasets being used, the year of publication (if the paper is published), the method of estimation, the country or sector examined *etc*. This possibility is in fact one of the big advantages of MRA. Not only is it possible to infer a more precise estimate for any given variable, but MRA also enables the researcher to find out which socio-economic circumstances might skew the estimated results and lead to under- or overestimation of the effect in question. Finding and explaining these differences via MRA is based on statistical, not economic theory and can thus help to shed light into controversies between different schools of thought.

The third step then consists of a two-step regression in which the first regression points at the presence or absence of publication selection bias (called the Funnel asymmetry test, or FAT-test) – which in the existing MRA literature has almost always been found – while the second regression tries to estimate this very publication selection bias and the 'true value' of the parameter in question (called the Precision effect test, or PET-test).

3.2 | The basic model

Following Stanley and Jarrell (2005), the most common approach to do meta-analysis in economics consists in using effect sizes in reported econometric studies. The following section builds mostly on Stanley and Doucouliagos (2012), as well as the guidelines published by the MAER network (Stanley et al., 2013). The notation used in the following section is orienting itself on Paldam (2015).

In order to be used for MRA, studies that estimate the Kaldor-Verdoorn effect are collected only when they meet two conditions. First, the studies collected must be estimating comparable effects (Becker and Wu, 2007). In order to make them comparable MRA studies are using effect sizes.

Secondly, the studies have to be transparent, in that the researcher is able to gather at least the estimated coefficient, its corresponding standard deviation or t-value, and the number of observations used in the study the results were taken from in order to compute the corresponding partial correlations. Partial correlations are helpful because they are

able to standardise effect sizes of different size and quality, a difficulty that is encountered very often in MRA. Their ability to make all studies comparable to each other is their most desirable property, as it enables the researcher to get more information about the state of the literature. Partial correlations will be computed as presented,

$$r = \frac{t}{\sqrt{t^2 + df}}$$

with its corresponding standard error being $se_r = \sqrt{\frac{1-r^2}{df}}$. Partial correlations are not easy to interpret, as their nature is more statistical rather than economic. Standardized partial coefficients can be interpreted as the number of standard deviations the dependent variable increases for every increase in the standard deviation of the independent variable, holding all other variables constant. It is therefore a good idea to use additional effect sizes to get results that can easily be interpreted in economic terms. Nevertheless the desirable properties that partial correlations have with respect to other effect sizes makes them the most used effect size in MRA.

MRA uses the relation between an effect size b_i and its precision (the inverse of its standard error se_i) to draw its conclusions. Consider a sample of perfectly homogeneous estimated studies with an underlying effect γ_0.

$$b_i = \gamma_0 + \gamma 1 se_i + \epsilon_i \tag{7}$$

In this case, the reported estimates should all be normally distributed around the 'true value', γ_0, which should correspond to the average of the perfectly homogeneous estimated studies. As the term 'true value' can be seen as rather problematic, the term 'meta-average' will be used from now on, since all that MRA does is constructing an average of all estimates corrected for publication bias (Stanley and Doucouliagos, 2012).

The idea of publication selection assumes that researchers with a smaller sample and thus higher standard errors are forced to search longer for statistically significant results than their colleagues with bigger samples (for example via searching for additional data or for reasons to eliminate 'potential outliers'). The latter ones will be satisfied with their potentially smaller, but significant estimates. Hence, in the case of publication selection, the estimate will be positively correlated with the standard error se_i. This forces the estimates to become larger than they should be (i.e. there is overestimation) in order to become statistically significant. If the null hypothesis is true and no publication selection bias is present, the estimate will be equal to the meta-average ($b_i = \beta_0 + \epsilon_i$ if $se_i \to 0$). Since MRA is using estimates from different studies, those estimates will typically embody differing variances, which will have to be taken into account in order to take care of heteroskedasticity issues. The errors can be weighted via dividing equation 7 over the standard error. Dividing by se_i will give us a weighted-least-squares (WLS) estimation of equation 7, which is in fact a basic MRA of the estimate's t-value against its precision, $p = \frac{1}{se_i}$. In case of homogeneity, the former error divided by the measured sampling error must be equal to 1.

$$t_i = \gamma_M p_i + \gamma_F + u_i \tag{8}$$

t_i refers to the estimate's t-value and γ_M is the 'meta-average' – the average effect of the primary literature corrected for publication bias – with p being the 'precision score' $\frac{1}{se_i}$. Equation 8 can equally be rewritten as $t_i = \gamma_M \frac{1}{se_i} + \gamma_F + v_i$. Both parts of equations 7 and/or 8 (depending on the chosen effect size) are being used for testing.

Testing γ_1 in equation 7 or γ_F in equation 8 for the null hypothesis that $\gamma_1 = 0$ or $\gamma_F = 0$ is called the 'funnel-asymmetry test' (FAT-test) and checks for heterogeneity. A rejection of the null hypothesis points at the existence of publication selection bias. $\gamma_0 = 0$ in equation 7 and $\gamma_M = 0$ in equation 8 represents the 'precision estimate test' (PET-test) and is used to estimate the meta-average in case of publication selection bias. Again, both tests rely on the assumption that the reported estimates are normally distributed around the underlying effect. Thus, estimates far away from the underlying effect should have low precision, while estimates closer to the 'true effect' should have high precision. At the same time, the precision score acts as a weight. Estimates with a higher precision will have a higher weight when estimating the meta-average than low level precision estimates.

The FAT-PET test thus enables MRA to not only find out about the possible existence of publication selection bias, but to also correct the ordinary average of the reported estimates for the estimated publication selection bias in order to get a 'cleaner' estimate closer to the actual underlying effect (provided such an effect exists). However, even the PET-test gives a biased estimate of the empirical effect in case of publication selection.

Doucouliagos and Stanley (2009) and Stanley and Doucouliagos (2012) offer an improved correction for publication selection that uses the effect size's variance (i.e. the square of the standard error) in MRA modelling, the Precision-Effect Estimate with Standard Error (PEESE) test.

$$b_i = \gamma_0 p_i + \gamma_1 se_i^2 + u_i \tag{9}$$

The FAT-PET-PEESE tests are supposed to be used one after another. Monte Carlo simulations have shown that the PEESE provides a better estimate of the underlying true effect (Stanley and Doucouliagos, 2014). However, this is not true when there is no effect and only publication selection. If the PET-test indicates a genuine underlying effect then the researcher is expected to run the PEESE-test for a more robust estimate.

3.3 | Multiple MRA

Clearly, it will often be the case that potential misspecification in the literature will not be able to be explained solely by publication bias. Rather, there might be reasonable differences amongst the available studies that can explain part of this misspecification. That being said, it could be interesting to obtain more details about publication bias, what study-specific characteristics drive it, and when there might be more general sources of misspecification that transcend the population sample (such as a dominant theory that is perceived to perform better than others or certain results that are expected by the scientific community beforehand).

The basic MRA equation 7 can be expanded in order to take these intricacies into account.

$$b_i = \gamma_0 + \sum \gamma_k Z_{ki} + \gamma_1 se_i + \sum \delta_j se_i K_{ji} + \epsilon_i \tag{10}$$

Equation 10 can be read similarly to equation 7. The reported estimates b_i are still assumed to be normally distributed around the meta-average γ_0, with two different sources of misspecification present. The first, $\sum \gamma_k Z_{ki}$, represents all the discrepancies due to heterogeneity amongst the studies and the second, $\gamma_1 se_i + \sum \delta_j se_i K_{ji}$, represents publication bias. δ represents dummy variables which are called 'moderator variables' in the MRA literature. Moderator variables can help gathering more information about the available literature than represented by just their respective output tables. The most used moderator variables include the year of publication, the journal of publication, the year

span covered in the dataset and many other study-specific characteristics.

4 | THE DATASET

The dataset used in this study is created completely anew and will be published in the meta-data repository shortly after this study is accepted for publication. It consists of 22 published studies starting in 1975 and ending in 2017 with a total amount of 195 estimates. As such, it represents the first database on Kaldor-Verdoorn coefficient estimates so far.

The platforms used for finding those studies cover the biggest array possible in order to account for as many studies as possible and consist of Econlit, JStore, Google Scholar and Google Search. Keywords for the searching process were 'Verdoorn effect' and similar terms such as 'Kaldor-Verdoorn effect' and 'Kaldor's second law', 'productivity', 'productivity-growth nexus' etc. The data set was finished in March 2018.

The following step included extracting t-values, standard deviations, the estimated coefficient, the number of observations and/or the degrees of freedom from every specific regression for every single study. Additionally, several other variables of possible interest were recorded as dummies for further analysis. It has to be made clear that treating every single regression as a single entry might introduce some bias, as papers with several control estimation will be overrepresented. How to tackle this issue is not agreed upon in the economics MRA community (Stanley and Doucouliagos, 2012). In this case cluster-robust standard errors have been used. Other possibilities include the use of the inverse number of estimates per paper as respective weights.

A key issue is that most of the studies found were not reporting all the key variables needed. For an MRA to be done, the database needs to contain at least the estimate, and either the corresponding standard error or its t-value (since the t-value is the ratio of the estimate divided by the standard error, assuming that the null hypothesis is $b = 0$). At this point, it is vital to mention that nearly none of the 68 studies examined explicitly stated their null hypothesis. In theory this makes it impossible to calculate missing standard errors or t-statistics if needed (and thus the resulting partial correlations). For the present study, the null hypothesis was assumed to be $b = 0$ if not stated otherwise. The omission of the null hypothesis is no trivial problem. If not stated anywhere in the literature, it is not possible to follow the authors' calculations in a transparent way, as any null hypothesis could be assumed in order to get statistically significant results. For example, regressions in Stoneman (1979) exhibit positive estimates but a negative t-statistic. This is only possible if the null hypothesis is assumed to be smaller than 0 - but this has never been mentioned in the respective study! Assuming $b = 0$ for the null hypothesis might thus severely underestimate publication bias if practices of null hypothesis manipulation should be broadly used in the respective field.

For robustness checks in form of other effect sizes, more variables like the number of observed variables/the degrees of freedom should be included, since they can be used to compute partial correlations which are another effect size apart from the t-value commonly used in MRA. This proved more difficult than expected and, as a result of the 68 studies present at the end of the literature research, only 22 studies were in an acceptable state to be included into the database - the biggest reason for not being able to include studies were missing reports of the number of observations. This might be explained by their date of publication. Econometric standards were not as agreed upon in economics in the 1980s as they are today. Furthermore, without the use of powerful statistical programs as we have available today, doing econometric estimations was far more challenging. One might simply be less motivated to calculate important test statistics if one has to do so by hand. This naturally diminishes the explanatory power of this MRA since less studies can be investigated upon. On the other hand 13 of the 48 studies not included were published since 2000, with the last study having been published in 2017.

Figure 2 presents the combined 303 observations from 22 studies on the Kaldor-Verdoorn effect with years of

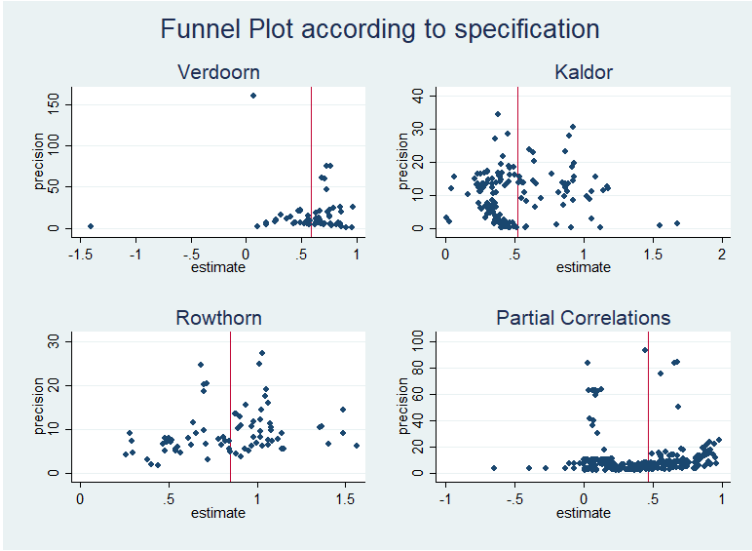

FIGURE 2 Funnel Plot

publication ranging from 1975 to 1999 in a scatter plot called the 'funnel plot'. It plots the estimates against their precision (the inverse of their corresponding standard error). In case of homogeneity, the reported estimates should be normally distributed around the meta-average, with estimates decreasing in precision the farther away they are from it. A skewed distribution of reported estimates hints at the possible existence of publication selection bias. The funnel plot, even though only being descriptive in nature, is still useful for an initial overview of the existing literature. It plots the distribution of all reported estimates. The average estimated Kaldor-Verdoorn effect depends on wether the Verdoorn specification (0.58), Kaldor specification (0.52) or Rowthorn specification (0.84) is observed. Additionally, we construct partial correlations to synthesise all available information. The average partial correlation amounts to 0.47. While the funnel for the Kaldor specification seems to show two precision spikes instead of just one, the other plots indicate a tendency towards one most precise point. No graph really shows a normal distribution of estimates/partial correlations which can be interpreted as a first hint at potential publication bias.

With descriptive analysis giving us first insights, we can now turn to a more thorough investigation.

5 | A META-REGRESSION ANALYSIS ON THE KALDOR-VERDOORN EFFECT

Since the variance of the estimated effect and hence u will vary from reported estimate to estimate, estimation of model 7 has to deal with heteroskedasticity, which is why weighted least square (WLS) estimation as explained in equation 8, is being used. As every estimate gets weighted with its corresponding standard error, estimates with large standard errors are given smaller weight while more precise estimators are given more weight. This makes WLS-MRA more resistent to outliers. Nevertheless, we used studentised residuals in order to minimise the effect of outliers. To test, first regressions were run whithout specifying vce parameters like weights or cluster-robust standard errors. Then studentised residuals were created. Since the residuals behave like t-statistics the critical value for elimination was chosen to be 1.96. If the absolute value of the residuals exceeded this critical value, the respective data point were considered as an outlier and

deleted from the final sample. After this, the normal regressions with vce parameters were run. All in all, 28 estimates had to be dropped after using this method.

Another problem usually faced in meta-analysis is the fact that different studies report a different number of estimates. Thus, single studies with a high number of reported estimates might dominate the overall sample (Stanley and Doucouliagos, 2012, pp.99). Cluster-robust standard errors were used in order to take this possibility into account.

MRA uses a regression between a reported effect size and its standard error as a more objective method of finding and measuring potential publication selection bias. In the absence of publication selection bias, there should be no significant correlation between the estimate and its standard error, while the opposite would be true in case of publication selection bias.

A further advantage of MRA is the use of dummy variables to account for the impact of omitted variables and their impact on publication selection bias. Especially in economics, where researchers are often working with pre-compiled data-sets and important variables might not be taken into account, omitted variable bias might indeed be one of the biggest drivers of misspecification. Similarly, other study-specific properties might be of interest to the researcher if a good summary of the respective literature is desired. Other often used variables include the difference in proxies used to represent the respective effect, nature and origin of the dataset, the estimation technique used in the paper as well as year and journal of publication (if published), sources of funding, etc.

Table 1 explains the dummies used in this meta-regression analysis. Most of the dummies have been created either due to the historical debates around the Kaldor-Verdoorn effect (i.e. d_capitalstock, d_wages and d_manufacturingsector) or try to catch specific characteristics of the primary studies (i.e. d_regionalleveldata, d_industryleveldata, d_crosssectional, d_timeseries, d_FE, d_FE, d_IV, d_TSLS and d_auto_reg). Additionally, d_OECD and d_G8 have been coded as proxies due to interest whether the Kaldor-Verdoorn effect (if existing) would be stronger in the more advanced – in the pure sense of capitalism's logic regarding capital accumulation – countries due to a bigger manufacturing sector. d_dataendbefore1980 should reflect possible structural breaks in the data set. Our idea is that the Kaldor-Verdoorn effect might have become weaker over time due to a structural shift in modern capitalism away from a Fordist, manufacturing-based mode of accumulation towards a finance-based mode of accumulation.

Table 2 shows the regression results for the FAT-PET-PEESE tests for all the three different specifications, as well as a control estimation using partial correlations. The numbers in parentheses are cluster-robust standard errors. The FAT-PET test is defined as $b_i = \gamma_0 p_i + \gamma_1 se_i + u_i$, the PEESE test as $b_i = \gamma_0 p_i + \gamma_1 se_i^2 + u_i$. The dependent variable,b_i is the reported estimate of study i, with "standard error" being its standard error. Underneath the constant, which represents the meta-average, the term 'β_1' represents the meta-average values of the respective specifications transformed into the Verdoorn specification.

Since we have estimates that are comparable with each other (once the difference in specification has been taken care of) we can directly regress the estimated Kaldor-Verdoorn effect against its standard error (in the case of the FAT-PET test) or against its squared standard error (in the case of the PEESE test). The standard error gives insight about the nature of γ_1 - is there a sign of publication selection bias? Here the null hypothesis cannot be rejected at the five percent significance level for any specification - there seems to be no publication bias when the respective specifications are looked at just by themselves. Even when pooling all different estimation specifications together using partial correlations, there seems to exist negative publication bias – the effect as a whole seems to be underestimated. This finding is even reinforced when using the PEESE test instead of the FAT-PET test.

However it has to be taken into account that the FAT-test is seen as a relatively weak test by the MRA-community (Stanley and Doucouliagos, 2012). Thus even though the null hypothesis could not be rejected the PET-test should nevertheless be used. The FAT-test might not be able to include all possible forms of publication selection bias and in the case of absence the meta-average which is the result of the PET-test should be very close to the unweighted average

TABLE 1 Overview of used dummies

Name of dummy	Explanation
d_capitalstock	The estimation controls for the stock of capital
d_wages	The estimation controls for the growth of wages
d_manufacturingsector	Data from the manufacturing sector were used for estimation
d_OECD	Data from OECD member countries were used for estimation
d_G8	Data from G8 member countries were used for estimation
d_dataendbefore1980	The data set for the respective estimate ends before 1980
d_totalfactor inputs	Total factor inputs were used as proxy for the respective estimation
d_regionalleveldata	The estimate is based on regional-level data
d_industryleveldata	The estimate is based on industry-level data
d_crosssectional	The estimate is based on cross-sectional data
d_timeseries	The estimate is based on timeseries data
d_FE	The estimate was obtained using fixed effects models
d_RE	The estimate was obtained using random effects models
d_IV	The estimate was obtained using the independent variable (IV) approach
d_TSLS	The estimate was obtained using three-staged least squares estimation
d_auto_reg	The estimate was obtained using auto-regressive estimation

TABLE 2 FAT-PET-PEESE test

	Verdoorn	$\hat{y} = \alpha_1 + \beta_1 * \hat{q}$	Kaldor	$\hat{e} = -\alpha_1 + (1 - \beta_1) * \hat{q}$	Rowthorn	$\hat{q} = \frac{\alpha_1}{1-\beta_1} + \frac{R^2}{1-\beta_1} * \hat{e}$	Partial	Correlations
	FAT-PET	PEESE	FAT-PET	PEESE	FAT-PET	PEESE	FAT-PET	PEESE
Regional level data	-0.179*	-0.179*						
	(0.061)	(0.061)						
Total factor inputs	0.166*	0.166*	-0.461***	-0.461***				
	(0.058)	(0.058)	(0.038)	(0.038)				
Wage growth	0.338***	0.338***	0.133**	0.133**				-0.133*
	(0.061)	(0.061)	(0.029)	(0.029)				(0.051)
Manufacturing sector	-0.219**	-0.219**	0.185***	0.185***				
	(0.061)	(0.061)	(0.031)	(0.031)				
IV	-0.285***	-0.285***	-0.023***	-0.023***			-0.491***	-0.499***
	(0.004)	(0.004)	(0.003)	(0.003)			(0.028)	(0.033)
Times series data	-0.483***	-0.483***	-0.144***	-0.144***	0.131*		0.297**	0.245*
	(0.059)	(0.059)	(0.008)	(0.008)	(0.050)		(0.078)	(0.091)
Data end before 1980			0.199***	0.199***			0.314***	0.272***
			(0.021)	(0.021)			(0.063)	(0.061)
Capital stock			-0.089*	-0.089*	-0.362***		-0.123**	
			(0.030)	(0.030)	(0.043)		(0.034)	
OECD country			-0.351***	-0.351***			-0.165***	-0.197***
			(0.043)	(0.043)			(0.037)	(0.024)
Random effects			-0.236***	-0.236***	0.316***		0.324***	0.316***
			(0.041)	(0.041)	(0.030)		(0.041)	(0.023)
Industry level data			-0.301***	-0.301***			-0.293**	-0.467***
			(0.014)	(0.014)			(0.089)	(0.107)
Fixed effects			-0.218**	-0.218**	0.261***		0.289***	0.212***
			(0.041)	(0.041)	(0.028)		(0.049)	(0.025)
$se_{i,pc}$							-2.771***	
							(0.378)	
Cross-sectional data							0.118**	0.121*
							(0.033)	(0.044)
$se^2_{i,pc}$								-7.097***
								(1.098)
constant	0.775***	0.775***	1.064***	1.064***	1.037***	0.908***	0.912***	0.784***
	(0.018)	(0.018)	(0.030)	(0.030)	(0.035)	(0.068)	(0.021)	(0.019)
β_1 (the Verdoorn coefficient)	0.775***	0.775***	-0.064***	-0.064***	0.443***		0.912***	0.784***
N	65	65	140	140	76	76	274	274
R-sqr	0.979	0.979	0.905	0.905	0.578	0.000	0.897	0.890
dfres	10	10	7	7	5	5	16	16
BIC	-195.1	-195.1	-282.7	-282.7	-68.9	-12.0	-439.2	-421.4

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

(0.63).

The PET-test should thus be taken into account as well. It represents the meta-average, corrected for potential publication selection bias even if there was none reported via the FAT-test. This time, the null hypothesis of $\gamma_0 = 0$ is being rejected even under the harshest commonly used significance level for all specifications (0.01). The estimated Kaldor-Verdoorn effect cannot directly be compared across the different specifications, the results are transformed using the identity $\hat{y} \overset{!}{=} \hat{q} - \hat{e}$ as laid out in section 2. It is clear that the choice of specification does change the estimated Kaldor-Verdoorn effect significantly. While (McCombie et al., 2002) find that the overall effect size might vary between 0.3 and 0.6, this studies' findings hint at an even wider range. Nevertheless, the estimated effect is strong, very much so in the case of the Verdoorn specification ($\beta_1 = 0.775$). The Kaldor specification leads to the lowest meta-average of $\alpha_1 = -0.06$, a very surprising result given the vast literature that finds average estimates around 0.48. A value that the meta-average for the Rowthorn specification is quite close to (0.44). Taking into account the PEESE test as a control against weak estimation of the meta-average, the resulting values only change in the case of the Rowthorn specification. However, as R^2 becomes nil, no transformation into the Kaldor-Verdoorn effect has been done.

Clearly, it can be seen for all the three specifications that the choice of control variables, countries studied or methods of estimation change the overall estimate dramatically in some cases. For example, the use of an OECD countries' data does only have a significant effect on the Kaldor specification, but there it increases the Kaldor-Verdoorn effect by 35 percentage points, turning a non-existing into an existing effect.

The partial correlation has the advantage that it renders all estimates comparable with each other and thus the meta-average can be estimated based on a higher amount of observations. On the other hand, its interpretation is not straightforward, as partial correlations have more of a statistical meaning, rather than an economic one. Following Doucouliagos's2011 guidelines on interpreting partial correlations, a small economic effect can be inferred from a partial correlation of 0.07 or higher, a medium one from 0.17 onwards and a large one from estimates higher than 0.32. This would translate the meta-average of the Kaldor-Verdoorn effect into a (very) large effect ($r = 0.91$ for the FAT-PET test and $r = 0.78$ for the PEESE test).

The effect of the dummy variables on the estimate often varies according to the specification chosen. Due to issues of collinearity, the variables d_auto_reg, d_TSLS and d_G8 had to be dropped. Additionally, in the case of the Rowthorn specification, d_OECD and d_wages together with d_industryleveldata had to be dropped for the same reason.

While the addition of the stock of capital in the estimation regression increases the overall Verdoorn effect in the case of Kaldor and Rowthorn specification, for the estimation of all studies using partial correlations the effect is negative. A surprising finding is that, contrary to what the existing literature suggests, the Kaldor-Verdoorn effect seems to be weaker in the manufacturing sector, rather than stronger. Taking into account all the primary studies as a whole, no difference between manufacturing and non-manufacturing sectors can be found. The effect of d_OECD on the Kaldor-Verdoorn effect is positive in the case of the Kaldor specification, but negative when using partial correlations. Studies with data sets ending before the 1980s find lower Kaldor-Verdoorn estimates in the case of the Kaldor specification, but higher overall when taking into account all estimates at once - this might indicate that there was indeed some kind of structural change in contemporary capitalism and that the Kaldor-Verdoorn effect got weaker over time. Thus, empirical studies should test for structural breaks. The inclusion of wage growth, controlling for the 'Webb-effect', finds a positive impact on the result in the Verdoorn specification, but a negative one when using the Kaldor specification (this negative impact turns into a positive one when transformed into the Verdoorn Coefficient). Including this possible relationship does reduce the overall strength of the Kaldor-Verdoorn effect. Taking into account again all studies using partial correlations, the overall effect seems to be negative.

6 | CONCLUSION

This study tries to summarise the plethora of empirical estimates surrounding the Kaldor-Verdoorn effect, the relation between growth in aggregate output/demand and productivity growth. Conventional literature reviews are very limited, in both the amount of pages dedicated to such an enterprise, as well as the level of detail they can delve into. Using a method known as Meta-regression analysis (MRA), the estimates of 22 studies in a newly created dataset along with several study-specific properties were accumulated and analysed by the FAT-PET test using weighted least square (WLS) regression.

Three main findings can be drawn from this study. First, none of the commonly used estimation specifications for themselves show signs of publications bias. This is unusual, as nearly all MRA studies find existing publication selection bias in the studied field, although the strength of the bias might be quite different every time. It has to be pointed out however that theoretically there might still be publication selection bias which could not be measured by the FAT-test. When pooling all available estimations together using partial correlations however, there is publication bias.

Secondly, the existence of a meta-average hints at the presence of a genuine underlying effect linking both output/demand growth and productivity growth. Following this meta-regression analysis, the Kaldor-Verdoorn effect seems to be real. This might have important implications for many different fields of research, such as economic development, trade and growth theory. It is also a surprising finding to many economists who would assume the Kaldor-Verdoorn effect to be non-existent. A good example might be the reappearance of the 'secular stagnation' idea (Hansen, 1938; Gordon, 2015), where reasons for long-term slow economic growth are usually only found using supply-side arguments. The existence of an effect as reported by Verdoorn (2002) might hint at the importance of demand-side explanations and possible solutions (Storm, 2017). But even when the existence of this effect is acknowledged, its' interpretation as well as its' relation to supply- or demand-side arguments is different according to the specification chosen.

Thirdly, the choice of estimation specification matters. The overall effect differs strongly depending on the specification used, even more so than indicated by the overall literature. While both the Verdoorn specification and the Rowthorn specification find strong Kaldor-Verdoorn effects (0.78 and 0.44), the Kaldor specification finds a very weak, and even a negative one (-0.06).

While this study adds to the existing literature via both a collection into a new data-set and grouping of existing estimates, there is still work to be done. Most of the primary literature could not be coded, as it did not report all the key variables needed to do so. One could argue that it might be preferable to even code studies that do not report the number of observations, as it would give the researcher more information when estimating the single specifications. On the other hand, no new information is being added for the use of partial correlations. Especially in fields of research like the Kaldor-Verdoorn effect is being measure using different specifications, partial correlations are even more important than in conventional MRA studies.

As this study tried to show, even when using the same data set, contradictory results can be found according the the type of specification that is preferred. These type of specifications are being used based on probably unsolvable differences regarding the kind of assumptions about contemporary capitalism we believe to be real. The results show that the estimates are very sensitive with regards to the type of data used, the specification as well as the control variables and time period analysed, and should therefore be interpreted as a suggestion to proceed with caution when creating estimation models. Similarly, it should be seen as a plea for other researchers to include fundamental test statistics in their published regression outputs, so that it can give rise to an increase in the use of meta-regression analysis in economics in general.

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NOTES

[1]'Kaldor's first law' characterises a positive relationship between the growth rate of manufacturing output and aggregate output. The third law states a positive relation between productivity growth in the manufacturing sector and the non-manufacturing sector, based on the assumption of decreasing returns to scale in the latter.

[2]This is also known as 'Marx-biased technical change' and similar to efficiency wage theory in its arguments.

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A | APPENDIX

TABLE 3 Mean and Standard Error of used variables

	Verdoorn Specification		Kaldor Specification		Rowthorn Specification	
	Mean	**Standard Error**	**Mean**	**Standard Error**	**Mean**	**Standard Error**
est	0,583	0,039	0,523	0,024	0,848	0,033
se_final	0,198	0,054	0,832	0,235	0,139	0,009
d_capitalstock	0,373	0,060	0,558	0,041	0,600	0,055
d_wages	0,015	0,015	0,204	0,033		
d_manufacturingsector	0,627	0,060	0,871	0,028	0,763	0,048
d_OECD	0,672	0,058	0,735	0,037	0,550	0,056
d_crosssectional			0,224	0,035	0,238	0,048
d_timeseries	0,104	0,038	0,327	0,039	0,500	0,056
d_totalfactorinputs	0,358	0,059	0,776	0,035	0,613	0,055
d_regionalleveldata	0,060	0,029	0,347	0,039	0,125	0,037
d_industryleveldata			0,306	0,038	0,450	0,056
d_FE	0,015	0,015	0,007	0,007	0,025	0,018
d_RE	0,015	0,015	0,007	0,007	0,025	0,018
d_IV	0,224	0,051	0,048	0,018	0,225	0,047
*d_dataendbefore*1980	0,328	0,058	0,320	0,039	0,925	0,030