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CONTENTS

Technological Change, Automation and Employment: A Short Review of Theory and Evidence

K.V.Ramaswamy

Indira Gandhi Institute of Development Research,

Mumbai 400065, India

Email: swamy@igidr.ac.in

Abstract

A selective survey of recent papers in the area of technological change, automation and employment is presented. The objective is to convey analytical ideas and the empirical evidence that have informed studies in this area of contemporary policy relevance. Automation occurs when a machine does work that might previously have been done by a person. How robots and automation affect the availability of jobs for labor force? There are very few emerging studies that address the issue with detailed data on robots usage and employment in different sectors of the economy. Based on our review of available studies and empirical evidence the following statements can be made: (1) Increasing automation and robots adoption do not seem to cause loss of employment in the aggregate (2) Low skilled workers in routine jobs are more likely to suffer job losses. (3) There will be demand for new types of skilled workers or new specializations within occupations. Prospective automation intensifies the degree of uncertainty in labor markets across countries.

Keywords: Technological change, Automation, Robots, Skill Bias, employment

JEL Code: J24, O31 and O33

1. INTRODUCTION

New developments in production technologies taking away jobs or the idea of machines replacing humans is a new source of anxiety in both developed and developing economies. Elon Musk, CEO of Tesla, world's leading manufacturer of electric vehicles and energy storage products, is reported to have said that Artificial Intelligence (AI) is a threat to human civilization[1]. Lead companies in the Global Production Networks (GPNs) in shoe and apparel manufacturing industries like Nike and Adidas are reported to have invested in automation to reduce production costs and lowering lead times.[2] Frequent reports in the media citing research studies that predict automation and digital technologies causing job losses has accentuated the anxiety. In September 2017, HfS research, a global services consulting firm, predicted that Indian IT sector will lose 7 lakh low skilled jobs to automation by 2022.[3] Low skilled workers are those conducting simple entry level process driven tasks with little abstract thinking. High skill workers are those undertaking complicated tasks that require experience, expertise, abstract thinking and autonomy. Knowledge of wage cost differences between low and high skilled jobs will be important in this context. The US Council of Economic Advisers (CEA) ranked occupations originally found to be at risk of automation by Frey and Osborne (2013), by wages per hour.[4] They found that, 83 percent of jobs making less than $20 per hour would come under pressure from automation, as compared to 31 percent of jobs making between $20 and $40 per hour and 4 percent of jobs making above $40 per hour. Another study (Arntz, Gregory and Zierahn, 2016) following similar methodology has reported classification of jobs at risk of automation by education levels and found that less-educated workers (those with less than a high school degree) are more likely to be replaced by automation than highly-educated (those with a bachelor degree) ones. A new report from Oxford Martin School (2016) explores the varying impact that automation of jobs will have on countries and cities around the world. It is called "Technology at Work v2.0: The Future Is Not What It Used to Be". It is based on new World Bank data that builds on the methodology followed in Frey and Osborne (2013) and finds that 47% of jobs in the US and 57% of jobs on average in the OECD countries are at risk of automation. The risks of job automation in developing countries are found to vary across countries. It is estimated to range from 55% in Uzbekistan to 85% in Ethiopia. In emerging economies the risk of automation is estimated to be relatively high with 77% of jobs in China and 69% in India found to be at risk. Notice that Frey and Osborne (2013) methodology is based on a subjective assessment of the automatability of 702 occupations using judgment of experts in automation technology. The estimated numbers of occupations indicate what is technologically feasible but does not conclusively suggest real implementation as information on costs of automation and profitability of implementation are not taken into consideration. Therefore, it is difficult to be definitive (based on such numbers) about future quantitative employment outcomes of the automation technologies.

In this context, the present paper presents a selective introductory survey of recent literature in the area of technological change, automation and employment. There are very few emerging studies that address the issue with detailed data on robots usage and employment in different sectors of the economy. These studies are related to but quite distinct from the traditional studies of the impact of IT and computers on the labor market. Their focus is different because robots are programmable, flexible (have 'arms and hands') and are powered by AI to do multi tasks and they can directly replace tasks performed earlier by workers. The broad objective is to convey analytical ideas and the empirical evidence that have informed the studies in this area of great importance to economists and labor economists in particular. Throughout in this paper our focus is on employment. Studies of technical change and income or wage inequality will not be covered though the interconnections are obvious[5].

2. ANXIETY OF AUTOMATION

Automation occurs when a machine does work that might previously have been done by a person (The White House, 2016a).[6] The term refers to both physical work and mental or cognitive work that might be replaced by Artificial Intelligence (AI hereafter). AI is an umbrella term for a machine's ability to imitate a human's way of sensing things, make deductions and communicate. AI solutions often make use of the methods of machine learning. For example, a machine can be taught to identify phenomena with the help of mathematical and statistical methods. In this case, "teaching" means loading numerous images, numeric values, or text that represent the phenomenon to be learned into an algorithm. As a result of this teaching, the algorithm is gradually able to become increasingly better at identifying a particular phenomenon.[7] “Robots” are machines endowed with AI and should be distinguished from single purpose machines (though controlled by computer numerical codes), for example, sheet metal stamping machines used in manufacturing. The International Federation of Robotics (IFR), measures deliveries of “multipurpose manipulating industrial robots” based on the definitions of the International Organization for Standardization (ISO). The ISO definition refers to a “Manipulating industrial robot as defined by ISO 8373: An automatically controlled, reprogrammable, multipurpose manipulator programmable in three or more axes, which may be either fixed in place or mobile for use in industrial automation applications” (Cited in Graetz and Michaels,2017, page 3).[8] Industrial robots are machines capable of doing different kinds of tasks like painting, welding, ironing, assembling and packaging with minimum human intervention.

These capabilities clearly distinguish and differentiate current wave of automation based on robots (AI) from standard information technologies (IT) or IT enabled technologies.

The current anxiety of automaton and potential loss of jobs due to robots is not unprecedented (Mokyr, Vikers and Ziebarth, 2015). In early nineteenth century England (1811-16) "the Luddite" riots during which workers smashed textile machinery was partly attributed to fear of displacement by machines.[9] This fear resurfaced in the US in 1960s when unemployment was high. President Kennedy has been quoted to have stated in 1962 " The major domestic challenge of the sixties is to maintain full employment at a time when automation is replacing men. It is a fact that we have to find over a ten-year period 25,000 new jobs every week to take care of those displaced by machines and those who are coming into the labor market".[10] Recent unemployment problem following the Great Recession of 2007-09 when 12 million Americans are estimated to have lost their jobs has further accentuated the automation anxiety. One study stated "In July of 2011, 25 months after the recession finally ended, the main US unemployment rate remained at 9.1 %,less than 1 percentage point better than it was at its worst point."[Brynjolfsson and McAfee, 2011, p.2]. In this context, Erik Brynjolfsson and Andrew McAfee wrote a book called "Race Against The Machine" in 2011 and advanced the argument that digital technologies can now perform mental tasks that had been the exclusive domain of humans in the past and that could cause technological unemployment. In their second book Brynjolfsson and McAfee (2014) present numerous examples of what they call "The Second Machine Age" such as the driverless car, the largely autonomous smart factory, service robots or 3D printing. These technologies are driven by advances in computing power, robotics process automation (RPA) and AI.

Given high levels of unemployment in the US and other EU countries David Autor (Autor 2015a) posed the question whether labour scarcity is actually declining in the US? He draws our attention to two other parallel developments in the US.[11] First, there has been a decline in the wages of non-college educated males between 1979 and 2012. Second, during this period real full-time weekly earnings of male high school graduates fell by 15% and those of male high school dropouts fell by 25%. Male employment to population ratios have fallen in demographic groups (ages 25-39) with low and falling earnings. These two facts read along with the fact of falling share of labour in national income has been interpreted to suggest that the demand for less skilled workers has substantially declined. In other words, a significant fraction of less-educated adults in the US have been unable to find gainful employment at prevailing wages. This is considered as equivalent to technological unemployment (Autor 2015a).[12] A related development in the US and Europe has been the 'polarization' of employment by skill level and the corresponding inequality in wage incomes between three skill groups of high-skill, middle-skill and low-skill occupations (Goos, Manning and Solomons (2014); Autor and Dorn (2013).[13] Large increase in the employment share of high-skill and low-skill groups with a decline in the share of middle-skill group has been characterized as "polarization". In general, the concern has been the falling share of labor in national income in a large number of countries and the increasing wage gap between unskilled and skilled labor (college and high-school educated workers). The corporate gross value added share of corporate labour in a sample of 59 countries declined from 64% in 1975 to 59% in 2012 (Karabarbounis and Neiman, 2014). This recent empirical development has contradicted the stylized fact of constancy of labor income share supposed to be consistent with the received neoclassical theory of economic growth and distribution. This brings us to the analytical models that have provided the framework for discussing the relationship between technological change, automation and employment in the recent literature.

3. FACTOR AUGMENTING TECHNOLOGY versus TASK BASED FRAMEWORK

Technological progress and its effects on factors of production and the distribution of income have been one of the central themes of economic growth and development literature.[14] The pioneering writings of John Hicks (Theory of Wages,1932) introduced the idea of biased technical progress (factor bias in technological change) and further extended by Roy Harrod (1939) and others . It is useful to begin with some clarity on the usage of terms in this literature.[15] Let us assume that production in the economy can be represented by an aggregate production function subject to constant returns to scale that takes the following form:

$$\mathrm{Y}\,(\mathrm{t}) \;=\; \mathrm{F}\,[\mathrm{L}\,(\mathrm{t}), \mathrm{K}\,(\mathrm{t}), \mathrm{A}\,(\mathrm{t})] \text{........ (1)}$$

Where L is labor, K is capital (or skilled labor), t denotes time and A(t) represents technology. Technological change is called L-biased, if it increases the relative marginal product of factor L compared to factor K. The key point to note is that biased technological change shifts out the relative demand curve for the specified factor (labor in this example). As a result its relative marginal product (therefore its relative price) increases at given relative factor proportion. If K in equation (1) denoted skilled-labor, to make it more relevant, then K-biased (skill-biased) technological progress would increase the relative marginal product of skilled labor and the skill premium would emerge as a consequence. A critical parameter in the context of models of biased technical progress is the elasticity of substitution often denoted by sigma (σ). The form of production function that is used to shed light on the underlying mechanism of biased technical progress is the Constant Elasticity of Substitution (CES) production function. The properties of CES production function are well-known and it takes the following form:[16]

$$Y(t) = [(A_L\,(t)\;\; L(t))^{\sigma-1/\sigma} \;+\; (A_K\,(t)\; K(t))^{\sigma-1/\sigma}\;\;]^{\sigma/\sigma-1} \text{......... (2)}$$

Where A_L (t) and A_K (t) denote the two technology terms (factor-augmenting parameters) corresponding to labor and capital and σ is the elasticity of substitution parameter between labor and capital, the two specified factors. If $\sigma = 1$ then the production function is Cobb-Douglas and if $\sigma = 0$ then the production function is reduced to Leontief form. The important conceptual idea is to understand that factor-biasedness of technological change (that could be either L-augmenting or K-augmenting) depends on the parameter σ. In order to understand this we need to calculate the relative marginal product of the two factors. It is easy to show that it takes the following form:

$$MP_K / MP_L \quad = \; (A_K\,(t) \,/\, A_L\,(t))^{\sigma-1/\sigma} \quad (K\,(t)/\,L\,(t))^{-1/\sigma} \; .... (3)$$

From equation 3, it is evident that the relative marginal product of K is decreasing in its relative abundance measured by K/L due to the substitution effect driven by the negative relationship between relative supplies and relative marginal products. However, the effect of A_K (t) on the relative marginal products depends on σ. If $\sigma > 1$ then an increase in A_K (t) relative to A_L(t) increases the relative marginal product of K and if $\sigma < 1$ then an increase in A_K (t) reduces the relative marginal product of K. In short, when the two factors are gross substitutes ($\sigma > 1$) K-augmenting technical change will turn out to be K-biased. When two factors are gross complements ($\sigma < 1$) K-augmenting change is L-biased. In the case of Cobb-Douglas production function $\sigma=1$ and therefore K-augmenting or L-augmenting technological change does not have any factor bias effect[17]. Using equation (2) we can find the marginal product of capital and then find the expression for the income share of capital (= rK/Y). It is related to σ in the following way.[18]

$$MP_K \text{ x } K/Y = r.K/Y = (A_K)^{-1/\sigma} \ (K/Y)^{(\sigma-1)/\sigma} \quad \text{...........} (4)$$

It is inferred from this that, given the value of A_K, there is direct relationship between income share of capital and capital deepening when $\sigma > 1$.[19] In other words, the income share of labor could decline due to biased technological change, which is biased in favour of capital[20] Notice that in this modeling framework, technological changes only work to augment either capital or labor (that is, improve their productivities) but there is no explicit labour replacing technological change like robotics technologies (guided by Artificial Intelligence), which could replace workers in different occupations or tasks. This insight suggested that models should look beyond factor-augmenting technological change to understand the impact of computers and robotic technology on employment and wages.

3.1 Routine-biased Technical Change

Which types of tasks are likely to be automated using computers? How does one differentiate between task and skill? Autor, Levy and Murname (2003) presented a simple theory of how the rapid adoption of computer technology changes the tasks performed by workers at their jobs and finally the demand for human skills. This task based approach has been further developed and applied others.[21] In this framework, machines substitute for routine tasks performed by workers. Hence it is called routine-biased technical change (RBTC). A task is considered as “routine” if it can be accomplished by machines following explicit programmed rules. However “...there are many tasks that people understand tacitly and accomplish effortlessly but for which neither computer programmers nor anyone else can enunciate the explicit “rules” or procedures” (Autor, 2015b, p.11). Such categories of tasks are labeled ‘non-routine” tasks. In other words, if the task involves problem-solving, complex communication activities and tacit knowledge then it is called 'non-routine.[22] In Table 2 we have a shown a representative categorization of routine and non-routine tasks and their potential computerization possibilities based on judgment. Status of several activities is likely to change depending on technological advances in the robotics technology.

The production function in the task-based approach may be written as

Y = F (Routine Labor (LR), Computer Capital (CC), Non-Routine Labour(LN)),

Where LR and LN are routine and non-routine labour inputs and CC is computer capital, all measured in efficiency units. The actual form of this production is assumed to be Cobb-Douglas. The supply of CC is perfectly elastic at market price r per efficiency unit. Over time r will be falling due to exogenous technical advances and the model explains how this fall in CC prices (outcome of technological change) impacts demand for LR and LN within industries and occupations. It is assumed that CC and LR are perfect substitutes ($\sigma=\infty$) in carrying out routine tasks. The elasticity of substitution between LR and LN tasks is same ($\sigma=1$). Importantly, CC is more substitutable for LR than for LN. This model predicts that industries that were intensive in LR tasks in the pre-computer era would make relatively larger investments in computer capital. At the same time they would reduce labor input of LR tasks as they substitute such tasks with CC and increase demand for LN task inputs because CC is a complement to LN input in production. Their empirical study found substantial decline in the share of the labor force employed in occupations intensive in routine cognitive and routine manual tasks between 1970 and 1998 in the US labor force. They observed a negative relationship between industry computerization (percentage of workers using computers at work) and changes in routine task input are uniformly negative in the 1970s, 1980s, and 1990s.

The task-based model has been further extended by Autor and Dorn (2013) to incorporate the services sector to explain the phenomenon of polarizing employment in the

US. First, they point out that employment changes in the US between 1980 and 2005 were strongly U-shaped in skill level. The relative employment share of middle level skill declined but those at the tails (high-skill and low-skill) gained relatively. This is referred to as employment polarization as we noted earlier. Second they formulate a task-based model to explain this polarization. In their model technological change takes the form of decline in the cost of computerization of routine tasks. There are two sectors in the economy. The first sector is engaged in the production of "goods" and the second sector produces "services". They define "goods" to include manufacturing as well as skilled services like banking and education. The dominant activity of services sector is the provision of low-skill in-person services like hair-cutting, house-keeping, food service etc. There are three types of labour (task) inputs available in the economy, namely, manual labor (LM), routine labour (LR) and abstract labour (LA). Computer capital (CC) is the fourth factor which can be used as intermediate good as well as provider of routine task services. All inputs are measured in efficiency units. Goods are produced by the following production function: Yg =F (LR, LA, CC). In this production function LR and LA are substitutes with $\sigma=1$. LR and CC have an elasticity of substitution $\sigma>1$. Therefore, by implication CC is a relative complement to LA and a relative substitute for LR. Services are produced using only routine–manual labor using a fixed coefficient production function as follows: Ys = αLM, where LM is manual labor. If we assume the elasticity of substitution in production between CC and LR is high relative to the elasticity of substitution in consumption between goods and services, then it is straight forward to see that as the prices of CC falls, CC is substituted for LR and excess LR in production causes wages of LR to fall to such an extent that it is lower than manual labor in services sector. LR flows from goods production to services sector causing employment polarization in the economy. This outcome is possible because routine tasks have well-defined procedures which are easy to computerize. However routine-manual tasks like those in services occupation like housekeeping or janitorial services have been found to be expensive to computerize. Computers are complements in non-routine or abstract tasks and substitute for routine tasks but do not have direct role in performing routine-manual tasks. As costs of computerization falls over time, routine non-manual tasks in goods production get automated (employment share falls) and the productivity of abstract labour improves (they remain in goods production). Computerization lowers the relative wages of LR (relative to LM) and they workers in goods production shift to routine-manual tasks in services occupations. Consequently, employment polarization emerges in the labour market with lower share of mid-skill group and high share of high-skill and low-skill service occupations.

Table 1: Potential Computerization of Workplace Tasks

Analytic or Non-Manual Tasks	
Routine	**Non-Routine (abstract labour)**
Record-book-keeping, Calculation, Clerical work Repetitive customer service (e.g., bank teller) or monitoring activity	Forming/testing hypotheses Medical diagnosis, Legal writing Marketing/selling, Personnel management or coordinating tasks
Substantial substitution ↑	Strong complementarities ↑
Manual Tasks	
Picking or Sorting, Machine Operators Repetitive line assembly	Janitorial services ,Personal care like Nursing and Child care, Housekeeping, Table-services in restaurants
Substantial substitution ↑	Limited opportunities for substitution or complementarity ↑
Source: Based on Autor, Levy and Murname (2003)	

Technological advances lead to automation of tasks in specific occupations. Bessen (2017) following the task-based model literature develops a model that integrates technology (automation of tasks) and occupations. He begins with the observation that automating a task is not equivalent to automating an occupation. Complete automation of all tasks within an occupation results in net loss of jobs but partial automation does not. Bessen draws our attention to the 1980s when desktop publishing software automated some tasks of type setting in publishing industry. Computerized publishing reduced employment of typesetters and compositors but increased the employment of graphic designers. In this case there is substitution of one occupation (typesetters) by another (designers using computers). Technological change affect jobs by making occupations substitute or complement each other. Computer use (automation) is labor augmenting and therefore reduces the price of occupational service measured in efficiency units. The firm produces output using multiple occupational services and capital K: Y= f (L1, L2, L3…, K), where Li is the i^{th} occupational service. Factor augmentation (productivity improvement due to computer use) of occupation j will decrease or increase occupations j and k depending on the elasticity of substitution between k and j, elasticity of demand for product Y, and share of wage-bill going to service j. This follows from standard neoclassical theory of demand for factors of production. Here instead of factors occupational services are distinguished. Bessen (2017) goes on to argue that computer use is highly correlated with the rated “degree of automation” of an occupation. He uses data from Current Population Surveys (CPS) in the US, which reported response of adult workers whether they directly used computer at work. He studies 317 occupations through the years 1984 to 2003 and finds that occupations that use computers substitute of other occupations. In other words, inter-occupational substitution offsets the direct growth effects of computer use. On average computer use is found to be associated with small employment growth and not job losses.[23]

A question of direct interest is how robots replace human labor and why this might lower the quantity of jobs in the labor market and what are the general equilibrium effects? This question is addressed by Acemoglu and Restrepo (2017) and they provide some empirical estimates based on local labor markets data in the US (US commuting zones).[24] In this model each industry produces output by combining a continuum of tasks $s \in [0, S]$ and they are combined in fixed proportions. Only subsets of these tasks, say [0, M], in each industry are "technologically automated" and can be performed by robots and the remaining set of tasks are performed by using labour alone. In other words, industrial robots are modeled as machines that can perform some of the tasks previously carried out by workers in the given industry. They highlight three different forces affecting demand for labor (partial equilibrium) in this set up: (a) Displacement Effect: robots displace workers and reduce the demand for labor. This happens because a given amount of output can be produced with fewer workers when robots are used. (b) price-productivity effect: use of robots (automation) lowers the cost of production in the given industry (lowers the price of output) and this leads to higher industry output and increases its demand for labor. (c) scale-productivity effect: the reduction in costs results in the expansion of output of all industries (aggregate output) and raising demand for labour in all industries. The final (general equilibrium effect) outcome in terms of employment depends on the strength of price-scale-productivity effect relative to the displacement effect. The magnitude of the productivity effect depends on the cost savings from the substitution of robots to human labor (automation). In their empirical exercise they go on measure the US exposure to robots (penetration ratio of robots to baseline employment). In other words, the response of employment and wages to adoption of robots can be measured. In their econometric work, they use the stock of robots by industry from the IFR. IFR data is based on yearly surveys of robot suppliers.[25] In manufacturing, they use data for the use of robots in 13 roughly three-digit industries. Their regression analysis focuses on 722 commuting zones in the US. Commuting zones are clusters of US counties with a minimum population of 100,000. They estimate the impact of industrial robots on employment between 1990 and 2007 (before the onset of recession) on US local labor markets. The US increased robots adoption by approximately one new robot by per thousand workers from 1993 to 1997. This is equivalent to an increase of 120,000 robots over the same time period. They measure the impact of robots by regressing the change in employment on the exposure to robots in each local labor market. A commuting zone with an exposure to robots equal to the US average experienced 0.37 percentage point lower employment to population ratio or equivalently reduction of employment of 6.2 workers (assuming no trade between commuting zones). They report a range of estimates based on alternative assumptions and find that employment loss to range between 3 (manufacturing sector only) and 5.6 (national economy) workers losing their jobs as result of the introduction of one more robot in the US national economy. They argue that the total number of jobs lost is approximately 360,000 to 670,000 (Acemoglu and Restrepo, 2017, p.36). In other words, in the total US economy robots use caused an annual job loss that range from 21,000 to 39,000 during the period 1990 to 2007. These estimates of job loss have to be cautiously interpreted because IFR data do not measure actual robot use by sub-national units like commuting zones. They are estimated by using distribution of employment by industry in commuting zones and the industrial distribution of robots usage in European countries. This is an innovative first step as the authors themselves point out their methodology measures "only the effect of robots on employment in a commuting zone relative to other commuting zones that have become less exposed to robots" [Acemoglu and Restrepo,2017,p.37]. And they have not been able to capture the technological responses to factor price changes due to the introduction of robots as predicted by their theoretical model.

Graetz and Michaels (2017) have used data on actual robot use within countries (by industries) to measure the impact of robots on productivity, wages and employment. Their cross-country study used panel data on robot adoption (based on the same source that is, IFR data) within industries (14 in number) in 17 countries from 1993 to 2007. First, they observed a steep fall in the price of robots in six developed economies. In 2005 the quality-adjusted prices of industrial robots were about one fifth of their 1990 level. During this period they found robot density (the stock of robots per million hours worked) in 17 countries increased over this period by more than 150 percent, from 0.58 to 1.48. Interestingly they found industries that experienced rapid increases in robot density also found to have higher rate of growth of labor productivity. This raised the issue of reverse causality (growth in productivity leading to robot density!). In order to rule out this possibility they construct two instrumental variables. First is called "replaceable" and it is constructed using data on "robot applications" which classify the tasks performed by robots. It measures the fraction of each industry's hours worked in 1980 that was performed by occupations that subsequently became prone to replacement by robots. Second is called "reaching & handling," which builds on technological advances made in the use of robotic arms. Here they measure the extent to which industries used occupations requiring reaching and handling tasks, compared to other physical tasks in 1980. These two indices are used as instruments for robot densification and the method of two-stage least squares (2SLS) estimates showed that robot densification led to increased labor productivity and not the other way.

The model underlying their study is also based on task-based approach. Workers are assumed to perform all tasks, while robots can only be used in a limited set of tasks whose share varies by industry. There is a choice of technology between one that uses both robots and labor, and one that only uses labor. In tasks that can be performed by robots, robots and workers are perfect substitutes. Robots can be hired at an exogenous rental rate of r. The technology choice rule for a firm is simple: adopt robots when profits from doing so exceed profits from using the labor-only technology by at least the fixed setup cost. They prove that robots are only adopted in sectors whose share of replaceable tasks exceeds a critical value. How employment changes when robots become cheaper? The answer depends on two critical parameters namely, elasticity of substitution (σ) and the elasticity of demand (ε). A fall in the rental rate R leads to a rise (a fall, no change) in the robot-using industries' employment relative to that of the others if and only if $\varepsilon > \sigma$ ($\varepsilon<\sigma$, $\sigma = \varepsilon$). The intuition is straight forward. A decline in robot prices induces firms to substitute robots for labor and at the same time reduce their relative output price. Consumers, in turn, buy relatively more of the robot-using industries' output (relatively cheaper). The increased demand for output causes greater relative demand for labor if $\varepsilon > \sigma$ (consumer response greater than the firm's response to fall in relative price of robot).

Their findings suggest that increased robot use contributed approximately 0.37 percentage points to annual labor productivity growth but did not significantly reduce total employment. They have reported estimates of the share of hours worked by high-skilled (usually college graduates), low skill (typically high school dropouts) and middle-skilled workers (those with intermediate levels of schooling). The impact of robots adoption on low-skill group is found to be consistently negative.[26] Robots adoption is found to be associated with reduction of employment share of low-skilled workers. This result of Graetez and Michaels (2017) contradict the argument that use of robots adversely affects the middle-skill workers reported by other studies in the literature.

4. CONCLUDING OBSERVATIONS

Use of robots and automation is the most recent technological advance in production activity and studies of their impact on employment and wages naturally fall under the rubric of studies of technological change, growth and labor markets. The use of industrial robots is currently estimated to be around 1.6 million in 2015 (UNCTAD 2017). It is estimated to increase to 2.5 million by 2019 and to 4 to 6 million by 2025 (two alternative projections by Boston Consulting Group (BCG, here after), 2015). How robots and automation affect availability of jobs for labor force? There are very few emerging studies that address the issue with detailed data on robots usage and employment in different sectors of the economy. These recent studies have attempted to explain the impact of robots on employment and jobs in the task-based model framework. They are found to be very useful in explicating the underlying mechanisms. A reading of this literature suggests that both optimistic as well as pessimistic scenarios are possible. If we assume that robots can only substitute for routine jobs (as in Acemoglu and Autor (2011) and others) then the outcome is likely to be optimistic or less pessimistic. This is because of two reasons. First, there always remain large classes of occupations not amenable to automation. Second, it is possible for the introduction of new tasks in which labor has a comparative advantage (Acemoglu and Restrepo, 2016) and that can offset the loss of occupations due to automation. On the contrary, as assumed in the recent paper by Susskind (2017) the range of tasks which robots can substitute could be much larger. It is possible, following Susskind (2017), to distinguish between two types of capital. They are 'traditional capital' and 'advanced capital', the former refers to machinery that cannot perform the same type of tasks as labour and the latter (read robots) can perform tasks performed by labor including complex tasks. In short, robots can perform even the so-called non-routine complex tasks in which human labor was assumed to have comparative advantage. Labor can be viewed as performing a set of tasks complemented by traditional capital. But advanced capital can displace all such tasks and compete away the comparative advantage of human in all such tasks. Then the share of labor total available tasks could dramatically shrink. This suggests a pessimistic scenario that can be visualized given the technological advances in automation and robotics.[27] However it is hard to predict the actual outcome and the likely response of different decision making units in the economy to the threat of automation.

Based on our review of available studies and empirical evidence the following statements can be made: (1) Increasing automation and robots adoption do not seem to cause loss of employment in the aggregate (2) Low skilled workers in routine jobs are more likely to suffer job losses.(3) There will be demand for new types of skilled workers or new specialization within occupations.. Example, U.S. demand for software engineers who program computers to understand human speech grew faster than workers with any other skill.[28] In short, there could be sea change in terms demand for diversified skills. The acquisition of new skills (occupation-specific) may be challenging for workforce and may require investment (Bessen 2017)

It is important to recognize that technical capabilities (functionality) of industrial robots are rapidly improving and their operating costs are declining in recent years. Newer robots can be more flexible and do more tasks. The cost of purchasing and installing robotics for spot welding in the US automotive industry has declined from $182,000 in 2005 to $133,000 in 2014 and expected to decline further to $103,000 by 2025 (BCG, 2015). Another example is equally instructive. In the US electronic and electrical; equipment industry, the cost of a generic robotics system is estimated to be $28 per hour, which is expected to fall below $20 per hour by 2020 which is below the cost of human labor (including benefits).

This type of cost reduction is likely spread across different industries. Does it mean the proportion of automated tasks is likely to reach 100 percent? The answer is in the negative because of two factors: (a) inter-industry differences in relative cost-effectiveness of robots adoption (b) differences in the ease or difficulty of adopting robots due to task specific or industry specific features. The first factor is straightforward. Industries with labour costs of more than 15 or 30 percent (just a thumb rule) of total costs will have greater incentive to adopt robots. Countries high per hour of labor costs like Australia ($55 per hour in 2014) will have more incentive than India ($5.24 in 2014) to adopt robots. The second factor is more relevant for developing countries because certain tasks in labor intensive industries are not amenable to use of robots or more accurately to use of cost-effective robots. Automated cutting machines are now becoming a widely available technology, and robots capable of sewing – called ‘Sewbots Technology’. But picking up pieces of cloth, align them and fed them to sewing machine to be sewn into garment are done efficiently by humans. Cost of such robots per hour is likely to remain exceedingly high and pose less threat to low skilled workers in developing countries.[29] Manufacturers of footwear are yet to find a method for putting shoe laces though smart shoes which has been a completely manual process. It takes approximately 120 steps involved in manufacturing sneakers but robots have not yet been able to master, at least not on an industrial scale, according to Adidas CEO Kasper Rorsted.[30] Its competitor Nike has invested in automation to produce high end sports shoes called Flyknit. The most difficult part of a sneaker is it upper that contains 40 different parts. A pair of Nike Roshe shoes costs $75 without Flyknit uppers, compared to as much as $130 with Flyknit uppers.[31] Nike has introduced automation along with its technology collaborating companies like Flex and Grabit, innovations like laser-cutting, automated gluing etc. They have been introduced to bring production closer to the high end US customer. Our discussion of substation in consumption and substitution in production is relevant here. Nothing like clear prediction is possible here. Secondly, new technologies (Internet of Things that enables devises to talk to each other, collaborative robots[32] called ‘Cobots’ etc., which do not necessarily displace workers) contribute to enhance productivity and at the same create demand for labor that complements production and services activities. In other words new machines can improve productivity and therefore generate demand for labor in other sectors and industries apart from demand for new occupation-specific jobs within the same industry. The challenge is how to augment the supply of required skilled people with the right kind of education and training to match the demand for diversified skills in the near future. Overall, our reading of the literature on automation and employment suggest that the overall macroeconomic effects of automation are not clearly understood. However one fact is abundantly clear. The new development on technologies (or the lack of understanding of their impacts) greatly adds to the uncertainty of labour market outcomes in terms of employment and wages in different countries.

References:

Acemoglu, Daron. (2009), *Introduction to Modern Economic Growth*, Princeton: Princeton University Press.

Acemoglu, Daron. (2002), “Technical change, inequality, and the Labor market,” *Journal of Economic Literature*, 40(1): 7-72.

Acemoglu, Daron and David Autor (2011), “Skills, tasks and technologies: Implications for employment and earnings” In: Card, D and Ashenfelter, O, eds. *Handbook of Labor Economics*, Volume 4B. Amsterdam and New York, North Holland: 1043–1171.

Acemoglu, Daron and Pascual Restrepo (2016), “The Race between Machine and Man: Implications of Technology for Growth, Factor Shares and Employment” NBER Working Paper No. 22252, National Bureau of Economic Research, Cambridge, MA.

Acemoglu, Daron and Pascual Restrepo (2017), “Robots and jobs: Evidence from US Labour Markets”. Working Paper No. 23285, National Bureau of Economic Research, Cambridge, MA.

Arntz, Melanie, Terry Gregory, Ulrich Zierahn, (2016), "The Risk of Automation for Jobs in OECD Countries: A Comparative Analysis", OECD Social, Employment and Migration Working Papers, No. 189, OECD Publishing, Paris. http://dx.doi.org/10.1787/5jlz9h56dvq7-en, accessed September 25, 2017.

Autor, David, Frank Levy and Richard Murnane, (2003), “The skill content of recent technological change: An empirical exploration”, *Quarterly Journal of Economics*, 118(4):1279–1333.

Autor, David and David Dorn, (2013), "The growth of low-skill service jobs and the polarization of the US labor market", *American Economic Review*, 103(5): 1553–1597

Autor, David (2015a), "Paradox of Abundance" in Subramanian Rangan (edited), *Performance and Progress: Essays on Capitalism, Business, and Society*, Oxford University Press, Oxford.

_____________ (2015b), "Why Are There Still So Many Jobs? The History and Future of Workplace Automation". *Journal of Economic Perspectives,* 29 (3): 3-30.

Bessen, James (2016), "*How Computer Automation Affects Occupations: Technology, Jobs, and Skills*", Boston Univ. School of Law, Law and Economics Research Paper No. 15-49. Available at SSRN: https://ssrn.com/abstract=2690435 or http://dx.doi.org/10.2139/ssrn.2690435.

Boston Consulting Group (2015), "*The Robotics Revolution: The Next Great Leap in Manufacturing*", available at https://www.bcg.com/perspectives/197062, accessed October 30, 2017

Brynjolfsson, Erik, and Andrew McAfee (2011), *Race Against the Machine*. New York: Digital Frontier Press

Brynjolfsson, Erik, and Andrew McAfee (2014), *The Second Machine Age: Work, Progress, and Prosperity in a Time of Brilliant Technologies*. W. W. Norton & Company.

Conniff, Richard (2011), "*What the Luddites Really Fought Against* ", in Smithsonian Magazine, March 2011, available at http://www.smithsonianmag.com/history/what-the-luddites-really-fought-against-264412/ accessed September 26, 2017

Dunlop, John (Editor) (1962), *Automation and Technological Change*, Englewood Cliffs, New Jersey: Prentice-Hall Inc.

Fergusson, C.E. (1969), *The Neoclassical Theory of Production and Distribution*, Cambridge University Press: London.

Financial Times (2016), “Meet the cobots: humans and robots together on the factory floor”, May 5, 2016, available at https://www.ft.com/content/6d5d609e-02e2-11e6-af1d-c47326021344, accessed October 24, 2017.

Financial Times (2017a), “Stitched up by robots: the threat to emerging economies”, in The Financial Times, July 18, 2017, available at https://www.ft.com/content/9f146ab6-621c-11e7-91a7-502f7ee26895, accessed October 26, 2017.

Financial Times (2017b), “Nike’s focus on robotics threatens Asia’s low-cost workforce” in The Financial Times, October 22, 2017, available at https://www.ft.com/content/585866fc-a841-11e7-ab55-27219df83c97, accessed October 30, 2017.

Fortune (2017a), “Why Elon Musk Is Wrong About”, July 27, 2017, available at http://fortune.com/2017/07/27/elon-musk-mark-zuckerberg-ai-debate-work, accessed October 23, 2017.

Fortune (2017b), “These Robots Are Using Static Electricity to Make Nike Sneakers”, Fortune, August 30, 2017, available at http://fortune.com/2017/08/30/robots-static-electricity-nike-sneakers, accessed October 30, 2017.

Frey, Carl Benedikt and Michael Osborne, (2013): *The future of employment: How susceptible are jobs to computerisation?* Oxford Martin School Working Paper, Oxford. Available at: http:// www.oxfordmartin.ox.ac.uk/downloads/academic/The_Future_of_Employment.pdf, accessed October 15, 2017.

Goos, Maarten, Alan Manning, Anna Salomons, (2014): “Explaining Job Polarization: Routine-Biased Technological Change and Offshoring,” *American Economic Review*, 104(8), 2509–26.

Graetz, Georg, and Guy Michaels, (2017): "*Robots at Work*," available at http://personal.lse.ac.uk/michaels/Graetz_Michaels_Robots.pdf (a revised version CEP Discussion Paper No. 1335), accessed October 25, 2017.

HfS (2017): "*Impact of Automation and AI on Services Jobs; 2016-2022*" available at https://www.hfsresearch.com/market-analyses/impact-of-automation-and-ai-on-services-jobs-2016-2022,accessed October 24, 2017.

International Federation of Robotics (2017): *The Impact of Robots on Productivity, Employment and Jobs*, available at https://ifr.org/ifr-press-releases/news/position-paper, accessed October 25, 017.

Karabarbounis, Loukas, and Brent Neiman, (2014): "The Global Decline of the Labor share". *Quarterly Journal of Economics*, 129(1): 61–103.

Mokyr, Joel, Chris Vickers, and Nicolas Ziebarth, (2015): "The History of Technological Anxiety and the Future of Economic Growth: Is This Time Different?" *Journal of Economic Perspectives*, 29(3): 31-50.

Oxford Martin School (2016):"*Technology at Work v2: The Future Is Not What It Used To Be*", available at (http://www.oxfordmartin.ox.ac.uk/downloads/reports/Citi_GPS_Technology_Work_2.pdf), accessed October 3, 2017.

Quartz (2017): "*One very basic job in sneaker manufacturing is testing the limits of automation*", Marc Bain in Quartz, April 24, 2017, available at https://qz.com/966882/robots-cant-lace-shoes-so-sneaker-production-cant-be-fully-automated-just-yet/ accessed October 30, 2017.

Susskind, Daniel (2017): "*A Model of Technological Unemployment*," University of Oxford Working Paper No.819, Revised July 2017, available at https://www.economics.ox.ac.uk/materials/papers/15126/819-susskind-a-model-of-technological-unemployment-july-2017.pdf, accessed October 30, 2017.

The White House (2016a): "*Preparing for the Future of Artificial Intelligence*," October 2016, available at (https://www.whitehouse.gov/sites/default/files/whitehouse_files/microsites/ostp/NSTC/preparing_for_the_future_of_ai.pdf), accessed October 10, 2017.

The White House (2016b): "*Artificial Intelligence, Automation, and the Economy*", December 2016, available at https://obamawhitehouse.archives.gov/sites/whitehouse.gov/files/documents/Artificial-Intelligence-Automation-Economy.PDF, accessed October 10, 2017.

UNCTAD (2017): *Trade and Development Report 2017*, United Nations, Geneva.

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[1] Fortune (2017a)
[2] Financial Times (2017b)
[3] HfS Research (2017)
[4] White House(2016b)
[5] Studies of income inequality are inspired by the large decline in income share of labor in the developed countries. The declining labor share has turned out to be a global phenomenon and has been at the center of inequality debate.
[6] Office of the President of the United States has issued two reports which contain excellent discussion of the issue of Automation and economy. The first report cited here gives a clear discussion of technical terms and their origin.
[7] See https://www.arcusys.com/blog/the-tools-of-the-future-today-what-is-robotic-process-automation-artificial-intelligence-and-machine-learning, accessed on September 25,2017
[8] UNCTAD (2017) and IFR (2017). Different types of robots are in use like those for professional use and robots for domestic/household tasks.
[9] Recently it was pointed out that they were not actually against machines but against wrongful use of machines and poor wages See (Conniff, 2011).
[10] Dunlop (1962, p.1).
[11] This paragraph is based on Autor(2015a)
[12] Autor (2015a) calls this "Paradox of Abundance" and the continuing substitution of abundant capital for scarce labor has reduced the 'scarcity' value of labor. He attributes this to three factors, namely, capital biased technological change, deunionization and globalization. For details see the original paper Autor (2015a).
[13] See also several other earlier papers cited in Goos, Manning and Salomon (2014)
[14] We will not attempt an extensive survey of this literature. Several good surveys and text book discussions are already available (see Acemoglu (2002 and 2009). See Ferguson (1969) for an early detailed presentation of neoclassical theory production and distribution.

[15] The following brief explanation borrows from Acemoglu (2009). See the cited text for an excellent detailed discussion of directed technical change in economic growth models.
[16] We are assuming share parameters αl and αk are equal, that is αl=αk=1/2, to simplify the exposition.
[17] The income share of labor (= wL/Y) will be constant over time under the assumption of Cobb-Douglas production function. This implication is found to be inconsistent with empirical data in both developed and developing countries where labor share is found to have declined in recent years of globalization and that has led to alternative models to understand the reasons for this decline in labor share. See (Karabarbounis and Neiman. 2014).
[18] We have dropped time subscript for simplification.
[19] This is the basis for the argument by Thomas Piketty (see Thomas Piketty Responds to Criticisms from the Left, interview with Piketty in Potemkin Review, available at http://www.potemkinreview.com/pikettyinterview.html, January 2015, 2017) that rising income share of capital and capital to output ratio could be obtained even in neoclassical frameworks.
[20] Similar production function with two types of labor has been used to explain the skill-biased technological change (SBTC) which leads to wage gap between skilled and unskilled workers. Acemogulu and Autor (2011) call it the canonical model
[21] Acemoglu and Autor (2011), Goos, Manning and Salomon (2014)
[22] Autor (2015b) contains a discussion of tacit knowledge in non-routine tasks.
[23] I must add that the above summary hardly does justice to the insightful and detailed analysis of Bessen (2017)
[24] Their model is derived from the task-based model framework of Acemoglu and Autor (2011) and Acemoglu and Restrepo (2016). The description of their model here is highly simplified to convey their central argument. See the cited original papers for details.
[25] The IFR aims to capture the universe of robot suppliers: "The statistical data collected in the present World Robotics are based on consolidated data provided by nearly all industrial robot suppliers world-wide" (IFR, 2012, p.19) cited in Graetz and Michaels (2017).
[26] Regression coefficient of Low in Table 4 (Graetez and Michaels (2017),p.44)
[27] Susskind calls this 'new pessimism at work' (Susskind 2017,p. 5)
[28] The Economic Times, November 2, 2017,available at https://economictimes.indiatimes.com/jobs/techies-watch-out-these-guys-are-coming-to-take-away-your-jobs/printarticle/61449224.cms, accessed November 3,2017
[29] Financial Times (2017a)
[30] Quartz (2017, p.2), "The biggest challenge the shoe industry has is how you create a robot that puts the lace into the shoe," he said. "I'm not kidding. That's a complete manual process today. There is no technology for that."
[31] Financial Times (2017b)
[32] Financial Times (2016)

Notes:

IMPACT OF INFRASTRUCTURE ON ECONOMIC GROWTH:

A PANEL DATA APPROACH USING PMG ESTIMATOR

Esra KABAKLARLI (Selçuk University, Turkey)[1]

Fatih Mangır (Selçuk University, Turkey)[2]

Bansi Sawhney (University of Baltimore)[3]

Abstract

Growth theory asserts that infrastructure investments promote economic growth by improving the quality of life and increasing private sector productivity . Transport services, water utility services and telecommunication services provide better facilities to attract FDI (foreign direct investment) and increase productivity across sectors. The aim of this article is to analyze whether transport infrastructure investments have a strong effect on the economic growth. It also attempts to analyze the differential impact of each type of infrastructural spending on economic growth. Our data set covers annual data from 1993 to 2015 period for 15 OECD countries (Austria, Turkey, Czech Republic, Spain, Finland, Japan, Germany, Ireland, Italy, France, Korea, Mexico, Netherlands, Poland, U.K) and China.

In this study, we employ a Pool Mean Group (PMG) estimator to find long run and short run relations between the variables. Output elasticity of air transport is found to be positive and significant at five percent level and there exists a long run relationship between GDP per capita and other explanatory variables such as transport infrastructure indicators, gross capital formation and labor force. The crowding- out hypothesis is also supported by coefficients on county specific results. Our data set includes infrastructure variables such as Railways, (million passenger-km), Air transport, (freight, million ton-km), Individuals using the Internet (% of population).

[1] Selçuk University, Faculty of Economics and Administrative, Department of Economics, Konya,Turkey
e-mail: etalasli@selcuk.edu.tr

[2] Selçuk University, Faculty of Economics and Administrative, Department of Economics, Konya,Turkey
e-mail: fmangir@selcuk.edu.tr

3 Merrick School of Business, University of Baltimore, MD. USA. E-mail: bsawhney@ubalt.edu

IMPACT OF INFRASTRUCTURE ON ECONOMIC GROWTH:

A PANEL DATA APPROACH USING PMG ESTIMATOR

Introduction

Economists in both developed and developing countries have recognized that infrastructure spending plays a crucial role in the process of economic growth of a country. Output elasticity of such spending has been found to be high and significant in the U.S. and other developed countries (Aschauer, 1989). According to the economic theory, the marginal productivity of public investment should be even higher in the case of less developed countries where the stock of public capital is much lower compared to developed countries. In fact, the Global Monitory Report of the World Bank (2005) calls for a big push in such spending for many countries.

Infrastructure affects growth through various transmission mechanisms. Public infrastructure investments improve private sector by increasing enterprise productivity(Aschauer 1989; Barro, 1990). Roads, bridges, highway and various transportation facilities , water , sanitation and electric system, waste disposal and public utilities promote economic activities by decreasing cost of the goods and services..(Orszag, 2009) Water utility services, cheap and clean energy , developed roads , bridges , highways and telecommunication facilities serve as stimulus to increase efficiency in all sectors, which could lead to increased employment and income levels and a reduction in poverty (Asian Development Bank, 2012).Infrastructure can be classified as:

- transport infrastructure: roads, airports, seaports, rail
- energy and utilities infrastructure: electricity, water, gas
- telecommunication infrastructure: fixed line penetration, mobile cellular penetration

as well as social infrastructure, including healthcare, education and cultural facilities. (Singhal, 2011)

A large majority of studies have used a production function approach to determine the role of public expenditure in economic growth measuring the direct contribution of such spending. However, public spending may have substantial indirect effects that facilitate private capital formation by reducing transportation and communication costs of production.

It has also been found that infrastructure spendings lead to improvements in health and education outcomes, which further contribute to economic growth (Agenor and Moreno-Dodson, 2006). It has also been found that improvements in communication have helped farmers receive the latest information on prices of imports and their products. This information helps them to make the optimal decisions. Access to increased inputs such as electric power and water supply have reduced the cost in both agricultural and industrial sectors in many countries and contributed to improvements in economic and social life of their citizens (Sahoo and Dash, 2012).

From public policy standpoint, the decision makers need to maximize total welfare gains from spending in infrastructure. Such decisions require optimal allocation of total spending where the marginal social benefits and social costs are equated for each type of spending. In this paper, we try to analyze the role of infrastructure spending in different sectors of the economies in 16 countries.

1.Literature Review

Investigating the relationship between infrastructure spending and economic growth has received a great deal of attention from economist in both developed and developing countries. There is extensive literature analyzing the effects of public investment on economic development and growth. A large number of studies have concluded that public investment affects growth positively. The theoretical argument in these papers is based on the simple Keynesian macroeconomic model in which spending on infrastructure leads to higher aggregate demand and greater incomes and through multiplier effects it further increases GDP.

Literature review shows two different results for infrastructure effects on economic growth. The majority of the literature advocates positive effects of infrastructure on economic growth. Caldero´n, and L. Serve´n. analyzed 101 countries applying GMM panel data approach for the period 1960–1997. They found that positive and significant estimates of the real GDP contributions of all three infrastructure (telecom, transportation and energy) output considered. Salahuddin and Alamthe (2015) used Pooled Mean Group Regression to examine short- and long-run effects of Information and Communication Technology (ICT) use, electricity consumption and economic growth. They also run causalities tests for OECD countries using data for 1985–2012. According to their results ICT use causes electricity consumption and economic growth. Jalilian and Weiss' (2004, p. 3). Iradian (2005) used A panel dataset for 82 countries for the period 1965–2003 . They also argue that social infrastructure spending on health, education, and social sector are necessary to combat poverty and improve human health. The linkage between social infrastructure spending and income distribution is powerful, and public spending on social sectors like education and health improves income distribution in the long run. Sahoo and Dash use Panel Cointegration and Granger causality techniques for a panel of four South Asian countries for the period 1980–2005, find positive and significant long-run relationship between real GDP and infrastructure along with other explanatory variables. The results reveal that real domestic capital formation, labor force, real export , expenditure on health and education lead to a positive contribution to real GDP.

The seminal paper by Aschauera(1989), concludes that infrastructure spending has a highly significant effect on national output and that output elasticity of infrastructure spending is between 0.38 and 0.56 for the U. S. He uses time series data and estimates the impact of public investment on total factor productivity by employing a production function approach. His finding of such a high number for output elasticity, which in some exceeds the contribution of total capital, has attracted the attention of many scholars and subsequent studies using cross-section as well as time series data find a much lower number for such elasticities Munnell (1990),for example, uses data for seven OECD countries over the 1963-1988 and finds that elasticity coefficient of output and infrastructure is 0.49. Heyden's (2004) study includes a sample of 46 countries and finds that output elasticity is 0.31 These studies support Ashauer's findings. However, several other authors do not agree with these findings and using alternative models and data sets discover lower elasticities in their research. For example, Fin (1993) uses U. S. data over the 1950-1988 period and finds a positive effect of infrastructure but the elasticity number is only 0.16. Bajo and Sosvilla (2003), use a production function approach over 1964-1988 period and comes up with the elasticity number that is only 0.13. Similar findings are reported in Calderon and Serven 2003. They use data from 101 countries over 1960-1997 and conclude that output elasticity is only 0.16.

As noted above, the findings of a majority of studies supports the growth-enhancing impact of infrastructure as they find a positive output elasticity of infrastructure spending. There are other researchers who are not in agreement with their findings. They claim that public spending may have a negative impact on economic growth. According to them, public spending decisions are politically motivated and public spending projects are not productive since they are influenced by political considerations. The Marginal productivity of such spending is close to zero or even negative. Further, they may also replace or reduce private investment spending. This case is referred to as crowding -out by Agessor and Morren-Dodson. As is commonly observed in less developed countries spending on infrastructure maintenance is often mis-allocated which may adversely affect productivity and growth and leads to higher levels of corruption. Moreover, it may be argued that the financing of public spending negatively impacts productivity when distortionary taxes are imposed or public debt is increased due to these types of spendings. Infact there are several studies that have found a negative impact of infrastructure spending. For instance, Devarajan et al. (1996), in their study, using a sample of 43 countries concludes that there is a negative correlation between public investment and growth. Similarly, Sanchez-Pobles (1998) find a negative correlation between output and public investment for a sample of 96 countries.

Barro (1990) shows investing in public infrastructure has both negative as well as positive effects. Public expenditures for productive infrastructure investment increases the GDP per capita and therefore leads sustained per capita growth. However increase in unproductive infrastructure investment which is financing by taxing income reduces per capita GDP growth. Agenor and Moreno-Dodson (2006) concluded that infrastructure has a negative role in economic growth . Public spending on infrastructure make crowding out,effect that in the short run, an increase in public spending on infrastructure would decrease finance opportunities of private sector. This negative crowding out effect of infrastructure may turn into a long-term negative effect if the decrease in private capital formation persists over time (Dissou and Didic 2013).Ghali (1998) argues that public investment in economic infrastructure enables operation of private investment in undeveloped countries. He applied vector error-correction model for Tunisia over the period 1963-1993. According to this paper , public investment has a negative impact on GDP growth and private investment in the long run, and also that public investment has no impact on GDP growth in the short run.

It is to be noted that several studies have found a statistically insignificant relationship between public investment and output. For example, Evans and Karras (1994) find insignificant relationship between public capital and output in the case of OECD countries over 1963-1988. In the case of U.S., Hamatuck (1996) find elasticity to be only 0.03 between public capital and output. Similar results are obtained by Hutton and Schwab (1991). Kavanaught (1997) uses data for Ireland over 1958-1990 and finds insignificant relationship between output and public investment. (For a more comprehensive survey see Pereira and Adraz, 2013).

Infrastructure decreases transport and production costs and facilitates business activity and foreign direct investment. Égert et al. (2009) applied time series and panel data approach using the data on 24 OECD countries for the years between 1960-2005. They find that infrastructure investment in non-transport sectors such telecommunications and the electricity sectors have a strong positive effect on GDP growth rate in the long term. However , transport infrastructure (railways and motorways) coefficients are found to be statistically insignificant. Pereira and Roca-Sagalés (2003) estimate VAR models for Spain using transportation (railroads , airports, roads, port) and communication indicators as representative of public infrastructure between the years 1970-1995 . They found the marginal productivity of public capital is 2.892, it means that one-euro increase in public capital leads to a long-term accumulated increase in private output of 2.892 euros.

As noted above, a great deal of effort has been devoted to examine the relationship between output growth and infrastructure. The results have varied and no consensus has emerged. Some studies have found significant, while others have found an insignificant or even negative impact of infrastructure spending on growth. Differences in results may be due to different model specification and statistical methods used. They may also vary over different time- periods and across countries and thus call for more studies in this field. This paper focuses on various components of infrastructure. It attempts to analyze the differential impact of different types of infrastructure spending on economic growth in 16 countries. It is not just the total spending that matters but what matters is where and how that money is spent. The findings of this study will have important policy implications in suggesting which sectors of the economy get maximum benefits from public spending.

2. Data and Methodology

In the empirical part of our study, we analyze the infrastructure and economic growth relationship i.e. effects of infrastructure investment on economic growth. Our dependent variable is natural logarithm of GDP per capita (constant 2010 US$).We include major infrastructure indicators as follow ; natural logarithm Air transport, freight (million ton-km), natural logarithm Railways, passengers carried (million passenger-km), Individuals using the Internet (% of population). We also use ,Gross capital formation (% of GDP), natural logarithm labor force as additional regressors. The gross fixed capital formation(% of GDP), is employed as the measure of investment . The labor is explained as total labor force . All of our data are obtained from the World Bank databank. Table 2 denotes the definition of the variables.

Table 1. Definition of Variables

Variables	**Indicator Name**
Index	Principle Composite index of transport infrastructure
lnAIR	Air transport, freight (million ton-km)
lnRAIL	Railways, passengers carried (million passenger-km)
GDP GRWT	Natural Logarithm of GDP per capita (constant 2010 US$)
GFC	Gross capital formation (% of GDP)
INTERNET	Individuals using the Internet (% of population)
LNLABOUR	Labor force, total

Our data set covers annual data from the 1993-2015 period for 16 OECD countries (Austria, China, Czech Republic, Finland, France, Germany, Ireland, Italy, Japan, Korea, Mexico, Netherlands, Poland, Spain, Turkey, and the U.K. We got all the data from the World Bank databank. Considering the heterogeneous nature of our data set we define a dummy variable to control for cross-country differences. The dummy takes value of 1 if it is an developed country and 0 if it is an developing country. Since factors such as infrastructure indicators , railway, air transport , internet and investment are affected by a country's development level, slope dummies (which are obtained by multiplying the dummy variables with the variables of interest) allows us to distinguish between development level differences . For example, multiplying air transport per capita with the dummy variable shows us whether growth rate gets affected by infrastructure differently in advanced and emerging economies.

2.1. Cross-section dependency and homogeneity Analysis

Cross section dependence can emerge due to many factors, such as excluded observed common factors, spatial spill over effects, unobserved common factors, or general residual interdependence that could remain even when all the observed and unobserved common effects are considered (Breitung and Pesaran,2008 :295). A shock that affects one country may spill over on other countries. Because of this one essential step to be taken in a panel data analysis is examining for cross-sectional dependency throughout the countries. (Nazlıoğlu,at all, 2011:6618).

$$y_{it} = \alpha + \chi_{it}{}^{'} \beta'_i + u_{it} \qquad (1)$$

Where i indexes the cross-section dimension and t time, ,x_{it} is a k x1 vector of rigidly exogenous regressors with slope parameters .$\beta_{i..}$ Breusch and Pagan (1980) advanced a LM statistic for testing the null hypothesis of cross-sectional independence.The test is based on the following LM statistic:

$$LM = T \sum_{i=1}^{N-1} \sum_{j=i+1}^{N} \hat{p}\, 2_{ij} \qquad (2)$$

Where ρ^ij is the sample estimate of the pair-wise correlation of the residuals from individual ordinary least squares (OLS) estimation of the Eq. (1) for each i. However,LM test is likely to cause substantial size distortions with large N and small T (Peseran at all, 2008). Pesaran (2004) developed a more general cross-sectional dependency tests (CD) to manage the large N bias of the LM test.

$$CD = \sqrt{\frac{2T}{N(N-1)}} \left(\sum_{i=1}^{N-1} \sum\nolimits_{j=i+1}^{N} \hat{p}_{\mathrm{i}J} \right) \qquad (3)$$

The results from cross-section dependency tests reported in table 3 point out the null hypothesis of cross-sectional independence is rejected at different level of significance. The existence of cross-sectional dependency requires that we must carry out a unit root analysis which consider for dependency in modelling affects of infrastructure on economic growth (Nazlıoğlu at all, 2014)

Table.2 Cross-section dependency tests

constant	Rail Statistic	p-value	Air Statistic	p-value	internet Statistic	p-value
CD_{lm} (BP,1980)	195.875	0.000	301.153	0.000	243.803	0.000
CD_{lm} (Pesaran, 2004)	4.898	0.000	11.693	0.000	7.991	0.000
CD (Pesaran, 2004)	0.759	0.224	-2.568	0.005	-2.712	0.003
LM_{adj} (PUY, 2008)	2.869	0.002	7.182	0.000	5.019	0.000
constant	GDP Statistic	p-value	GFC Statistic	p-value	Labour Statistic	p-value
CD_{lm} (BP,1980)	192.586	0.000	171.755	0.001	146.631	0.050
CD_{lm} (Pesaran, 2004)	4.685	0.000	3.341	0.000	1.719	0.043
CD (Pesaran, 2004)	-1.801	0.036	-0.350	0.363	-2.589	0.005
LM_{adj} (PUY, 2008)	9.615	0.000	0.410	0.341	-1.404	0.920

2.2. Unit Root Analysis

Before examining the impact of infrastructure on economic growth, the stationarities of the series, should be checked. Dealing with the problem of cross-section dependence, the cross section augmented Dickey–Fuller (CADF) test is used to check whether the series have a unit root or not. The cross section augmented Dickey–Fuller (CADF) test is based on the following regression (Peseran, 2007)

$$\Delta y_{it} = a_i + \emptyset y_{i,t-1} + b_i \bar{y}_{t-1} + c_i \bar{y}_t + e_{it} \qquad (4)$$

Having found the presence of cross-sectional dependence in the panel, an appropriate unit root test is the cross-sectionally augmented ADF (CADF) test for unit roots in heterogeneous panels was performed by Pesaran (2007). The critical values and CADF statistics are shown in table 4.

Table 3. Panel Unit Root Test, Peseran CADF and Fourier panel stationarity test

	CADF-stat			Fourier panel stationarity test	
	Lags	Constant	Constant and Trend	Constant	Constant and Trend
GDP GRWT	3	-1.28	-1.51	1.2375 (0.1080)	16.7891 (0.0000)
lnAIR	3	-1.96	-2.24	2.3543 (0.0093)	13.1612 (0.0000)
lnRAIL	3	-1.20	-2.14	24.4847 (0.0000)	12.6535 (0.0000)
INTERNET	3	-2.33**	-2.29	1.4127 (0.0789)	11.4864 (0.0000)
LNLABOUR	3	-1.57	-1.86	0.3819 (0.6487)	5.5375 (0.0000)
GFC	3	-1.74	-2.13	16.3183 (0.0000)	16.1529 (0.0000)
		10%		5%	1%
Critical values at constant		-2.07		-2.15	-2.32
Critical values at constant and trend		-2.58		2.67	2.83

*Max lag is considered 3 and selected as , Schwarz information criteria

The individual statistic is based on the Fourier panel stationarity test, which examine the null of stationary, showing that labor and GDP per capita series are stationary, I(0) on the contrary, internet, railway, airline and gross capital formation series are non- stationary at the % significance level. According to CADF-stat (constant and trend) all the series are stationary at the first difference, all of them are I (1).

Examining whether slope coefficients are homogeneous or heterogeneous is essential in a panel cointegration analysis. Delta test $\tilde{\Delta}$t and Adjusted Delta test $\tilde{\Delta}$t approach are used to test the homogeneity of a subset of slope coefficients (Pesaran and Yamagata, 2008).

$$\tilde{\Delta} = \sqrt{N}\left(\frac{N^{-1}\tilde{S} - k}{\sqrt{2k}}\right) \quad (4)$$

$$\Delta_{adj} = \sqrt{N}\left(\frac{N^{-1}\tilde{S} - E(\tilde{z}_{iT})}{\sqrt{Var(\tilde{z}_{iT})}}\right) \quad (5)$$

Where, $\Delta^{\sim}$ is the cross section dispersion of individual slopes weighted by their relative precision. The null hypothesis of interest is

$H_0 : \beta_i = \beta$ for all i,

against the alternatives

$H_1 : \beta_i = \beta_j$

When we reject null hypothesis, then we can conclude that series are homogeneous. Results of our cross section dependency test and slope homogeneity test are shown in table 5

Table 4. Cross section dependency test and slope homogeneity test

Cross Section Dependency test			**Homogeneity test**		
Test	Statistics	P value		Statistics	P value
LM (Breusch & Pagan 1980)	184.879	0.000	Delta_tilde	9.744	0.000
CD lm (Pesaran 2004)	4.188	0.000	Delta_tilde_adj	11.578	0.000
			Swamy Shat	718.353	0.000
CD (Pesaran 2004)	3.908	0.000			
LMadj	4.736	0.000			

2.3. Cointegration Analysis

We employ LM bootstrap test for the null hypothesis of cointegration and Westerlund cointegration test for the null hypothesis of no cointegration in panel data. Results of the panel cointegration tests are presented in Table 6. All the test statistics reject the null of no cointegration hypothesis at 10 and 5 percent level of significance for

Westerlund cointegration test. We accept the null of cointegration hypothesis according to Bootstrap p-value for LM bootstrap cointegration test**.**

Table. 5. Cointegration Test

Tests	Statistic	Asymptotic p-value	Bootstrap p-value
LM bootstrap			
(Ho: cointegration)			
LM_N^+	24.911	0.000	0.509

Tests	Statistic	Critical values	
Westerlund		1.28	10%
Durbin_h Tests,			
(Ho:No cointegration)		1.645	5%
dh_g	-1.895**		
dh_p	-1.346*	2.333	1%

The results exhibit the cointegration between GDP per capita and infrastructure indicators. The cointegration parameters are estimated by the pooled mean-group (PMG) estimator of Pesaran, Shin, and Smith, which provides short and long term parameters with error correction components are shown in table 7 (Paseran at all 2007). PMG estimator allows coefficients and error variances to differ freely across countries in the short run . However PMG assumes long run homogeneity among the panel group. PMG estimator gives advantage to calculate error correction term which measures the speed of adjustment towards the long-run equilibrium (Fedderke and. Kaya ,2013)

Table 6. Long Run and Short Run Parameters of Panel PMG Results

	Equation 1		Equation 2 with Dummy Variables	
	Coef.	P value	Coef.	P value
Long Run				
Air	-0.065	0.252	-0.085	0.26
Rail	-0.098	0.423	0.020	0.86
Internet	0.002	0.190	0.002	0.26
labor	1,470	0.147	0.567	0.71
GFC	0.007	0.001	0.007	0.00
dumair			0.019	0.76
dumrail			0.002	0.98
duminternet			0.002	0.24
Short Run				
Error Correction	-0.383	0.000	-0.365	0.00
D(Air)	0.024	0.049	0.033	0.02
D(Rail)	-0.045	0.302	-0.049	0.27
D(Internet)	-0.001	0.021	0.0004	0.18
D(labor)	0.388	0.016	-0.352	0.03
D(GFC)	0.002	0.000	0.002	0.00
dumair			-0.009	0.24
dumrail			0.006	0.12
duminternet			0.0002	0.37

The error-correction term is negative and significant. All the long-run coefficients of panel estimation are insignificant except gross capital formation (% of GDP) which we used as a proxy of investment, will lead to 0.07 % increase in GDP per capita growth in the long term. All the short run coefficients except railway, exhibit significant relationship with GDP per capita. As mentioned in section 1, we define a slope dummy variable to classify countries as a developing or a developed country according to the specification used by the IMF. Then we multiply this dummy with infrastructure indicators(air transport , railway , internet) add it as an extra regressor to decompose the developing - developed country effect. Appropriately, the slope dummy term for infrastructure has insignificant coefficient. This shows that emerging countries infrastructure policies effects on the growth do not differ from developed countries. Because of this insignificant dummy effect we consider only equation 1 .

According to growth theory , we expect infrastructure expenditures to affect economic growth positively. In parallel with our expectations, air transport coefficient is significant with a positive sign in the short run panel PMG estimation. The short -run coefficient of air transport (proxy for infrastructure) is 0.027 and is significant , indicating that a 1% increase in the air transport is probably to increase GDP per capita by about 0.024%. Contrary to our expectations, internet coefficient is significant with a negative sign in the short run. Railway coefficient is insignificant with a negative sign. 10 percentage point increase in investment expenditures to GDP ratio will lead to a 0.02 percent increase in growth. One percent increase in labor will lead to a 0.38 % increase in economic growth. The short term parameters of panel PMG estimation suggest that countries which are included our model must focus on labor , air transport and investment to stimulate economic growth .

Table 7. Long Run Country PMG Estimation Results

Countries	Labor	GCF	Air	Rail	internet
Austria	0.549 (0.287)	0.007*** (0.010)	0.047 (0.127)	-0.203** (0.025)	0.001* (0.011)
Czech Republic	0.627 (0.859)	0.014 (0.126)	0.175 (0.313)	-0.958 (0.223)	0.002*** (0.000)
France	11.373 (0.746)	-0.005 (0.923)	-0.691 (0.765)	0.341 (0.813)	-0.009 (0.758)
Finland	0.244 (0.649)	0.011*** (0.000)	-0.116** (0.021)	0.634*** (0.012)	0.001*** (0.001)
Germany	-0.528 (0.354)	0.010*** (0.001)	-0.174*** (0.000)	0.437*** (0.000)	0.001*** (0.000)
Ireland	3.859** (0.059)	0.001 (0.893)	-0.360 (0.470)	-0.653 (0.425)	-0.004 (0.210)
Italy	-0.944 (0.304)	0.010*** (0.009)	0.100* (0.064)	0.052 (0.836)	0.001 (0.164)
Japan	3.364** (0.025)	0.001 (0.750)	-1.187** (0.037)	-0.478 (0.142)	0.001*** (0.000)
Korea, Rep.	2.878*** (0.000)	-0.0008 (0.516)	0.011 (0.730)	0.112** (0.022)	0.0006*** (0.000)
Mexico	0.737 (0.815)	0.006 (0.165)	0.0008 (0.987)	-0.008 (0.318)	0.001 (0.238)
Netherlands	1.780** (0.054)	0.004 (0.164)	0.115 (0.412)	0.080 (0.518)	-0.0003 (0.733)
Poland	-3.092 (0.444)	0.011* (0.084)	-0.014 (0.930)	-0.098 (0.802)	0.004* (0.076)
Spain	-0.076 (0.604)	0.004*** (0.000)	0.128*** (0.000)	0.509*** (0.000)	-0.0001 (0.637)
Turkey	-4.560 (0.690)	0.024 (0.588)	0.213 (0.829)	-0.783 (0.653)	0.012 (0.499)
United Kingdom	-1.023 (0.171)	0.020*** (0.000)	-0.146* (0.068)	0.144 (0.328)	0.001*** (0.000)
China	9.004*** (0.000)	-0.006 (0.373)	-0.146 (0.356)	0.694 (0.230)	0.012*** (0.010)

Note: Figures in parentheses refer to p value. ***, ** and * denote statistically significant at 1%, 5% and 10%, respectively.

The above table lists results of all variables used in the study. For countries such as Mexico, Turkey ,Netherlands, France and Ireland, none of the variables are significant .This finding is important since it supports the crowding-out hypothesis.

Only one of the infrastructural variables is important for Italy, Czech Republic, Japan, Poland and China. Countries such as Spain, Austria, Korea and U.K. show better results but only in two countries, Finland and Germany, we find that all three infrastructure variables (internet, railway and airway) are positive and significant .

Table 8. Short Run Country PMG Estimation Results

Countries	ΔLabor	ΔGCF	ΔAir	ΔRail	Δinternet
Austria	-0.636 (0.127)	0.0003 (0.869)	-0.007 (0.794)	0.085 (0.146)	-0.001* (0.075)
Czech Republic	0.581 (0.556)	0.003** (0.013)	-0.0008 (0.965)	0.187* (0.095)	-9.83e-06 (0.982)
France	-0.527* (0.065)	0.004*** (0.000)	-0.012 (0.485)	0.039 (0.394)	0.0002 (0.180)
Finland	0.637 (0.405)	0.00009 (0.978)	0.080** (0.030)	-0.523** (0.030)	-0.0005 (0.372)
Germany	0.863* (0.082)	-0.0006 (0.708)	0.015 (0.645)	-0.322*** (0.003)	-0.0002 (0.381)
Ireland	1.503 (0.370)	0.002 (0.487)	0.140 (0.329)	-0..041 (0.868)	-0.004** (0.044)
Italy	-0.034 (0.917)	0.001 (0.457)	0.005 (0.630)	0.019 (0.767)	0.0002 (0.550)
Japan	1.208* (0.076)	0.006** (0.012)	0.096 (0.160)	0.097 (0.353)	0.0003 (0.929)
Korea, Rep.	0.522 (0.256)	0.002*** (0.000)	0.027** (0.024)	-0.013 (0.563)	-0.0005*** (0.006)
Mexico	0.281 (0.585)	0.0005 (0.903)	-0.006 (0.864)	-0.021* (0.073)	-0.0008 (0.515)
Netherlands	1.003 (0.128)	0.007** (0.042)	0.081 (0.166)	0.007 (0.944)	0.0003 (0.238)
Poland	-0.623 (0.866)	0.001** (0.030)	-0.005 (0.605)	-0.014 (0.722)	-0.0004 (0.414)
Spain	-0.049 (0.749)	0.0021 (0.000)	-0.030 (0.218)	-0.177 (0.005)	0.0008 (0.604)
Turkey	-0.516 (0.217)	0.003 (0.004)	-0.032 (0.526)	0.070 (0.322)	-0.001 (0.434)
United Kingdom	0.510 (0.312)	0.001 (0.474)	0.004 (0.815)	0.020 (0.710)	-0.0005*** (0.013)
China	0.929 (0.562)	-0.0008 (0.481)	-0.034 (0.176)	-0.135* (0.011)	-0.001 (0.335)

Note: Figures in parentheses refer to p value. ***, ** and * denote statistically significant at 1%, 5% and 10%, respectively. Δ refers to first difference all of the variables.

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Table 8 above reports the short-run results which are not significantly different than the long run results.

Conclusion and Summary

In this study, we examined the effect of infrastructure on economic growth in 16 countries after controlling for other principal variables such as gross capital formation (proxy for investment), labor force. We used Pool Mean Group panel analysis for the period 1995 to 2015. Railways, passengers carried (million passenger-km), Air transport, freight (million ton-km), Individuals using the Internet (% of population), variables are used as proxy for the infrastructure.

The results of the panel analysis for the period 1995–2015 display that GDP per capita elasticity of labor is positive and significant in the short run. The impact of capital formation (investment) on GDP is also positive and significant in both the long and short run. Additionally, our study has important implications that the GDP per capita elasticity of the air transport is positive and statistically significant at 5% level. Contrary to our expectations, internet coefficient is significant with a negative sign in the short run. Railway coefficient is insignificant with a negative sign.

Our results are in line with the findings of Agenor and Moreno-Dodson (2006) and Dissou and Didic (2013) who found negative and insignificant coefficients of public spending. Because of the crowding -out effect, heavy public infrastructure spending adversely affects private investment in the economy. It may also lead to more corruption and negative productivity growth.. The slope dummy term for infrastructure has insignificant coefficient. This shows that for emerging countries, infrastructure policies' effects on growth do not differ from developed countries. If developing countries focus on more infrastructure investment such as roads, bridges, highways, and neglect very productive manufacturing sectors then it will lead to negative effects on per capita GDP.

We also report results for specific counties using PMG estimation technique. Only developed countries such as Finland and Germany show positive and significant relation between public investment and per capita growth. All of the PMG estimation parameters are insignificant for countries such as Turkey and Mexico in the long run . Specific country short run PMG estimation results show that a majority of countries have insignificant infrastructure parameters. Future studies should further explore the impact of infrastructure spending at individual country level and see if the level of economic development matters.

BIBLIOGRAPHY AND REFERENCES

Agenor P-R, Moreno-Dodson B (2006) Public infrastructure and growth: New channels and policy implications. World Bank Policy Research Working Paper 4064 (November), Washington, DC

Asian, Development Bank. Infrastructure for Supporting Inclusive Growth and Poverty Reduction in Asia, edited by Development Bank Asian, Asian Development Bank, 2012

Barro RJ (1990) Government spending in a simple model of endogenous growth. J Polit Econ 98 (5):103–125

Barro RJ., (2003) "Determinants of Economic Growth in a Panel of Countries," Annals of Economics and Finance, Society for AEF, vol. 4(2), pages 231-274, November.

Caldero´ n, C., and L. Serve´n. 2003. The output cost of Latin America's infrastructure gap. In The limits of stabilization: Infrastructure, public deficits, and growth in Latin America, ed. W. Easterly, and L. Serve´n, 95–119. Washington, DC: Stanford University Press. CESifo Working Paper 1229; IZA Discussion Paper 1240.[970].

Cobb, C.W.; Douglas, P.H. 1928. A theory of production. The American Economic Review Supplement, Papers and Proceedings of the Fortieth Annual Meeting of the American Economic Association (Mar., 1928) 18 (1): 139-165.

Devarajan,s.,Swaroop,v. and Zou,H.,(1996).The Composition of Public expenditure and Economic Growth,Journal of Monetary Economics 37:313-344

Dissou and Didic (2013*) Infrastructure and Growth*, edit Cockburn, J et all in Infrastructure and Economic Growth in Asia, Springer.

Égert, B., T. Koźluk and D. Sutherland (2009), "Infrastructure and Growth: Empirical Evidence", OECD Economics Department Working Papers, No. 685, OECD Publishing, Paris.

Engel, Eduardo, Ronald Fischer and Alexander Galetovic, 2008. "Public-Private Partnerships: When and How". http://www.econ.uchile.cl/uploads/publicacion/c9b9ea69d84d4c93714c2d3b- 2d5982a5ca0a67d7.pdf

Fedderke, J.W. and. Kaya, T.E (2013) The Productivity Impact of Infrastructure in Turkey, 1987 – 2006, ERSA working paper 333, March.

Forrer, John, James Kee, Kathryn Newcomer, and Eric BoyerForrer, 2010. "Public-Private Partner- ships and the Public Accountability Question". Public Administration Review, Vol. 70, pp. 475-484

Ghali, Khalifa H. (1998) Public investment and private capital formation in a vector error-correction model of growth, Applied Economics, 30:6, 837-844,

Iradian, Garbis (2005) IMF Working Paper Middle East and Central Asia Department Inequality, Poverty, and Growth: Cross-Country Evidence.IMF Working Paper.

Jalilian H, Weiss J (2004) Infrastructure, growth and poverty: some cross-country evidence. Paper prepared for ADB Institute annual conference on 'Infrastructure and Development: Poverty,Regulation and Private Sector Investment', 6 Dec 2004, Tokyo

Jens K. Roehrich, Michael A. Lewis, Gerard George, Are public–private partnerships a healthy option? A systematic literature review, Social Science & Medicine, Volume 113, July 2014, Pages 110-119

Nazlıoğlu,Ş, Özcan, C, Adıgüzel,U and Şahbaz, A. (2014) The Nature of Shocks to Turkish exchange rates: what panel approach says? 03 June 2014, 2nd Economics & Finance Conference, Vienna

Nazlioglu, S., Karul, C. (2015) The Flexible Fourier Form and Panel Stationary Test with Gradual Shifts International Conference on New Trends in Econometrics and Finance Conference, March 23 -28, 2015, Sharjah-Dubai.

Orszag,Peter R. (2009), I Infrastructure: Rebuilding, Repairing and Restructuring, edited by Jason R. Baren, Nova Science Publishers, Incorporated, 2009.

Pereira, Alfredo Marvão and Roca-Sagalés, Oriol (2003) " Spillover effects of public capital formation: evidence from the Spanish regions "Journal of Urban Economics, Volume 53, Issue 2, March, Pages 238-256

Pesaran, M, Shin, Yongcheol and Smith, Ronald, (1997), Pooled Estimation of Long-run Relationships in Dynamic Heterogeneous Panels, Cambridge Working Papers in Economics, Faculty of Economics, University of Cambridge

Pesaran, M. H. (2007), A simple panel unit root test in the presence of cross-section dependence. J. Appl. Econ., 22: 265–312.

Pesaran,, M. Hashem Yamagata, Takashi (2007) Testing slope homogeneity in large panels, Journal of Econometrics, Volume 142, Issue 1, January 2008, Pages 50-93, ISSN 0304-4076, https://doi.org/10.1016/j.jeconom..05.010

Pesaran, M. Hashem ∗,Ullah Aman And Takashi Yamagata (2008) A Bias-Adjusted Lm Test Of Error Cross-Section Independence ,*Econometrics Journal* Volume **11**, Pp. 105–127.

Pesaran, M.H., 2004. General Diagnostic Tests for Cross Section Dependence in Panels.

Sahoo,P.and Dash, (2009) .Infrasturture Development and economic growth in India.Journal of asia Pacific Economy 14:351-365

Salahuddin,, Mohammad and Alam, Khorshed (2015), "Internet usage, electricity consumption and economic growth in Australia: A time series evidence", *Telematics and Informatics,* Volume 32, Issue 4, November 2015, Pages 862-878

Shaleen Singhal , Graeme Newell & Thi Kim Nguyen (2011) The significance and performance of infrastructure in India, Journal of Property Research, 28:1, 15-34

Sahoo, Pravakar and Dash, Ranjan Kumar (2012) Economic growth in South Asia: Role of infrastructure, The Journal of International Trade & Economic Development, 21:2, 217-252.

Sanchez-Robles,B.1998.Infrastuctureinvestment and growth:some empirical evidence. Contemporary Economic policy 16:98-108.

Notes:

Dynamics of Tobin's Q and US Stock Performance

Matiur Rahman*

Chase Bank Endowed Professor of Finance

College of Business

McNeese State University

Lake Charles, LA 70609

Email: mrahman@mcneese.edu

Phone # 337-475-5577

Muhammad Mustafa

Professor of Economics

South Carolina State University

Orangeburg, SC 29117

E-Mail: mmustafa@scsu.edu

*Contact Author

Dynamics of Tobin's Q and US Stock Performance

ABSTRACT

To study the dynamic effects of changes in Tobin'Q on stock prices of selected 249 US public companies of different industry categories. Panel unit roots tests and cointegration tests are implemented. Next, DOLS and GMM models are estimated. Annual data for the 2004-2012 period are used for the above selected US companies. Panel unit root tests provide somewhat mixed evidence of non-stationarity of both variables. There is clear evidence of cointegration between the above variables. The negative coefficient of the error-correction term shows convergence toward long-run equilibrium, though at slow pace. The estimates also reveal short-run net positive interactive feedback effects between the variables. Both DOLS and GMM estimates display similar picture of overvaluation of stocks in terms of upward movement in Tobin's Q beyond 0-to-1 range. For most parts of the sample period, the US stock market was in declining mode due to heightening of economic uncertainties during the Great Recession and several years beyond. Tobin's Q should be improved to boost stock prices. This is more of a long-run phenomenon. In the short run, both reinforce each other. The topic is unique and the existing literature on this topic is scant. Relatively new econometric techniques have been applied for estimation using panel data. The results are quite insightful, in our view.

Key Words: Tobin'Q, Stock Performance, Panel Cointegration, Panel ECM, GMM, DOLS

JEL Classifications: G20, G29

Dynamics of Tobin’s Q and US Stock Performance

I. Introduction

The objective of this study is to empirically investigate the dynamic influences of changes in Tobin’s Q on stock prices of 249 US companies of different industry-categories over the period of 2004-2012. To this effect, sophisticated heterogeneous panel cointegration, heterogeneous panel dynamic OLS and dynamic GMM (Generalized Method of Moments) econometric procedures are applied. The relevant data are obtained from the Federal Reserve’s “Flow of Funds Accounts of United States Z1”.

Tobin (1969) contributes the Q ratio (known as Tobin’s Q). For a company, Tobin’s Q is calculated as a ratio of the market value of installed capital to the replacement cost of capital. A low Tobin’s Q (between 0 and 1) means that the market value is less than the recorded value of the assets of the company. This suggests that the market undervalues the company with implication for undervaluation of its stock. Conversely, a high Tobin’s Q (greater than 1) implies that a firm’s stock is overvalued. High Tobin’s Q encourages firms to invest more in capital because they are worth more than the price they paid for them. Such measure of stock valuation is the driving factor behind investment decisions in Tobin’s Model. The ratio has considerable macroeconomic significance and usefulness as the nexus between financial markets and markets for goods and services. In other words, movements in stock prices largely reflect changes in consumption and investment.

Usually, stock prices are predicted by dividend yield and price-to-earnings ratio individually as a causal variable. Tobin’s Q also significantly helps predict both the above causal variables. As a result, Tobin’s Q should have better predictive power for stock returns (%

changes of stock prices). To add further, diversified companies have a lower Tobin's Q as compared to focused companies because the market penalizes the value of the firm assets (Lang and Stulz, 1994). For more details, please see the **Appendix.**

The remainder of the paper proceeds as follows. Section II briefly reviews the related literature. Section III outlines the empirical methodologies. Section IV reports empirical results. Finally, section V offers conclusions.

II. Brief Review of Related Literature

A growing interest among macroeconomists and financial economists is to better understand price behaviors in the asset markets by investigating the ability of various macroeconomic and financial variables in forecasting stock returns (e.g., Cochrane 1991b; Cooper and Priestley, 2005; Lamont, 2000; Lettau and Ludvigson, 2001a; Menzly, Santos and Veronesi, 2004). By recognizing how various macroeconomic variables influence stock returns, investors and portfolio managers alike can manage their investments and risks. Empirically, Tobin's Q has significant statistical power in predicting stock price-to–earnings ratio and dividend yield. Tobin's Q thus contains important information in predicting stock returns.

Although Black and Scholes (1974) and Miller and Scholes (1982) suggest that the relationship between stock returns and dividend yield does not seem to exist, numerous studies have produced empirical evidence to the contrary. Blume (1980) indicates a significantly positive association between yields and stock returns. Litzenberger and Ramaswamy (1982), and Morgan (1982) support Blume's findings that a positive (yet nonlinear) link between equity returns and dividend yields exists. Kiem (1985) also finds positive relationship between stock returns and dividend yield. Furthermore, Fama and French (1988) show that stock returns can be forecasted by dividend yields. Hodrick (1992) finds that changes in dividend yields can forecast expected stock returns. The empirical documentation of the positive relationship between stock returns and dividend yields is, furthermore, evidenced in Naranjo, Nimalendran and Ryngaert (1998). Other studies have established an inverse relationship between stock returns and price-to-earnings ratio. For instance, Basu (1977) reports that portfolios of stocks whose price-to-earnings ratios are low, exhibit higher risk-adjusted returns than the portfolios of stocks whose price-to-earnings ratios are high. Similar findings are documented in Peavy and Goodman (1983). Campbell and Shiller (1988) show an increase in price-to-earnings ratio induces lower growth in equity price. In another paper, Harney and Tower (2003) show that Tobin's Q is better than price-to-earnings ratio in forecasting stock returns.

To add further, Jiang and Lee (2007) find that excess equity risk premiums can be explained by a linear combination of dividends and book-to-market ratio in 1095. Sum (2013a) shows that dividend yield and price-to-earnings ratio Granger-cause the movement in stock market returns. In addition, Sum (2013b) shows that Tobin's Q ratio changes forecasts about 67.53% to 67.78% of price-to-earnings ratio at the two-quarter to eight-quarter horizons. Another study by Sum (2013c) finds that changes in aggregate Tobin's Q forecasts about 6.43% of the S&P 500 dividend yield at the 3-quarter horizon and 11.22% at the 8-quarter horizon. Other studies have used Tobin's Q as a proxy for corporate value or firm's performance [e.g., Cho (1998), Lang and Stulz 91994), McConnell and Servaes (1990), Morck et al. (1998)].

III.Empirical Methodologies

Panel data as a combination of cross-sectional and time series observations are used in this study. This provides a convenient way to study phenomenon where a statistically adequate number of cross-sectional and time series observations are not available. The pooled data argument both quality and quantity. Otherwise, it would be impossible to use only one of these two dimensions for meaningful analyses (Gujarati, 2003). This study provides an example of such situation where incorporating observations on the variables over successive time periods allows to expand the informational content of the data. Furthermore, since the length of the time series is small compared to the number of cross-sections, the effects of autocorrelation are small, if not negligible. Panel data estimation models include the constant coefficient (pooled), the fixed effects and the random effects regression models.

In order to test for the existence of a long-run equilibrium relationship among variables in a heterogeneous panel, the following model is specified:

$y_{it} = \alpha_i + \beta_i x_{it} + \gamma_t D_{it} + e_{it}$ ………………………………….(1)

Where, y = log of stock price (STR) and x = log of Tobin's Q (TBQ)

i=1,…., N and t= 1, …., T. The panel data set thus has altogether N*T observations.

In model (1), α_i shows the possibility of company-specific fixed effects and β_i allows for heterogeneous cointegrating vectors. γ_t represents time-dependent common shocks, captured by common-time dummies (D_{it}), that might simultaneously affect all the 249 US companies included in this study. Model (1) estimates by following Pedroni (2000, 2001) panel Fully-Modified Ordinary Least Squares (FMOLS) cointegration technique, which adjusts for the presence of endogeneity and serial correlation in the data. This method is an appropriate technique, especially if there are endogenous macroeconomic factors that can cause co-movements in the above variables.

Before estimating model (1), it is required that the order of integration of the variables be determined by using four panel unit root tests. If all variables are found to be I (1), then by using the Pedroni panel cointegration tests (1999, 2000, 2001) are applied to investigate whether they are co-integrated. The above mentioned tests and techniques are preferred to make sure that no spurious regression phenomenon exists in the estimation of β_i. In order to test for the presence of a unit root in the panel data under study, panel unit root tests as proposed in Im, Peseran and Shin (2003); Hadri (1999); Levin, Lin and Chu (2002) and Breitung (2000) are employed. For all these tests, the null hypothesis is non-stationarity in the data exists, except Hadri test relating to null hypothesis of stationarity of variables. The rejection of the null hypothesis of nonstationarity or stationary requires that the computed values of the coefficients exceed the respective critical values at 1% and /or at 5% levels of significance.

Subsequently, the following panel vector error- correction model in the spirit of (Engle and Granger, 1987) is estimated on the evidence of cointegrating relationship among variables of interest:

$$\Delta y_{it} = \alpha + \sum_{q=1}^{k} \beta i \Delta\, y_{it-q} + \sum_{q=1}^{l} \phi i \Delta\, x_{it-q} + \pi \hat{e}_{it-1} + \mu_{it} \text{ ....(2)}$$

To restate, *y* = log of stock price (STR) and *x* = log of Tobin's Q (TBQ)

For long-run convergence and causal relationship, the estimated coefficient ($\hat{\pi}$) of the error-correction term ($\hat{e}_{it-1}$) is expected to be negative. The associated t-value indicates its statistical significance. The estimated β_i, and ϕ_i reveal short-run interactive feedback relationships. The appropriate lag-lengths are determined by the Akaike (1969) information criterion.

Next, Stock and Watson (1993) show that DOLS(Dynamic Ordinary Least Squares) is more favorable, particularly in small samples, compared to a number of alternative estimators of long-run parameters, including those proposed in Engle and Granger (1987), and Phillips and Hansen (1990). Furthermore, Short-run elasticity counterparts are also derived via robust dynamic error-correction models (ECMs).

For panel data, the estimating base equation is specified as follows:

$Y_{it} = \alpha_0 + \alpha_1 X_{it} + e_{it}$ ……(3)

Prior to testing for panel cointegration, four panel unit root tests LLC (Levin, Lin and Chu, 2002),Breitung (2000), IPS (Im, Pesaran and Shin, 2003) and Hadri (1999) are implemented.

Following Pedroni (2000), the following model for cointegration between the variables is estimated by DOLS;

$Y_{it} = \alpha_i + \beta_i X_{it} + \gamma_t D_{it} + \mu_{it}$ ……..(4)

Y_{it} is dependent variable with pooled data and X_{it} is explanatory variable with the same.

α_i captures possible company-specific fixed effects and β_i allows for heterogeneous cointegrating vector. γ_t captures time-dependent common shocks of common time dummies (D_{it}).

The DOLS procedure basically involves regressing any I(1) variables on the other I(1) variables, any I(0) variables and leads or lags of the first differences of any I(1) variables. However, since an investigation of the short-run dynamics are also of interest in the analysis, the panel bi-variate ECM formulation is described as follows in drawing inferences on the long-run and the short-run dynamics:

$$\Delta Y_{it} = \sum_{j=1}^{k} \emptyset_{ij}\, \Delta y_{t-j} + \sum_{j=0}^{m} n_j\, \Delta x_{i-j} + EC_{it-1} + \epsilon_t \ldots\ldots (5)$$

Intuitively, when the variables are cointegrated, then in the short term, deviations from this long-term equilibrium will feed back on the changes in the dependent variable in order to force the movement revert towards the long-term equilibrium. If the dependent variable is driven directly by this long-term equilibrium error, then it is responding to this feedback. If not, it is responding only to short-term shocks to the stochastic environment. The significance tests of the 'differenced' explanatory variables give an indication of the 'short-term' effects, whereas the 'long-term' causal relationship is implied through the significance or otherwise of the't' test of the lagged error-correction term, which contains the long-term information since it is derived from the long-term cointegrating relationship(s). The coefficient of the lagged error-correction term, however, is a short term adjustment coefficient and represents the proportion by which the long-term disequilibrium (or imbalance) in the dependent variable is being corrected in each short period. Non-significance or elimination of any of the 'lagged error-correction terms' affects the implied long-term relationship and may be a violation of the underlying theory.

Finally, this study also invokes Generalized Method of Moments (GMM), as developed in Hansen (1982), for robust and efficient estimates. GMM is one of the most widely used econometric tools in finance. A set of moment conditions is used to estimate model parameters by GMM. In general, the number of moment conditions is larger than the number of model parameters. A model misspecification for over-indentifying restrictions can be tested by GMM J-statistic. GMM does not require strong distributional assumptions for applications in finance.

Since this paper employs panel data, GMM dynamic panel estimation is more appropriate than the original GMM estimation. On differencing of the regression equation, unobserved company-specific effects and the use of differenced lagged regressors eliminate parameter inconsistency arising from simultaneity bias (Arellano and Bond, 1991). Monte Carlo simulations of the model offer discernible improvements in both efficiency and consistency (Blundell and Bond, 1997).

IV. Empirical Results

The panel unit root tests results for Tobin's Q and stock prices are reported as follows:

Table1: Panel Unit Root Tests

METHOD				
Variable (level)	**LLC**	**Breitung**	**IPS**	**Hadri**
TBQ	72.8444 (0.0000)	-42.0320 (0.0000)	56.1335 (0.0000)	4.41853 (0.0000)
STR	4.85344 (0.0000)	-0.76434 (0.2223)	18.8687 (0.000)	0.9793 (0.0000)
VARIABLE (DIFFERENCES)	LLC	Breitung	IPS	Hadri
Δ (TBQ)	38.1543 (1.0000)	-12.8539* (0.0000)	36.3133 (0.0000)*	0.57732* (0.2819)
Δ (STR)	37.9687 (1.0000)	-3.60093* (0.0002)	34.9772* (0.0000)	2.01616* (0.0219)

Where, TBQ = log of Tobin's Q; STR = log of stock price, and total number of observations (NT) 249X9 = 2241 Note: LLC = Levin, Lin, Chu (2002) IPS = Im, Pesaran and Shin (2003). The statistics are asymptotically distributed as standard normal with a left hand side rejection area, except on the Hadri test, which is right sided. *, indicates the rejection of the null hypothesis of nonstationarity (LLC, Breitung, IPS) or staitonarity (Hadri) at the 1 and 5 percent level of significance.

As observed above in Table 1, LLC, Breitung and IPS tests show that log of Tobin's Q (TBQ) and log of stock prices (STR) are nonstationary at 1 percent level of significance. Their counterpart (Hardi) test leads to a contrasting inference at 1 percent level of significance. Furthermore, Brietung test provides evidence of stationary in log of stock prices. In short, the evidence is somewhat mixed for nonstationarity of both variables. Subsequently, tests are performed for panel cointegration between TBQ and STR.A battery of seven panel cointegration tests results are reported as follows:

TABLE 2: Pedroni Panel Co-integration Tests

Test	Constant trend	Constant + Trend
Panel v-Statistic	-0.95430 (0.1700)	-1. 36881 (+ 0.9145)
Panel rho-Statistic	-136.8948 (0.0000)*	-112.3302 (0.0000)*
Panel PP-Statistic	-46.42832 (0.0000)*	-51.53257 (0.0000)*
Panel ADF-Statistic	-29.93782 (0.0000)*	-33..5417 (0.0000)*
Group rho-Statistic	-125.967 (0.0000)*	-97.17934 (0.0000)*
Group PP-Statistic	-54.0987 (0.0000)*	-54.90720 (0.0000)*
Group ADF-Statistic	-34.4988 (0.0000) *	-35.37046 (0.0000)*

*indicates significance at 1 % level.

The above panel for cointegration tests are applied on the null hypothesis of no-cointegration. Six tests confirm cointegrating relationship between TBQ and STR at 1 percent level of significance with constant trend and constant + trend except panel v- statistic. Thus, the evidence in favor of cointegration between the above variables is overwhelming revealing tendency toward long-run convergence.

DOLS results are provided below:

Table 3: Panel Dynamic Least Squares (DOLS) Estimates

Dependent Variable: STR

Variable	Coefficient	Std. Error	t-Statistic	Prob.
STR(-1)	1.000000	1.50E-17	6.68E+16	0.0000
TBQ(-1)	- 2.68E-17	9.75E-18	- 2.751418	0.0060
R-squared	1.000000	Adjusted R-squared		1.000000

The DOLS estimates, as reported in Table 3, show short-run negative effects of changes in TBQ and STR with one-year lag on current stock prices. The results show that higher values of TBQ above 1 indicate overvaluation of stocks since for most parts of the sample period, the US stock market slid. This would depress investment further pushing stock prices downward.

GMM estimates are as follows:

Table 4: Panel Generalized Method of Moments (GMM) Estimates

Dependent Variable: STR

Variable	Coefficient	Std. Error	t-Statistic	Prob.
STR	- 0.538783	0.018453	- 29.19736	0.0000
TBQ	0.137443	0.012535	10.96475	0.0000
TBQ(-1)	0.084778	0.012914	6.565022	0.0000
J-statistic	36.44975	Prob (J-statistic)		0.000000

The above GMM estimates disclose that current and preceding TBQ in conjunction with preceding STR exert short-run dynamic effects on current STR. Such net effects are negative implying overvaluation of stocks TBQ being above 1. Moreover, the GMM J-statistics at 36.44975 confirms no misspecification of the model. Both DOLS and GMM estimates portray similar pictures with regard to overvaluation of a majority of 249 US company stocks since 2008 during the sample period for the above reason. However, there are some magnitudinal differences in the coefficients and the associate t-values.

Finally, the estimates of the VECM are reported as follows:

$$\Delta \mathrm{STR}_{it} = \underset{(-0.5600)}{-0.0074} + \underset{(14.3745)}{0.4925}\Delta STR_{\mathrm{it-1}} + \underset{(8.9978)}{0.2805}\Delta \mathrm{STR}_{\mathrm{it-2}} - \underset{(-8.8978)}{0.19742}\Delta \mathrm{STR}_{\mathrm{it-3}}$$

$$- \underset{(-9.7408)}{0.1974}\Delta \mathrm{TBQ}_{\mathrm{it-1}} - \underset{(-9.7573)}{0.2446}\Delta \mathrm{TBQ}_{\mathrm{it-2}} + \underset{(6.\ 1393)}{0.0825}\Delta \mathrm{TBQ}_{\mathrm{it-3}}$$

$$- \underset{(-10.6637)}{0.3938}\mathrm{EC}_{\mathrm{it-1}} \ldots \ldots \quad (5)'$$

$$\bar{R}^2 = 0.4435,\ \mathrm{F} = 251.9438$$

Estimated equation (5)' corresponds to equation (5) in section III. Clearly, the error- correction term (EC_{it-1}) has expected negative sign for long-run convergence with high statistical significance in terms of the associated t-value (-10.6637). The short-run interactive net feedback effect of lagged changes in TBQ is negative showing that stock prices decline with TBQ being above one implying overvaluation of stocks. Presumably, most of the stocks included in this study seemed overvalued for the sample period since 2008 due to global economic and financial turmoils.

V. Conclusions

To sum up, the log of Tobin's Q and that of stock prices have somewhat mixed evidence on nonstationarity of both variables. However, both variables are clearly cointegrated. The DOLS estimates reveal overvaluation and consequent slide in stock prices due to rising TBQ above unity. The GMM estimates also provide a similar picture in the short run. However, there are some differences in the computed coefficients and their associated t-values.The estimates of the vector error-correction model show statistically significant convergence toward long-run equilibrium at slow pace and net negative effect implies overvaluation of stocks relating to TBQ.

In closing, changes in Tobin's Q have significant effects on stock overvaluation and hence decline in stock prices as an aftermath. Investors should closely monitor changes in TBQ to set and revise investment strategies in light of the aforementioned.

Bibliography and References

Akaike, H. (1969). "Fitting autoregression for prediction", Annals of the Institute of Statistical Mathematics, 21: 243-247.

Arellano, M. and Bond, S. (1991). "Some tests of specification for panel data: Monte Carlo evidence and an application to employment equations", Review of Economic Studies, 58: 277-297.

Basu, S. (1977). "Investment performance of common stocks in relation to their price-earnings ratios: A test of the efficient market hypothesis", Journal of Finance, 32(3): 663-682.

Black, F. and Scholes, M. (1974). "The effects of dividend yield and dividend policy on common stock prices and returns", Journal of Financial Economics, 1(1): 1-22.

Blume, M. E. (1980). "Stock returns and dividend yields: Some more evidences", Review of Economics and Statistics, 62(4): 567-577.

Blundell, R. and Bond, S. (1997). "Initial conditions and moment restrictions in dynamic panel data models", University College London, Discussion Paper in Economics, 97-107.

Breitung, J. (2000), "The local power of some unit root tests for panel data, in B. Baltagi (ed.), nonstationary panels, panel cointegration and dynamic panels", Advances in Econometrics, 15: 161-178.

Campbell, J. Y., and Shiller, R.J. (1998). "Valuation ratios and the long-run stock market outlook", Journal of Portfolio Management, 24(2): 11-26.

Cho, M.H. (1998). "Ownership structure, investment, and the corporate value: An empirical analysis", Journal of Financial Economics, 47(1): 103-121.

Cochrane (1991b). "Production-based asset pricing and the link between stock returns and economic fluctuations", Journal of Finance, 46: 207-234.

Cooper, I. and Priestley, R. (2005). "Stock return predictability in a production economy", Proceedings of the 2005 American Finance Association, Boston, MA.

Engle, R. and Granger, C.W.J. (1987). “Co-integration and error-correction: representation, estimation, and testing”, Econometrica, 35:315-329.

Fama, E.F., and French, K. R. (1988). “Dividend yields and expected stock returns”, Journal of Financial Economics, 22(1): 3-25.

Gujarati, D. (2003). “Basic econometrics”, Fourth Edition, McGraw- Hill.

Hadri, K. (1999). “Testing the null hypothesis of stationarity against the alternative of a unit root in panel data with serially correlated errors”, Manuscript, Department of Economics and Accounting, University of Liverpool.

Hansen, L. P. (1982). “Large sample properties of generalized method of moments estimators”, Econometrica, 50:1029-1054.

Harney, M., and Tower, E. (2003). “Predicting equity returns using Tobin’s Q and price-earnings ratios”, Journal of Investing, 12(3): 58-70.

Hodrick, R. J. (1992). “Dividend yields and expected stock returns: Alternative procedures for inference and measurement”, Review of Financial Studies, 5(3): 357-386.

Im, K. S., Pesaran, M. H. and Shin, Y. (2003). “Testing for unit roots in heterogeneous panels”, Journal of Econometrics, 115: 53-74.

Jiang, X., and Lee, B.S. (2007). “Stock returns, dividend yield, and book-to-market ratio”, Journal of Banking and Finance, 31(2): 455-475.

Kiem, D. B. (1985). “Dividend yields and stock returns: Implications of abnormal January returns”, Journal of Financial Economics, 14(3): 473-489.

Lamont, O. (2000). “Investment plans and stock returns”, Journal of Finance, 55: 2719-2745.

Lang, L.H.P., and Stulz, R.M. (1994). “Tobin’s Q, corporate diversification, and firm performance”, Journal of Political Economy, 102(6): 1248-1280.

Lettau, M., and Ludvigson, S. (2001a). “Consumption, aggregate wealth, and expected stock returns”, Journal of Finance, 56: 815-849.

Levin, A., Lin, C.F., and Chu, C. (2002). “Unit root tests in panel data: Asymptotic and finite sample properties”, Journal of Econometrics, 108:1-24.

Litzenberger, R. H., and Ramaswamy, K. (2012). “The effects of dividends on common stock prices tax effects or information effects?”, Journal of Finance, 37(2): 429-443.

McConnell, J.J., and H. Servaes. (1990). “Additional evidence on equity ownership and corporate value”, Journal of Financial economics, 27(2): 595-612.

Menzly, L., Santos, T., and Veronesi, P. (2004). "Understanding predictability", Journal of Political Economy, 112: 1-47.

Miller, M. H., and Scholes, M. S. (1982). "Dividends and taxes: Some empirical evidence", Journal of Political Economy, 118-1141.

Morck, R., Shleifer, A., and Vishny, R.W. (1988). "Management ownership and market valuation: An empirical analysis", Journal of Financial Economics, 20: 293-315.

Morgan, I.G. (1982). "Dividends and capital asset prices", Journal of Finance, 37(4): 1071-1086.

Naranjo. A., Nimalendran, M., and Ryngaert, M. (1998). "Stock returns, dividend yields, and taxes", Journal of Finance, 53(6): 2029-2057.

Peavy III, J. W., and Goodman, D. A. (1983). " The significance of P/Es for portfolio returns", Journal of Portfolio Management, 9(2): 43-47.

Pedroni, P. (1999). "Critical values of cointegration tests in heterogeneous panels with multiple regressors", Oxford Bulletin of Economics and Statistics, 61:653-670.

Pedroni, P. (2000). "Fully modified OLS for heterogeneous co-integrated panels, in Baltagi, B. and C. D. Kao (Eds;), advances in econometrics, nonstationary panels, panel cointegration and dynamic panels", New York: Elsever Science, 93-130.

Pedroni, P. (2001). "Purchasing power parity tests in cointegrated panels", Review of Economics and Statistics, 83:727-731.

Phillips, P.C.B., and Hansen, B.E. (1990). " Statistical inference in instrumental variables regression with I(1) processes", Review of Economic Studies, 57: 99-125.

Stock, J.H., and Watson, M. (1993). "A simple estimator of cointegrating vectors in higher order integrated systems", Econometrica, 61: 783-820.

Sum, V. (2013a). "The orthogonal response of stock returns to dividend yield and price-to-earnings innovations", Accounting and Finance Research, 2(1): 47-53.

Sum, V. (2013b). "Dynamic effect of Tobin's Q on price-to-earnings ratio", Managerial Finance, 40(6): 634-643.

Sum, V. (2013c). "Stock market dividend yield and Tobin's Q", Working Paper, University of Maryland.

Tobin, J. (1969). "A general equilibrium approach to monetary theory", Journal of Money, Credit and Banking, 1(1): 15-29.

Appendix: The q Theory of Investment in Brief

Tobin's q is defined as the ratio of the market value of installed capital to its replacement cost. To define,q= market value of installed capital/replacement cost of installed capital. The market value of installed capital is priced in the stock market and is the number of shares outstanding times their market price. The replacement cost of installed capital depends on the situation in the capital goods sectors. If the demand for capital goods is strong, the price of capital goods will rise.

If $q<1$, the firms have an incentive to increase their capital stock because capital once installed and producing goods and services is priced more highly than its cost. If $q>1$then firms should scrap capital, close plants, etc.However, as the Dixit and Pindyck analysis suggests, firms may delay expansion or contraction for some time and may only do so if q remains significantly above or below unity.

The Efficient Markets Hypothesis (EHM) suggests that share prices and thus the market valuation /capitalization of businesses reflect all available information regarding the business, its environment and its prospects. Thus, observed share prices impound information about business fundamentals such as earnings(profits), dividends, managerial performance, market conditions and the market's expectation of the future trends in such variables.

In theory, the share price and market capitalization should be driven by arbitrage to accurately reflect the intrinsic value of companies. If a share price rises above the consensus view of the intrinsic value of the stock, agents will sell driving the price back to it's fundamental value.

Thus, the numerator of the q equation provides a correct indication of the current worth and likely prospects for the business. If a firm faces a $q>1$, then this is a signal that it should buy additional capital because the present value of the future earnings from such capital will be greater than its cost. Clearly, when a firm expands its capital stock it will face diminishing returns, i.e. the marginal product of capital will fall as the capital stock grows. This will tend to cause q to revert back towards unity. However, if the EHM is correct, share prices will provide firms and agents with correct signals regarding how to allocate capital. If a firm is well regarded by the markets, then q will rise and the firm should increase its capital stock. This can be achieved by either purchasing capital equipment or by taking over the assets of other firms.

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http://www.slideshare.net/RafikAlqeria/a-brief-summary-of-q-theory

The Hubbert Curve and Rare Earth Elements Production

Mr. Zachary Gann,
Economics Major Student, College of Business, Metropolitan State University of Denver, P. O. Box 173362, Denver, CO 80217-3362.

Abstract

This paper intends to apply the Hubbert curve to the production of rare earth elements by the United States, China, and total global production. The goal of this research is to see if the production of rare earth elements follows the predicted production forecasted by the Hubbert curve and to observe if the curve can create usable predictions of future production. Global demand for rare earth elements has drastically increased in the modern era due to their unique properties. Global production has increased as well to meet this increased demand.

Rare earth elements are a collection of seventeen chemical elements that are used in the production of advanced technologies. The demand for rare earth elements has increased in the modern era with new applications for them being discovered and the increasing demand for green energy which requires rare earth elements in its production.

The United States was chosen to be examined due to its long history of producing rare earth elements. The United States was also the largest supplier of rare earth elements before China overtook them in rare earth element production. Ever since China became the top producer of rare earth elements, the United States' production of rare earth has declined. Production reached zero in 2016 due to the lone company that mines rare earth elements in the country filing for bankruptcy. This caused their only mine to be put on care and maintenance. This meant that the United States had to import all of the rare earth metals it requires until the mine reopens or until new mines are created.

China was chosen as the other country to analyze because it has the largest known reserves of rare earth metals and is the largest supplier of rare earth elements in the world market today. China's supply of rare earth metals for the market is also affected by its own increasing demand for rare earth due to its rising industrial sector and their government trying to preserve their reserves of rare earth metals.

It was concluded that observed REE production does follow the trend predicted by the Hubbert curve, but the Hubbert curve does not create accurate predictions of future REE productions due to its simplicity.

The first section of this paper is a literature review that scrutinizes previous research done about rare earth elements and the Hubbert curve. The reasoning behind this analysis is to get a better understanding of the state of the rare earth elements market and to create a basis for the research of this paper to be conducted on. Correspondingly in this section, the equation of the Hubbert curve and the theoretical implications of its results will also be discussed. The data and regressions will be described that look at the application of the Hubbert curve to the United States' rare earth element production, China's rare earth element production and global rare earth production in the next section. The results of this research will be thoroughly described in the conclusion alongside what implications these results have as well. A bibliography citing all material used within this project will be the last part of this paper.

The Hubbert Curve and Rare Earth Elements Production

Section 1:

Rare earth elements are integral to the future advancement and production of technology. This paper applies the Hubbert curve which was originally used to analyze oil production to the production of rare earth elements by the United States, China, and the global production as a whole. This is done in order to see if the past production of rare earth elements follows the Hubbert curve as derived by Hubbert (1956) and to see if the Hubbert curve can be used to create accurate predictions of future production. Seventeen chemical elements compose the group known as rare earth elements. They have unique properties that make them desirable in the production of advanced technology. The demand for rare earth elements has drastically increased in the modern era due to new applications for them being discovered and because of the increasing demand for green energy which requires rare earth elements in its production.

The United States will be examined due to its long history of producing rare earth elements and due to them being the largest supplier of rare earth elements in the past. This changed in the last few decades when China overtook the United States in rare earth element production. In that time period the United States' production of rare earth has declined with it reaching zero in 2016 due to the only company that produces rare earth elements in the country filing for bankruptcy and causing their only mine to be put on care and maintenance. This meant that the United States had to import all of the rare earth metals it required.

China was chosen because she has the largest reserves of rare earth metals and is the largest supplier of rare earth elements in the world market in the modern times. China's supply of rare earth metals for the market is also affected by its own increasing demand for rare earth due to its rising industrial sector and their government trying to preserve their reserves of rare earth metals.

The first section of this paper is a literature review that examines previous research done surrounding rare earth elements and the Hubbert curve. This is done to get a better understand of the rare earth elements market and to create a foundation for the research of this paper to be conducted on. This section also describes the equation of the Hubbert curve and the theoretical implications of its results. The next section is the research section. This is where the data and regressions will be described that look at the application of the Hubbert curve to the United States' rare earth element production, China's rare earth element production and global rare earth production. The results of this research is thoroughly described in the conclusion with what repercussions these results have. The final piece of this paper is a bibliography citing all references used within this project.

Section 2:

There has been research done on the Hubbert curve. In 1956, M. King Hubbert presented his paper to the American Petroleum Institute. In it he concluded that the rate of oil production of an oil reserve follows a bell shaped curve and that United States oil production would peak between 1965 and 1970. In their 2016 paper, Istemi Berk and Volkan n Ş. Ediger applied the Hubbert curve to the coal production of Turkey's lignite fields to forecast the future coal production. They determined that the largest lignite fields would start to decline in production in the near future and that most of the coal reserves would remain unused if the trend continued into the future. In his 2011 paper, Brian Gallagher created an idealized Hubbert curve for global oil production. He predicted peak oil production would occur in 2009 with 83.2 million barrels a day and deduced that the idealized Hubbert curve could be a useful tool for prediction. Cavallo examined if the Hubbert curve should be used for determining peak oil given that it has it has failed in the past. He concluded in his 2004 paper that the Hubbert curve can't be used to predict ultimate oil reserves, but it has importance as an econometric model. In their 2015 paper, Chavez-Rodriguez, Szklo, and Frossard Pereria de Lucena applied the Hubbert curve to oil production in Peru. They found that a multi-Hubbert approach had a better fit to Peru's oil production and that Peru could reach a second peak oil after the first peak in 1982, but this would depend on oil production in Amazonia.

There also has been numerous research done on rare earth metals and predictions for their future production. In 2015, Schlinkert and van den Boogaart constructed an economic model in their paper to depict what the past and future of the rare earth element market looks like. They found that the mining and separation of rare earth elements could be focused in China and the market itself could change into an oligopoly due in part to increasing demand for rare earth elements. Paulick and Machacek analyzed the rare earth element exploration boom that lasted from 2010 to 2014 and analyzed the mineral resource definitions that occurred. In their 2017 paper, they found that rare earth element mineral resources outside of China reached 98 million metric tons by 2015 and that a large percentage of those resources have a higher heavy rare earth element to light rare earth element ratio than other rare earth element minerals. Klossek, Kullik, and van den Boogaart (2016) examined the problems with the rare earth market that caused China to dominate the rare earth market. They identified four systematic problems which were competing political economic models, resource nationalism, lack of market transparency, and absence of trust. Rui Wan and Jean-François, in their 2017 paper, created a three country trade model of a rare earth elements market to examine how the three different polices of a downstream subsidy, an upstream export tariff, and an upstream pollution tax would affect welfare and the market. They determined that equilibrium policies and their outcomes depend on the coefficient of the local environmental cost function, the coefficient of the global environmental benefit function, and the amount of competitors in the market downstream.

Now it is time to explain the Hubbert curve. M. King Hubbert theorized that the cumulative production of a nonrenewable resource follows this logistic curve over time (Cavallo, 2004):

$$Q(t) = \frac{Q_{max}}{(1 + ae^{bt})}$$

In this equation $Q(t)$ is the cumulative production at time t, Q_{max} is the total amount of the resource available and a and b are constants. According to this model, production of the resource begins slowly, then production grows exponentially till it reaches the maximum yearly production were it declines afterwards. This equation also makes the curve symmetric about the point of maximum yearly production. Two further equations can be used to determine the maximum yearly production and the year that it occurs. Maximum annual production (P_{max}) can be calculated by the equation (Cavallo, 2004):

$$P_{max} = \frac{Q_{max}|b|}{4}$$

The year of maximum annual production (t_{max}) is calculated by the equation (Cavallo, 2004):

$$t_{max} = \left(\frac{1}{b}\right) \ln\left(\frac{1}{a}\right)$$

Section 3:

To test how well the Hubbert curve fits the data, the logistic equation will be plotted against data of cumulative rare earth element production and time (years) for the United States, China and Global production respectively. The data were gathered from the United States Geological Survey and put into an Excel spreadsheet. All rare earth element amounts throughout are in metric tons (t). These data, however, only have annual production data, not cumulative data. To correct this, the earliest point of data was called year 1 and cumulative production was calculated by adding each annual production together up to the desired year. These data were then put into Stata and a nonlinear regression was run to determine the values of Q_{max}, a and b. The resulting values were then put into the logistic equation and ran through Excel to determine the theoretical cumulative production of earth elements. Theoretical yearly production for a given year was calculated by subtracting the theoretical production for the previous year from the theoretical production of the desired year.

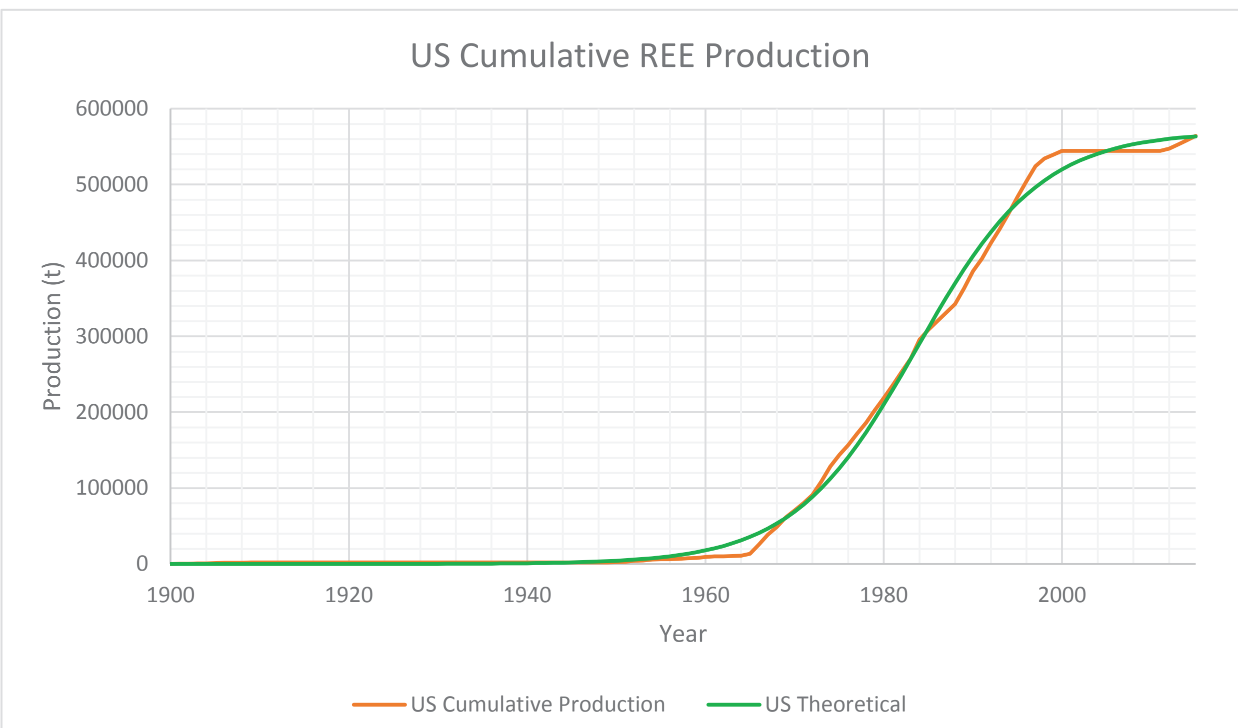
Table 1

Source	**SS**	**df**	**MS**	**Number of obs**	116
Model	8.110e+12	3	2.7034e+12	**R-squared**	0.9986
Residual	1.141e+10	113	101002701	**Adj R-squared**	0.9986
Total	8.122e+12	116	7.0015e+10	**Root MSE**	10050.01
				Res. Dev.	2464.111

Constant	**Coef.**	**Std. Err.**	**t**	**P>t**	**[95% Conf.**	**Interval]**
$\boldsymbol{Q_{max}}$	569720.2	3429.438	166.13	0.000	562925.8	576514.5
$\boldsymbol{a}$	203251.5	45435.1	4.47	0.000	113236.3	293266.7
$\boldsymbol{b}$	-.144263	.0027636	-52.20	0.000	-.1497382	-.1387878

The data for the United States can be found in the appendix. The data were of annual rare earth production from 1900 to 2015. There were some missing production data for a few years with most occurring between 1911 and 1949. The results of the regression for the United States can be found in the Table 1 above. The determined value for Q_{max} was 569,720.2 metric tons and the determined values for constants a and b being 203,251.5 and -.144263 respectively. The R-squared and adjusted R-squared were 0.9986 and 0.9986 meaning that a lot of the variation in U.S. cumulative REE production is explained by Hubbert's model. This is clearly visible in Figure 1 where U.S. cumulative production is graphed alongside U.S. theoretical production across time. The theoretical cumulative production closely follows the actual cumulative production. The high t-statistics for Q_{max}, a and b illustrates that these values are significant at the 95% level. This means that there is some type of relationship occurring here.

Figure 1



This is further supported by the p-value of 0.000 for all of the tested variables which goes further to say that each variable is significant at the 99.99% level.

Figure 2

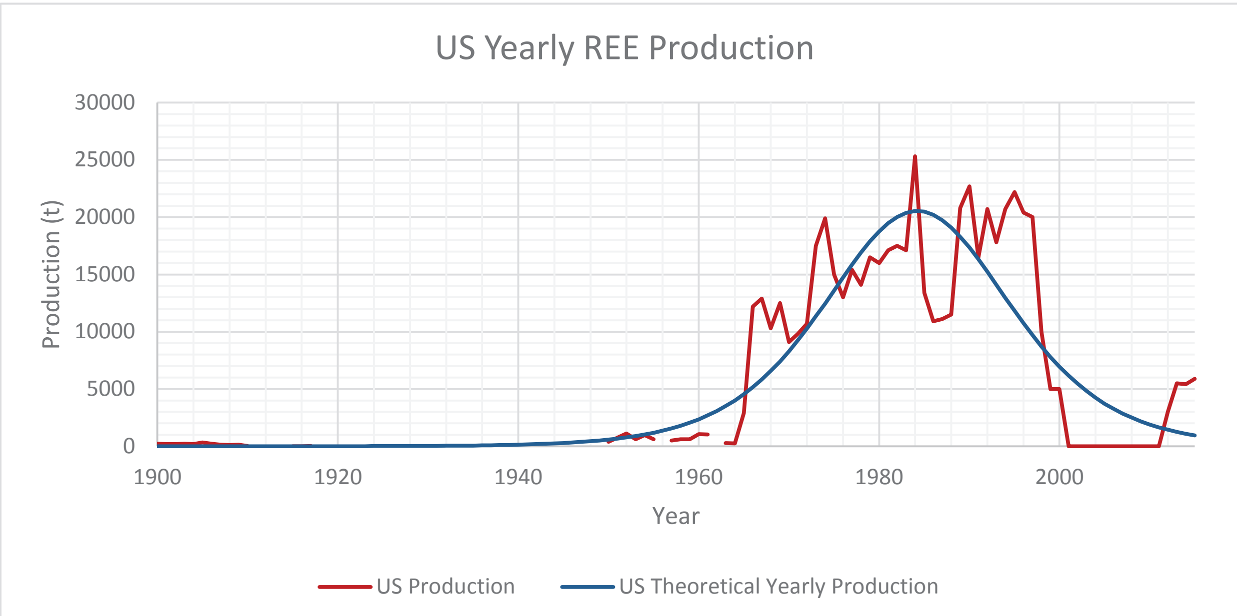


Figure 2 shows U.S. yearly production and U.S. theoretical yearly production over time. This graph illustrates that while theoretical cumulative production follows actual cumulative production, actual yearly production is much more volatile than the predicted yearly production. According to Hubbert's equations, maximum annual production should have been roughly 20,547.39 metric tons of REE and it should have occurred between 1983 and 1984. Actual maximum annual production was 25,300 metric tons and occurred in 1984. While the time period is accurate, the estimated value for maximum production is off by almost 20%. This discrepancy is clear with other data points in Figure 2. The figure also shows that yearly production started to significantly increase in 1965 and decreased to 0 metric tons in 2001. This corresponds to the production of the Mountain Pass Mine. This mine was the sole producer of rare earth elements in the United States (Castor, 2008). The mine was forced to shut down in

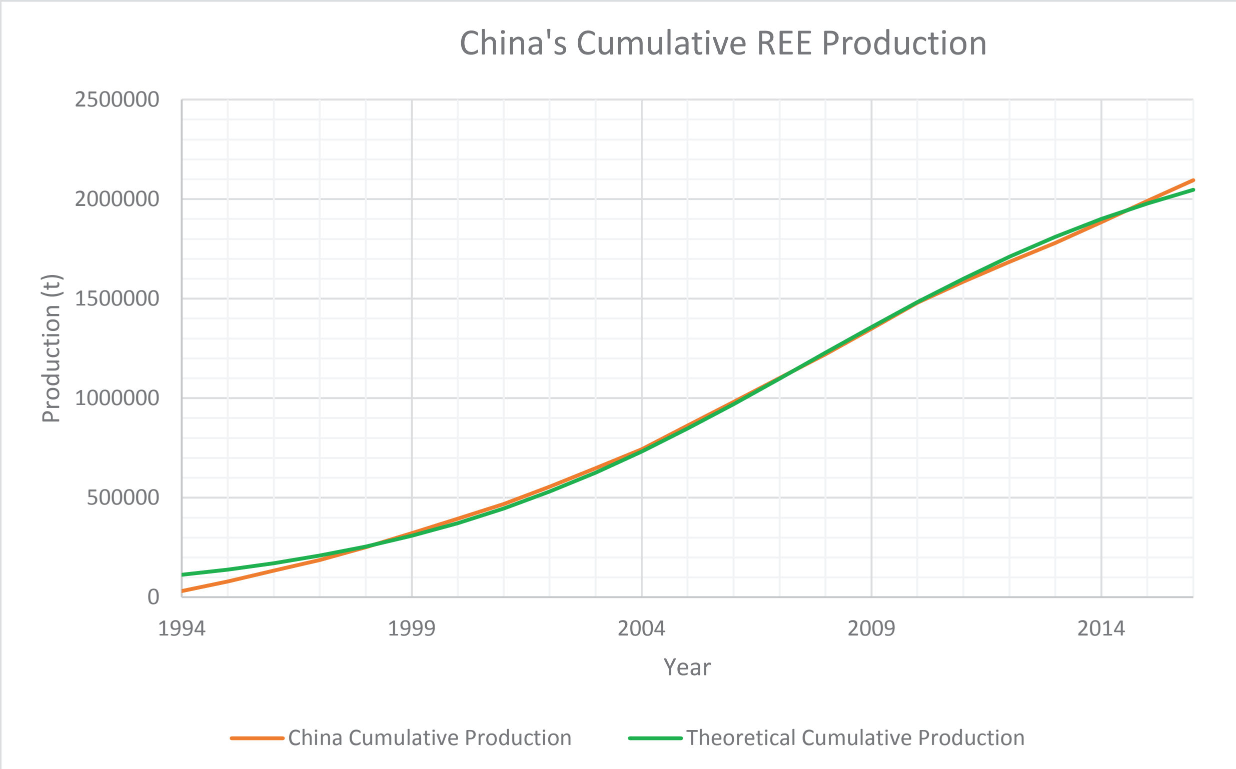
2002 due to competition from China and environmental constraints. Production resumed in 2012 but stopped again in 2016. Now the mine is under new ownership that plans to reopen the mine. This illustrates a problem with the Hubbert curve, its simplicity. The model has no variables to adjust for political and technological factors. There is no way the model could have predicted the Mountain Pass mine would be forced to close down with its limited parameters. This result suggests that the annual production of REE calculated by the Hubbert curve is not suitable to accurately predict the actual annual REE production.

Table 2

Source	**SS**	**df**	**MS**		**Number of obs**	23
Model	3.070e+13	3	1.0234e+13		**R-squared**	0.9994
Residual	1.976e+10	20	987998558		**Adj R-squared**	0.9993
Total	3.072e+13	23	1.3358e+12		**Root MSE**	31432.44
					Res. Dev.	538.4141
Constant	**Coef.**	**Std. Err.**	**t**	**P>t**	**[95% Conf.**	**Interval]**
Q_{max}	2380213	56607.42	42.05	0.000	2262132	2498294
a	24.89001	1.47325	16.89	0.000	21.81686	27.96316
b	-.2185454	.0069499	-31.45	0.000	-.2330426	-.2040481

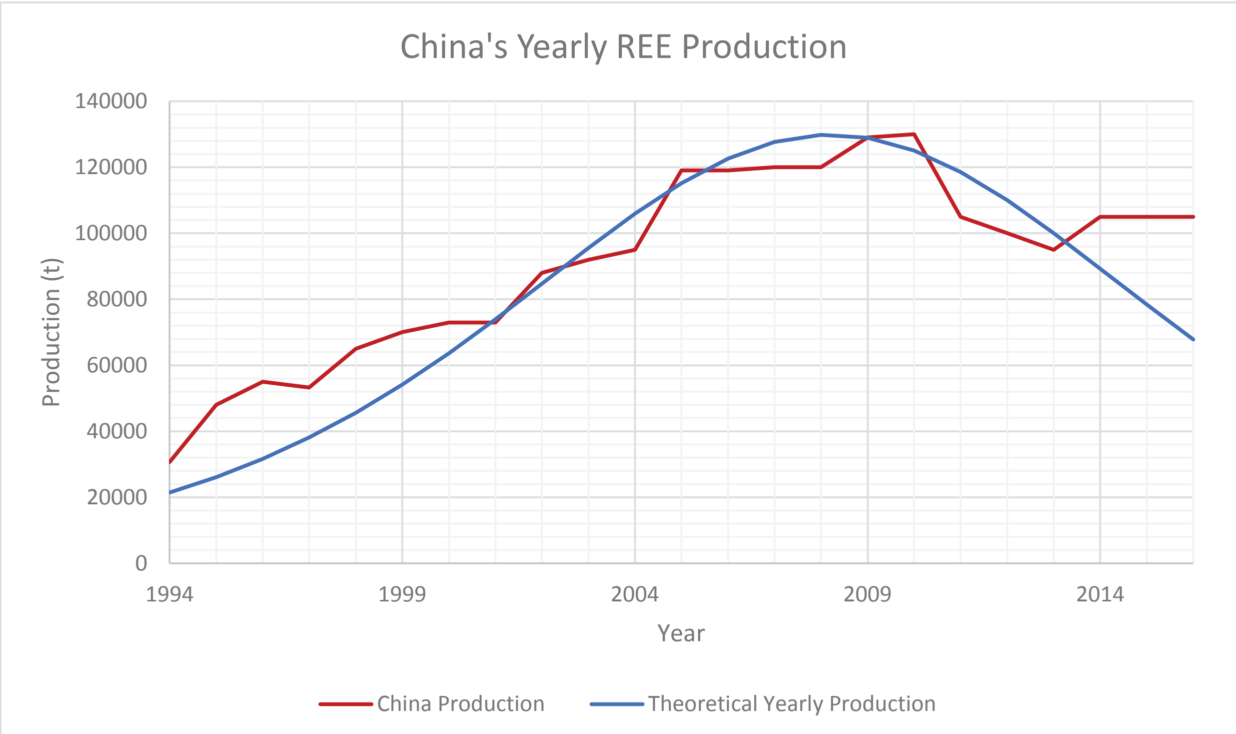
The data for China can also be found in the appendix. The data were of annual rare earth production from 1994 to 2016.The results of the regression for China can be found in the Table 2 above. The determined value for Q_{max} was 2,380,213 metric tons and the determined values for constants a and b were 24.89001and -.2185454 respectively. The R-squared and adjusted R-squared were higher than they were for the U.S. at 0.9994 and 0.9993.This again means that a lot of the variation in China's total REE production is explained by Hubbert's model. This is also

Figure 3



clearly visible in Figure 3 where China's cumulative production is graphed alongside their theoretical production across time. The theoretical cumulative production again closely follows the actual cumulative production. The same story is also repeated when the t-statistics and p-values of the variables are examined. The high t-statistics for Q_{max}, a and b illustrates that these values are significant at the 95% level. This again means that the Hubbert curve is effective at predicting cumulative production. These results also have a p-value of 0.000 for all of the tested variables which once again goes on to say that each variable is significant at the 99.99% level. Figure 4 shows both China's yearly production and its theoretical yearly production over time. Like with Figure 2, this graph illustrates that while theoretical cumulative production follows actual cumulative production, actual yearly production is much more volatile than the predicted

Figure 4



yearly production. According to Hubbert's equations, maximum annual production should have been roughly 130,046.15 metric tons of REE and it should have occurred between 2007 and 2008. Actual maximum annual production was 130,000 metric tons and occurred in 2010. While the estimated value for maximum production is accurate, the estimated time period is off. Though the estimated annual production for China more closely follows the actual production of REE than it did for the U.S., it still is off in its prediction. China's large yearly production can be attributed to China aggressively promoting its REE industry and not being hindered by standard market factors (Castor, 2008). This led to the overproduction of rare earth elements which in turn lead China announcing it would assert control over the industry and restrict exports of rare earth elements (Castor, 2008). Once again, the Hubbert curve does not have enough parameters to have been able to predict this would happen. This is also supported by recent announcements by

China. On October 18, 2016, China's Ministry of Industry and Information Technology announced that they would limit the yearly production of rare earth elements to 140,000 metric tons by 2020 (Aspa, 2016). This illustrates that China expects there yearly REE production to still be around 140,000 metric tons in 2020. According to the model, yearly REE production in 2020 should be around 34,188.73594 metric tons which is well below the expected yearly production. This again leads to the conclusion that the estimated annual REE production calculated by the Hubbert curve is not suitable to accurately predict the actual annual REE production, unlike its ability to predict the total production.

Table 3

Source	SS	df	MS		Number of obs	116
Model	1.160e+14	3	3.8657e+13		R-squared	0.9995
Residual	5.727e+10	113	506802933		Adj R-squared	0.9995
Total	1.160e+14	116	1.0002e+12		Root MSE	22512.28
					Res. Dev.	2651.216
Constant	**Coef.**	**Std. Err.**	**t**	**P>t**	**[95% Conf.**	**Interval]**
Q_{max}	8438208	377526.9	22.35	0.000	7690260	9186157
a	4607.965	170.8803	26.97	0.000	4269.42	4946.51
b	-.0690139	.0008164	-84.54	0.000	-.0706313	-.0673966

Now it is time to apply the Hubbert curve to global rare earth element production. The data for world rare earth element production can also be found in the appendix. The data were of annual rare earth production from 1900 to 2015. The results of the regression for global production can be found in the Table 3 above. The determined value for Q_{max} was 8,438,208 metric tons and the determined values for constants a and b were 4,607.965 and -.0690139 respectively. The R-squared and adjusted R-squared were higher than they were for both the U.S. and China at 0.9995 and 0.9995 respectively. Like with the other regressions, this means that a lot of the variation in China's total REE production is explained by Hubbert's model. This is also clearly visible in Figure 5 where world cumulative production is graphed alongside their theoretical production across time. The theoretical cumulative production again closely follows the actual cumulative production. The same story is also repeated when the t-statistics and p-values of the variables are examined. The high t-statistics for Q_{max}, a and b illustrates that these values are significant at the 95% level. This once again indicates that the Hubbert curve is effective at predicting cumulative production. Like with the other tests, this regression has a p-value of 0.000 for all of the tested variables which goes further on to say that each variable is significant at the 99.99% level.

Figure 5

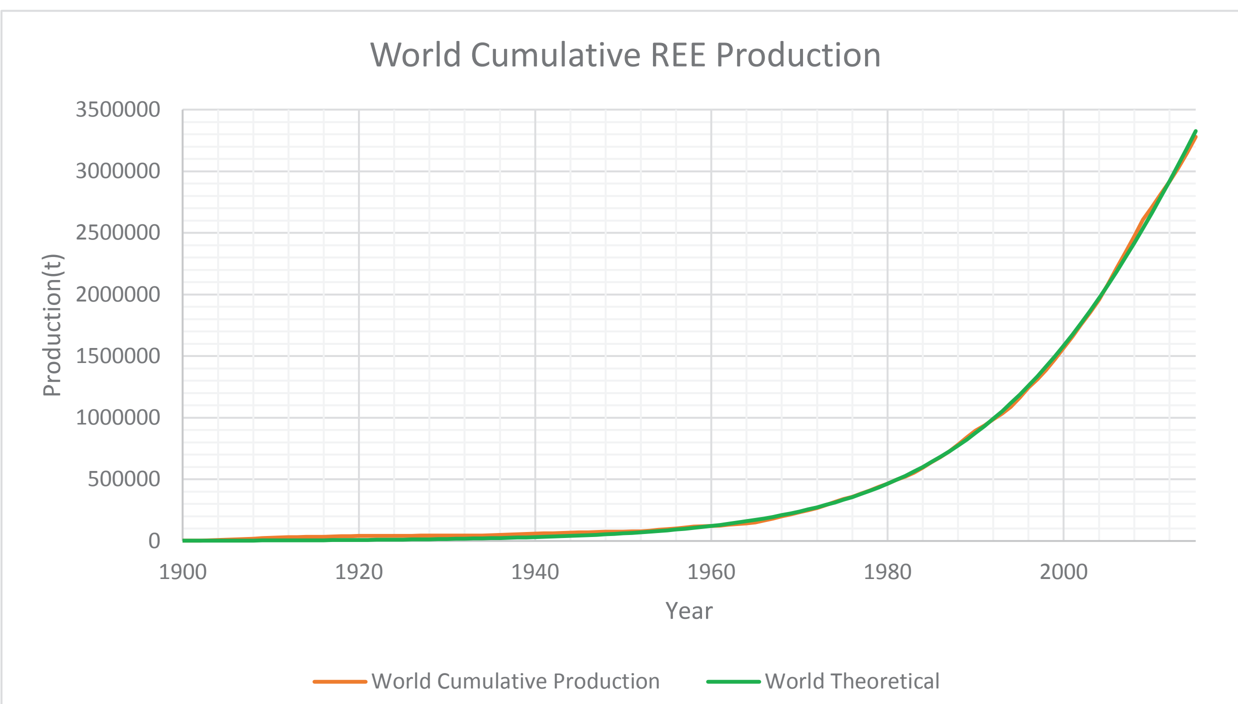


Figure 6

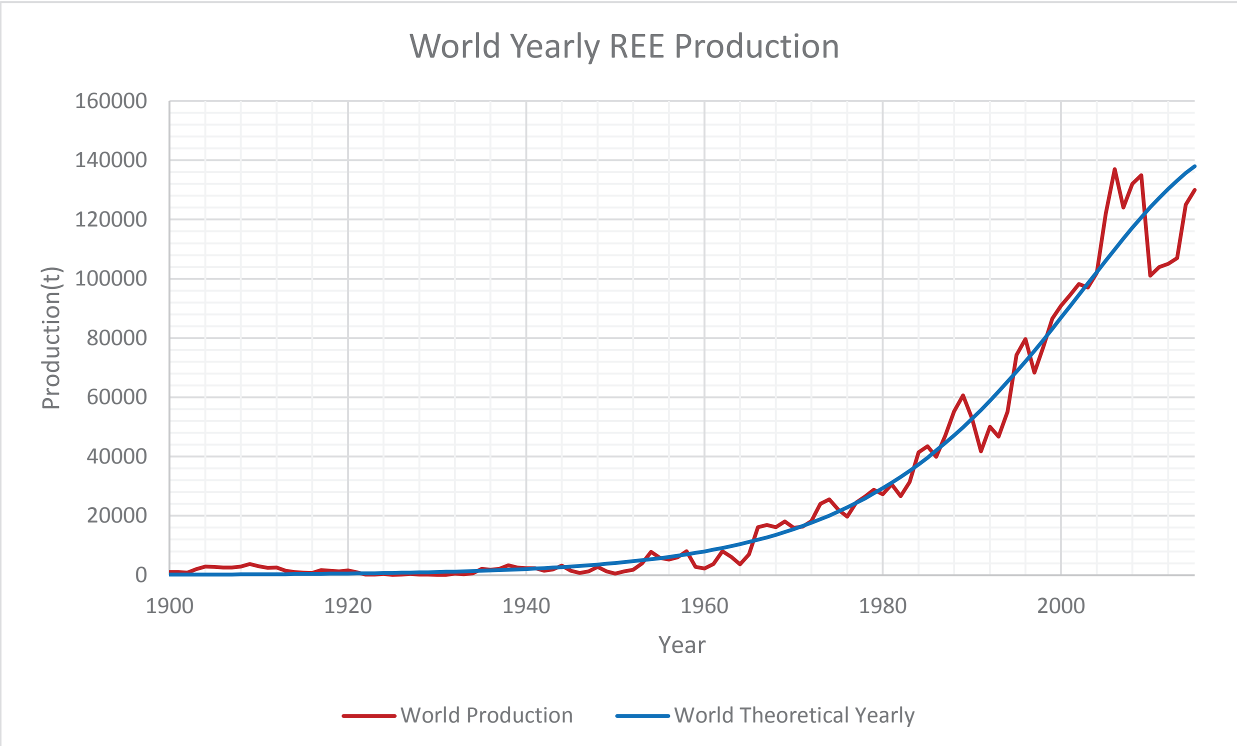


Figure 6 shows both global yearly production and global theoretical yearly production over time. Like with the previous figures 2 and 4, this graph demonstrates that while theoretical cumulative production follows actual cumulative production, actual yearly production is much more volatile than the predicted yearly production. Though the variation is not as pronounced as it was for U.S. yearly production, it is still varying across the theoretical yearly production. According to Hubbert's equations, maximum annual production should have occurred between 2021 and 2022 at a value of 145,588.4108 metric tons. The ability of this Hubbert curve to create accurate predictions of future is doubtful once again due to the simplicity of the model. It was shown previously shown that accurate predictions for China's REE production were not created which is problematic for global predictions due to China composing over 90% of global rare earth element production in recent years. This once again confirms that the Hubbert curve cannot be used to create accurate predictions of future rare earth element production.

Section 4:

This paper sought to apply the Hubbert curve to rare earth element production for the United States, China and global production. The goal was to see if observed REE production followed the predicted REE production created by the Hubbert Curve and to see if the Hubbert Curve could be used to created accurate predictions of future REE production. To test this, Hubbert curves were created for the United States, China and global production. In all three cases, the trend of cumulative prediction and annual production followed the predicted path created by the Hubbert curve; however, it was also determined that the Hubbert curve could not be used to create accurate predictions of future REE production. This is due to the simplicity of the model which does not have enough parameters for all the political and technological factors that determine REE production for a country. Though this result illustrates its inability to create accurate predictions, the Hubbert curve clearly has a use in examining the trends in the production of rare earth elements.

Appendix 1

Year	China Yearly Production	Time	China Cumulative Production	Theoretical Cumulative Production	Theoretical Yearly Production
1994	30600	1	30600	113323.0929	21387.5162
1995	48000	2	78600	139383.0465	26059.95359
1996	55000	3	133600	170983.7718	31600.7253
1997	53300	4	186900	209080.4879	38096.7161
1998	65000	5	251900	254686.9367	45606.44885
1999	70000	6	321900	308826.4248	54139.48807
2000	73000	7	394900	372457.8314	63631.40666
2001	73000	8	467900	446374.7041	73916.87271
2002	88000	9	555900	531080.6487	84705.9446
2003	92000	10	647900	626651.9888	95571.34007
2004	95000	11	742900	732608.0552	105956.0664
2005	119000	12	861900	847817.6953	115209.6401
2006	119000	13	980900	970473.3848	122655.6896
2007	120000	14	1100900	1098157.474	127684.089
2008	120000	15	1220900	1228007.189	129849.715
2009	129000	16	1349900	1356959.852	128952.6633
2010	130000	17	1479900	1482036.189	125076.3371
2011	105000	18	1584900	1600607.595	118571.4055
2012	100000	19	1684900	1710598.34	109990.7451
2013	95000	20	1779900	1810593.545	99995.20556
2014	105000	21	1884900	1899849.515	89255.96965
2015	105000	22	1989900	1978224.754	78375.23846
2016	105000	23	2094900	2046061.546	67836.79245

Appendix 2

Year	Time	US Yearly Production	US Cumulative Production	US Theoretical Production	US Theoretical Yearly Production	World Yearly Production	World Cumulative Production	World Theoretical Production	World Theoretical Yearly
1900	1	227	227	3.238008729	3.238008729	1040	1040	1961.608974	130.7840487
1901	2	187	414	3.74050515	0.502496421	1090	2130	2101.733187	140.1242134
1902	3	200	614	4.320981823	0.580476673	863	2993	2251.864264	150.1310773
1903	4	215	829	4.991539969	0.670558146	2030	5023	2412.716443	160.8521785
1904	5	186	1015	5.76615865	0.774618681	2860	7883	2585.05488	172.3384369
1905	6	335	1350	6.660986142	0.894827492	2780	10663	2769.699274	184.6443941
1906	7	211	1561	7.694676518	1.033690377	2600	13263	2967.527744	197.8284696
1907	8	137	1698	8.888778447	1.194101928	2580	15843	3179.480978	211.9532349
1908	9	105	1803	10.26818429	1.379405848	2840	18683	3406.566686	227.0857072
1909	10	135	1938	11.8616489	1.593464606	3690	22373	3649.864349	243.2976629
1910	11	25	1963	13.70238881	1.840739909	3020	25393	3910.530322	260.6659738
1911	12		1963	15.82877444	2.126385631	2490	27883	4189.803289	279.2729662
1912	13		1963	18.2851296	2.456355157	2500	30383	4489.010093	299.2068044
1913	14		1963	21.12265494	2.837525346	1480	31863	4809.571995	320.5619024
1914	15		1963	24.40049465	3.277839711	992	32855	5153.011357	343.4393619
1915	16	9	1972	28.18696842	3.786473764	870	33725	5520.9588	367.9474426
1916	17	9	1981	32.56099437	4.374025955	731	34456	5915.160863	394.2020631
1917	18	25	2006	37.61373255	5.052738174	1730	36186	6337.4882	422.3273375
1918	19		2006	43.45048289	5.836750344	1470	37656	6789.944348	452.4561476
1919	20		2006	50.19287728	6.742394391	1210	38866	7274.675103	484.7307552
1920	21		2006	57.98141092	7.788533633	1590	40456	7793.978558	519.3034546
1921	22		2006	66.97836549	8.996954574	929	41385	8350.315829	556.3372708
1922	23		2006	77.37118464	10.39281915	189	41574	8946.322532	596.0067033
1923	24		2006	89.37637135	12.00518671	138	41712	9584.821053	638.498521
1924	25		2006	103.2439877	13.86761633	348	42060	10268.83366	684.0126089
1925	26	0.499	2006.499	119.2628495	16.01886186	12	42072	11001.59653	732.7628722
1926	27		2006.499	137.7665231	18.5036736	146	42218	11786.57473	784.9781993
1927	28		2006.499	159.1402462	21.37372307	352	42570	12627.47822	840.9034879
1928	29		2006.499	183.8289154	24.68866916	180	42750	13528.27896	900.8007389
1929	30		2006.499	212.3463026	28.51738724	197	42947	14493.22918	964.9502198
1930	31		2006.499	245.285688	32.93938543	17	42964	15526.88088	1033.651703
1931	32		2006.499	283.3321241	38.04643606	50	43014	16634.10667	1107.225785
1932	33		2006.499	327.2765782	43.94445406	530	43544	17820.12195	1186.015284
1933	34		2006.499	378.0322367	50.75565854	302	43846	19090.50868	1270.386729
1934	35		2006.499	436.6532955	58.62105884	564	44410	20451.24062	1360.73194
1935	36		2006.499	504.3566072	67.70331167	2130	46540	21908.71032	1457.469703
1936	37		2006.499	582.5466092	78.19000198	1840	48380	23469.75787	1561.047544
1937	38		2006.499	672.8440162	90.29740698	2150	50530	25141.70148	1671.943613
1938	39		2006.499	777.1188257	104.2748096	3310	53840	26932.37016	1790.668675
1939	40		2006.499	897.5282607	120.409435	2510	56350	28850.13837	1917.76821
1940	41		2006.499	1036.560353	139.0320919	2370	58720	30903.96301	2053.82464

1941	42		2006.499	1197.08396	160.5236077	2380	61100	33103.42268	2199.459669
1942	43		2006.499	1382.406114	185.3221541	1500	62600	35458.75943	2355.336752
1943	44		2006.499	1596.337679	213.9315647	1900	64500	37980.92312	2522.163693
1944	45		2006.499	1843.268433	246.9307538	3200	67700	40681.61849	2700.695365
1945	46		2006.499	2128.252776	284.9843436	1440	69140	43573.35506	2891.736576
1946	47		2006.499	2457.107381	328.8546049	721	69861	46669.50011	3096.145051
1947	48		2006.499	2836.522192	379.4148106	1300	71161	49984.33467	3314.834555
1948	49	20	2026.499	3274.186268	437.6640765	2720	73881	53533.11281	3548.778142
1949	50		2026.499	3778.930005	504.7437366	1290	75171	57332.12435	3799.011534
1950	51	383	2409.499	4360.885255	581.9552499	470	75641	61398.76095	4066.636609
1951	52	747	3156.499	5031.664815	670.7795603	1240	76881	65751.58597	4352.825014
1952	53	1110	4266.499	5804.562544	772.8977291	1820	78701	70410.40784	4658.82187
1953	54	615	4881.499	6694.775054	890.2125094	3960	82661	75396.3574	4985.949567
1954	55	983	5864.499	7719.645392	1024.870338	7840	90501	80731.96903	5335.611629
1955	56	608	6472.499	8898.928342	1179.28295	5760	96261	86441.26566	5709.296623
1956	57		6472.499	10255.07581	1356.147473	5230	101491	92549.84775	6108.582095
1957	58	499	6971.499	11813.53923	1558.463418	5980	107471	99084.98624	6535.138487
1958	59	625	7596.499	13603.08364	1789.544411	8060	115531	106075.7192	6990.733009
1959	60	600	8196.499	15656.10547	2053.021825	2810	118341	113552.9527	7477.233411
1960	61	1050	9246.499	18008.94211	2352.836641	2270	120611	121549.5643	7996.611609
1961	62	1030	10276.499	20702.15702	2693.21491	3690	124301	130100.5114	8550.947091
1962	63		10276.499	23780.77814	3078.62112	8020	132321	139242.9414	9142.430043
1963	64	278	10554.499	27294.46085	3513.682708	6060	138381	149016.3055	9773.364096
1964	65	256	10810.499	31297.53874	4003.077894	3680	142061	159462.4741	10446.16861
1965	66	2900	13710.499	35848.91707	4551.378326	6960	149021	170625.8545	11163.38038
1966	67	12200	25910.499	41011.75484	5162.837776	16200	165221	182553.5091	11927.6546
1967	68	12900	38810.499	46852.87375	5841.118905	16900	182121	195295.2742	12741.76507
1968	69	10300	49110.499	53441.82596	6588.952216	16200	198321	208903.8774	13608.60325
1969	70	12500	61610.499	60849.55146	7407.725498	18100	216421	223435.0537	14531.17628
1970	71	9110	70720.499	69146.56021	8297.008745	15900	232321	238947.6572	15512.60347
1971	72	9820	80540.499	78400.5895	9254.029293	16400	248721	255503.7684	16556.11127
1972	73	10700	91240.499	88673.71432	10273.12482	18200	266921	273168.7948	17665.02639
1973	74	17500	108740.499	100018.9318	11345.21744	24000	290921	292011.5615	18842.76672
1974	75	19900	128640.499	112476.3006	12457.36881	25600	316521	312104.3915	20092.82993
1975	76	15000	143640.499	126068.7923	13592.49175	22100	338621	333523.1708	21418.77933
1976	77	13000	156640.499	140798.0958	14729.3035	19700	358321	356347.3975	22824.22672
1977	78	15400	172040.499	156640.7015	15842.60569	24500	382821	380660.2093	24312.81176
1978	79	14100	186140.499	173544.6619	16903.9604	26500	409321	406548.3871	25888.1778
1979	80	16500	202640.499	191427.4594	17882.79745	28800	438121	434102.3305	27553.94341
1980	81	16000	218640.499	210175.3946	18747.93524	27300	465421	463416.0001	29313.66957
1981	82	17100	235740.499	229644.8251	19469.43048	30600	496021	494586.8221	31170.82203
1982	83	17500	253240.499	249665.4284	20020.6033	26600	522621	527715.5506	33128.72847
1983	84	17100	270340.499	270045.4549	20380.02649	31400	554021	562906.0808	35190.53025
1984	85	25300	295640.499	290578.6947	20533.23979	41400	595421	600265.2092	37359.12841
1985	86	13400	309040.499	311052.6569	20473.9622	43500	638921	639902.333	39637.1238

1986	87	10900	319940.499	331257.289	20204.63211	39900	678821	681929.0841	42026.75108
1987	88	11100	331040.499	350993.4856	19736.19662	46900	725721	726458.891	44529.80687
1988	89	11500	342540.499	370080.6666	19087.18104	55300	781021	773606.4629	47147.5719
1989	90	20800	363340.499	388362.8381	18282.17148	60700	841721	823487.1905	49880.72765
1990	91	22700	386040.499	405712.7558	17349.91765	52900	894621	876216.4584	52729.26789
1991	92	16500	402540.499	422034.0509	16321.29518	41700	936321	931908.8644	55692.40598
1992	93	20700	423240.499	437261.4062	15227.35523	50100	986421	990677.3431	58768.47871
1993	94	17800	441040.499	451359.0494	14097.64324	46700	1033121	1052632.191	61954.8482
1994	95	20700	461740.499	464317.9518	12958.9024	55100	1088221	1117879.995	65247.80328
1995	96	22200	483940.499	476152.1598	11834.20801	74300	1162521	1186522.457	68642.46229
1996	97	20400	504340.499	486894.6787	10742.51892	79700	1242221	1258655.137	72132.67967
1997	98	20000	524340.499	496593.2681	9698.589357	68300	1310521	1334366.095	75710.95885
1998	99	10000	534340.499	505306.4292	8713.16107	77100	1387621	1413734.47	79368.37436
1999	100	5000	539340.499	513099.778	7793.348843	86600	1474221	1496828.976	83094.50641
2000	101	5000	544340.499	520042.9169	6943.138894	90900	1565121	1583706.368	86877.3914
2001	102	0	544340.499	526206.8497	6163.932848	94500	1659621	1674409.86	90703.49195
2002	103	0	544340.499	531661.9364	5455.086695	98200	1757821	1768967.55	94557.69008
2003	104	0	544340.499	536476.3469	4814.410459	97100	1854921	1867390.857	98423.30718
2004	105	0	544340.499	540714.9554	4238.608473	102000	1956921	1969673.011	102282.1541
2005	106	0	544340.499	544438.6067	3723.651364	122000	2078921	2075787.625	106114.6145
2006	107	0	544340.499	547703.6856	3265.078815	137000	2215921	2185687.389	109899.7633
2007	108	0	544340.499	550561.923	2858.237432	124000	2339921	2299302.912	113615.5229
2008	109	0	544340.499	553060.3839	2498.460945	132000	2471921	2416541.768	117238.8569
2009	110	0	544340.499	555241.5853	2181.201329	135000	2606921	2537287.769	120746.001
2010	111	0	544340.499	557143.7048	1902.119534	101000	2707921	2661400.499	124112.7299
2011	112	0	544340.499	558800.8488	1657.144014	104000	2811921	2788715.156	127314.6566
2012	113	3000	547340.499	560243.3531	1442.504287	105000	2916921	2919042.716	130327.5597
2013	114	5500	552840.499	561498.0988	1254.745713	107000	3023921	3052170.448	133127.7321
2014	115	5400	558240.499	562588.8294	1090.730576	125000	3148921	3187862.793	135692.3451
2015	116	5900	564140.499	563536.4589	947.6295428	130000	3278921	3325862.611	137999.8181

Bibliography

Aspa, Jocelyn. "China Puts Annual Limit on Rare Earth Production." Investing News Network. October 18, 2016. Accessed November 24, 2017. https://investingnews.com/daily/resource-investing/critical-metals-investing/rare-earth-investing/china-puts-limit-on-rare-earth-production/.

Berk, Istemi, and Volkan S. Ediger. 2016. "Forecasting the Coal Production: Hubbert Curve Application on Turkey's Lignite Fields." Resources Policy 50, 193-203. EconLit with Full Text, EBSCOhost (accessed October 17, 2017)

Castor, Stephen B. "Rare Earth Deposits of North America." Resource Geology 58, no. 4 (2008): 337-47. Accessed November 24, 2017. doi:10.1111/j.1751-3928.2008.00068.x.

Cavallo, Alfred J. "Hubbert's Petroleum Production Model: An Evaluation and Implications for World Oil Production Forecasts." Natural Resources Research 13, no. 4 (2004): 211-21. Accessed October 17, 2017. doi:10.1007/s11053-004-0129-2.

Chavez-Rodriguez, Mauro F., Alexandre Szklo, and Andre Frossard Pereira de Lucena. 2015. "Analysis of Past and Future Oil Production in Peru under a Hubbert Approach." Energy Policy 77, 140-151. EconLit with Full Text, EBSCOhost (accessed October 17, 2017).

Gallagher, Brian. "Peak Oil Analyzed with a Logistic Function and Idealized Hubbert Curve." Energy Policy 39, no. 2 (February 2011): 790-802. EconLit with Full Text, EBSCOhost (accessed October 17, 2017).

Hubbert, M. King. 1956. Nuclear Energy and the Fossil Fuels. Drilling and Production Practice. Accessed October 17, 2017. http://www.hubbertpeak.com/hubbert/1956/1956.pdf

Klossek, Polina, Jakob Kullik, and Karl Gerald van den Boogaart. 2016. "A Systemic Approach to the Problems of the Rare Earth Market." Resources Policy 50, 131-140. EconLit with Full Text, EBSCOhost (accessed October 17, 2017).

Paulick, Holger, and Erika Machacek. 2017. "The Global Rare Earth Element Exploration Boom: An Analysis of Resources Outside of China and Discussion of Development Perspectives." Resources Policy 52, 134-153. EconLit with Full Text, EBSCOhost (accessed October 17, 2017).

Schlinkert, Dominik, and Karl Gerald van den Boogaart. 2015. "The Development of the Market for Rare Earth Elements: Insights from Economic Theory." Resources Policy 46, 272-280. EconLit with Full Text, EBSCOhost (accessed October 17, 2017).

USGS. 2017. "Rare Earths Statistics and Information." USGS. Accessed October 17, 2017. https://minerals.usgs.gov/minerals/pubs/commodity/rare_earths/.

Wan, Rui, and Jean-Francois Wen. 2017. "The Environmental Conundrum of Rare Earth Elements." Environmental And Resource Economics 67, no. 1: 157-180. EconLit with Full Text, EBSCOhost (accessed October 17, 2017).

Detecting Multiple Bubbles and Exuberance in Financial Data: An Extensive Empirical Examination over Four Major Foreign Indexes.

Swarna D. Dutt
Department of Economics
Richards College of Business
University of West Georgia
Carrollton, GA 300118

and

Dipak Ghosh*
Campus Box 4039
School of Business
Emporia State University
Emporia, KS 66801
Email: dghosh@emporia.edu

*Corresponding author.

Abstract

History is replete with incidents of financial crisis, which ex-post become a wakeup call for policy makers and the people. But there were no tests which could identify and date financial bubbles in real time, till now. Phillips, Shi and Yu [2015] provides the first and only model to recursively examine for multiple bubbles. Their "flexible window" methodology provides consistent results and has successfully identified the well-known historical episodes of exuberance and collapse. This accuracy provides very useful "warning alerts" to central bankers, fiscal regulators and policy makers to pre-emptively act and possibly eliminate an impending implosion.

We extensively examine for the presence and recurrence of multiple bubbles, over four major financial indexes. We find evidence of bubbles and explosive sub-periods over the long-term data for all of the indices, including deciphering the technology bubbles of the 1990s and early 2000s, and the financial crises of 2008.

Keywords: Financial bubbles, Financial crisis, Multiple bubbles, SADF, GSADF.
JEL Codes: F65, G10.

Detecting Multiple Bubbles and Exuberance in Financial Data: An Extensive Empirical Examination over Four Major Foreign Indexes

INTRODUCTION

History is replete with incidents of financial crisis, which ex-post become a wakeup call for policy makers and the people. Again, and again it was stated by experts that the present crisis was preceded by "asset market bubbles" and / or "excessive credit expansion." But the fact of the matter remains that we do not have good quantitative markers which can ex-ante indicate the genesis of a momentum being built in the asset / credit markets which may lead to a catastrophe down the line. Thus, we had to accept that there was no practical way to identify the "red flags" of a crisis. Thus, the task at hand is to try to decipher possible quantitative markers from the data, that a speculative bubble is probably taking shape.

In the economics literature we have multiple tests to detect ex-post the crisis, and then explain it. (1) But there was no test to ex-ante identify the origination of a bubble which is in the making, i.e., there were no econometric detectors of a future market crisis. Phillips, Wu and Yu [PWY henceforth, 2011] presented a recursive method to detect exuberance in asset prices during an inflationary phase. The advantage here being that the early detection (ex-ante acknowledgement) can help banks / regulators / policy makers to address the problem in its nascent state. PWY was very effective in the early detection of bubbles, provided there was a single bubble in the data sample. They proved the effectiveness of the test using NASDAQ PWY [2011] and the US housing bubble in Phillips and Yu [PY henceforth, 2011].

But then came the question of "economic reality" which showed that there usually were multiple recurring financial crises, over long periods. Ahmed [2009] gave us evidence of 60 different financial crises, in the 17th century alone. A test to clearly identify periodic collapsing and recovering economic data was simply not there. Thus, the next step in the evolution of these detection tests was to create the one that could decipher multiple bubbles in the same sample period. This recursive identification is extremely complex, compared to identifying a single bubble. The main problem is computationally handling the non-linear structure of multiple breaks / bubbles in the data. With the presence of multiple break points in the data, the discriminatory power of the detectors goes down dramatically, and hence the upswings and downswings are not separable in the same data stream.

The challenge here was not only to come up with a statistical metric which can detect multiple factual fractures in the non-linear data stream, but at the same time, also be powerful and effective enough to distinguish between a false negative detection (to avoid unnecessary policies) and a true positive detection tolerance (so as to ensure good and early effective policy application.)

This is where the Phillips, Shi and Yu [PSY henceforth, 2014] research comes into effect. This paper offers the first powerful and credible "quantitative metric" to detect exuberance in financial data, right where it is originating. Once detected, the counteractive policies can be promulgated and implemented. Looking at long term S&P 500 data from 1871 - 2010 (about 140 years), the authors propose a recursive algorithm, which can diagnose and identify ex-ante the signs of "turbulence within the force" if you will. This procedure helps us pinpoint the start of the problem and can thus help us monitor the markets. Since we know that history has proven that it has a bad habit of repeating itself, this early warning diagnostic tool will come in handy, in helping make / alter policies to avert the impending crisis. The best part of this test is that it can be implemented on current data in real time to detect the "fault lines."

PSY [2014] presents a recursive econometric technique to detect / test / date financial bubbles in the same sample data and separate them when multiple bubbles are present. Here the authors extend on their [PWY, 2011] methodology, which is based on a sequence of forward recursive right tailed ADF unit root tests, using the Sup ADF (designated SADF) measure. This process allows for a dating strategy to identify the origination and termination dates of a specific bubble. This is achieved by using "backward regression techniques." In case of a single bubble, the PWY test is consistent, (as shown in Phillips and Yu 2009.) This detection algorithm is better able to date the ups and downs of financial data, as opposed to the CHOW tests, CUSUM tests etc. as evidenced by Homm and Breitung [2012].

But what if there are multiple bubbles, originating and decaying in sequence over time. PWY is not proven to be consistent in such cases. It cannot be confidently used in examining long term market data where exuberance and collapse are evident ex-post. Here PSY [2014] present an extension of the SADF tests, in form of a generalized SADF called the GSADF method. It includes a recursive backward regression technique, to time identify the origin and collapse of bubbles. It is a right tailed ADF test but has a flexible window width to separate one bubble from the next, to the next sequentially, since their lengths are bound to be different. It's an ex-ante procedure to detect different start and end points of bubbles in real time data, i.e., identify and separate multiple bubble episodes over the same sample set. This test has been proven to consistently give good results, when multiple bubbles are present. Thus, it can credibly be applied to analyzing long term historical data. Along with the ex-ante dating algorithm and the GSADF test, the authors develop a modified PWY algorithm, which reinitializes the test sequentially, after the detection of each bubble. This sequential test works in deciphering multiple bubbles from explosion to collapse and separate them over time. It is applied to the S&P 500 stock market data from January 1871- December 2010. It has been able to identify all the historically documented bubble episodes, like the 1929 crash, 1954 boom, 1987 black Monday and the latest dot-com bubble.

In quite possibly a first, we use this powerful metric, to extensively examine for multiple bubbles over four major data indices, namely the FTSE 100, CAC, DAX and the NIKKEI. (2) Section 2 describes the reduced form model, the new rolling window recursive test and its limit theory. Section 3 elaborates the data stamping strategies to identify and separate multiple bubbles in the same sample period, and discusses the size, power and performance of the dating strategy tests. In section 4, we apply the PWY test, the sequential PWY test and the CUSUM test, and do an extensive examination for the presence of multiple bubbles in all four of the above-mentioned foreign indexes. Section 5 concludes.

SECTION 1. ROLLING WINDOW TEST FOR BUBBLES

It originates with the standard asset pricing model(3)

$$P_t = \sum_{i=0}^{\infty}\left(\frac{1}{1+r_f}\right)i\ E_t(D_{t+i} + U_{t+i}) + B_t \qquad (1)$$

where

P_t = after dividend price of an asset

D_t = payoff (dividend) from the asset

r_f = risk free interest rate

U_t = unobservable fundamentals

B_t = bubble component

Here $P_t^f = P_t - B_t$ (market fundamentals) and B_t satisfies the sub martingale property

$$E_t = (B_{t+1}) = \left(1 + r_f\right)B_t \tag{2}$$

This equation sets up the alternative scenarios for the presence / absence of bubbles in the data. For example: If there are no bubbles, the $B_t = 0$, then the degree of non-stationarity [I(0) or I(1)] of asset prices is controlled by asset payoffs or dividends (D_t) and the unobservable economic / market fundamentals. A possible outcome would be like this: If D_t is an I(1) process, the U_t has to be either I(0) or I(1) and asset prices can at the most be a I(1) process. But based on eq. (2), if there are bubbles, then asset prices will be explosive. Thus, when the fundamentals are I(1) and D_t is first difference stationary, we can infer bubbles if asset prices show evidence of explosive behavior. Eq (1) is one way to include a bubble variable in the standard asset pricing model, but the jury is still out on this. [4, 5] The advantage of the reduced form model is that it pretty much encompasses all standard formulations as intrinsic bubbles [Froot and Obstfeld, 1991], herd behavior [Abreu and Brunnermeier, 2003] and also time varying discounting [Phillips and Yu, 2011.] Shi [2011] provides an excellent overview of this literature.

According to Phillips and Magdalinos [2007], explosive behavior in asset prices is a primary indicator of market exuberance, which can be identified in empirical tests using the "recursive testing procedure" like the right-side unit root test of PWY. This recursive procedure starts with a martingale null (with drift to capture long historical trends in asset data.) The model specification is:

$$y_t = dT^{-n} + \theta_{yt-1} + \epsilon_t \tag{3}$$

where ϵ_t is iid $(0, \sigma^2)$, $\theta = 1$, and d is a constant, T is the sample size, and the parameter η controls the magnitude of the intercept and the drift, as $T \rightarrow \infty$. Solving eq. 3, gives us the deterministic trend, dt/T^n. The three possibilities here (in sequence) are that if n>0, the drift will be small compared to the linear trend, if n>1/2, the drift is small relative to the martingale and if n=1/2, the output behaves like a Brownian motion, which is evident in many financial time series data.

The emphasis is on the alternative hypothesis, because departures from market fundamentals are the markers of interest. But as with all types of model specifications, we know that they are sensitive to intercepts, trends and trend breaks etc. Eq. 3 is tested for exuberance using the rolling window ADF approach or the recursive approach. The basic logic is that if the rolling window regression starts from the r_1^{th} fraction and ends with the r_2^{th} fraction (from sample size T), then $r_2 = r_1+r_w$, where r_w is the size of the window. This model is:

$$\Delta y_t = \propto_{r1,r2} + \ \beta_{r1,r2}\ y_{t-1} + \Sigma_{i=1}^{k}\ \gamma_{r1,r2}^{i}\ \Delta_{yt-1} + \in_t \tag{4}$$

where k is the lag length, and $\in_t$ is iid, with $(0, \sigma^2_{r1,r2})$. The basic form is reformulated to include the presence of "multiple bubbles" to separate the market switching time periods from explosion to contraction, and again explosion sequentially. They use the Sup ADF test called SADF. It is a recursive / repeated estimation procedure with window size r_w., where r_w goes from r_0 (smallest sample window fraction) to r_1 (largest sample window fraction), and sample end point $r_2 = r_w$, going from 0 to 1. The SADF statistic is: [6]

SADF (r_0) n= $\sup_{r2\in[r0,1]} ADF^{r2}_0$ (4a)

The ADF regression is run on eq. 4, recursively, but continuously on sub-samples of the data based on window width chosen according to r_0, r_1, r_2……r_w. The subsamples chosen here are more extensive than the SADF test. The difference here is that we allow the window width to change within the feasible range where $r_w = r_2 - r_1$.

The GSADF statistic is:

GSADF (r_0) = sup $r_2 \in [r_0, 1]$ {ADF^{r2}_{r1}} (5)

$r_1 \in [0, r_2 - r_0]$

The limit distribution of the GSADF holds, but with the intercept and the assumption of a random walk structure, we have no drift or small drift. The GSADF's asymptotic distribution depends on the "smallest window width size r_0." It depends on the number of observations in the sample. If T is small, r_0 has to be made large enough to ensure the inclusion of an adequate number of observations. But, if T is large, r_0 should be set small, so as to be able to include different "explosive" burst in the data. Simulations in PSY (2014] show that as r_0 decreases, the critical values (CV's, henceforth) of the test statistic increases. GSADF statistic CV's are larger than the SADF statistic, which in turn is larger than the ADF statistic, and its concentration also increases, increasing confidence in the test outcomes. The backward SADF statistic is the sup value of the ADF sequence run over this interval, BSADF r_2 (r_0) = sup $_{r1 \in [0,\, r2-r0]}$ {ADF $^{r2}_{r1}$}.

Empirically we determine the ADFr_2 and the sup ADF within the feasible range of r_2 (from r_0 to r_1.) This procedure imposes the condition that the bubble marker is the existence of a critical value greater than L_T = Log (T). This separates the short and temporary market blips (which happen all the time in real life) from actual exuberance. Dating is done using the formula:

$$\hat{r_e} = inf_{r2 \in [r0,1]}\{r_2 : ADF_{r2} > cv^{\beta T}_{r2}\} \tag{6}$$

and

$$\hat{r_f} = inf_{r2 \in [\hat{r_e} + \frac{\log(T)}{T,1}]}\{r_2 : ADF_{r2} < cv^{\beta T}_{r2\}}\} \tag{7}$$

where $cv^{\beta T}_{r2}$ is the 100(1-$\boldsymbol{\beta}_T$) % critical value of the ADF statistic based on [T_{r2}] observations. Here $\boldsymbol{\beta}_T \rightarrow 0$, as $T \rightarrow \infty$.

SECTION 2. DATA STAMPING STRATEGIES

The idea is to identify bubbles in real time data and then look for the "markers" identifying those bubbles / episodes of market exuberance. The problem is that the standard ADF test can identify extreme observations, as r = [T_r], but cannot separate between a bubble phase observation from one which is part of a natural growth trajectory. Market growth is not an indication of bubbles. Thus, ADF tests may result in finding "pseudo bubble detection." So, how to make this distinction is the major contribution of this PSY (2014] test. The authors run backward sup ADF or backward SADF tests, to improve the chances of deciphering a bubble from a growth trajectory. The recursive test means running SADF backwards on the sample, increasing the sample sequence using a fixed sample r_2, but varying the initial point from 0 to (r_2-r_0). This gives the SADF statistic: {$ADF^{r2}{}_{r1}$} ∊|0, r_2 -0|. Bubbles are inferred from the backward SADF statistic or the BSADF $r_2(r_0)$. The origin of the bubbles, the date and timing is the first observation whose BSADF statistic exceeds the critical value of the BSADF. The bubble ending date / time frame is the first observation whose BSADF is below the BSADF critical value. The intermediary time frame is the duration of the bubble. The origination / termination dates are calculated thus:

$$\hat{r_e} = inf_{r2\in[r0,1]}\{r_2: BSADF_{r2}(r_0) > scv_{r2}^{\beta T} \tag{8}$$

$$\hat{r_f} = r_{2\in}[inf_{\hat{r_e}+\left[\frac{\partial \log(T)}{T,1}\right]}\{r_2: BSADF_{r2}(r_0) > scv_{r2}^{\beta T} \tag{9}$$

where $scv^{\boldsymbol{\beta}T}{}_{r2}$ is the 100(1-$\boldsymbol{\beta}_T$)% critical value of the sup ADF statistic, based on [T_{r2}] observations. $\boldsymbol{\beta}_T$ goes to zero, as the sample size approaches infinity. The distinction between the SADF and the GSADF (backward sup ADF) tests, both run over r_2 ∊[r_0,1] is given by the statistic, SADF (r_0) = $sup_{r2\in[r0,1]}$ {ADF_{r2}} and GSADF (r_0) = $sup_{r2\in[r0,1]}$ {$BSADF_{r2}(r_0)$. The authors [PSY, 2014] elaborate on the details and derivations of the limit theorems for bubble identification covering all cases, from normal asset price trajectories, i.e., no bubbles to identification of single and most importantly multiple bubbles. (7) The empirical process for detection of multiple bubbles involves more complex dating strategies. The model generation equation is:

$$X_t = X_{t-1}\{t \in N_0\} + \delta_t X_{t-1} 1\{t \in B_1 \cup B_2 + \left(\Sigma_{k=r1f+1}^{t} \in_k + X_{r1f}^{*}\right) 1\{t \in N_1\} +$$

$$\left(\Sigma_{t=r2f+1}^{t} \in_t + X_{r2f}^{*}\right) 1\{t \in N_2\} + \in_t 1\{j \in N_0 \cup B_1 \cup B_2\} \quad (10)$$

where $N_0 = [1+\tau_{1e})$, $B_1 = [\tau_{1e}, \tau_{1f}]$, $N_1 = [\tau_{1f}, \tau_{2e}]$, $B_1 = [\tau_{2e}, \tau_{2f}]$, and $N_2 = (r_{2f}, \tau]$. The observations $\tau_{1e} = [T_{r1e}]$ and $\tau_{1f} = [T_{r1f}]$ are the origination and termination dates of the first bubble. Similarly, $\tau_{2e} = [T_{r2e}]$ and $\tau_{2f} = [T_{r2f}]$ is the origination and termination dates of the second bubble, where τ is the last observation in the sample. Once the first bubble collapses, X_t resumes its normal martingale path till $[r_{2e}\text{-}1]$, where the second bubble begins at r_{2e}. The expansion goes on till r_{2f} collapses to X_{r2f}^{*}. The martingale process kicks in after this and ends with sample period τ. Here we assume that the expansion duration of the first bubble is greater than that of the second bubble, so, $r_{1f} - r_{1e} > r_{2f} - r_{2e}$.

The data stamping process requires calculating $r_{1e,}$ r_{1f}, r_{2e} and r_{2f} from the following equations.

$$\hat{r_{1e}} = inf_{r2 \in [r0,1]}\{r_2 : ADF_{r2} > cv_{r2}^{\beta t}\} \quad (11)$$

and

$$\hat{r_{1f}} = inf_{r2 \in [\hat{r}_{1e + \frac{\log(T)}{T}},1]}\{r_2 : ADF_{r2} < cv_{r2}^{\beta T}\} \quad (12)$$

while

$$\hat{r_{2e}} = inf_{r2 \in \left[r_{1f} \;\; ,1\right]}\left\{r_2 : ADF_{r2} > cv_{r2}^{\beta t}\right\} \quad (13)$$

and

$$\hat{r_{2f}} = inf_{r2 \in [r_{2e + \frac{\log(T)}{T}},1]}\left\{r_2 : ADF_{r2} < cv_{r2}^{\beta T}\right\} \quad (14)$$

Then we use the backward sup ADF (BSADF) test to calculate the original and termination points based on the following equations.

$$\hat{r_{1e}} = inf_{r2\in[r0,1]}\{r_2: BSADF_{r2}(r_0) > scv_{r2}^{\beta t}\} \quad (15)$$

and

$$\hat{r_{1f}} = inf_{r2\in[\hat{r}_{1e+\frac{\log(T)}{T}},1]}\{r_2: BSADF_{r2}(r_0) < scv_{r2}^{\beta T}\} \quad (16)$$

while

$$\hat{r_{2e}} = inf_{r2\in[\hat{r_{1f}},1]}\{r_2: BSADF_{r2}(r_0) > scv_{r2}^{\beta t}\} \quad (17)$$

and

$$\hat{r_{2f}} = inf_{r2\in[\hat{r}_{2e+\frac{\log(T)}{T}},1]}\{r_2: BSADF_{r2}(r_0) < scv_{r2}^{\beta T}\} \quad (18)$$

One could sequentially apply this process detecting one bubble at a time, and then re-applying the same algorithm again and again. Once the first bubble has been detected, and it terminates at $r_{1f,}$ we use the equation below to date stamp the second bubble.

$$\hat{r_{2e}} = inf_{r2\in[\hat{r}_{1f+\epsilon T},1]}\{r_2: \hat{r_{1f}}ADF_{r2} > cv_{r2}^{\beta t}\} \quad (19)$$

and

$$\hat{r_{2f}} = inf_{r2\in[\hat{r}_{2e+\frac{\log(T)}{T}},1]}\{r_2: \hat{r_{1f}}ADF_{r2} < cv_{r2}^{\beta T}\} \quad (20)$$

where $\hat{r_{1f}}ADF_{r2}$ is the ADF statistic calculated over $(\hat{r_{1f}}, r_2]$. (8) We apply eq. (10) at the rate:

$$\frac{1}{cv^{\beta t}} + \frac{cv^{\beta t}}{T^{\frac{1}{2}}\partial_T^{\tau-\tau e}} \to 0, as\ T \to \infty\ eq. \quad (21)$$

Using the ADF detector, can identify the origin / termination of the first bubble, but not the second bubble, if the duration of the second bubble exceeds the first bubble, i.e., if $\tau_{1f} - \tau_{1e} > \tau_{2f} - \tau_{1e.}$ If the reverse is true, that is the duration of the first bubble is shorter than the second bubble, i.e., if $\tau_{1f} - \tau_{1e} < \tau_{2f} - \tau_{1e,}$ then under rate condition

$$\frac{1}{cv^{\beta t}} + \frac{cv^{\beta t}}{T^{1-\propto/2}} \rightarrow 0, as\ T \rightarrow \infty \tag{22}$$

this procedure can still detect the first bubble, but detects the second bubble with a delay as

$$(\hat{r_{2e}}, \hat{r_{2f}}) \xrightarrow{P} (r_{2e} + r_{1f} - r_{1e}, r_{2f}) \tag{23}$$

Under the BSADF methodology, we again apply eq. (10) at the rate of eq. (21). With continuous re-initialization, the BSADF detector can consistently estimate

$$(\hat{r_{1e}}, \hat{r_{1f,}} \hat{r_{2e}}, \hat{r_{2f,}}) \xrightarrow{P} (r_{1e}, r_{1f}, r_{1e}, r_{2f}) \tag{24}$$

of the origin and termination points of the first and second bubbles. Then under the sequential PWY methodology, using the same sequence of eq. (10) and rate eq. (21), we can consistently estimate in eq. (24), the origin and termination points of the first and second bubbles. Both the BSADF and the sequential PWY methodology, provide consistent estimates of the origin and termination of sequential bubbles. (9)

SECTION 3. EMPIRICAL APPLICATION

We apply the PSY [2014) methodology to identify for the presence of multiple bubbles in four major foreign i.e., non US financial indices, namely, the Financial Times Stock Exchange 100 Index, also called the “FTSE 100” or "Footsie", which is a share index of the 100 companies listed on the London Stock Exchange with the highest market capitalization, the benchmark French stock market index the CAC 40, which represents a capitalization-weighted measure of the 40 most significant values among the 100 highest market caps on the Euronext Paris, the DAX, which is a blue chip stock market index consisting of the 30 major German companies trading on the Frankfurt Stock Exchange, and the Nikkei 225, more commonly called the Nikkei index, which is a stock market index for the Tokyo Stock Exchange. [10]

We use monthly data for the FTSE 100 for the period December 1983 to November 2017, for a total of 408 observations; CAC for the period July 1987 to December 2017 for a total of 366 observations; DAX for the period December 1964 to November 2017 for a total of 636 observations; and the NIKKEI for the period April 1950 to December 2017 for a total of 813 observations. This data set was obtained from DataStream. The data used is the respective stock price index for the relevant month. We then conduct the SADF and the GSADF tests on the stock price index according to the basic model in eq. (1). The results are given in tables 1 - 4. Also given are the critical values of the two tests obtained from 2000 replications of the data in each case.

Table 1
FTSE 100

	Test Statistic	Finite Sample Critical Values		
Number of observations = 408		90%	95%	99%
SADF	1.8058	1.1423	1.4172	1.9799
GSADF	2.1761	1.9810	2.2173	2.7783

Table 2
CAC

	Test Statistic	Finite Sample Critical Values		
Number of observations = 366		90%	95%	99%
SADF	2.9994	1.1485	1.3784	2.0150
GSADF	3.0691	1.9324	2.1542	2.6512

Table 3
DAX

	Test Statistic	Finite Sample Critical Values

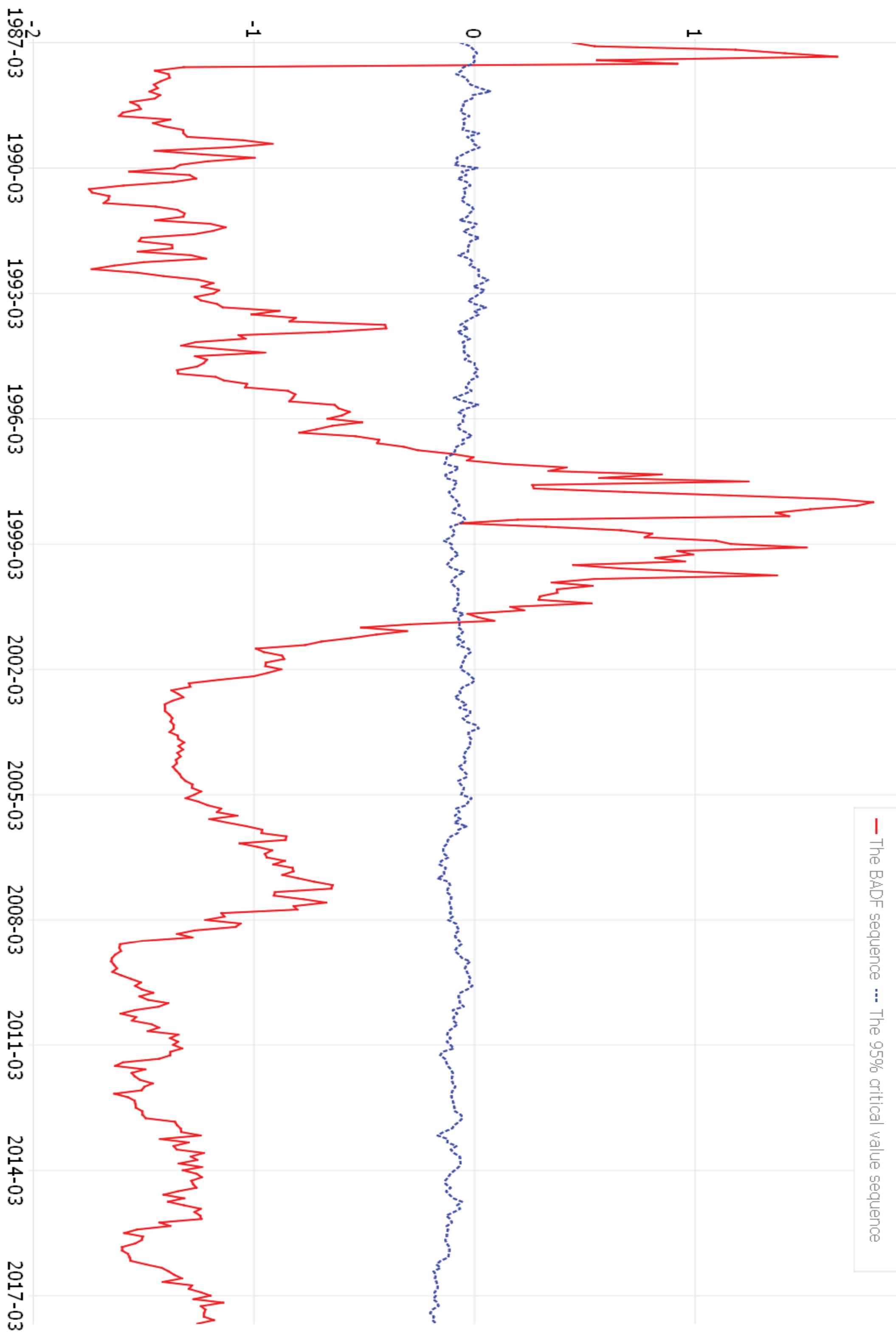
Number of observations = 636		90%	95%	99%
SADF	6.4794	1.2490	1.4934	2.0042
GSADF	6.4794	2.0746	2.2951	2.8082

Table 4
NIKKEI

	Test Statistic	Finite Sample Critical Values		
Number of observations = 813		90%	95%	99%
SADF	10.0832	1.2527	1.5407	2.0509
GSADF	10.0832	2.0745	2.2773	2.6917

Both tests find evidence of bubbles or explosive sub-periods over the long-term data in all 4 of the indices (test statistics in each case exceed the critical values for both test statistics considered). We then conduct a bubble monitoring exercise for each index using the backward ADF test and its critical value (using the PWY strategy), and the backward SADF statistic and its critical value (using the PSY strategy). This is done in graphs 1 – 8. In each graph the solid line represents the relevant test statistic, and the broken line represents the critical value. Figures 1, 3, 5, and 7 presents results from the use of the backward ADF test from the PWY paper, while figures 2, 4, 6, and 8 present results from the use of the backward SADF statistics from the PSY paper.

Figure 1 FTSE 100 Backward ADF statistic



In Figure 1 we look at the FTSE 100 and the existence of a bubble (test statistic greater than the critical value) is evident in the late 1990s to early 2000s, which corresponds with the technology bubble and its subsequent bursting. There is, however, no bubble around the financial crisis of 2008-09, which is surprising but in line with results that we have found in our study of U.S. indices.

Figure 2 FTSE 100 Backward SADF statistic

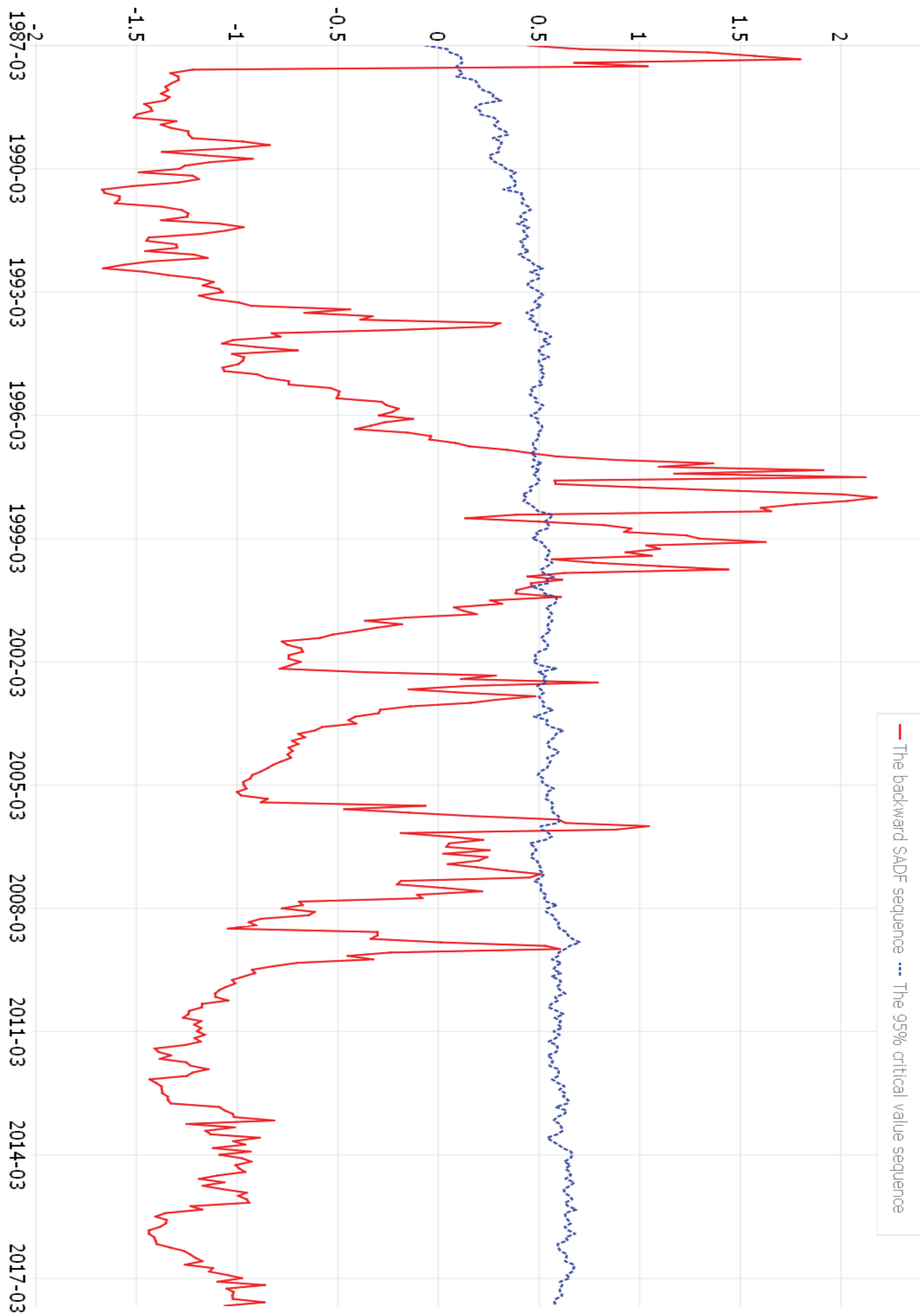


Figure 2 shows a bubble again for the late 1990s to early 2000s (just like in figure 1), but also seems to show bubbles (short ones) around 2003, 2006 and perhaps around 2007 and 2009. The ability of the BADF statistic to detect multiple bubbles is suspect, and therefore the results in Figure 2 (based on the PSY paper) are more reliable.

Figure 3 CAC Backward ADF statistic

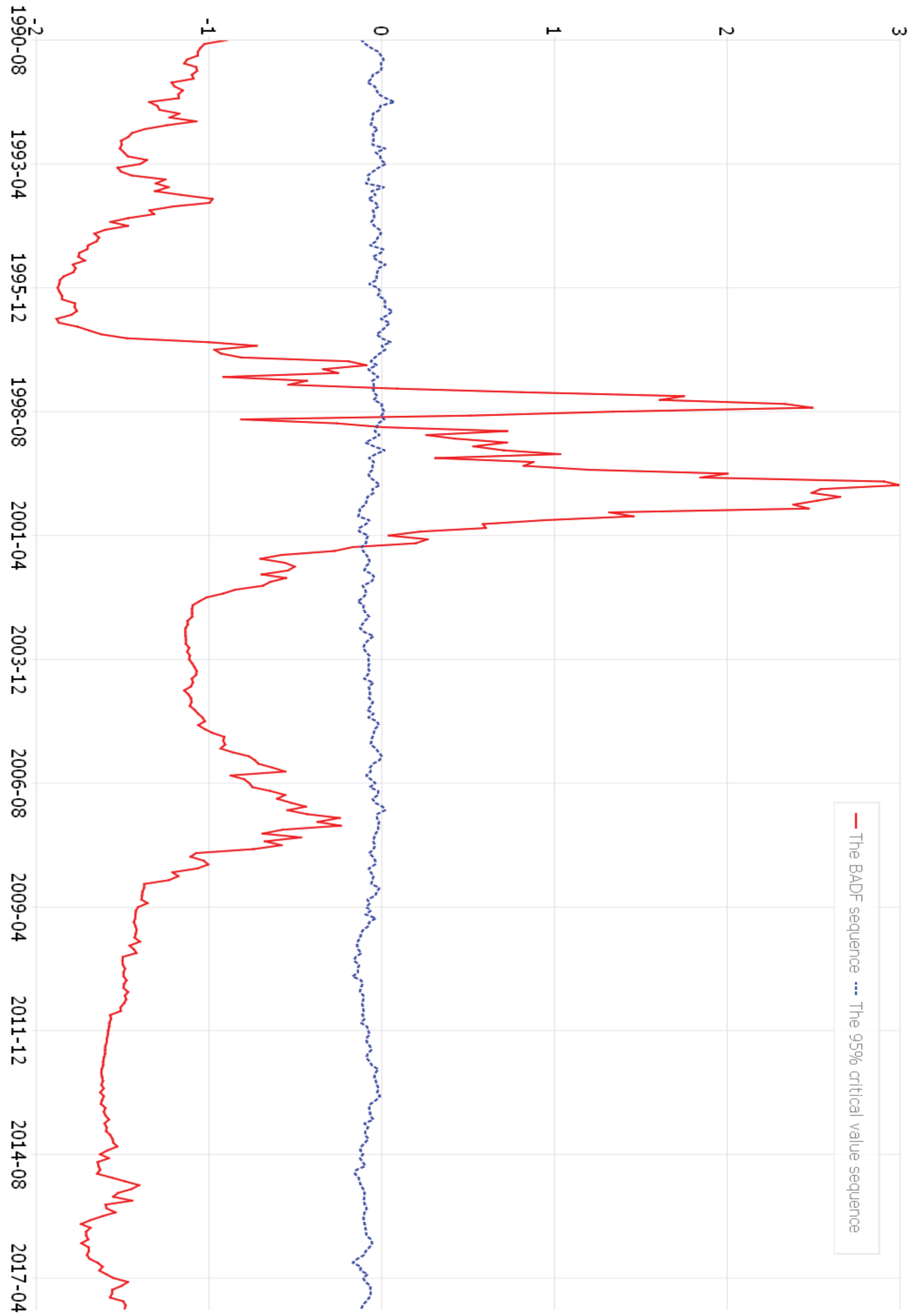
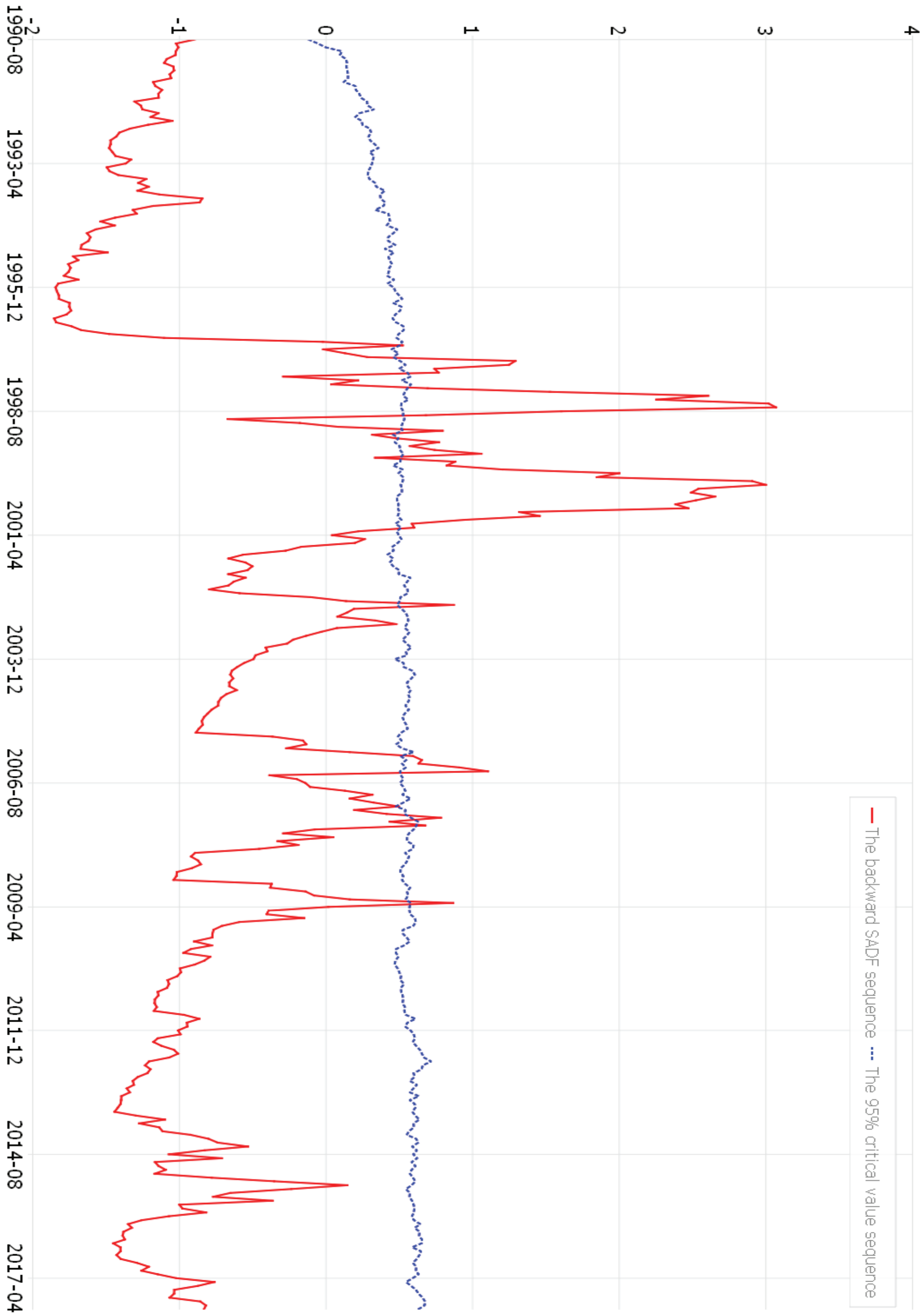


Figure 4 CAC Backward SADF statistic



A similar bubble monitoring exercise is carried out for the CAC index in figures 3 and 4. Figure 3 indicates a bubble around later 1990s to the early 2000s. Figure 4 indicates the existence of multiple bubbles for the CAC data. These bubbles occur in the late 1990s to early 2000s, also around 2002, 2005 and then again 2007, and then 2009.

Figure 5 DAX Backward ADF statistic

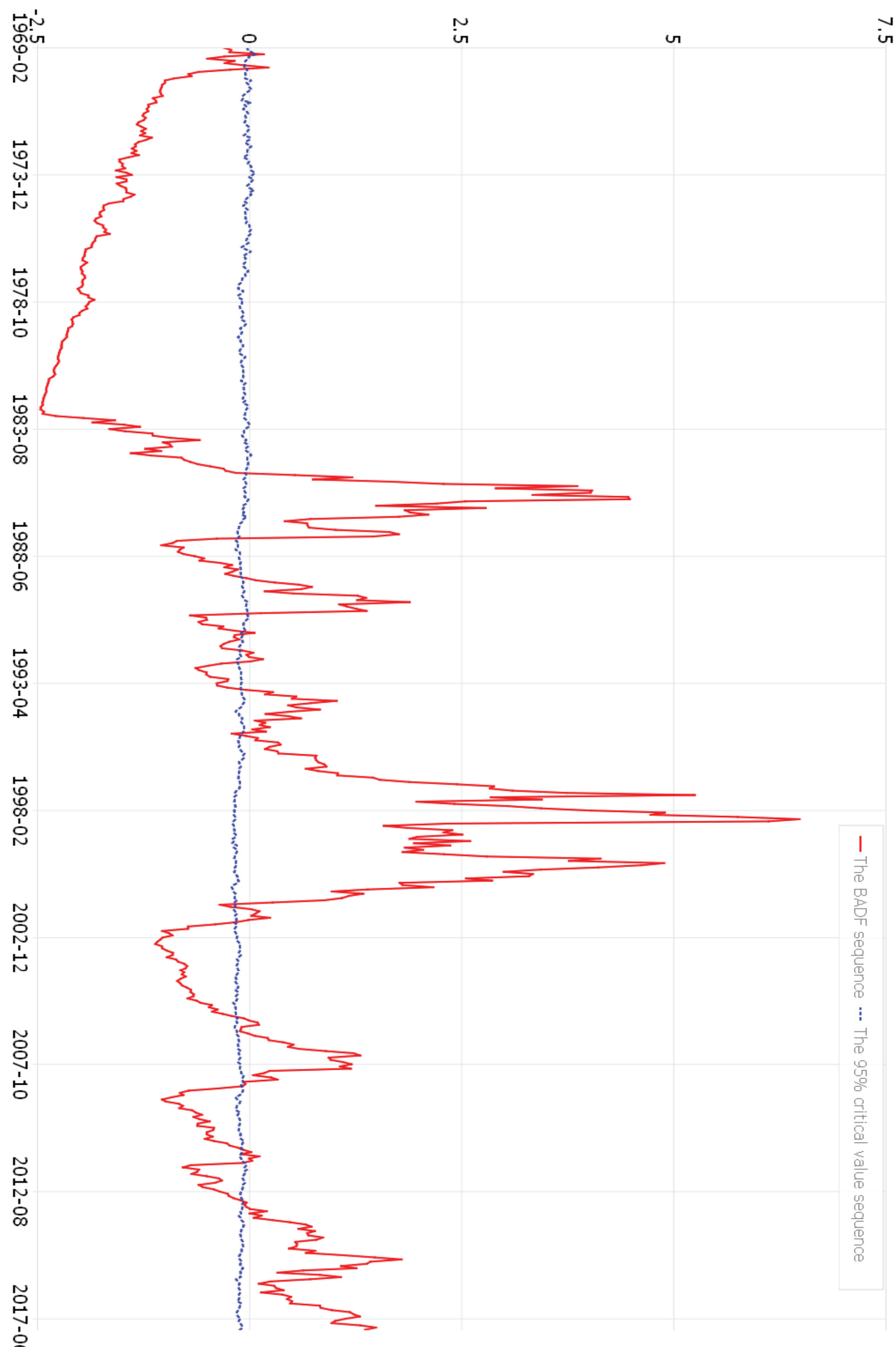
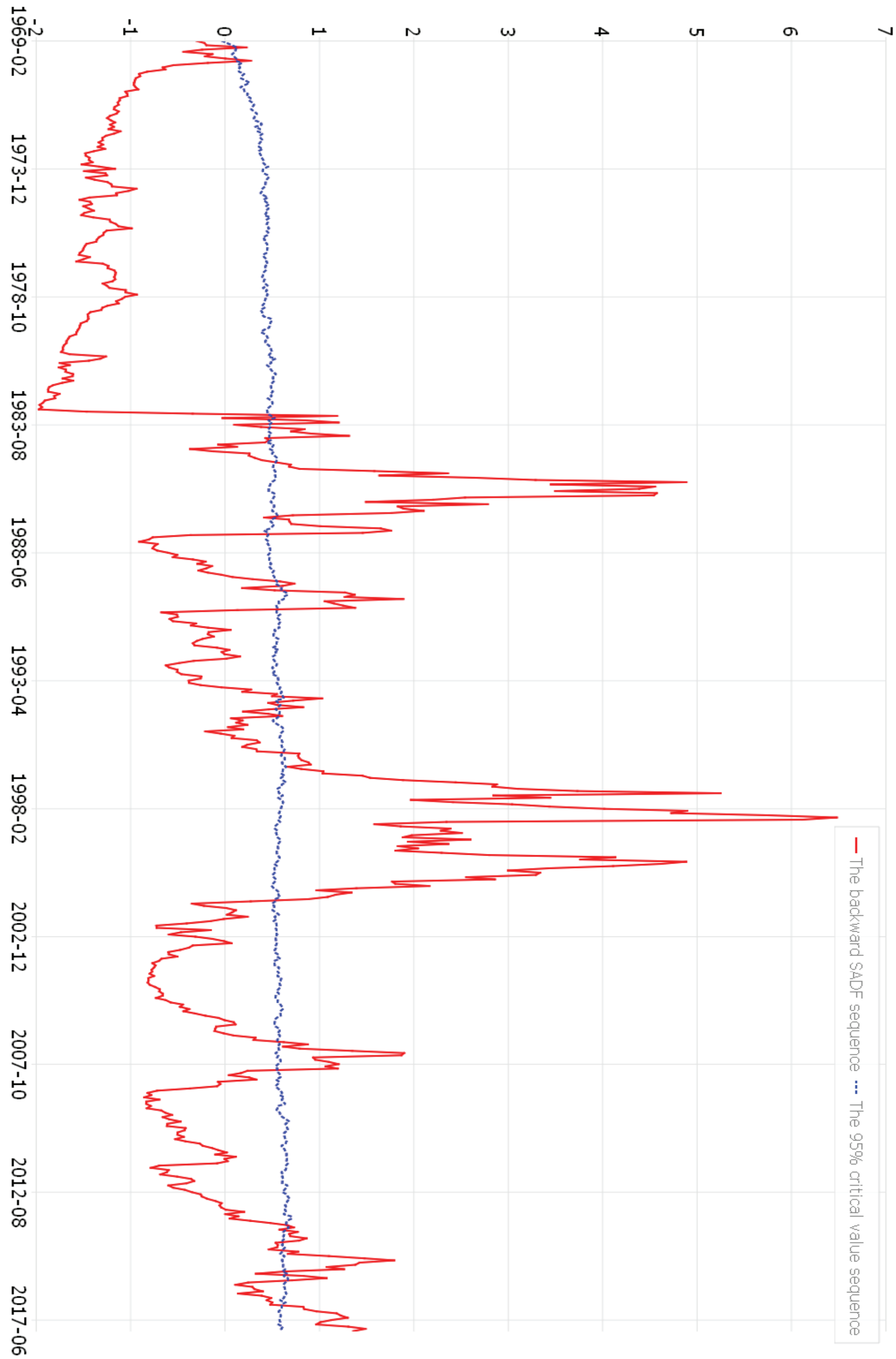


Figure 6 DAX Backward SADF statistic



Results for the DAX index are presented in figures 5 and 6. Figure 5 (BADF statistic) indicates the existence of bubbles in the mid and late 1980s, through most of the 1990s, then around 2007 and then again from about 2013 onwards. Figure 6 (backward SADF statistic) indicates very similar results for the DAX.

Figure 7 NIKKEI backward ADF statistic

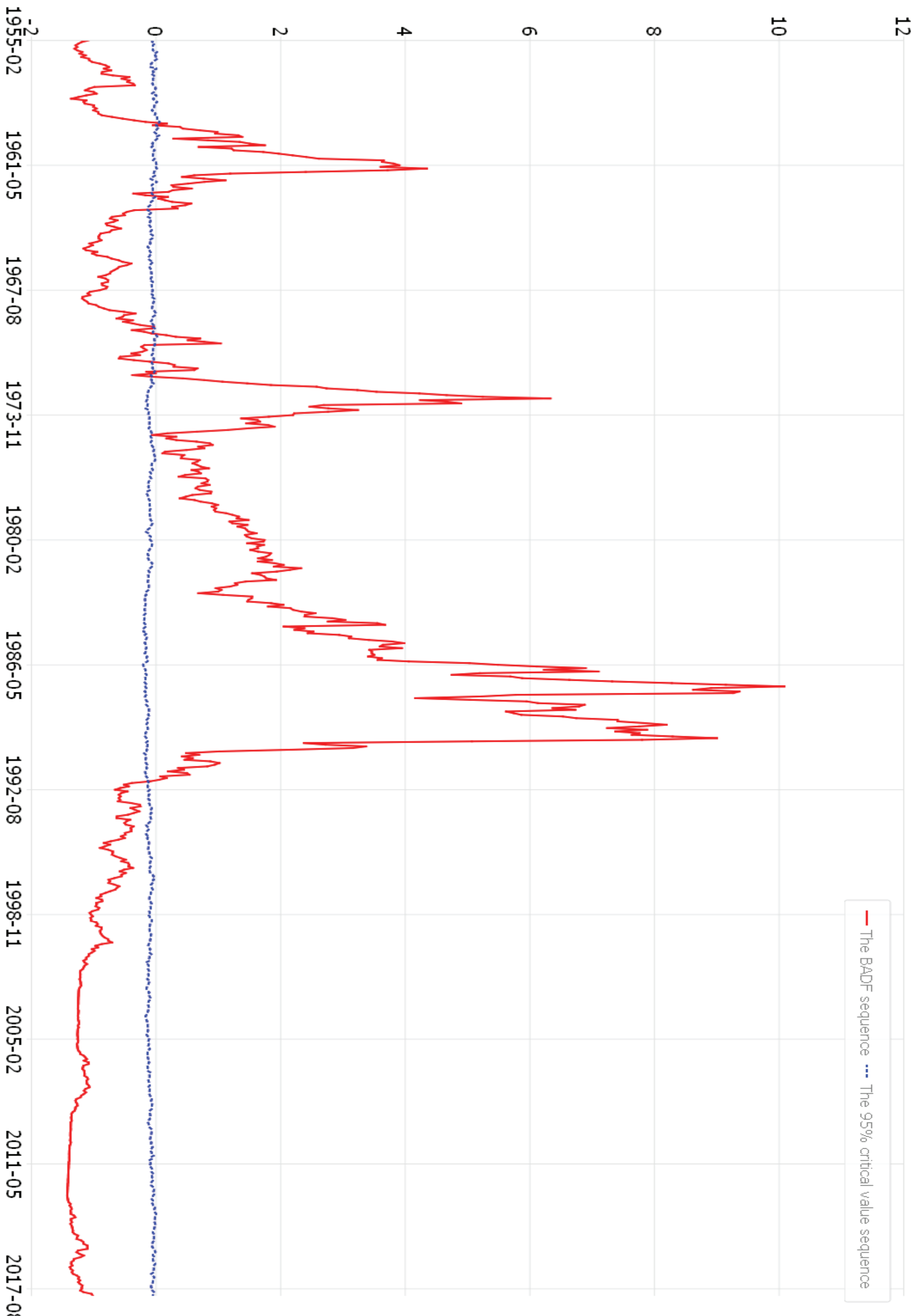
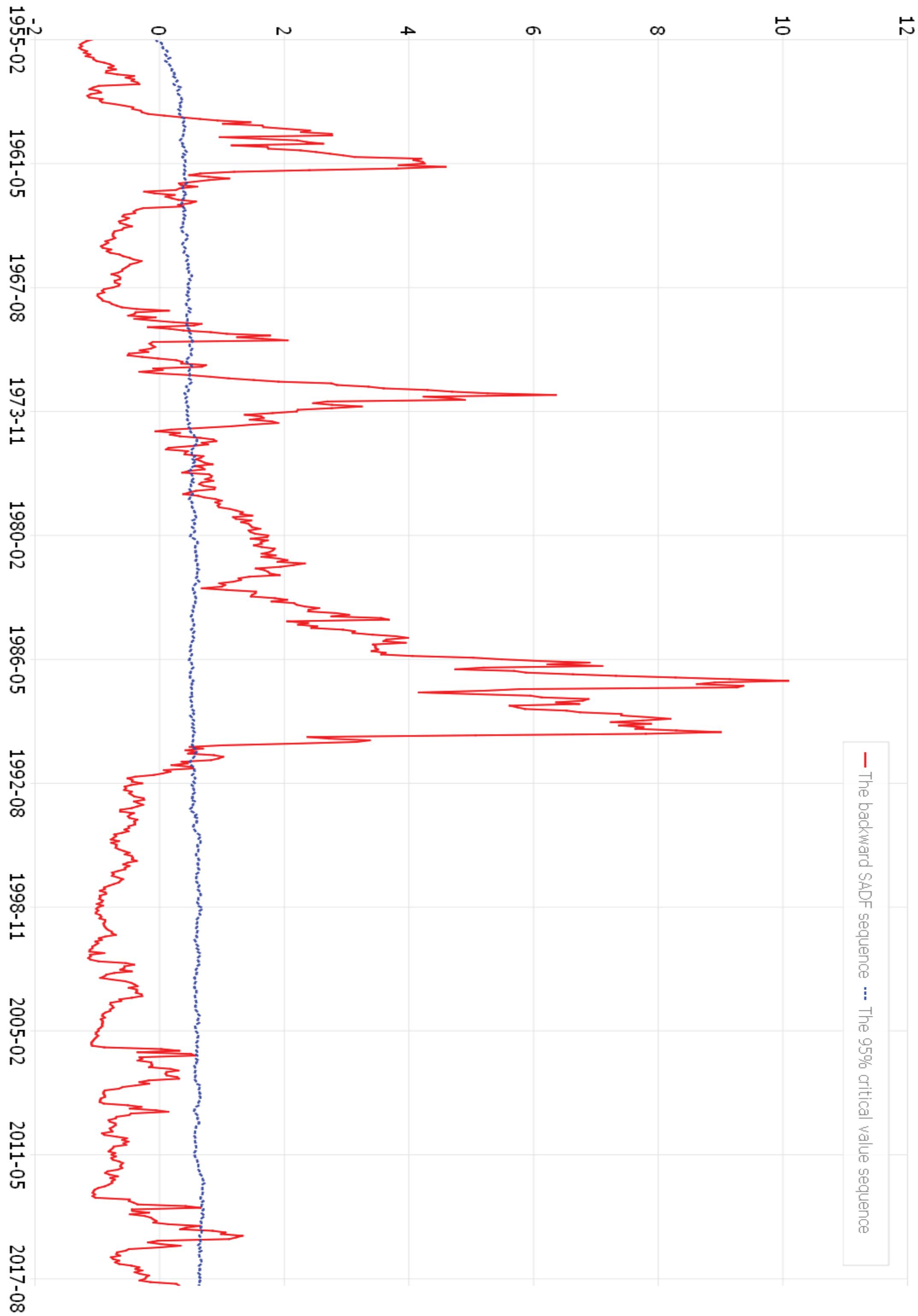


Figure 8 NIKKEI Backward SADF statistic



The NIKKEI index results are presented in figure 7 (BADF) and figure 8 (backward SADF). The span of the data for the NIKKEI index also happens to be the largest in our data set. Figure 7 indicates the existence of bubbles in the later 1950s and early 1960s, then from the mid-1970's all the way to 1992, and then no other bubbles including around 2008-09. Figure 8 shows very similar results for the NIKKEI.

Results from the backward ADF and the backward SADF statistic are quite different for the FTSE 100 and the CAC, both of which have data from the mid-to-late 1980s to 2017 and are quite similar for the DAX and the NIKKEI, for which we have data for much longer span (from 1964 (DAX) and from 1950 (NIKKEI). The backward SADF statistics (Figures 2, 4, 6, and 8) are considered more reliable for investigating multiple bubbles. We have data for the FTSE 100 and the CAC only from the 1980s, and this is clearly not enough to investigate whether there were bubbles in that time period. We have data for the DAX and the NIKKEI at least from the 1960s and these do indicate (in both cases) the existence of bubbles in the 1980s. All 4 indices have evidence for bubbles in the 1990s, up-to about the early 2000s, almost right when the technology bubble burst. We clearly do have proof of a bubble in the 1990s, and therefore we can conclude that there is evidence to support the widely referred "technology bubble" in the late 1990s and early 2000s. There is very limited evidence to indicate the existence of bubbles in 2007-2009, around the time of the financial crisis.

SECTION 4. CONCLUSION

The new test, the GSADF procedure is a recursive test, able to detect multiple bubbles. It's a rolling window, right sided ADF unit root test, with a double sup-window selection criterion. The SADF test is good, but it cannot credibly detect multiple bubbles over the same sample data set. The GSADF test overcomes this weakness and has significant discriminatory power in detecting multiple bubbles. It makes it very relevant in studying the "time trajectory" of long historical data sets. We have evidence for the existence of bubbles in the1990s for all 4 indices, thus providing evidence for the "technology bubbles" of the 1990s and early 2000s. There is limited evidence for bubbles in the 2000s and later, including around the time of the financial crises of 2008. This may indicate that the financial crisis, while its effects were felt worldwide and practically in all industries, may not have been a stock market bubble, but was a housing bubble which affected the stock market in many countries as the problems in the housing sector spread throughout the economy in many countries.

The technology bubble of late 1990s early 2000s (for which we do have evidence) was confined to the technology sector and did not spread to other sectors of the economy. Technology companies are directly part of stock indices and to that extent affect stock markets, but they do not (at least in the 1990s and 2000s) seem to have impacted the rest of the economy. The housing market seems to have had a far more significant and broader impact on the economy than the technology industry did, but the housing market does not seem to have caused a bubble in the stock markets worldwide.

Notes

1. Gurkaynak (2008) is a good review of this documentation.

2. DataStream proprietary data was purchased from EIKON, which was made possible due to a research grant of Professor Dutt, from the Richards College of Business, University of West Georgia. Our data is taken from DataStream International. ***As required by the IRBE journal, we are submitting the data set used in this research, but since it is proprietary, it can only be used to replicate our results, and is not for any other use, academic, research or otherwise.***

3. Sections 2 and 3 are a discussion of the PSY (2014) test, as implemented by us.

4. Cochrane (2005) debates the rationale of including "bubble components" in an asset pricing model, while Cooper (2008) expresses bewilderment at the literatures attempt to rationalize the well accepted NASDAQ bubble, as an accurate reflection of the changing market times and environment.

5. Interestingly, the experts agree more on the presence of market exuberance leading to panics, either rationally or irrationally. It's based on changing economic fundamentals, arising from behavior alterations of market players, or due to changing discount rates over time etc.

6. Then there is the Markov-switching test of Hall, et.al (1999), to detect explosive behavior in the data sample, but it is open to suspicion since Shi (2013) found it to be susceptible to "false detection of explosiveness." Also, according to Funke et.al. (1994) and van Norden and Vigfusson (1998), general filtering algorithms cannot differentiate between spurious explosiveness (the marker being high variance) as opposed to generic explosive behavior. The general approach of SADF is also used by Busetti and Taylor (2004) and Kim (2000) among others, to study "market bubbles" but the simulation study done by Homm and Breitung (2012) finds the PWY (SADF) test to be the most powerful metric in detecting multiple bubbles.

7. We briefly outline the two cases of no bubbles, and a single bubble. PSY (2015) develops the limit theories and consistency properties in case of single and multiple bubbles. PSY (2015, b) is a supplement describing the robustness checks of this testing procedure. If the null is of no bubbles, i.e., the data path is a normal growth trajectory, the ADGF and the SADF (extracted from Theorem 1) is that the backward ADF is nothing but the special case of GSADF when $r_1 = 0$, with fixed r_2, while the backward SADF is the special case of the GSADF test with $r_1 = (r_2 - r_w)$ and fixed r_2. Based on the limit theorem, the advantage here is that under the null of "no bubbles" the chances of a false positive (spurious detection) of a bubble origination and termination using backward ADF statistic and the SADF statistic, tends to zero and so, $P_r \{\hat{r}_e \{ \hat{r}_e \in [r_0, 1]\} \to 0$, and $P_r \{\hat{r}_f \in [r_0, 1]\} \to 0$. But if single bubble episode is studied using this reduced form equation:
$X_t = X_{t-1} 1\{t < r_e\} + \partial_t X_{t-1} 1\{r_e \le t \le r_f + \left(\Sigma_{k=rf+1}^{t} \epsilon_k + X^*_{rf}\right) 1\{t > r_f\} + \epsilon_t\ 1\{j \le r_f\}$ eq. (25)
to detect a martingale behavior, with the genesis of an explosion (or birth), its existence and eventual collapse from origin to renewal of the subsequent behavior. In equation (25), $\delta_t = 1+cT^{-\alpha}$ with $c>0$ and $\alpha \in (0, 1)$ and error ϵ_t is iid $(0, \sigma^2)$, and $X^*_{rf} = X_{re}+X^*$ with $X^* = O_p(1)$. Here r_e =

$[Tr_e]$ dates the origin of the bubble expansion while $r_f = [T_{rf}]$ dates the collapse of the bubble. The bubble expansion period is given by $B = [r_e, r_f]$, with the expansion rate given by the autoregressive coefficient δ_t. Even mildly explosive features capture the market exuberance quiet well. Over time the bubble collapses to X^*_{rf} and then follows a standard martingale over the subsequent period $N_1 = (r_f, T)$. This equation captures single bubbles very well, as demonstrated by the PSY (2014.) Their simulations show that under eq. (25) both ADF and BSADF provide consistent estimates of the origination and termination dates of a single bubble episode.

8. This sequential procedure (for proper and credible application) requires a long set of observations, the longer the better, in order to re-initialize the test process after a bubble.

9. Other conclusions PSY (2014) arrived at are:

   1. In case of a single bubble, the power of PWY, sequential PWY and CUSUM are the same, but less than GSADF.

   2. As the bubble duration increases, so do the power of these tests.

   3. In case of a single bubble, the PWY and CUSUM are reasonably accurate, but the sequential PWY tests tend to overestimate the bubble number.

   4. In case of two bubbles, the outcomes are mixed. Here the bubble duration becomes an important variable, and the possibilities are:

      a) If the first bubble is larger than the second bubble, PWY underestimates the numbers, because in most cases it identifies the first bubble but not the second one.

      b) If the second bubble duration is larger than the first, the PWY test can more confidently detect both bubbles. It is the same for the CUSUM test. The sequential PWY performs as well as the PSY test.

10. This is a part of a bigger project, where we are examining for the presence of multiple bubbles and exuberance episodes, using the major USA financial indexes like the DOW, NASDAQ and the S&P 500. In an attempt to make the testing more comprehensive and worldwide, here in this extension, we examine four major foreign indexes.

Reference

Abreu, D., and M. K. Brunnermeier, Bubbles and crashes", Econometrica, 71 (2003), 173-204.

Ahmed, L., Lords of Finance: The Bankers Who Broke the World, (New York: Penguin Press, 2009).

Busetti, F., and A. M. R. Taylor, \Tests of stationarity against a change in persistence," Journal of Econometrics, 123 (2004), 33-66.

Cochrane, J. H., Asset Pricing (Princeton: Princeton University Press, 2005).

Cooper, G., The Origin of Financial Crises: Central Banks, Credit Bubbles and the Efficient Market Fallacy (New York: Vintage Books, 2008).

Froot, K. A., and M. Obstfeld, Intrinsic bubbles: The case of stock prices," American Economic Review, 81(1991), 1189-1214.

Funke, M., Hall, S., and M. Sola, Rational bubbles during Poland's hyperinflation: implications and empirical evidence," European Economic Review, 38 (1994), 1257{1276.

Gurkaynak, R. S., Econometric tests of asset price bubbles: taking stock," Journal of Economic Surveys, 22 (2008), 166 -186.

Hall, S.G., Psaradakis, Z., and M. Sola, Detecting periodically collapsing bubbles: A Markov switching unit root test," Journal of Applied Econometrics, 14 (1999), 143{154.

Homm, U., and J. Breitung, Testing for speculative bubbles in stock markets: a comparison of alternative methods," Journal of Financial Econometrics, 10 (2012), 198-231.

Kim, J. Y., Detection of change in persistence of a linear time series," Journal of Econometrics, 95 (2000), 97-116.

Phillips, P. C. B., and Magdalinos, T., "Limit theory for moderate deviations from a unit root," Journal of Econometrics, 136 (2007), 115-130.

Phillips, P. C. B., Shi, S., and Yu, J., "Specification sensitivity in right-tailed unit root testing for explosive behavior," Oxford Bulletin of Economics and Statistics, 76 (2014), 315-333.

Phillips, P.C.B., Shi, S., and Yu, J., "Testing for Multiple Bubbles: Limit Theory of Dating Algorithms," International Economic Review, forthcoming (2015).

Phillips, P.C.B., Shi, S., and Yu, J., "Supplement to Two Papers on Multiple Bubbles," Manuscript, 2015b, available from https://sites.google.com/site/shupingshi/TN_GSADFtest.pdf?attredirects=0&d=1.

Phillips, P.C.B., Wu, Y., and J. Yu, "Explosive behavior in the 1990s Nasdaq: When did exuberance escalate asset values?" International Economic Review, 52 (2011), 201-22.

Phillips, P. C. B., and Yu, J, "Limit theory for dating the origination and collapse of mildly explosive periods in time series data," Unpublished manuscript, Sim Kee Boon Institute for Financial Economics, Singapore Management University, 2009.

Phillips, P.C.B., and J. Yu, "Dating the Timeline of Financial Bubbles During the Subprime Crisis," Quantitative Economics, 2 (2011), 455-491.

Shi, S., Econometric Tests for Nonlinear Exuberance in Economics and Finance," PhD thesis, The Australian National University, (2011).

Shi, S., Specification sensitivities in the Markov-switching unit root test for bubbles," Empirical Economics, 45 (2013), 697-713.

van Norden, S. and R. Vigfusson, Avoiding the pitfalls: can regime-switching tests reliably detect bubbles?" Studies in Nonlinear Dynamics & Econometrics, 3 (1998), 1-22.

Notes:

RETESTING THE DUAL SECTOR MODEL IN INDIA AND BRAZIL

Ms. JIADE XIAO,

Graduate Student, Korbel School of International Studies

2201 South Gaylord Street, *University of Denver.*

Denver, CO 80208.

Email: Jiade.Xiao@du.edu.

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ABSTRACT

Indian and Brazil are developing countries and emerging markets, enjoying economic development in the recent decades. The development experience of both countries may provide persuasive evidences in supporting or disapproving the economic theories. Arthur Lewis' structural-change theory focuses on the transition of economic structure with the character from depending heavily on agricultural sector to the character with more contribution from industrial sector occurring in the developing countries. His model of dual sector, as an important part of the structural-change theory, argues that the labor moving from agricultural sector to industrial sector associated with the migration from rural area to urban area contributes to the economic development as well as the alleviation of overpopulation in agricultural sector and the stagnation of marginal product resulted from the population growth and technology advancement in the developing countries. This paper explores the adaptability of the assumptions and the arguments of the Arthur Lewis' Model in India and Brazil in the structural change between the agricultural and industry sectors. There is quite some evidence supports the argument of dual sector model, though the model is not fully explanatory on the economic development of the two developing countries.

RETESTING THE DUAL SECTOR MODEL IN INDIA AND BRAZIL

Introduction

Arthur Lewis' Model was considered as one of the most popular and most explainable model for the development of the developing countries in 1960s and 1970s (Todaro, 2000), which still has legacies for the research of economic development of developing countries today. This paper will explore the explanatory power of the Arthur Lewis' Structural Adjustment Model based on the case study of Brazil and India. India and Brazil are two typical developing countries experiencing economic development in the recent decades. Despite the similarities shared by the two countries in colonial history, in the memberships of BRICS, there are a lot of differences between the two countries on culture, regime types in modern history, economic and welfare policies, population density and etc. These differences increase the credibility of the evidence for the test on the dual sector model on the two countries. The paper includes three sections besides the introduction. In the first section, the paper reviews the Arthur Lewis model of dual sector with its assumption, its main argument and its limitations. In the second section, the paper provides empirical evidences of India and Brazil supporting or opposing the dual sector model, and discusses the adaptability as well as limitations of the model in the two countries. In the last section, the paper draws conclusion with the discussion of possible implementation of the analysis.

Arthur Lewis' Dual Sector Model

Arthur Lewis' Dual Sector Model is the most well-known section of his Structural Adjustment Model. This model is firstly published in "Economic development with unlimited supplies of labor" by *The manchester school* in 1954. The model is inspired but not limited to neo-classical economic theory. This model focuses more on a closed economy with merely focus on closed domestic economy with very limited interest in trade, also this model creatively put surplus labor as the main source of capital creation and economic development, which provides possible approach for the developing countries to adopt.

Assumptions of Arthur Lewis' Dual Sector Model

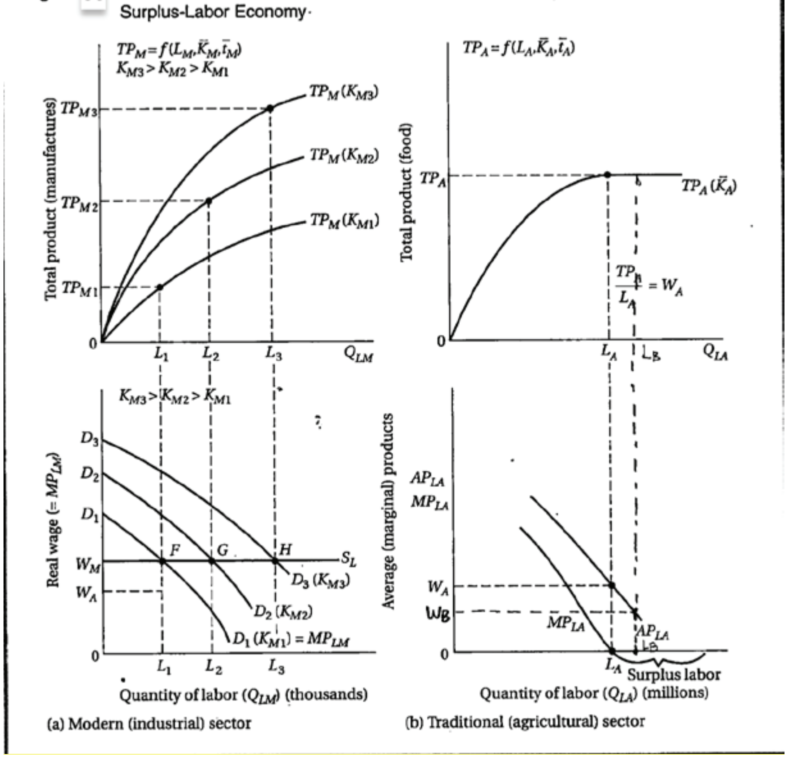
First, Arthur Lewis defines two sectors in economic structure, including the primary as the subsistence or agricultural sector and the secondary sector as capitalist or industrial sector, and he assumes that there are only these two sectors in an economy.

Second, Arthur Lewis assumes that there would be unlimited supply of labor in the economics with particularly large population compared to capital and natural resources, where the marginal productivity of labor is negligible, zero, or even negative in many sectors (1954). This idea was originally adopted from the classics that "the classics, from Smith to Marx, all assumed, or argued, that an unlimited supply of labor was available at subsistence wages" (Lewis, 1954). He argues that the surplus of labor is common in the developing countries, and particularly common among the Asian countries. The unlimited supply of labor contributes to the possibility of creating capital without the input of more scarce land or capital. This provides a new approach of accumulating capital beyond the neo-classical model. This also makes Lewis' model particularly beneficial for the developing countries, as surplus of labor is very common among the developing countries and other resources, such as land and (particularly) capital, are usually comparatively scarce in these economies.

Main Argument of the Model

Arthur Lewis argues that as more population surplus occurs in the agricultural sector, the agricultural sector marginal product (MP) of labor become close to zero. This means despite the increasing labor put in agricultural sector, the overall output of the sector tends to increase less and less before remaining almost same in the end. This suggests that the living standard of people being employed in the agricultural sector will decrease as overpopulation occurs in the sector, and the wage rate is always limited to subsistence. However, in industrial sector, the marginal product of labor is more than zero, and as the increase of more labor in this sector, the output of the sector will continue to grow. What's more, the technology of product in the industrial sector can be better and with more rapid development compared to the agricultural sectors, which can increase the profit of the industrial sector. The reinvestment of the profit will lead to the consequence that the wage rate in industrial sector may continuously be higher compared to the agricultural sector and thus a lot of labor may be attracted from the agricultural sector to industrial sector for better living standard. At the same time, there will be large migrations from rural area to urban area accompanied with the migrations from labor surplus rural sector to industrial sector. Thus, a structural adjustment occurs both in the economic sectors as well as in the population residency in the developing countries.

Figure A The Lewis Model of Modern-Sector Growth in a Two-Sector Surplus-Labor Economy



Source: Todaro (2000)

As shown in Figure A (b), the total product TPA(KA) becomes a constant as the amount of labor reaches LA and becomes surplus. At this point, the average wage of the labors in agricultural sector is WA =TPA/LA. Given surplus labor in the agricultural sector and the amount labor reaches LB, the average wage of the labors in agricultural sector at this point becomes WB= TPA/LB. As LA < LB, WA > WB. This shows that with surplus labor in the agricultural sector, the average wage of the labors in the sector will decrease.

As shown in Figure A(a), the total product of industrial sector $TP_M(K_{M1})$ can always continue to increase as the total amount of labor increases. As the increase of labor in the industrial sector, the average wage of industrial sector will decrease as it is in agricultural sector as well with the same reinvestment compared to last time-period. However, as argued by Lewis, “there is really only one class that is pretty certain to reinvest its profits productively, and that is the class of industrialists” (1954). Ideally, the capitalists will reinvest the profit gained from last time-period in order to pursue profit-maximizing and thus the total input capital in the sector will increase, and the total product of the industrial sector will shift from $TP_M(K_{M1})$ to $TP_M(K_{M2})$ in the next time-period and then from $TP_M(K_{M2})$ to $TP_M(K_{M3})$ in the following time-period. In this way, the average real wage of the labor in the industrial sector will maintain same without decrease. This process is considered as self-sustaining growth and more labor can be absorbed as time goes by in the industrial sector (Todaro, 2000). During this process, the living standard of people in the society can be increase by more labors with better wage in industrial sector as well as the better wage of the labors in the agricultural sector resulted from less surplus labor.

Limitations of the Model

As mentioned by Todaro (2000), there are also limitations of the model. First, the model assumes naturally high reinvestment rate and efficient job creation that “the rate of labor transfer and employment creation in the modern sector is proportional to the rate of modern-sector accumulation" (Todaro, 2000). To begin with, the capitalists can adopt Western ways of living or be addicted to Ragnar Nurkse's "international demonstration effect", which will increase the consumption and thus decrease the reinvestment. Given a high reinvestment rate in total, there is still possibility of limited reinvestment rate in industry resulted from the increasingly reinvestment rate in financial sector or savings for better profit or lower risks. Given the high reinvestment rate in industrial sector, there is still possibility of non-efficient job creation rate as expected by this model. It is highly possible that the capitalists reinvest in technology innovation or in machines and equipment instead of in recruiting more workers. This is even more possible as the increasing of worker wages and the mature of technology in automation.

Second, the model will be problematic if there is full employment in the urban areas (Todaro, 2000). Given full employment in the urban areas, the industrial sector cannot absorb more labor from agricultural sector even if there are surplus labor there. Unemployment is particularly severe among the developing countries. Third, as argued by Todaro, the assumption that a competitive modern-sector labor market guarantees the continued existence of constant real urban wages up to the point where the supply of rural surplus labor is exhausted is unreal (2000). There are institutions and movements always making efforts in improving the income and welfare of the labors and thus limiting the competitive labor market, and this is why the ideal fully competitive labor market is hardly to be achieved anytime.

Apart from the limitations argued by Todaro, urbanization itself resulted from the structural adjustment may also be problematic. For example, because of the large migration from rural to urban sector and the very limited infrastructure preparation, many developing countries are experiencing slum issues accompanied with significant sanitation and security problems. Also, many over crowed cities has severe traffic jam, which significantly decrease the efficiency of people's live as well as economic activities. Moreover, urbanization always associated with environmental pollution and degradation, which does serious harm to people's lives as well as economic development.

Empirical Section

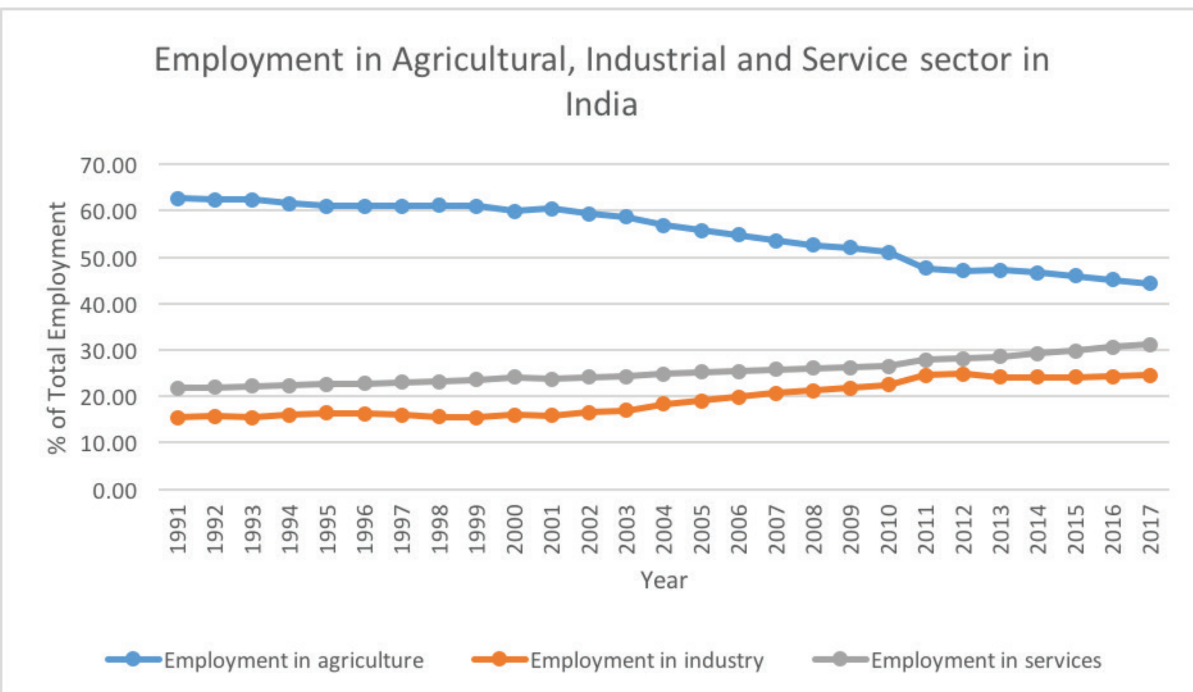
In this sector, the paper explores the adaptability of the dual sector model in India and Brazil, in terms of its assumption and argument with discussion of limitations of the model in the two countries. First, the paper elaborates the applicability of the assumption of the models in the two countries.

Applicability of the Assumptions

The assumption of two sectors: As shown in Figure 1 and Figure 2, service sector has become an increasingly important sector in India and Brazil in terms of its added value in total GDP apart from the agricultural and industrial sector defined by Arthur Lewis. Particularly for Brazil, we can realize that its service sector has surpassed 50% since 1991 according to Figure 2, and the proportion of this sector measured by added value in total GDP has been continuously increasing since then in general. The proportion of this sector in India measured by added value in total GDP has also increased beyond 50% since 2012. What's more, it has been well-known that Indian people has achieved phenomenal success in software industry, as a symbolic representative of service sector, and the revenue of this industry has been increasingly essential for the country (Athreye, 2005). Therefore, it has been increasingly hard to explain the economic development by focusing merely on the two sectors as assumed in the dual sector model. Nevertheless, it is arguable whether service sector and industrialized agriculture should be included as a part of the capitalist sector instead of the tertiary industry or the primary industry respectively, as Lewis defined the capitalist sector as "that part of the economy which uses reproducible capital and pays capitalists thereof" (1954). This is particularly true for Brazil as industrialized agriculture with large capital, land and technology input while very limited labor input contributes significantly for its export and total economy.

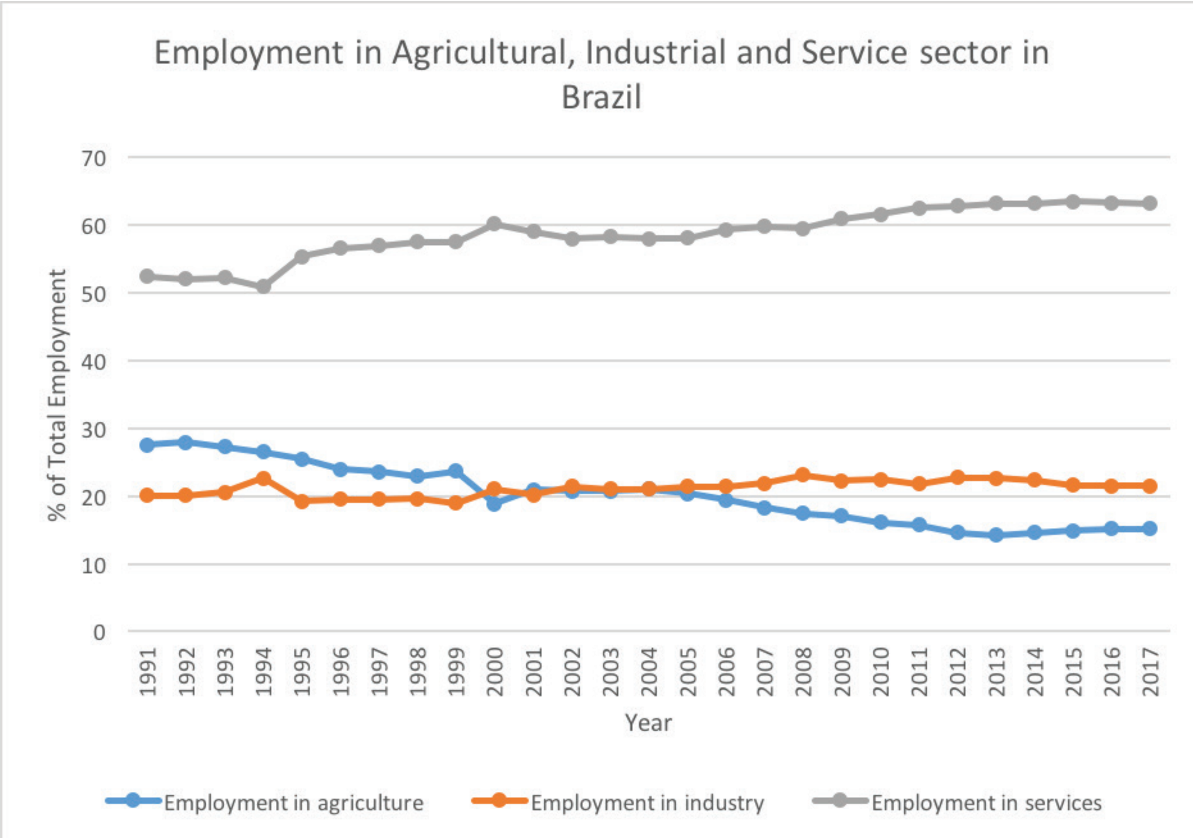
The assumption of unlimited supply of labor: As assumed by the dual sector model, Lewis assumes that there is a large amount of surplus labors in agricultural sectors in developing countries, which can be migrant from agricultural sector to industrial sector. As shown in Figure 1 and Figure 2, the proportion of employment in agricultural sector has indeed experience significantly decrease in India and Brazil since 1960 to 2017, while the proportion of employment in industrial sector has generally increased in India and has somehow increased in Brazil since 1960. This support the assumption of the existence of surplus labor in the agricultural sector in both countries.

Figure 1. Employment in Agricultural, Industrial and Service sector in India (1991-2016)



Source: World Bank Data

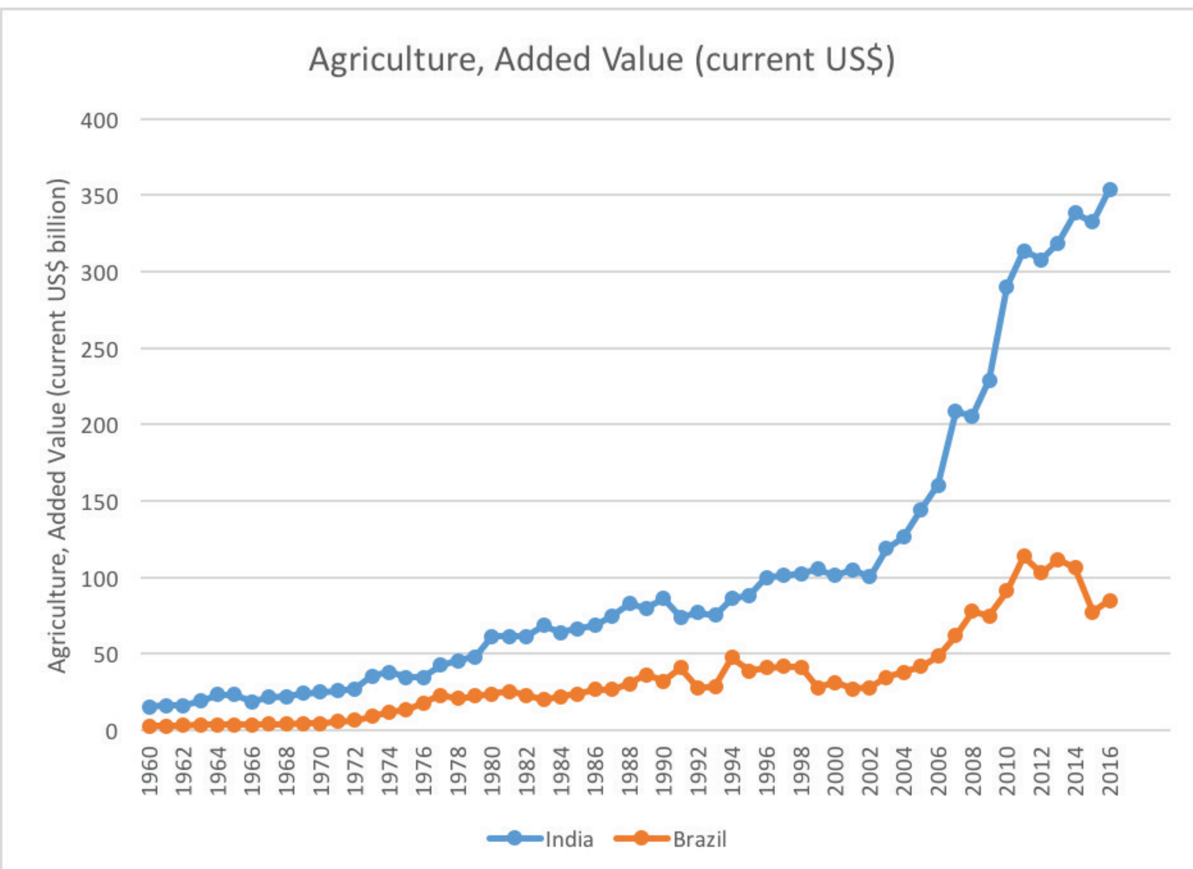
Figure 2. Employment in Agricultural, Industrial and Service sector in Brazil (1991-2016)



Source: World Bank Data

The dual sector model also assumes a constant output of agricultural sector despite a decreasing of surplus labors in the sector. However, as shown in Figure 3 the added value of agriculture measured by current US$ has increased continuously since 1960 and significantly since 2002, particularly in India. On one hand, as there isn't any decreasing in the agricultural sector suggested by the data provided by the Figure 3 despite the decreasing proportion of employment in the sector, we can make the argument that the evidence supports the existence of surplus labor in both countries. Then, how can we explain the increasing of the added value of agriculture measured by current US$ in both countries? First, it is possible that the advancement of technology and the industrialization of agriculture has increased the productivity of agricultural sector in both countries. In both countries, large transnational agricultural company has played increasingly significant role in agricultural sector. The seeds of genetically modified food, the modernized and efficient machines and equipment have been largely used in agriculture in the two countries. In Brazil, there have been lots of fields and farms focusing on the plantation of a particular crop, such as soybean, merely for export (USDA, 2018). Second, it is possible that there has been inflation of US dollar and the appreciation of the domestic currency of India and Brazil. Brazil currency experienced appreciation resulted from the domestic economic policy before and after economic crisis in 2008 (Barbosa, 2010). Although these two possible phenomenon is not discussed in the Lewis' model, they resulted to even more surplus labor in agricultural sector than Lewis expected at least logically. Thus, the assumption of the model that there are surplus labors in the agricultural sector in both countries is supported.

Figure 3. Agriculture, Added Value (current US$) in India and Brazil



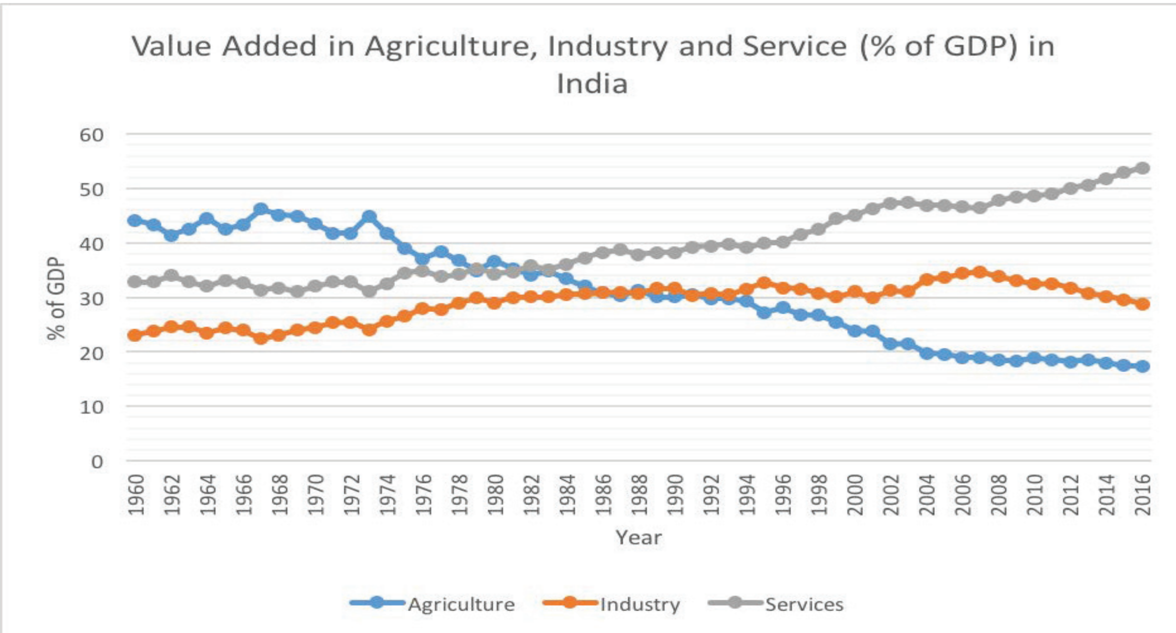
Source: World Bank Data

Applicability of the Arguments

Labor force moving from agricultural sector to industrial sector: As is shown in Figure 1 and Figure 2, there have been significantly decreasing of the proportion of employment in the agricultural sectors in India and Brazil, which is exactly expected by the dual sector model. However, there isn't any increasing on the proportion of employment in the industrial sector in any of the two countries as significant as the decreasing in agricultural sector. For India, there has been generally decreasing in the proportion of employment in the agricultural sector as shown in Figure 1, while the decrease is comparatively subtle in Brazil as shown in Figure 2. We may make the argument that Brazil has achieved the structural adjustment before 1991 and there had been large amount of labor force transit from agricultural sector to industrial sector by then, as this is supported by the large proportion of employment in service sector always beyond 50% since 1991. For India, we can realize from Figure 1 that the proportion of employment in agriculture sector has always been the largest among the three sectors despite its continuous decreasing. We may make the argument that the more time is needed for more labor force moving from agricultural sector for India on one hand as the decreasing in the proportion of employment in the agricultural sectors in India tends to be more rapidly in the most recent years. It is also possible that the lacking of technology for most peasants and the caste system constraint the development of surplus labor and the movement of them into other sectors.

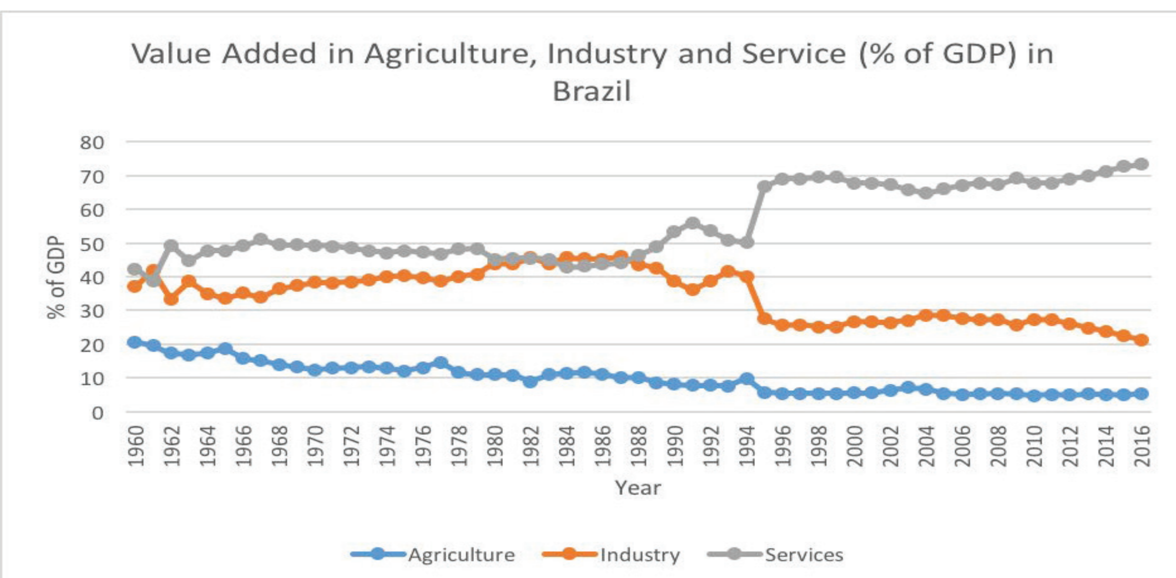
On the other hand, there is also sign that more proportion of employment in the service sector instead of industrial sector increases as shown in Figure 1. If we consider service sector as an apart of capitalist sector, then the evidence perfectly supports the dual sector model. If we do not think so, we may argue that this is beyond the explanatory of the dual sector model. It is particularly notable that since 2013 the proportion of employment in the agricultural sectors increased in Brazil and the proportion of employment in the industrial sector decreased, which is on the opposite to the expectation of the dual sector model. As we mentioned above, it is possible that this is resulted from the industrialization of agriculture and the profitability and thus more reinvestment in this sector by the capitalists, or it can be resulted from the large unemployment in the industrial sector and the retreatment of labors from the sector.

Figure 4. Value Added in Agriculture, Industry and Service (% of GDP) in India (1960-2016)



Source: World Bank Data

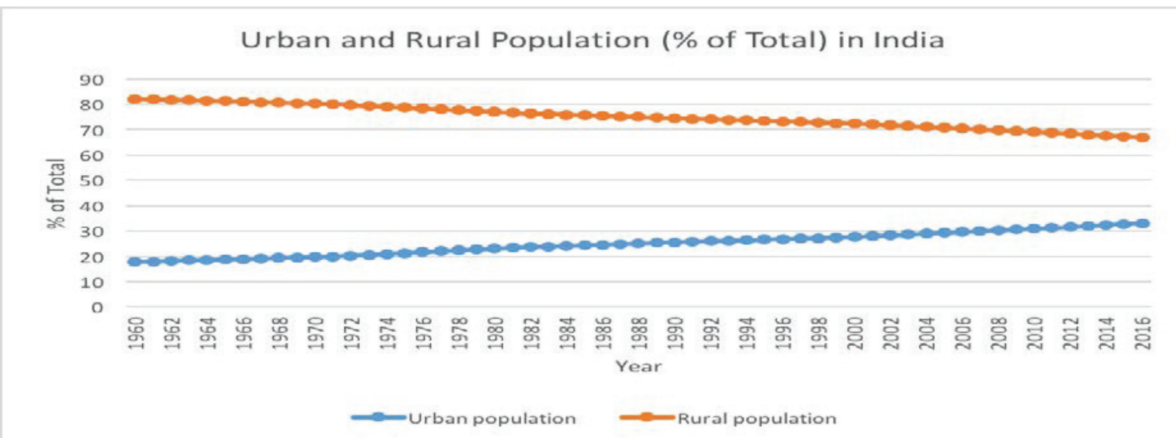
Figure 5. Vale Added in Agriculture, Industry and Service (% of GDP) in Brazil (1960-2016)



Source: World Bank Data

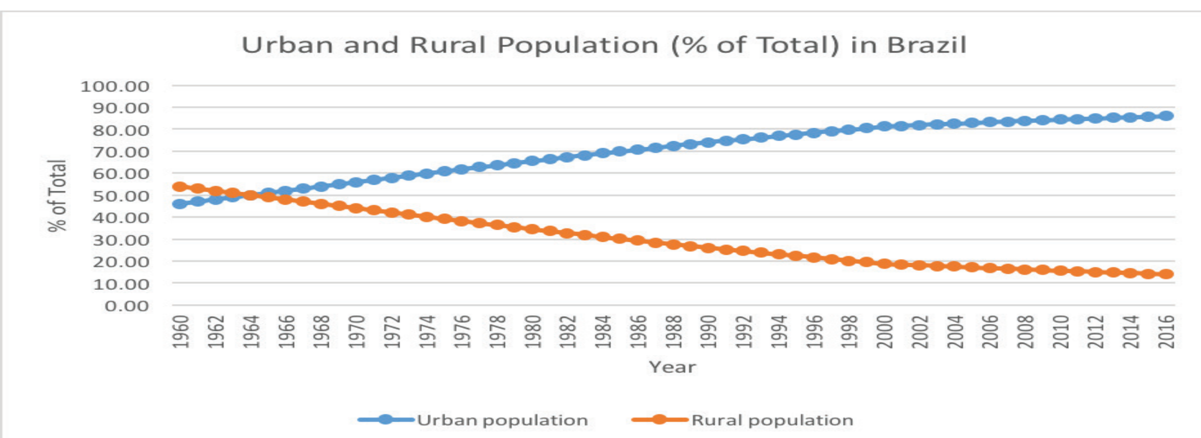
Structural Adjustment in terms of economic sectors: As shown in Figure 4, we can realize that India has experienced an economic sectors adjustment with the transition to higher proportion of value added in industry compared to agriculture around 1990. This supports the expectation of the dual sector model. As shown in Figure 5, we can see that since 1960, the value added in industrial sector has always been higher compared to the agricultural sector in Brazil. We may assume that the structural adjustment has already occurred before 1960 in Brazil. As temporary conclusion, we can argue that the evidences support the assumption of structural adjustment in terms of economic sectors in the dual sector model.

Figure 6. Urban and Rural Population (% of Total) in India (1960-2016)



Source: World Bank Data

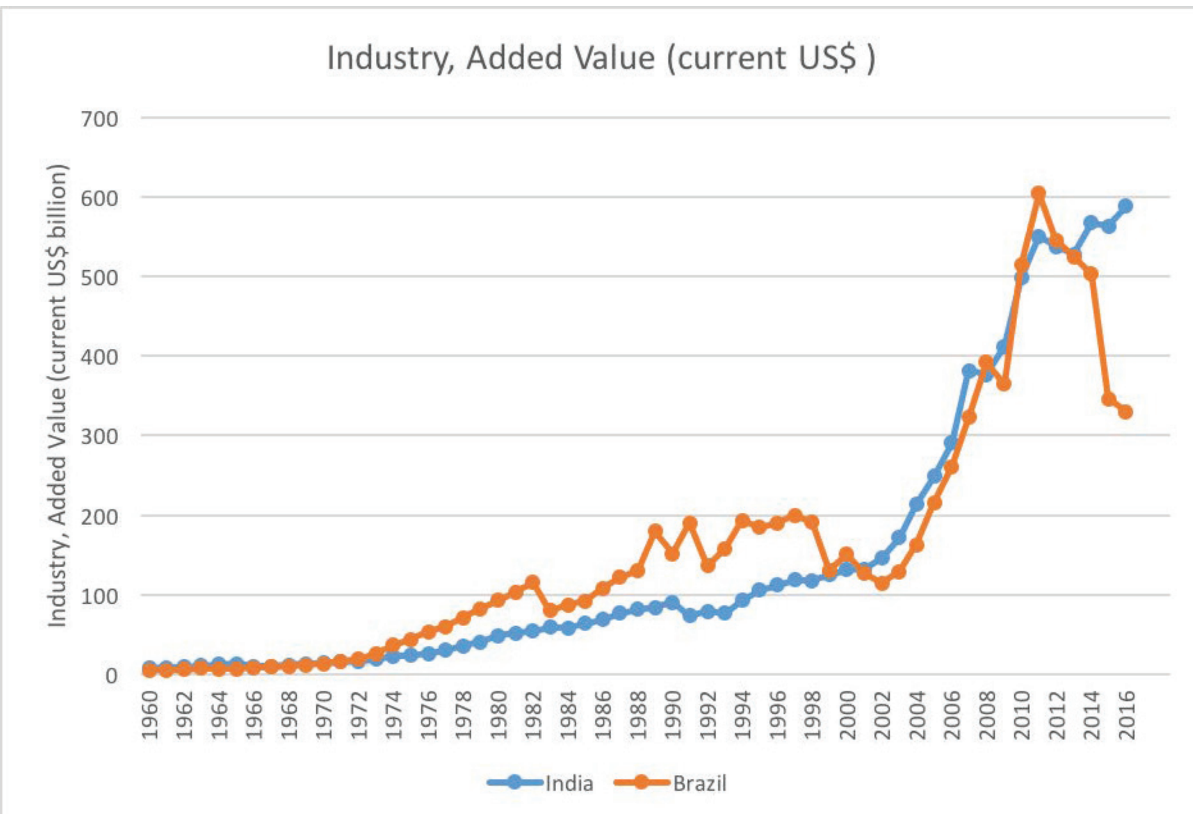
Figure 7. Urban and Rural Population (% of Total) in Brazil (1960-2016)



Source: World Bank Data

Migrations from rural area to urban area: As shown in Figure 6 and Figure 7, we can clearly recognize the occurrence of continuous urbanization in India and Brazil measured by the steady decreasing of rural population and the steady increasing of urban population. We can see that in India, there are still far larger rural population compared to urban population, while urban population has surpassed rural population in Brazil since 1965. This suggests that India may have more potential with further way to go in terms of urbanization compared to Brazil. Generally speaking, this evidence supports the expectation of dual sector model in the large migrations from rural area to urban area.

Figure 8. Value Added in Industry Sector (% of GDP) in India and Brazil (1960-2016)



Source: World Bank Data

Economic development: As shown in figure 8, there has been significantly increasing in the development of industry in India and Brazil and the industrial sectors of both countries has contributed significantly to the development of the two countries generally. This evidence supports the expectation of dual sector model that industrial sector will maintain sustainable development. However, Brazil experienced significant decreasing in the added value of industrial sector since 2010, with several minor decreases in the former years. Barbosa (2000) argues that there has been cyclical dynamic of economy in Brazil resulted from the subsidy policy particularly in industrial sectors, which may explain the minor fluctuation before 2010. However, with the reference of Figure 1, which shows a declination of value added in agricultural sector at the similar time as the industrial sector shown in this figure in Brazil, the most plausible explanation for the significant continuous declination of value added in Brazil's industrial sector shown in Figure 8 since 2010 may be the occurrence of a general decay in Brazilian economy. This is controversial to the expectation of the dual sector model and more research is needed to be done in order to further understand the sudden, significant and continuous decay of Brazilian economy since 2010.

Limitations

First, this model ignores the competitiveness of the sector in global markets. India is particularly competitive in calling sector and software sector, as the symbolic parts of service sector, resulted from their large educated labor. After the popularity of protectionism and the beginning of prevalence of the liberalization theories in economy domestically in India since 1990s, the industrial sector has been faced with severe challenges in the global market, while service sector, with the representative of calling service and then software industry, has enjoyed welcome by the Western developed countries and experienced rapid development. This may explain the significant increasing in Indian service sector and fluctuation as well as decreasing in its industry sector in their value added measured by the percentage of GDP. Resulted from the competition outside and the limitation of the capacity, the attraction of industrial sector and its ability in absorbing labors is far limited compared to the expectation of Lewis. For Brazil, its agricultural sector is very competitive particularly in exports, and this may explain why value added of the agricultural sector in the percentage of GDP maintains generally steady since 1994 and the labor in the sector even increased in the recent years. This may also contribute to the low reinvestment rate in industrial sector in Brazil. Brazilian capitalists are buying off the agricultural industries all over the world instead of investing in domestic industrial sector. The development of JBS, the largest meat processing company in the world by sales may provide a good example.

Second, the dual sector model ignores the reinvestment in as well as the growth resulted from technology. As shown in Figure 4, the value added in service sector measured by the percentage of GDP in India has surplus over the other two sectors, while the proportion of employment in the service sector maintains the second till most recently. This suggests that large output is resulted from the investment in technology or other resources instead of simply labor as assumed by the dual sector model. The value added in industrial sector also experienced a continuously decreasing since 2007. This may also suggest that the wage in industry sector is not as attractive as service sector, or the development of the sector is not sustainable as Lewis expected, or both.

Third, the model is with an assumption that labors can always adapt themselves into the jobs and touches very little on the unemployment issues after the migration occurs. Lewis mentioned that “Several writers have drawn attention to the existence of such ‘disguised’ unemployment in the agricultural sector, demonstrating in each case that the family holding is so small that if some members of the family obtained other employment the remaining members could cultivate the holding just as well (of course they would have to work harder: the argument includes the proposition that they would be willing to work harder in these circumstances) (1954)”. This leads to his argument that the living standard will increase if these surplus people can work in industrial sector gaining more wages and the average income of remaining employments in agricultural sector will increase at the same time. However, he ignores the possibility that people cannot adapt themselves to new sectors. Unemployment is a serious issue in the developing countries including Brazil and India. Among the unemployment, many of them resulted from the transition of the economic sectors and the failure of the labors in adapting themselves in new jobs. What's more, in extreme cases, it is possible that as argued by James Scott that the advancement of technology and industrialization becomes exploitation of lowest class of people (2008). It is not impossible that there are people who lose land at the same time of not being able to find job in the market. Land becomes more expensive and less affordable for the small farmers and industrial products become more expensive. Those people who cannot be adaptable to new skills or knowledge experience continuous frustration. For example, there are frequent news of suicide of peasants because of losing land and not being capable in paying debt in India (Umar, 2015) as well as unemployment in Brazil (Gillespie, 2017).

Last but not least, the dual sector does not mention any negative effects of urbanization, such as environmental damage and slums. Environmental damage is a severe challenge for quite a few developing countries, including Brazil and India. A report from Financial Times makes the point that environmental damage costs India $80bn a year (Mallet, 2016). Because of a series of economic activities as well as urbanization, deforestation in Brazil and particularly in Amazon area has been severe. Amazon is the biggest deforestation front in the world and interventions are urgently needed to prevent a large-scale, irreversible ecological disaster (WWF Global). What's more, the slum issue is very problematic in both countries accompanied by urbanization. Although the slum population as percentage of urban has decreased significantly in both countries due to the increasing in living standard and relative targeting policies according to World Bank, their existence is continuously leading to lots of problems in the two countries, including crime, public health problems, education problems and etc.

Conclusion

In this paper, we can conclude that the dual sector model still has quite some explanatory for the economic development of the developing countries. There is indeed a large proportion of labor force moving from agricultural sector to industrial sector in India and Brazil accompanied with migrations from rural to rural area, and generally the industrial sector has been contributing to the economic development of the two countries despite their differences. As a result, the dual sector model still has legacy for nowadays policy making of the developing countries in India and Brazil. First, developing countries should make efforts on infrastructure and urban planning of the cities in order to be more prepared for the large migration from rural area to urban area. Second, in the developing countries with large surplus labors, government should consider the possibility in promoting the development of industrial sector in order to create more employment opportunities. This policy is widely conducted particularly among the overpopulated countries in Asia and increasingly in Africa.

The limitations of the dual sector model also provide lessons for the policy makings of the developing countries as well. First, the developing countries should never ignore the negative effects of urbanization, and policies should be conducted to promote the alleviation on the negative effects. Most importantly, the pollution issues and environmental damage should be particularly attached importance to. Second, the developing countries should not be trapped in the myth of enlarging industrial sector under any circumstances. It is possible that the other sectors are more competitive in the global market instead of industrial sector. Third, the education especially informal skill education for labors to be adaptable in new economic sector and new lives should be arranged for the labors with less skills and the welfare targeting on the extreme poor should be improved in order to protect them in the structural change of society and its pressure on their live.

REFERENCES

1) Athreye, S. S. (2005). The Indian software industry and its evolving service capability. *Industrial and Corporate Change, 14*(3), 393-418.

2) Barbosa, N. (2010). Latin America: counter-cyclical policy in Brazil: 2008-09. *Journal of Globalization and Development, 1*(1).

3) Gillespie, P. (2017, June 1). Brazil's unemployment hits record high: 14 million people out of work. CNN. Retrieved from http://money.cnn.com/2017/06/01/news/economy/brazil-economy-unemployment/index.html.

4) Lewis, W. A. (1954). Economic development with unlimited supplies of labour. *The manchester school, 22(2),* 139-191.

5) Mallet, Victor (2013, July 17). Environmental damage costs India $80bn a year. *Financial Times*. Retrieved from https://www.ft.com/content/0a89f3a8-eeca-11e2-98dd-00144feabdc0

6) Scott, J. C. (2008). *Weapons of the weak: Everyday forms of peasant resistance.* Yale university Press.

7) Todaro, M. P. (2000). *Economic development, 7th ed.* Addison Wesley.

8) The State Council Information Office of the People's Republic of China, National Human Rights Action Plan (2009-2010), (April 2009). http://www.humanrights.cn/html/2014/3_0605/26.html

9) The World Bank, World Development Indicators (1960-2016). *Agriculture, Value Added (% of GDP).* Retrieved from https://data.worldbank.org/indicator/NV.AGR.TOTL.ZS

10) The World Bank, World Development Indicators (1960-2016). *Industry, Value Added (% of GDP).* Retrieved from https://data.worldbank.org/indicator/NV.IND.TOTL.ZS

11) The World Bank, World Development Indicators (1960-2016). *Service, Value Added (% of GDP).* Retrieved from https://data.worldbank.org/indicator/NV.SRV.TETC.ZS

12) The World Bank, World Development Indicators (1960-2016). *Agriculture, Value Added (% of GDP).* Retrieved from https://data.worldbank.org/indicator/SP.URB.TOTL.IN.ZS

13) The World Bank, World Development Indicators (1960-2016). *Urban population (% of total).* Retrieved from https://data.worldbank.org/indicator/SP.URB.TOTL.IN.ZS

14) The World Bank, World Development Indicators (1960-2016). *Employment in agriculture (% of total employment) (modeled ILO estimate).* Retrieved from https://data.worldbank.org/indicator/SL.AGR.EMPL.ZS

15) The World Bank, World Development Indicators (1960-2016). *Employment in industry (% of total employment) (modeled ILO estimate).* Retrieved from

https://data.worldbank.org/indicator/SL.IND.EMPL.ZS

16) The World Bank, World Development Indicators (1960-2016). *Employment in service (% of total employment) (modeled ILO estimate).* Retrieved from https://data.worldbank.org/indicator/SL.SRV.EMPL.FE.ZS

17) The World Bank, World Development Indicators (1960-2016). *Agriculture, Value Added (% of GDP).* Retrieved from https://data.worldbank.org/indicator/NV.AGR.TOTL.ZS

18) The World Bank, World Development Indicators (1960-2016). *Agriculture, Value Added current US$).* Retrieved from https://data.worldbank.org/indicator/NV.AGR.TOTL.ZS

19) The World Bank, World Development Indicators (1960-2016). *Industry, Value Added (current US$).* Retrieved from https://data.worldbank.org/indicator/NV.AGR.TOTL.ZS

20) United Nations Statistic Division, Millenium Development Goals Database. *Slum population as percentage of urban, percentage.* Retrieved from http://data.un.org/Data.aspx?d=MDG&f=seriesRowID%3A710

21) Umar, B. (2015, May 18) India's shocking farmer suicide epidemic. *Aljazeera.* Retrieved from https://www.aljazeera.com/indepth/features/2015/05/india-shocking-farmer-suicide-epidemic-150513121717412.html

22) USDA. (2018). *World Agricultural Production.* Retrieved from https://apps.fas.usda.gov/psdonline/circulars/production.pdf

23) WWF Global, Deforestation in Amazon. *WWF Global.* Retrieved from http://wwf.panda.org/about_our_earth/deforestation/deforestation_fronts/deforestation_in_the_amazon/

Notes:

2016 Rupee Demonetization (Dn): It's a Success!

Sudhanva Char
schar@life.edu
Life University, Atlanta, GA

JEL Code: E 52, H 26 and K42

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ABSTRACT

The November 2016 Dn of the rupee is a phenomenal event in India's monetary history with spillovers into every nook and corner of Indian economy, and yet it has hardly received the attention it warrants from economists and other professionals. To better understand the socioeconomic consequences this paper compiles and evaluates the positives and negatives of Dn in spite of challenges in quantifying them. There was uproar at the outset because of the market turmoil notebandi caused, but some twenty months later Indian economy is doing well on the Dn stress test. This is evident in a) the broadening of the tax base, b) the relatively higher degree of compliance with filing income tax returns and reduction in black money, c) the new business regulations related to Goods and Services Tax (GST) leaving little scope for corrupt ways, d) increasingly higher rates of growth in GDP and notably, e) the swift transformational change in economic behavior triggering better tax compliance as well as the exodus to digital payment modalities, and the concurrent reduction in habitual need for cash. The five structural changes above normally have a long gestation. However, the successful ongoing makeover in India in so short a time by itself calls for an intensive study tempting one to suspect if nation-state pride is one of the drivers of reform.

2016 Rupee Demonetization (Dn) : It's a Success!

VENAL AND ALTRUISTIC ASPECTS OF DN

The November 2016 Demonetization (Dn hereafter) was stunning in scale, scope, and was also ground-breaking. It was arguably the largest event of its kind in India's monetary history, withdrawing ₹500 and ₹1000 denomination currency notes as legal tender. The two notes did the heavy-lifting obligations of the role of money as a medium of exchange, store of value, unit of account and means of deferred payments. The two bills accounted for a massive 86 percent of total currency notes in circulation. No one seemed to hear the Prime Minister plead for the 50-day period of fine-tuning and restoring supply chains to refurbish a semblance of normalcy to the markets. The nature of implementation of Dn appeared somewhat flawed because of the need for keeping the entire move under utmost confidentiality to prevent leaks lest it should unravel, thereby reducing the potential for success in mopping up tax-evaded, illegally- or unethically-gained cash.

Notebandi became a complex and thorny issue and needlessly so. Political predilections of the contending sides concentrated on either just the relatively transient depredations of Dn or on the salutary effects of Dn such as the transformational change in financial behavior of hundreds of millions of people. Many antagonists, mainly rentiers, have had vested interest (including large unaccounted cash resources) in *status quo ante.* They took full advantage of a flourishing democracy with a spirited social media including TV and Press to vehemently oppose the far-reaching changes. What could possibly take decades for cognitive, social, cultural changes to occur have occurred in a fraction of that time. This significant behavioral makeover has been sidelined by critics. Such predilections, by their very nature preclude objectivity and could be a stumbling block to the cause of rapid economic growth.

Economic growth is predicated by the integrity of political institutions and a modicum of fairness in inter-party and even intra-party conflicts and confrontations.[1] Preferably politics should not be determining what economic policies the country should have, and on the other hand it should be the merits of policy or economic measure such as Dn *per se* that should influence decision-making. Opposing groups even within the same political party have been involved in undermining policies, however excellent or desirable, rather than coming up with constructive criticism and helping the overall goal of rapid inclusive growth. This is all the more a good reason independent and objective “double-handed” economists undertake studies looking into the merits of a policy rather than anything else. What cannot be belittled is the criticality of fairness in political or economic discussion, routing for the whole truth or information, rather than bits of it. Full disclosure of interests in any discussion will help understand the root cause of opposition to otherwise good policies that have much merit. This is illustrated elsewhere with reference to taxation of incomes to avoid generation of black money which bids for drastic measures.

There are numerous aspects to Dn besides the indescribable suffering of individuals, the bankruptcy of numerous cash-based businesses in the informal sector, the concomitant joblessness due to business closures and the overall momentary decline in business and loss in industrial production and jobs. There is a good deal more to this historic event in India’s monetary history than just this collateral damage. A balanced account of all aspects of Dn is already behind schedule. Hence this treatise to come up with a narrative that scrutinizes all relevant issues and lets the reader make a measured assessment of the aftermath of notebandi.

NICOMACHEAN ETHICS

The Aristotelian dictum that it is the mark of an educated mind to be able to be able to entertain a thought without accepting it is pertinent to the current discussion of Dn. Such a mind can entertain opposite view points and come up with a wise *Tertium Quid*, or in this case, the greater good. After all this is the substance of Nicomachean Ethics aimed at the good of the entire community.[2] Pareto optimality or efficiency referred more to resource allocation than to economic measures such as Dn. And so Pareto efficiency criterion such as no one can be made better off without making someone worse off, is not pertinent to cases such as Dn.[3] On the contrary what is germane is that there has to be a balancing point between selfishness and altruism. Also relevant is the fact that the economy is still inside the production possibility frontier or in the pre-optimality stage of development or growth, a stage when all persons can be made better off by measures such as Dn and GST. Model-based simulation studies such as by Vanrolleghem et al propose are beyond the scope of this study.[4]

NATIONALISM PROPS UP DN AND GST

Dn is a singularity that caused transient discontinuities in economic growth. It influenced Indian financial psyche perceptibly with a salutary enticement. The coaxing is by way of carrots for compliance and stick for non-compliance as per the laws of the land. Dn also has direct and corollary effects on the economy. The consequent better compliance with the tax laws in particular the Goods and Services Tax is can only be regarded as a transformational change that is very tough to achieve in a litigious noisy democracy. It has been accomplished in a relative short time. The perception that to no mean extent this was due to the rising nationalistic ambiance in India cannot be dismissed. There is a craving for fast and clean economic and social progress without needless politicization of even the soundest of pragmatic ideas. Influenced by past history there is today more than a modicum of national unity clamoring for achieving India's potential as a major power like China, albeit within the framework of a functioning democracy. Ambience of this kind, also ubiquitous all over China, Europe including Russia, USA and elsewhere, has contributed to the success of numerous initiatives in those nations taken by even maverick leaders offering the alluring prospect of economic prosperity in one generation.[5] The interests of the nation become overriding and most people without private or vested interests accept that. In India too this explains the overwhelming discontent for 'business as usual' and the backing for measures such as Dn, GST, Swatch Bharat, promotion of indigenous medicine including ayurveda, yoga and so forth. A majority of people do not accept corruption as a way of life even after suffering it for decades, and are desperate for cleaner public life. The Government has been constantly tapping into this wellspring of antipathy for 'business as usual' and support for progressive good causes.

The November 08, 2016 Dn was not the first time such a measure was resorted to in India. The first Dn in recent times was tried on January 12, 1946 when notes of the denomination of Rs. 1000 and Rs. 10,000 were withdrawn. Even at that time it was to deal with unaccounted money which is income concealed from tax authority. Dn was again resorted to on January 16, 1978 when the Morarji Desai government withdrew notes of the denomination of Rs. 1000, 5000 and 10000. This was what the Wanchoo Committee had recommended to reduce the menace of black money. Because the implementation of the measure was perhaps not as much 'under the wraps' as the ground realities demanded, this Dn had less than limited success in curbing black money. Neither the Finance Minister at that time H.M. Patel nor the Governor of Reserve Bank of India I.G.Patel was in favor of the measure. Their reasoning was that black money would not be hoarded in cash form, but would be in real estate, jewelry, conspicuous consumption and other forms around which it is hard for the tax authorities or anyone else to wrap their arms around.[6] Without mindful planning and effective but veiled enforcement Dn may prove to be counterproductive.

DEMONETIZATION (DN) WORLD-WIDE

In a matter-of-fact way countries have undertaken Dn of varying scale and severity and with diverse objectives. Table 1 below is a partial list of countries that tried Dn with capricious outcomes with some exception, definitely without a modicum of success in achieving the objectives of curbing tax evasion and illegal activities.[7] In India's case there appears to be an exception. Human ingenuity being what it is, it could set at naught the objectives of such monetary initiatives. Operators take advantage of loopholes to launder tax-evaded tainted money into legit clean money. Against this backdrop of general failure of Dn to achieve stated objectives, what does the evidence in India regarding the November 2016 rupee Dn show? Do the outcomes resonate with those of other countries? Has there been a modicum of success or is the jury is still out? Is it too early to tell in the area of Indian economics and more specifically in behavioral economics? The analysis that follows shows that by contrast Indian Dn of November 2016 was a categorical success.

TABLE 1. DEMONETIZATION IN RECENT YEARS AND OUTCOMES

	Country	**Year**	**Result**	**Overall Conclusion**
1	Ghana	1982	Made economy weak. Unsuccessful	People continued to support the black market and resorted to investment in physical assets.
2	Nigeria	1984	Economy collapsed,	Debt-ridden and inflation did not take change well.
3	Myanmar	1987	Unsuccessful	Led to mass protest resulting in killing of many people.
4	Soviet Union	1991	Unsuccessful	People did not take change positively due to poor harvest.
5	Australia	1996	No side effects	Purpose was only to replace paper with plastic.
6	N. Korea	2010	Weak, unsuccessful	People left with no food and shelter.
7	Zimbabwe	2015	Unsuccessful	Face value of one hundred trillion Zimbabwe dollars dropped to US $0.5 dollar.
8	Pakistan	Dec 2016	Pak Senate recommends Rs. 5000 bills retired. Govt does not accept	People were to be given ample time to get their note exchanged. So no Dn of Pakistan Rupee happened.
9	India	Nov 2016	Rs. 500 and 1000 notes withdrawn. Conspicuous success.	Transformational long-term changes expected in economy and in Indian economic behavior. Benefits infinitely more than costs.

Source: Adapted by author from Ambalika Sinha , Divya Rai, Aftermath of Demonetization on Rural Population, *International Journal of Research in Economics and Social Sciences (IJRESS)* Available online at : http://euroasiapub.org Vol. 6 Issue 11, November - 2016, pp~223~228

NOVEMBER 2016 DEMONETIZATION

There are obviously conflicting perceptions about Dn as noted earlier. By marshalling all evidence, for and against, one can tease out the net effects. One bit of proof of success that overwhelms all others is the visible transformation of attitudes about government inaction, corruption, needless politicization, and other ‘business as usual’ ways of dealing with issues whether it is Dn, GST, Aadhar-backed financial ID for all citizens, the Clean-Up Movement or Swatch-Bharat, tax compliance and so forth. This is not to deny large-as-life presence of apathy and even antipathy about most every economic issue. But thanks to social media and other info channels, there is much less of apathy, and public anger is vented more instantly than before. One angry tweet has negative (angry) reaction up to three degrees of separation.[8]

Dn as an economic measure has made an unprecedented attempt at changing economic, financial and ethical behavior. In practice it is difficult to come across one hundred percent honest tax compliance. Tax evasion is often conflated with tax avoidance and justified on that ground. Avoidance is generally accepted as tax planning, making intelligent use of loopholes in tax laws and provisions in the law for contributions to charities, parking incomes and resources in retirement funds such as (just for illustration purposes) the New Pension Scheme (NPS with 10 % annualized return) and the more popular Employee Provident Fund (EPF) Scheme with a fixed 8.5% return. Incomes set aside for such savings are deductible for tax purposes. Someone making use of such deductions is doing the right thing. But this is not the same as not declaring all incomes in order to avoid paying taxes, such as well-off persons buying farm land to set off unverifiable harvest losses against large non-farm incomes. This is something questionable ethically. Losses in farming, very often hard to figure out or similar activity are set off against profits in other businesses. This launders black into white money.

Some would like to think that evasion of taxes calculatedly with intent to do so without abiding by the spirit of the tax law could be perfidious. It is all the more so if persons with tax-evaded money enjoy all citizen-privileges of education, health care, social security, basic infrastructure such as roads, bridges, canals, electric power, street lights, traffic control, disease prevention, and the like. While this may be the stand of the general public, some business persons may think that evasion and avoidance are both defendable in view of the generally high rates of income taxation. Such a stand is not justified even if the tax rates are "high or even confiscatory." One may also observe the letter of the law and avoid taxes legally exploiting allowances and provisions of the law, and still undermine the spirit of the law by constructing escapes from tax liability, such uses not intended by law.

Specious arguments just like this for tax evasion, are available for numerous other issues including capitalist or mercantilist growth for growth sake, eliminating safety nets such as social security for the underprivileged sections, or for doing nothing about global warming. Tax evasion by the way is the fountainhead of black economy augmenting its magnitude incessantly. This is where the greater good should have the upper hand. India's Black economy size is estimated at about a quarter of the GDP by the World Bank. Under-invoicing exports and over-invoicing imports is indulged in order to build illegal funds abroad such as in legendary secretive Swiss bank accounts for later personal use by politicians and business persons. A streamlined and clean economy would help realize economic goals sooner and at less cost. This would also help reach economic growth all people, provide opportunities to one and all, and minimize the Gini coefficient.

BLACK, RED AND WHITE MONEY

Money is supposed to have three colors: Black, Red and White. The last variety is legal money that is post-income tax. The other two are monies concealed from and undisclosed to tax authority. The essential difference between the two is that while black money is income undisclosed to tax authority, red money is money received by way of bribes, commission received in a foreign currency such as the US dollar , under-invoicing of exports and over-invoicing of imports, and other illegal operations. Red money is generally tax-evaded illegal income stashed away abroad, whereas black money is mostly of indigenous origin. It is also dispersed to bribe voters or government officials, ministers as well as for payments for illegal, antisocial or antinational activities. Biggest users of black money are real estate, jewelry, politics and unorganized sectors such as the film industry, rural industries, minor and small scale and service businesses.

Account keeping is strenuous, but is not difficult. The Goods and Services Tax is now making it mandatory for every business however small to maintain books of accounts and file tax returns periodically and promptly, reducing the scope for generation of black money. Red money as well as black money can be laundered into white legal money through farm incomes, buying gold deposited as security at finance companies and pawn shops, lottery or gambling wins and several other ways. Laundering is not very hard to accomplish, but needs cooperation, concealment and confidentiality at several stages and it is not worth the effort.

INDIA'S NOTEBANDI

The good effects of Dn linger on even as GST and other administrative and legislative measures to improve economic efficiency, reduce transaction costs and otherwise streamline all economic activity roll on. There are also attempts at nudging the public, a majority of whom do not pay taxes taking advantages of loopholes and tax havens such as farm incomes which are generally income tax free even now.[9] Farm incomes have been well-used by well-off communities to escape taxation.[10]

There are other escape routes for one's black money such as by buying securitized gold from finance companies and pawn shops as noted above. However Draconian tax laws may be market economies will always scout for loopholes to dodge the laws and dodge compliance. For instance in Kerala holders of black money that have effectively evaded official maneuvers for tracking unaccounted resources, have been investing such monies to buy gold pledged with finance companies as security for loans. An amendment of 2015 to the Wealth (Tax) Act 1957 lets gold possessors free if such possessions exceeded a specified quantity. When collateral gold is sold to jewelers or anyone else black money gets laundered as white. Fugitive Nirav Modi also known as diamantaire and many like him have allegedly resorted to these swindles to conceal cash.[11]

TELL-TALE SIGNS OF SUCCESS OF DN

Counting the positives, during financial year 2018, over 200,000 non-filers have filed income tax returns and paid Rs. 64 billion by way of taxes. As many as 304,000 persons that had deposited cash up to Rs. 1 million or more in the post-Dn period have been notified to file tax returns and explain the source of their funds. Verification is being made online making use of big data analytics. Guidelines regarding online substantiation by PAN card holders together with other details are posted at *https://incometaxindiaefiling.gov.in.*[12] The website gives interesting facts that underscore the success of Dn.: Number of Registered Users 73.6 million, Registered and Aadhar Linked: 53.5 million, not registered but Aadhar linked 24.5 million, Verified Income Tax Returns 17.8 million. Often these numbers are multiples of numbers before Dn. Data Analytics used under "Operation Clean Money" detected Rs. 15,496 crores as undisclosed money and tax authorities seized Rs. 13920 crores.[13] There are millions who need to pay taxes and do not. It is this segment that is adapting quickly behaviorally to the new economic reformative milieu. Such enforcement activity puts fears in the minds of would be tax evaders, further adding to the success of Dn.

One of the non-economic benefits of Dn was one of outwitting those indulging in antisocial and anti-national activities. Nobel Laureate Kailash Satyarthi pointed out that there was a sharp drop in human sex trafficking. Black-money and counterfeit currency have funded stone-pelting in Kashmir on law-enforcing forces. This came to an abrupt end. How do we quantify these benefits in monetary terms?

The costs and benefits of Dn cannot be considered in isolation of supportive measures taken as a package to streamline Indian economy. High on the list of that package is the GST. It eliminated thousands of points of harassment and bribery on the supply chains of goods and services. It saved time and knitted the country's geographical area into a single common market. The relief brought to businesses and consumers by elimination of octroy and other central, state and local taxes and the time saved are too considerable to be neglected in any cost-benefit analysis of Dn. The measures in the package are mutually complementary and fitting. The provisions of GST, Income Tax and others help close in and pin down suspects of black money and wealth. GST enforces compliance discipline which comes in so convenient to the income tax authority. New big data analytical technology is a dragnet capable of grabbing even the sneakiest of tax evasion cases.

What the Governor of Reserve Bank of India (RBI) Urjit Patel states in a different context is true of Dn and related measures too. According to him the establishment of the GST Council, the amendments to the RBI Act and the enactment of the Insolvency and Bankruptcy Code were transformative and unprecedented.[14] The fundamental changes in terms of vesting the RBI with more power in creating the institutional infrastructure for monetary policy formulation is economic statesmanship. GST has been hailed as the best single piece of tax reform in India's 70 years of independence.[15] Similar approval of GST has been received from the IMF as a milestone reform that would unify the country and help create a common market between states in the country, besides promoting efficiency all around.[16]

HUMAN COSTS AND COST OF NEW CURRENCY

One of the negatives of the Dn was the cost of printing new notes to replace the Rs. 500 and Rs. 1000 denomination currencies declared non-legal tender. One way to figure the amount spent by the RBI to print new currency in the post-notebandi period is to process data relating to the dividend RBI paid to the Government. For the year ended June 30, 2018 the dividend was Rs. 500 billion which is 63 percent more than the previous year. Assuming the dividend recommended by the Government to be paid was the same amount as this year, and comparing it with the actual payment of Rs. 18.5 billion, it can be surmised that the difference of Rs. 31,500 not paid is the amount spent by the RBI to print new currency.[17]

Analysis of Dn without an examination of the collateral human cost would be piecemeal. Much has been written about the "disastrously botched," poor and "clumsy" execution of this bold step in India's perpetual hunt for black money and corruption: long lines at the banks in the initial months after the announcement, the abysmal helplessness of the poor who were particularly dependent on the lifeline of cash, old and sick customers collapsing in waiting lines that never seemed to end, the constantly changing rules and goalposts in what appeared as "learn as you go" implementation especially of re-monetization or the task of introducing the hot new legal tender so that lost liquidity could be made good on the double. Farmers could not buy seeds for new crops. What was the loss in farm output and the loss in incomes to farmers? Many office goers had to decide either to forego salary for a day or wait in line at banks to deposit cancelled currency.

EFFECTS OF LIQUIDITY SHOCK ON GDP

The liquidity shock of Dn was caused by lack of legal tender to replace the delegalized currency. Dn left a big gap in the intermediate range of payments between a small denomination □100 and large denomination □2000 by the retirement of notes worth □500, constituting 49% of money supply and □1000, being the other 37 %, together adding up to 86% of money supply. What further contributed to the chaos was the delay in replacement of old notes with new notes, dysfunction of ATMs, disruption in banking, and the pupation period for the payment mechanisms to emerge fully-fledged as a legit and mature payment system. In no small way did the disruption contribute to curb and constrict agriculture, construction, production, real estate business, jewelry, garment manufacturing, bus transportation, workshops and repair shops, and the economy as a whole. Black money facilitates much of construction, luxury goods, real estate, liquor, tobacco and other business and as noted earlier it overlaps with the informal sector. Nevertheless, the real story of the impact of Dn on output seems to be somewhat different as seen below in the data tables.

Fig. 1 below gives the annual GDP chart. Apparently there is no discontinuity in growth as can be discerned in the chart based on World Bank data in billion US Dollars. The economy seems to be chugging along normally. Numbers seem even incredible: growth during 2017 over 2016 is an impressive 14.21 percent, as much as $323.29 billion coming on top of $2274.20. However, it is the quarterly data as shown in Table 2 that captures the breaks in growth.

FIGURE 1. ANNUAL GDP GROWTH

FIGURE 2. GDP GROWTH RATES

During the Quarter ended June 2016 GDP reached the highest growth rate of 9.2 percent and over the next four quarters it kept declining. What is critical is that declines started not after Dn but much before that, some two quarters earlier. This would mean that the declines were not caused by Dn, but it is possible that the cash crunch caused by disruption in cash flows on account lack of overall liquidity in the economy contributed to accentuate the downward trends in total output. This was all the more aggravating particularly for businesses in the informal sector which woke up suddenly to find there would be not much of a resort to foot-loose funds or funds often not accounted for. As cash, the lifeblood of businesses became increasingly available, production in all sectors started picked up and this is seen in the histogram for quarter ending September 2017, the growth rate climbing from 5.6 % and reversing the trend. Somewhat the same trends for the 2016-17 period are seen in Table 3 presenting the value contributed by the construction sector in billions of rupees. After dipping below normal during this period, the revival in 2018 is perceptible.

Incrementally higher growth rate in GDP is expected to continue far into the future, even increasing to 8 to 9 percent, subject to stability in world trade, domestic political and economic atmosphere, weather conditions for farming, word oil prices, and so forth. More recently, Arvind Subramanian has expressed optimism that GDP growth would resume at a much higher level of 8.5 percent if: a) Demand picks up b) Restrictions on large transactions are eased and c) There is recapitalization of banks after minimizing bad debts they were burdened with.[18] There is a measure of dynamic scoring here, reckoning that the momentum of growth would have beneficial exogenous effects radiating on the economy. Arvind Panagariya has also mentioned more or less the same rates.[19]

Currently the economic fundamentals could not have been stronger. “Animal spirits” as termed by John Maynard Keynes has been unleashed in the Indian economy. It can be witnessed in investments in highways, ports, airports, railways, defense and ordnance industries, health care, rural electrification, river cleaning, toilets for the masses, farmer debt reduction, public sector bank recapitalization and so forth. In much of these endeavors there is Public and Private sector Partnership (PPP). High rates of growth have been supported by a transparent, corruption-free and time-bound administration. In any case, India is destined to emerge in its own right as a major power on the world stage with good possibilities of double-digit growth rates enabling doubling of GDP every 8-9 years, eventually to $20 Trillion by 2036 as per the simplistic rule of 72.

FIGURE 3. CSO QUARTERLY DATA ON VALUE OF CONSTRUCTION

OTHER CAUSES FOR POST-DN GDP RATE DECLINE

GDP decline that had started even before Dn in November 2016 was also due to the fall in farm output following less than adequate rain fall during both the rabi and khariff seasons of 2016. While in February 2016 the rainfall deficit was -59.5 percent of the long period average (LPA) it was +10 percent of LPA in February 2017, and so a better than normal rainfall.[20] There were external factors too that affected India's export performance. The Trump administration initiated world trade disrupting protectionist bustle and pursuits that impacted India's billings for software and internet services. There were cancellations of outsourcing back office contracts. For want of jobs and restrictions on hiring holders of H-1B visas in the USA, many of them returned to India or re-migrated to other countries such as Canada.[21] China's economy ceased to continue to operate at double digits and in fact had started to slow down to around 7 percent. Even these growth numbers are suspect because of lack of transparency and the growth numbers put out by China seem to be too linear not capturing variations in factors like iron imports, movie ticket sales, orders for earth-moving equipment, besides consumption and construction data.[22]

Indian exports declined for five consecutive quarters beginning Q_3 2015 and ended only Q_3 2017.[23]

Besides these global commerce factors there were a few domestic reasons too, domestically the decline in farm output was mentioned above. Next, there was the direct impact of the July 01, 2017 roll-out of General Sales Tax prompting businesses to destock inventory in June 2017 prior to price relabeling.[24] Second, there was a refiguring of wholesale prices. The unorganized sector overlaps with the underground economy or has a common Venn space with tax-evaded economy. Real estate business came to a standstill and lost buoyancy. With the waning of, if not complete loss of the practice of "Pagadi" or rent-seeking behavior of urban home vendors, the for-sale home inventory just seemed to fade away from the market. The demand for paying Pagadi or half the purchase price of apartments "in black" was almost gone contributing to substantial decline in business.

A remarkable observation while studying the impact of Dn on GDP was the robust spending all through 2016 and 2017 by the Union and State Governments. The well-off sections of society including in the rural areas apparently continued with their conspicuous as well as normal consumption by resorting to *inter alia*, non-cash media of payments such as credit cards and on-line. As a result the adverse aspects of Dn and cash crunch were cushioned by Government and personal consumption. This buoyancy in spending, and the resiliency in the economy, corroborated by the RBI prevented further declines in output.[25]

TRANSIENT UNEMPLOYMENT

Much cash was shredded or even burnt for fear of being prosecuted for unaccounted money. As incomes (mostly in the unorganized sector) fell consumption regressed too. There was one report claiming over 2 million street vendors were out of business because of cash shortage. Many live from day to day relying on daily cash earnings. Temporary job losses were there prompting critics to claim that the far-reaching monetary event was anti-people. But the real fact is that unemployment had hit the lowest rate by then as Table 2 and especially Fig. 4 show. The underground economy which is the sustainer and regenerator of tax-evaded money often overlaps and makes over into the informal unorganized sector. The conundrum here is that till recently about 98 percent of Indian economy was based almost wholly on cash.[26]

TABLE 2. LABOR AND UNEMPLOYMENT DATA

India Labor	Last (2016)	Previous (1983)	Highest	Lowest
Unemployment Rate (%)	3.46	3.49	8.30	3.46
Employed Persons (in Thousands)	29650.00	28999.00	29650.00	17491.00
Unemployed Persons (in Millions)	44.85	48.26	48.26	5.10
Labor Force Participation Rate (%)	52.50	50.90	52.90	50.90
Population (in Millions)	1299.00	1283.00	1299.00	359.00

FIGURE 4. RATES OF UNEMPLOYMENT[27]

THE PLUS SIDE: TRANSITION TO CASHLESS PAYMENTS

It is here that the second most welcome financial transformation and significant behavioral change are happening. Without Dn and GST, the lurch towards less ethical ways in real estate and other businesses would have been inconceivable. The government has taken initiatives for financial inclusion of millions still in a subsistence more or less 100 percent cash economy. The **J**an Dhan program has brought millions of persons with or without regular incomes under the banking sector by opening accounts in their names. Supplementing Jan Dhan is the **A**adhar unique identity card giving all Indians recognition and a modicum of credentials as citizens, not unlike the Social Security number for all Americans. A third thing that is most enabling of digital payments is the **M**obile Temporary phone. All three have a popular synonym of **JAM**. FinTech is substituting bank branches in unbanked areas making many remote areas and villages get connected for noncash payment systems. People are getting more tech-savvy, especially the Generation X, Y and Millennials. As a result the number of internet users has jumped from 302 million in 2014 to 900 million in 2018. About 350 million persons still outside the internet, will be covered in just about a year, enabling full-fledged e-commerce for the entire population.[28]

The world over, with India not being an exception, non-cash payments are increasing by leaps and bounds. According to the World Payments Reports (WPR) this growth is likely to be almost 11 percent per annum through 2020. For Asia and in particular for India and China the WPR projects a 30.9 growth rate, the largest growth being in B to C, B to B growing at a less impressive 6.8% because it is already highly digitized[29]. During 2014-15 the growth in noncash transactions volume was 11.02 %. Just in the first three months after Dn the growth of digital wallet companies has been phenomenal to the tune of 281 percent or by Rs. 191crores or $2.8 B.[30] The ecosystem for such leapfrogging in non-cash payments such as installing point of sale paraphernalia, mobile phones, WiFi apparatus is already there in the urban areas or in the blueprint stage. One instance of that is the Prime Minister Modi's proposed creation 100 smart cities which are citizen friendly and technologically adequate, leave alone being digital payment responsive.

Compared to Singapore, India is far behind in digitized payments as can be seen in Table 2 below.

TABLE 2. CASH DEPENDENCE

Country	% Cashless
1-Singapore	61%
2-Netherlands	60%
3-France	59%
4-Sweden	59%
5-Canada	57%
6-Belgium	56%
7-United Kingdom	52%
8-USA	45%
9-Australia	35%
10-Germany	33%
11-South Korea	29%
12-Spain	16%
13-Brazil	15%
14-Japan	14%
15-China	10%
16-India	2%

Source: MasterCard Advisor's

Though the data could be somewhat dated and not picking up more recent trends in post-Dn period, it shows India's relative rearwardness in ranks and how far ahead she can go in digitization.

MEASURING PROGRESS TOWARD A CASHLESS SOCIETY

Digitization is occurring faster than ever before looking at the number of cell phones sold in India and also the point of sale paraphernalia installed in stores and other business places including in petty shops, taxis, wayside vending units and such others. Between 2013 and 2018 the number of mobiles in India went up from 524.9 to 775.5 million or by 47.7 percent. The trend continues thanks, inter alia, also to the JAM scheme mentioned above. And then it can be assumed that most small payments would be made digitally as well as by online transfers from account to account and through credit cards, thereby bringing down use of cash further. This has implications for the stock of money and velocity of circulation, the latter increasing and the former decreasing. This topic has been dealt with separately under Currency in Circulation. Suffice here to note that the number of cash payments constitute 98% of all payments for India. In terms of value it is 68%. In other words 32% of the value of all payments are noncash payments. The latter number is closer to 50 percent today and the number of payments could constitute 80 percent of the total number of payments. These trends will receive further boost with the implementation of smart city program. The smart cities would have good externality effects rubbing off on neighborhood towns and villages. Reinforcing the positive development would be the emergence of demographic groups like Generation X, Y and Millennials which are more ready to switch to digital payments, as noted above, than baby boomers. Digital payment facilities are increasing by leaps and bounds and so also the digital transactions which can happen 24/7 enabling persons to shop till they drop. Consumption and investment expenditure would then trigger faster growth.

POSITIVES AND NEGATIVES OF DN

Assuming India's black economy is about a quarter of the overall economy, and given that the GDP is \$2.264 T (for 2016 at constant 2011-12 prices) there has to be a substitute medium of exchange for about \$566 billion of economic activity that has so far been sustained by the tax-evading and/or informal segment of business. Hitherto, the informal sector has operated on mostly cash basis and did not generally comply with the laws of the land in regard either production, distribution, commerce or any other aspect of business. After re-monetization and after GST, liquidity has returned to this sector and has also been supplemented by digital payment modalities. Digital systems and GST help trace such business activity making Indian economy more inclusive. This is a major gain of Dn. Digitization is being dealt with at the end.

The first negative was the deprivation of a large number of persons making a hand to mouth existence on daily cash earnings, or from paycheck to paycheck. Most persons had to stand in long ques at considerable cost to thousands of individuals. Some persons with physical complaints had their conditions further aggravated because of strain. The negative results were no doubt grave, as noted earlier. Dn shut out a whole lot of cash-based activity in the informal penumbra area of business. There were also dramatic revelations of caches of unaccounted money which got either deposited in the banks before the expiry dates for deposits of currency withdrawn from circulation. Some large amounts were distributed on trust and some amounts of currency were allowed to rot or dropped in temple hundis, or even shredded.

One of the main objectives of the Notebandi was to uncover black money hoards and this was achieved to some extent, though much less than 100 percent. This drastic measure was a significant part of the multi-pronged strategy to widen the tax base. Dn flushed out considerable amounts of black money compelling persons with such undeclared cash to deposit them in banks or lose them for good. Where such deposits were made, the authorities questioned the source of such funds especially when they were disproportionate to the declared or incomes shown on tax returns. Big data analysis techniques were pressed into service by the Income Tax Department (ITD) and 18 lakh persons were identified as persons of interest. Much of the work of the ITD is online: receiving online returns, queries addressed on line, and communications are online including refunds minimizing opportunities for bribes and foul play.[31]

In June 2018 there were reports that Indian funds parked in Swiss banks rose by as much as 550 percent or by Rs. 7000 crores. This was surprising because it reversed a 3-year trend, and in particular after the clampdown on black money. The report was nullified by the Acting Finance Minister Piyush Goyal making use of Bank for International Settlements (BIS) data. The data show that after 2014 deposits with Swiss banks by Indians fell by as much as 80 percent and during 2017 alone by as much as 34.5 percent. In discussions with Swiss authorities the latter faulted the reports claiming a 50% increase.

Interpretations of data of changes in deposits were erroneous. Since 2017 the Common Reporting Standard with many countries has enabled India to receive financial information of Indian residents and this in turn has been useful bringing unaccounted income and assets under purview of Indian taxes.[32]

Much of the funds that politicians collect from all sections of the society are for the purpose of not just enriching oneself, but also for building large caches for battling the elections and winning them so that the money-making scheme may continue. Money in circulation normally goes up at the time of election campaigning. In order to curb this practice, the Finance Minister announced that anonymous donations would be capped at Rs. 2000 from the present Rs. 20,000 per person.

Conversions into real estate are still being caught by government investigators. New laws are coming up to assess unaccounted and benami property, putting fear in such owners.

Deposits of over □250,000 were put under the scanner to demand payment of the penalty of 200 % of the amount of tax due. By tracing such flows to individuals and firms the enforcement authorities have been able to discover unaccounted amounts to the tune of □17,000 crores gathered from 58,000 bank accounts belonging to 35,000 deregistered companies. 224,000 companies have been classified as shell companies on account of non-compliance with post-Dn regulations. 1,773,000 suspicious cases have been identified that do not match the tax profile. Deposits worth □ 368,000,000 million are under scrutiny. Over 300,000 directors have been disqualified for the same reason.[33] No doubt there will be long litigation and the Government may not have the wherewithal to press them. Be that as it may, even if Dn has just nudged people towards better tax compliance and ethical behavior that could be regarded a major achievement. Similarly rent-seeking and corruption especially in areas such as real estate have come down visibly.

Among non-monetary benefits, besides behavioral change, over the longer run, there have been several more such as the reduction in violent political agitations. There are serious problems of evaluating these benefits in monetary terms so that such amounts serve as the benefits (numerator) to be divided by the costs (denominator) to figure the cost/benefit ratio for Dn.

TAX-EVADED MONEY UNCOVERED

If black money is 25% of GDP of $2.264 T, what part of this black segment of the economy of about $566 to $600 billion was mopped up? Another interesting question is: Is GDP data exclusive of the contribution of the black economy? Not all of this could be in cash, much of it already converted into property. So the focus is on checking increase in wealth.

The RBI Annual Report mentioned earlier has announced that about 99 percent of the demonetized currencies had found their way back to the banks. Vast sums have flowed into the banks, quite a windfall, considerably improving bank liquidity. Almost all of the estimated □15.4 lakh crores ($242 billion) in high-currency bills removed from circulation has returned to banks, the actual being □15.28 lakh crores. This means that directly or otherwise the notes returned and got exchanged for new notes or just got deposited. There are caveats here. First the tax-evading world includes both the all-cash world (up to 7 percent of the total,) as well as the in-kind world, in the form of bullion, real estate, and other assets. Second tax-evading money found ways to convert itself to clean money by employing mules and proxies for deposits, and benami purchases using backdated bills, and through collusion with some bank officials willing to bend rules. Dn would have to be followed up by other measures to trace black wealth. GST and other taxes could help tackle that. In this limited sense of scooping up funds of black money Dn has been a success.[34] In the future, in the absence of black money, Dn and digitization would serve as a great equalizer, everyone hopefully contributing their fair share of taxes according to their incomes and wealth. However in the absence of farm taxation, agriculture could continue to provide a tax haven to the rich.

There has been a deliberate attempt to broaden the tax base by means of cleansing the economy of unaccounted money and property. Dn was definitely one of the surgical attacks on such cache compelling many persons to deposit such cash in banks. Persons making large deposits were questioned, as stated above, and the number of such persons depositing monies disproportionate to their income is 1.8 million. They were asked to disclose the source of their undisclosed income. Current technology is being used for big data analysis and most of these inquiries through tax authorities is online including tax returns, queries, assessment orders, and where needed, refunds too.[35]

Dn delivered sizeable new liquidity to banks. The Government took advantage of this windfall and approved recapitalization of Public Sector Banks (BSB) in a front-loaded manner. The total allocation for this purpose is □ 2.1 trillion. It comprises of budgetary provisions (□ 181 billion), recapitalization bonds (□ 1.35 trillion), and raising of capital by banks from the market while diluting government equity share around □ 580 billion, thanks to the impact on black money.[36]

In any discussion of Dn, it is but natural to look at the efficiency of monetary policy transmission, one of the least-discussed matters. In the US the Duffie-Krishnamurthy Dispersion Index of money market rates purports to measure pass-through efficiency.[37] Typically a change in interest rates should be reflected in all money market rates such as rates on deposits, CDs, lending to households and businesses, to government and interbank lending. Friction-less pass-through transmission with low DK Dispersion Index is essential to achieve objectives for inflation and growth. It is easy to suspect that in India tax-avoiding unorganized sector could raise the Dispersion Index. As such the need for such an Index in India acquires new relevance.[38] In its absence there is the real possibility Dn or GST get scapegoated for any economic illness.

CURRENCY IN CIRCULATION

Currency in circulation is 12% of Indian GDP. Some 86% of the 12% or 10.32 % was withdrawn under Dn. The plus point is that a substantial part of the informal sector got formalized and financialized enabling monitoring by authorities. Bank liquidity improved substantially and brought down lending rates. People use rupees every day, but that amount is a fraction of the money in circulation. In India the measures of money supply are as follows:

$\mathbf{M_1}$ = Currency held by public (C) + Demand Deposits (DD) + Other Deposits with RBI (OD)

$\mathbf{M_2} = \mathbf{M_1}$ + Savings Deposits with Post Office Savings Banks (SD)

$\mathbf{M_3} = \mathbf{M_1}$ + Time Deposits with Commercial Banks (TD)

$\mathbf{M_4} = \mathbf{M_3}$ + Time Deposits with Post Office Savings Banks excluding NSC (National Savings Certificate)

A major plus is an appropriate rein on money supply in recent years. This has enabled better management of business needs. It also checks on inflation. And yet, as Fig 5 below shows there has been year upon year money supply growth in India of around 14 percent with inflation rates around 8 to 10 percent. Other countries with money expansion at the same rate as in India are successfully controlling the inflation rate at just 2% (Fig. 5). In China there is state control of much of the economy and it is not a surprise. In India

possibly, tax-evaded money or the informal economy may explain relative higher inflation.

The new inflation target mandated by the Government to the Monetary Policy Committee of RBI is 4%, not the glide path of current 8% → 6 % → 4%. It is also the mandated target for four years.[39] Inflation targeting just got a bit easier with the reduction of currency in circulation as well as by the increasing switch to digital payment systems. Considering that the number of points of sale (POS) has more than doubled in just one year soon after Dn, what is the reduction in currency in circulation? The answer is negative as Table 4 below shows, the last Difference Column in particular.

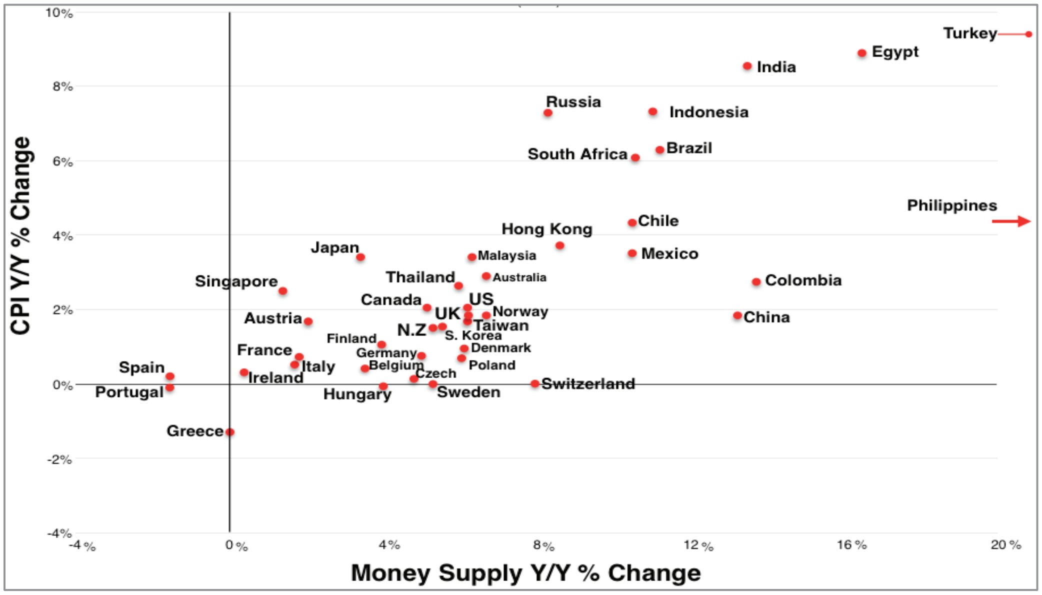
TABLE 4. MONEY STOCK MEASURES (□ BILLION)

Items	**As on May 25, 2018**	**As on Nov. 11, 2016**	**Difference**	**Difference as % of 2016**
1 Currency with the Public (1.1 + 1.2 + 1.3 – 1.4)	18,538.70	15,972.50	2,566.20	16.07
1.1 Notes in Circulation	19,050.60	16,415.60	2,635.00	16.05
1.2 Circulation of Rupee Coin	249.6	211.6	38.00	17.96
1.3 Circulation of Small Coins	7.4	7.4	0.00	0.00
1.4 Cash on Hand with Banks	768.8	662.1	106.70	16.12
2 Deposit Money of the Public	13,100.30	10,052.80	3,047.50	30.31
2.1 Demand Deposits with Banks	12,831.60	9,898.30	2,933.30	29.63
2.2 'Other' Deposits with Reserve Bank	268.6	154.5	114.10	73.85
3 M_1 (1 + 2)	31,639.00	26,025.40	5,613.60	21.57
4 Post Office Saving Bank Deposits	1,028.00	615.7	412.30	66.96
5 M_2 (3 + 4)	32,666.90	26,641.10	6,025.80	22.62
6 Time Deposits with Banks	108,206.50	90,150.80	18,055.70	20.03
7 M_3 (3 + 6)	139,845.50	116,176.20	23,669.30	20.37
8 Total Post Office Deposits	2,881.40	2,084.10	797.30	38.26
9 M_4 (7 + 8)	142,726.90	118,260.30	24,466.60	20.69

Source: Compiled by the author from period-relevant *Monthly RBI Bulletin*.

A direct answer to the question is hard considering that some are debit card-like, a payment facility that can be used after a deposit with the issuing bank. Others are credit card like, more in the nature of a loan that could possibly increase spending capacity. Subject to these caveats the key components of money in circulation and the differences if any between November 2016 and July 2018 are presented in Table 3 above. Each percent at the end of each row has a story to tell. For instance, the significant increase in Post Office Deposits by almost 67 percent in the post Dn period is indicative of the anxiety to find an inconspicuous parking place for one's unaccounted money, perhaps a little less dicey than a plain bank deposit.

FIGURE 5. COUNTRIES MONEY SUPPLY GROWTH vs INFLATION RATES (2014)[40]



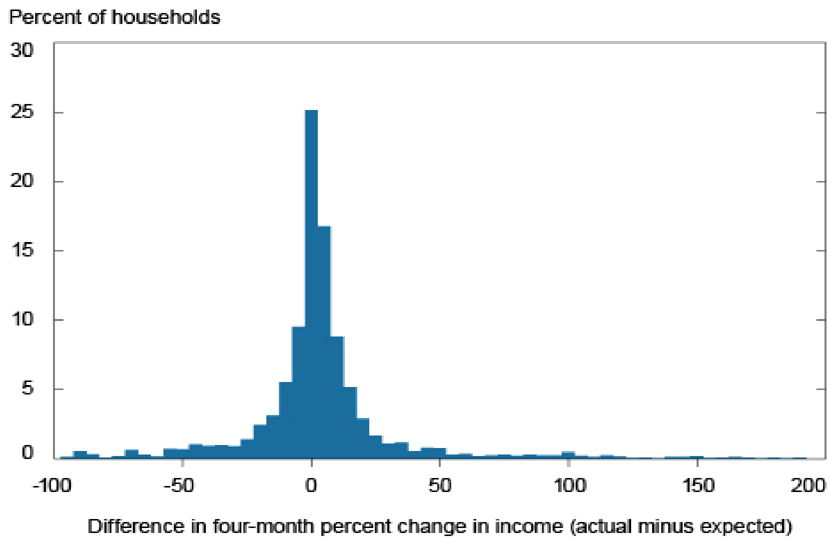
A debit-card like payment facility is part of a deposit that could be part of M_3. What is the impact of payment facility on velocity in circulation? What will be the new velocity in circulation, how much more than 1.3, the RBI rate? In 1960 velocity was as much as 4.464. Broad money as percent of GDP went up from 22.4 to 75.6 %. There is reason to believe that Dn and digital systems do bring down broad money as percent of GDP to less than 75%. This author believes that considered responses to these queries would help approximate, if not quantify the key parameters such as money supply and velocity of circulation.

LOSS OF INCOMES

For a sizeable number the workforce incomes are not always steady and do vary. (Fig. 6) Regardless of whether people adjust their consumption or even compromise on their standard of living, basic bills have to be paid. The fact of adjustments however difficult is a fact of life, however much unpalatable due to loss of jobs, loss of business, flood and other natural catastrophic losses, both expected and unexpected as shown on the left of the graph, and positive changes such as bonuses and pay-rises, on the right of the graph. In the west it may be normal for the typical worker to change jobs. Fig. 6 data may be somewhat true of people here too or it may not be so in India to a varying degree. Strong social links and networks cushion shocks.

One of the reasons for relative calm even after the upheaval of Dn is the fact that earnings of households and individuals in India also do vary as between actuals and expectations. New York Fed Survey of Consumer Expectations (Fig.6) shows that both pleasant and unpleasant changes in income (actual minus expected) occur to households sometime or the other.[41] There is zero change in incomes in the case of only 25 percent of households, and for the rest of the 75%, it changes seven times during the first ten years, which is about two-thirds of the person's career total.[42]

FIGURE 6. INCOMES EXPECTATIONS AND REALIZATIONS



Sources: New York Fed Survey of Consumer Expectations; authors' calculations.

MORE POSITIVES THAN NEGATIVES

What most observers were not ready for was the ease with which the common man everywhere came to accept despite the discontent. Dn was agreed to as a necessary disruption in order to: (1) Reduce black money so that the massive disparity between the rich and poor could be alleviated, if not eliminated. (2) Rein in terrorist activity. (3) Curb illicit money that is flooding borders states like Punjab and Rajasthan with addictive meth and heroin. (4) Prevent financing of other antisocial and anti-democracy rackets such as vote-buying and political donations. (5) Increase tax compliance and bring more revenue to the Indian government. The Finance Minister Arun Jaitley believes that in terms of achieving major objectives such as a less cash economy, digitization, formalization of the economy, widening the tax-base, formalization of the unorganized sector, clamping down counterfeit currency and so forth Dn has had extremely positive outcomes.[43] At least some of these benefits from Dn were unintended and even serendipitous perhaps like the swift makeover in behavior vis-à-vis compliance with tax law.

The deficiencies in implementation do not however detract from the rationale for Dn. A groundswell of validation of the radical move has come from Kenneth Rogoff to achieve objectives such as: a) reduce corruption and curb terrorism b) curb traffic in humans and such other undesirable activities c) digitize transactions so that regulatory authorities can overview suspicious trails of money flows and d) make rapid advance towards a minimal-cash economy with no big denomination currency. It shows how high-value currency can be phased out of the economy. Rogoff believes that there is an increasing trend towards digital payment systems including credit cards, and yet currency in circulation is pretty large. Where is the justification for a large currency in circulation?[44]

In some advanced economies problems related to stimulating consumption expenditure with the help of a zero lower bound (ZLB) as during the 2008 recession are relevant. However, for post-Dn India issues such as liquidity trap, ZLB, interest rate reduction issues and the like are not relevant and at best are of academic interest. Thanks to Dn banks are already flush with cash balances and many of them are using such surplus to reduce lending rates, engineer robust capital structures and rid their balance sheets of non-performing debts or assets which are about 19 percent on average. Notebandi will not eliminate all ills, but at least India will start addressing those issues more seriously.

When transactions are conducted on the basis of digital information rather than banknotes and coins which are legal tender, we enter the cashless economy. There has been general perceptible trend towards cashless societies where is cash is replaced by cash equivalent digital credits. There is nothing out of the ordinary in the realm of personal banking—roughly 12 percent of the population—are enabled to participate in the formal economy and learn pecuniary smarts. What is welcome is that personal banking is getting stronger thanks to the authentication provided by Aadhar ID cards, which now number more than 1.1 billion for India’s 1.3 billion. The results in Table 5 below show that the trend towards digital payments has been accelerated by Dn. Check payments in value had the lowest growth of 2.9 % in value. Growth in card usage at points of sale was the largest at 93.83 percent and in terms of value it was 82.98%. Real Time Gross Settlements (RTGS) had an impressive growth of 14.6% for volume and 20.36% for value. Retail Electronic Payments (REP) growth was 40.76% and 51.95% for volume and value respectively. Despite these sizeable differences, matched pair test shows that there is not enough evidence to reject the hypothesis of equality of means in the first and the third columns (Test t -1.3748, Critical t ± 2.3646, and P-value = 0.2116) as shown in the plot below (Fig.6).

The use of credit cards increased 33 percent during 2017-18 (coming on top of 30 % last year) compared to fiscal 2016-17 from 29.8 to 37.4 million and the value of transactions put through them almost doubled from Rs. 2.43 billion to Rs. 4.62 billion.[45]

To be sure, there are certainly enough hurdles, especially in India, that could make going significantly cashless fanciful, if not unattainable. The system requires a certain amount of sophistication and faith that may be hard to come by in the lowest strata of economic class; not to mention logistical challenges of shifting such a huge mass of population into a digital economy. Not all street vendors will invest in POS hardware. And then there are issues of cybersecurity where even one bad incident can spook millions of those living hand-to-mouth.

TABLE 5. SUMMARY RESULTS OF MEAN EQUALITY TEST FOR PRE-DEMONETISATION, DEMONETISATION AND POST-DEMONETISATION PERIODS

Payment Category		Monthly Average			Mean Equality Test Results
		Pre Dem ($\bar{x}_1$)	Dem ($\bar{x}_2$)	Post Dem ($\bar{x}_3$)	
Cheque	Volume	88.50	119.88	97.45	$\bar{x}_1 < \bar{x}_2 = \bar{x}_3$
	Value	6623.86	7095.49	6819.41	$\bar{x}_1 = \bar{x}_2 = \bar{x}_3$
Retail Electronic payments	Volume	306.93	391.57	432.04	$\bar{x}_1 < \bar{x}_2 = \bar{x}_3$
	Value	9087.21	12950.59	13808.39	$\bar{x}_1 < \bar{x}_2 = \bar{x}_3$
Card at POS	Volume	192.53	406.56	373.18	$\bar{x}_1 < \bar{x}_2 = \bar{x}_3$
	Value	390.37	726.52	714.29	$\bar{x}_1 < \bar{x}_2 = \bar{x}_3$
RTGS	Volume	8.49	9.54	9.73	$\bar{x}_1 = \bar{x}_2$; $\bar{x}_1 < \bar{x}_3$; $\bar{x}_2 = \bar{x}_3$
	Value	74410.61	87531.27	89561.59	$\bar{x}_1 = \bar{x}_2$; $\bar{x}_1 < \bar{x}_3$; $\bar{x}_2 = \bar{x}_3$

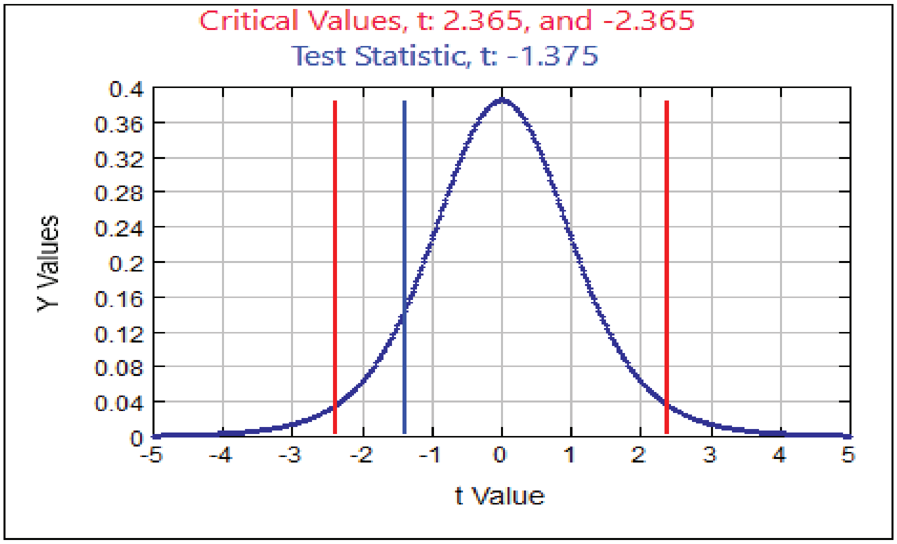
Source: Sasanka Sekhar Maiti, Mint Street Memo No. 07, *From Cash to Non-Cash and Check to Digital, The Unfolding Revolution in India's Payment Systems*, available at https://rbi.org.in/Scripts/MSM_MintStreetMemos7.aspx46. Data in Table 2 have been derived using a linear regression model and applied to time-series data separately for volume and value. The first three periods relate to volume and the last two to value. Details of the model are mentioned in source cited. The data relate to the following periods:

Apr'05-Feb'08	Mar'08-Oct'15	Nov'15-Aug'17	Apr'05-Oct'08	Nov'08-Aug'1

Skeptics who doubt the prospects of a cashless economy in India abound, and perhaps with good merit. But as of now, the results are palpable. Maharashtra government is going for a cashless payments system for fees, fines and taxes. The same Government is introducing BHIM-Aadhar biometric Pay app in rural areas. It will also continue with existing credit card and other modes of cashless system. Street vendors and auto drivers are switching over to digital wallets with payments going directly to their bank accounts. Since Notebandi was initiated, PayTM alone, the largest digital payments company, signed up some 20 million customers in just about a month, bringing its total number of customers to a sizeable 177 million. The growth would have been more but for its connection with the Chinese company Alibaba, the single largest shareholder. At this rate India will go significantly cashless sooner than most other countries and could be the first third world economy to successfully undergo the digital revolution.

This is no small achievement for an emerging economy with a sizeable illiterate and a much larger apathetic population. What are the implications of such a shift towards a cashless economy for Indian business and economy?

FIGURE 7. MATCHED PAIR TEST RESULTS.



Source: S. Char (2017) based on data in Table 3 above.

First there is the inclusion of vast sections of people and also vast unmonetized areas of the economy, enlarging the tax base, additions to quantity of money of legitimized ex-black money, less utilization of real estate as a buffer for inflation and as long-term investment. There will be more inclusion and more democratization. New trends may emerge in finance management for both households and business. Will the burgeoning cashless economy lead to better working capital management as well as less investment in non-performing assets? The trends compel positive outcomes.

TERTIUM QUID

The costs and benefits of Dn have been evident and this is because of the very nature of the Indian economy with a sizeable tax-evading economy which had become something of a way of economic life. It had embedded itself in every segment of the economy including religious places. There were many who wanted this pattern to continue or were apathetic and there were many more who wanted the cancer surgically chopped out of public life. The latter had zero tolerance for such economic behavior. Also it would be hypocritical to disparage Dn as anti-people and remain serene about corruption which citizens suffered for decades and which discouraged business, and even charity initiatives and entrepreneurship. Serendipity has helped too with rapid digitization of payment systems and making the economy more formal and inclusive, making it more difficult to be noncompliant. Now that business comes to know where policy chips my fall, and their pattern, there will be brisk investment activity.

While dealing with the costs of Dn one cannot ignore that the declining trend in output had already set in even before November 2016. It is possible that Dn accentuated it to some extent because of the cash-dependent informal sector. The same is true about job losses and unemployment. Again the trends are heading north after taking in their stride issues such as the new price-labeling in post-GST period, the confusion caused by wholesale price index changes, the liquidity crisis due to delays in making available new cash, malfunctioning of ATMs, and other hobbling hindrances.

Dn and other economic measures have the character of long-term measures with a gestation of about 2 years. They defy modeling and coming up with a template. The far-reaching measure is still impacting positively much of Indian economics. Besides bringing about behavioral changes in tax compliance, Dn along with GST and other economic measures is restructuring and streamlining the economy, eventually with not much of the informal sector left to throw spanner in the works of Indian economy.

ENDNOTES

[1] Daron Acemoglu and James Robinson (2012) Why Nations Fail: The Origins of Power, Prosperity and Poverty, Crown Publishers, New York, Chapter 13 Why Institutions Fail.

[2] For instance see Aristotle Nicomachean Ethics: "[F]or though admittedly the good is the same for a city as for an individual, still the good of the city is apparently a greater and more complete good to acquire and preserve." NE 1094b7-8, Terence Irwin, Hackett Publishing Co., 1985

[3] For an insightful discussion of this topic see: Eduard A. Jorswieck ; Erik G. Larsson (2008) The MISO interference channel from a game-theoretic perspective: A combination of selfishness and altruism achieves Pareto optimality, available at https://ieeexplore.ieee.org/abstract/document/4518872/

[4] P.A. Vanrolleghem,S. Gilot. Robustness and economic measures as control benchmark performance criteria, Water Science and Technology, Vol 45 No 4–5 pp 117–126 © IWA Publishing 2002. Available at http://modeleau.fsg.ulaval.ca/fileadmin/modeleau/documents/Publications/pvr300.pdf

[5] Leon P. Baradat (2009) Political Ideologies: Their Origin and Impact, Pearson, Upper Saddle, NJ. p.44

[6] I.G. Patel, *Glimpses of Indian Economic Policy: An Insider's View,* Oxford India Paperbacks, 2004, pp.44-45

[7] Ambalika Sinha , Divya Rai, Aftermath of Demonetization on Rural Population*, International Journal of Research in Economics and Social Sciences (IJRESS)* Available online at : http://euroasiapub.org Vol. 6 Issue 11, November - 2016, pp~223~228

[8] This is based on a study of 70 million emotional tweets: https://www.usatoday.com/story/news/nation/2013/09/24/anger-internet-most-powerful-emotion/2863869/

[9] R. Vaidyanathan (2017) Tax Heavens and Black Money, Westland Publications Ltd. Chennai 600095, pp. 87-89

[10] Sudhanva Char (1968) Agricultural Income Tax, Commerce Pamphlet No. 16, p.32

[11] Swarajya Staff (2018) Underground Traders In Kerala Take Advantage Of State's Love For Gold To Convert Black Money Into White, August 09, 2018

[12] For more information see: http://timesofindia.indiatimes.com/articleshow/56934242.cms?utm_source=contentofinterest&utm_medium=text&utm_campaign=cppst.

[13] See https://www.thehindu.com/business/cash-deposits-of-rs-289-lakh-crore-post-demonetisation-under-i-t-dept-radar/article19594442.ece

[14] Urjit Patel (2018) https://swarajyamag.com/insta/gst-ibc-and-rbi-act-truly-transformative-reforms-by-modi-government-rbi-governor-urjit-patel, August 03, 2018, Swarajya Magazine

[15] *The Banker* Modi's speech makes history, but raises questions, February 2018 p.10

[16] Swarajya staff (2018) https://swarajyamag.com/insta/imf-hails-gst-as-milestone-reform-commend-it-for-unifying-tax-regime-in-the-country

[17] Swarajya Staff and others (2018) https://swarajyamag.com/insta/rbi-pays-the-government-dividend-of-rs-50000-crore-an-increase-of-63-per-cent-from-last-year

[18] Some of this information is at https://swarajyamag.com/.../why-arvind-subramanian-thinks-8.5-per-cent-growth-rate-.https://rbi.org.in/Scripts/MSM_MintStreetMemos7.aspx

[19] *Economic Times* (PTI) July 18, 2017, India's GDP could rise to about $8 trillion over next 15 years: Arvind Panagariya available at https://economictimes.indiatimes.com/news/economy/finance/indias-gdp-could-rise-to-about-8-trillion-over-next-15-years-arvind-panagariya/articleshow/59649352.cms

[20] World Bank (2018) Ibid.

[21] Karen Weise and Saritha Rai (2018) The American Dream Leads to Canada, *Bloomberg Businessweek*, April 23, 2018,Pp.58-61

[22] Economics, China's Wrinkle-Free Growth, *Bloomberg Businessweek* April 23, 2018, p. 35

[23] World Bank (2018): http://documents.worldbank.org/curated/en/107761495798437741/pdf/115297-WP-P146674-PUBLIC.pdf, p.vii

[24] KR Srivats At 5.7%, Q1 GDP growth slumps to 3-year low, *The Hindu Business Line,* August 31, 2017 available at http://www.thehindubusinessline.com /economy/first-quarter-gdp-grew-57-per-cent-cso/article9838210.ece

[25] The RBI confirms this buoyancy in spending. See Annual Report 2016-17, Reserve Bank of India, available at *www.rbi.org.in*, p.1

[26] Business *Today* December 16, 2016 Available at https://www.businesstoday.in/current/economy-politics/here-are-the-top-cashless-countries-in-the-world/story/241430.html

[27] The data are from the UK Government as well as the ILO offices available at https://tradingeconomics.com/india/unemployment-rate

[28] PwC Global, Emerging Markets: Driving the Payments Transformation, available at https://www.pwc.com/gx/en/industries/financial-services/publications/emerging-markets-driving-payments.html

[29] World Payments Report 2017, Dynamic Regulatory Landscape Drives Collaborative Payments System, Non-Cash Volume Analysis, Capgemini and Pribas, available at https://mms.businesswire.com/media/20171008005016/en/617147/5/WPR2017-infographics-VF.jpg?download=1

[30] Dezan Shira and Associates, Growth Digital Payment Systems in India, Preparing for Cashless Society in India, India Briefing, July 27, 2017 available at https://www.india-briefing.com/news/growth-of-digital-payments-systems-in-india-14797.html/

[31] Arun Jaitley, https://www.facebook.com/notes/arun-jaitley/the-impact-of-the-government-polices-on-direct-tax-collections/812737325581484/

[32] https://www.thehindu.com/news/national/indian-money-in-swiss-banks-fell-345-in-2017-piyush-goyal/article24504477.ece

[33] Aman Sharma, Data shows Rs 17,000 crore deposited and withdrawn by 35,000 companies post demonetization, *Economic Times* 11/08/2017 Indian economy on 'very solid track': IMF chief Christine Lagarde, available at https://economictimes.indiatimes.com/news/economy/indicators/indian-economy-on-very-solid-track-imf-chief-christine-lagarde/articleshow/61087784.cms

[34] Gopika Gopakumar, *Hindusthan Times*, Aug. 31, 2017 quoting R. Gandhi, former Deputy Governor, RBI available at http://www.hindustantimes.com/business-news/rbi-says-99-of-demonetised-rs-500-rs-1000-returned-to-banking-system-after-pm-modi-s-surprise-move/story-jPFYdNpNw5nuEYcFNunknI.html

[35] Arun Jaitley, Ibid Facebook

[36] *The Hindu Businessline* Oct.25, 2017, Recapitalization will restore the health of banking system, says RBI chief, available at http://www.thehindubusinessline.com/money-and-banking/bank-recapitalisation-plan-is-a-monumental-step-forward-rbi-governor/article9922889.ece

[37] For a discussion of the Duffie-Krishnamurthy Dispersion Index in the USA see Gara Afonso, Adam Biesenbach, and Thomas Eisenbach, Mission Almost Impossible: Developing a Simple Measure of Pass-Through Efficiency, available

at http://libertystreeteconomics.newyorkfed.org/2017/11/mission-almost-impossible-developing-a-simple-measure-of-passthrough-efficiency.html

[38] The RBI Annual Report raises this issue of transmission efficiency in its Annual Report. See Viral Acharya, Monetary Transmission in India: Why is it important and why hasn't it worked well? Available at https://rbi.org.in/scripts/BS_SpeechesView.aspx?Id=1049

[39] Tamal Bandyopadhyay, RBI governor Urjit Patel: We've started seeing the upturn in economic growth*, Live Mint* , Oct. 09, 2017

[40]There is a good discussion how money supply need not always cause inflation. Sources of inflation are in distribution system. Cf:https://en.wikipedia.org/wiki/Money supply

[41]Fatih Karahan, Sean Mihaljevich, and Laura Pilossoph, Understanding Permanent and Temporary Income Shocks, http://libertystreeteconomics.newyorkfed.org/2017/11/understanding-permanent-and-temporary-income-shocks.html

[42] RH Topel, M.P. Ward , Job Mobility and Careers of Young Men, *The Quarterly Journal of Economics*, Volume 107, Issue 2, 1 May 1992, Pages 439–479, https://doi.org/10.2307/2118478

[43] Gopika Gopakumar *ibid.*

[44] Rogoff, Kenneth: The Curse of Cash, Princeton University Press, 2016, p. 2

[18] Nathaniel Popper, As Bitcoin Scrapes $10,000, an Investment Boom Like No Other, *New York Times*, 11/27/2017 available at https://www.nytimes.com/2017/11/27/technology/bitcoin-price-10000.html?emc=edit_th_20171128&nl=todaysheadlines&nlid=15089603&_r=0

[45] https://swarajyamag.com/insta/indians-warming-upto-credit-cards-shows-rbi-data-value-of-transactions-doubles-in-2017-18

[46]Source: Sasanka Sekhar Maiti, Mint Street Memo No. 07, From Cash to Non-Cash and Cheque to Digital, The Unfolding Revolution in India's Payment Systems, available at https://rbi.org.in/Scripts/MSM_ MintStreetMemos7.aspx

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May 25 (Saturday) and 26, (Sunday) 2019 at the Renaissance Hotel, 1000 Spring Street, Elizabeth, NJ at the Newark Airport Phone: 908-436-4600. Website: https://local.yahoo.com/info-10745952-renaissance-newark-airport-hotel-elizabeth?stx=renaissance%20hotel%20airport&csz=Newark,%20NJ&fr=lsrp

Members of the Conference Organizing Committee are happy to invite your participation and paper presentation in any India related areas, including in topics about economics, politics, business, religion, mathematics, and other social and natural sciences.

Paper or abstract submission Deadline: April 15, 2019 (early submissions are encouraged). Full paper submission and registration deadline: May 1, 2019.

Before April 15, 2019 the registration fee is for foreign residents is $300; for Indian residents the fee is Rs. 5000/-. After April 15, 2019, the registration fee is $400. Registration fee includes cost of two luncheons and tea breaks on both days of conference. Some discounted fees will be available to exceptional candidates. For registered students from all over the world, the registration fee is reduced to $100 or Rs. 3000/.

Electronic submissions should be emailed to kulkarnk@msudenver.edu

Papers should follow the standard format (AMA or Chicago style format is fine) for presentation consideration. For more information please follow author's guidelines listed on the journal website at www.irbejournal.com.

Please send abstract or completed papers, registration fees and inquiries to:

Dr. Kishore G. Kulkarni, Distinguished Professor of Economics and Chief Editor, IRBE, Campus Box 77, P. O. Box 173362, Metropolitan State University of Denver, Denver, CO 80217-3362, USA. E-mail: kulkarnk@msudenver.edu Tel: 001-720-244-3663 (USA, MST)

Participants are expected to make their own travel and living arrangements to New Jersey. A block of rooms is reserved at the conference hotel. Approximate daily rate of the hotel is $105.00 (plus taxes). More information about hotel stay is at the hotel website listed above.

Please note the following:

--Selected high quality papers from the conference will be published in the future IRBE issues.

--Eminent speakers are invited for lunch plenary sessions.

--Paper presenters are requested to present completed papers that are made available to attendees

--No "Absentee" or "Skype" presentations are possible.

---Special requests for presenting on a "specific" day of the conference can be considered, but are not guaranteed.

Conference Program Committee:

1) Bansi Sawhney, University of Baltimore, Baltimore, Maryland. bsawhney@ubalt.edu
2) Debasish Chakraborty, Central Michigan University, Mt Pleasant, Michigan. dchak@aol.com
3) Hrishikesh Vinod, Fordham University, New York. vinod@fordham.edu
4) Bansi Sawhney, University of Baltimore, Maryland, bsawhney@ubalt.edu
5) Amitabh Dutta, Florida Institute of Technology, Melbourne, FL. adutta@fit.edu.

BUSINESS & ECONOMICS JOURNAL

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December 22 (Sunday) and 23, (Monday) 2019 in Courtyard, Marriott (Earthspace) at the Auro University

Members of the Conference Organizing Committee are happy to invite your participation and paper presentation in any business related area.

Paper or abstract submission Deadline: September 15, 2019,(early submissions are encouraged). Full paper submission and registration deadline: November 15, 2019.

Before November 15, 2019 the registration fee is for foreign residents is $300; for Indian residents the fee is Rs. 5000/-. After November 15, 2019, the registration fee is $400 for foreign residents and Rs. 6000/- for Indian residents. Registration fee includes cost of two luncheons and tea breaks on December 22, and 23 2019. Some discounted fees will be available to exceptional candidates. For registered students from all over the world, and for participants (attendants and paper presenters) from developing countries the registration fee is reduced to $100 or Rs. 3000/.

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Papers should follow the standard format (AMA or Chicago style format is fine) for presentation consideration. For more information please follow author's guidelines listed on the journal website at www.irbejournal.com.

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Participants are expected to make their own travel and living arrangements in Surat. A block of rooms is reserved at the conference hotel. Approximate daily rate of the hotel is $120. More information about hotel stay is at the hotel website listed above. We recommend DSK Travels as the official travel agency to book for all your travel needs. Please send an e-mail to prathamesh@dsktravel.com or check their website at www.dsktravel.com

Please note the following:

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