IMPACT OF MGNREGA AND AUTOMATION ON THE INDIAN LABOUR MARKET

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Abstract

The past decade has been a period in which sectors have adopted automation on an unprecedented scale in their quest for greater efficiency and productivity. Another feature of the past two decades is a growing trend of unemployment and economic growth devoid of job creation. The two have since been linked and automation has been blamed for increasing unemployment. To tackle these fears, economists have put forward various schemes, the prominent ones being Universal Basic Incomes (UBI) and Job Guarantee Schemes (JGS).

In this paper, we analyse the impact of both robots and MGNREGA (a JGS in India) on employment in 27 sectors across all 35 states and union territories of India between 2004 and 2014. Using an index based on robotization trends in the USA, the paper analyses the predicted impact of robots on employment in India. It also aims to estimate the impact of MGNREGA program on employment by constructing a data set based on the weighted duration the scheme has been implemented in a state.

The analysis predicts that a 1% increase in industrial robots (appendix A) per million workers results in an average 0.14-0.16% fall in employment. It also estimates that states that have implemented MGNREGA witnessed an average 13-14% rise in relative employment levels. The control variable of population distribution predicts a fall of 0.34% in employment for every 1% increase in population of the state.

INTRODUCTION

Over the course of the last century, humanity has achieved astronomical success in the development of technologies and machines that make our lives and workplaces more efficient and less labor intensive. While these benefits are widely accepted, there is a growing concern that this progress is leaving significant portions of the labor force unemployed (Shewan, 2017). Although this concern has been around, arguably, since the times of the Ancient Greeks, the idea of technological unemployment has gained more traction among the masses since the Industrial Revolution (Campa, 2014). While economists agree that the introduction of new technology causes short-term unemployment, they lack a consensus on whether the unemployment caused is long-term (Wilson, 2019). Several studies have been conducted to empirically analyze the impact of machines on employment in the long-term, but the result of each study provides varying results (see section 1.IV in Literature Review).

This concern, along with growing wealth inequality, stagnant wages and the reemergence of poverty in developed nations, has created a clamor for viable solutions to protect the most vulnerable in society. Solutions such as shorter working hours (Leontief, 1983), public work programs (Forstater, 2014) and movements such as the Venus project (appendix B) have emerged in response. Out of these, economists have strongly advocated for either a Universal Basic Income (UBI) (Coppola, 2017) or Job Guarantee Schemes (Cfeps.org, 2019) as a solution to the issue. The two concepts both promise to provide an income to beneficiaries but differ fundamentally on how. While a Basic Income scheme guarantees an unconditional sum of money to beneficiaries, a Job Guarantee Scheme guarantees beneficiaries a job, usually provided by the government, in exchange for a basic minimum wage. UBI is a relatively new idea that has had very limited testing with inconclusive results but the idea of a jobs guarantee program has been implemented in many nations such as the Jefes de Hogar program run by Argentina, the Expanded Public Works Program run by South Africa and the Mahatma Gandhi National Rural Employment Guarantee Act in India (Cfeps.org, 2019). These programs have been met with

varying levels of success, but a general consensus is that they have had an overall positive impact on employment in their respective nations (Cfeps.org, 2019).

To properly understand how automation and a jobs program affect employment simultaneously, this paper analyses the nation of India. As of April 2019, India is the second most populous nation in the world, with a largely unskilled labor force, widespread poverty and high wealth inequality. The concern for unemployment due to technological advancement is amplified among the populace and has pushed hasty measures by the government, such as banning autonomous vehicles to prevent losses of driving-related jobs (BBC News, 2017). Although the country has been slow to adopt machines in the workplace, there has been a recent increase in the number of industrial robots (appendix A) being purchased, with future projections predicting a rapid growth in automation (Assemblymag.com, 2019).

Since 2005, the Indian government has been running a Jobs Guarantee scheme named the Mahatma Gandhi National Rural Employment Guarantee Act (MGNREGA). It is the largest program of its kind in the world and can directly benefit over 830 million people. The scheme aims to provide 100 days guaranteed employment to any rural resident of India at minimum wage and is primarily targeted towards agriculture laborers. MGNREGA has also been highlighted by the United Nations as a good method of achieving the Millennium Development Goals of tackling poverty (see section 2.III of literature review).

Automation/ Technological Unemployment

1. **Is the idea of technological unemployment new?**

   The idea of unemployment due to innovation was first explored by Aristotle, who predicted that if machines became sufficiently advanced, there would be no need for human labor (Campa, 2014). This prediction was based on his observation of unemployment among free laborers due to effects of labor-saving technologies and competition from slaves. Ancient civilizations and rulers responded to this by either providing free handouts, setting up public work programs or by regulating/banning new technologies.

Up until the Industrial Revolution, policy makers sought to curtail unemployment by banning labor-saving technologies (Osborne and Frey, 2013). At the onset of the industrial revolution, rulers and businesses began to be more accepting of technology in their everyday operations. This led to large-scale adoption of labor-saving technologies which, in turn, increased productivity and profits (Osborne and Frey, 2013). A perfect illustration of this can be seen in the United Kingdom. In the early 17th century, Queen Elizabeth I of England refused to patent a labor-saving knitting machine developed by William lee stating that it could drive her subjects out of employment (Osborne and Frey, 2013). Yet, during industrial revolution in the 19th century, the UK was at the forefront of technological innovation in business.

Workers, who were already dealing with a lack of employment opportunities caused due to a growing population, began fearing for their livelihoods. The anxiety reached a peak when several artisan weavers were left unemployed due to the introduction of mechanized handlooms and was one of the factors in the Luddite movement of the 19th century, with laborers destroying textile machinery in protest (Osborne and Frey, 2013).

2. Debates around Technology and Employment

Political and philosophical debates about technological unemployment intensified from the 19th century onwards (Wilson, 2019). The common view of economists was that while technological unemployment existed, it was not a long-term problem (Wilson, 2019). However, several economists such as Thomas Malthus, J.S. Mill and later, David Ricardo had a more pessimistic view. Ricardo, in the third edition of his paper 'On the Principles of Political Economy and Taxation', argued that technology could both push down wages and cause long-term unemployment (Ricardo, 1817, chap. On machines).

In response, Jean-Baptiste Say responded using Say's Law (The Economist, 2017) and asserted that any laborer displaced due to technology would find work elsewhere once the market adjusted. Say and Ramsey McCulloch described a range of effects to explain Say's Law, which were termed as compensation effects by Karl Marx (Marx, 1867, chap. 13; 1848, chap.18). The effects theoretically countered the labor-saving impact of technological innovation, but Marx fiercely criticized these effects in his paper 'Theories of Surplus Values'

(Marx, 1848). The compensation mechanisms and their critiques are as follows (Vivarelli, 2012):

a) Via additional employment in capital goods sector: The capital good, i.e. technology, requires labor to run it, thus creating jobs.

   Marx successfully struck down this effect with his reasoning: "…. the machine can only be employed profitably if it…is the product of far fewer men than it replaces. Thus, this effect is rarely used in recent debates.

b) Via decrease in prices: As technology creates efficiency, prices drop, thus demand for the product produced rises, creating additional requirement for labor employment.

   Malthus notes that although a decrease in prices could result in a rise in demand, the aggregate demand may actually fall due to the loss of demand from the newly unemployed laborer, which is in line with the theory of sticky prices in Keynesian economy (appendix C). Also, this effect depends on the assumption of a perfect market. For example, in a monopoly, cost-saving innovation may not translate into lower prices.

c) Via new investments: It takes a while for prices to drop due to new technologies. In the time it takes for prices to fall, extra profits are earned and invested, which creates new jobs.

   Marx refutes this by stating that the effect assumes that all extra profits are translated into new investments. He also states that if the intrinsic nature of the new investment is capital-intensive, the compensation to the newly unemployed is only partial.

d) Via decrease in wages: the direct impact of labor-saving technologies results in a price adjustment for wages which is lower than the initial wages and thus leads to more employment.

   The Keynesian Theory of effective demand directly clashes with this effect. While a decrease in wages encourages employment, a decrease in aggregate demand causes employers to hire fewer laborers. The same argument is also used in subsection b. Also, the hypothesis of perfect substitutability of labor and capital is inherent to this effect and is arbitrary.

e) Via increases in incomes: Costs saved due to technical progress are distributed among labor, which results in higher wages for still employer workers. This increases consumption, which increases demand and thus creates a need for additional labor employment. This was the Fordist mode of production.

   Critics of this effect argue that this effect was relevant only when the Fordist mode of production was the prevailing method of industry (1950s and 1960s). But the new market paradigm has weakened the traditional compensation mechanism and made the labor market more competitive and thus the Fordist mode of production is no longer relevant.

f) Via new products: Technological innovation can also create and help commercialize new products and thus creates employment opportunities for those products.

   Critics concede that this effect does indeed make a strong case for employment creation but argue that different technologies create different types of new products. These products considerably vary on whether they require a labor-saving or a labor-intensive production. For example, automobiles had a much higher labor-intensive effect than the diffusion of home computers. Therefore, critics conclude the true effect of new products is purely an empirical matter.

By the 20th century, the debate of technological unemployment was not significant to mainstream economic debates. This was primarily due to a strong employment trend that characterized the economy in USA. The two periods of mass unemployment in the century, the 1930s and 1960s, were alleviated by the Second World War and the Vietnam War respectively. Post the 1950s, the view was that government regulation would prevent long-term unemployment due to technology. In the 1980s, unemployment rose once again, and technological innovation was blamed in books such as the 'Peoples' Capitalism: The Economics of the Robot Revolution' by James Albus and 'The Global Trap' by Jeremy Rifkin. Yet, the criticism was not enough to change the general opinion that technology did not cause long-term unemployment.

The 21st century has been characterized by intense debate over technological unemployment. There have been numerous reports and studies that show increasing

productivity despite relatively falling employment number (appendix D) in sectors such as manufacturing and agriculture (Wilson, 2019). Recent recession recoveries have been majorly driven by jobless growth, which compounded fears among policy makers of a technological unemployment apocalypse (The Economist, 2010). In a recent report by the OECD (2016), current trends of technological innovation are termed as the second machine age. It states that encompassed by Artificial Intelligence, technology can now perform more complex tasks relative to the one-dimensional tasks performed by machines in the past. This new capability of machines will be the driving cause of future technological unemployment and will result in lasting technological unemployment.

3. The discussion in India

India is one of the fastest growing mixed economies of the world. It has a massive, young labor force which is predicted to grow for the next decade unlike most western and developed economies. The country adopted policies of globalization and liberalization in the 1990s, with the expectations of reducing poverty and creating more jobs as was the case in western economies that adopted similar policies. Yet, these goals were not achieved.

As of 2019, India has had a trend of rising unemployment. Since the low of 3.41% in 2014, unemployment has been steadily rising in the country, with ranging reports of 3.52% (Tradingeconomics.com, 2019) to over 6% (Aljazeera.com, 2019) unemployment in 2019. This is despite an average of over 7% GDP growth, sparking fears of jobless growth. Recent trends of increasing automation within the country have caused further concern about the future of millions of unskilled workers, who are expected to be hit hardest. For example, a paper by Frey & Osborne (2013) has estimated that up to 69% jobs in India are at risk of automation. A paper by Sunil Mani (2017) shows the exponential increase in robot density per 10000 workers in India's manufacturing sector, a sector that the Indian Government has been incentivizing to alleviate unemployment through programs such as Make in India. The IT sector, which is one of the most lucrative and sought-after jobs sectors in India (Ilavarasan, 2007), has seen increasing automation leading to job losses (Ilavarasan, undated). These reports suggest that most sectors in the Indian Economy are susceptible to technological

unemployment, but there is a lack of empirical studies on the subject for the country. Therefore, it is important to analyze the impact such trends have on employment.

4. Empirical Studies and analysis

There has been a plethora of studies in the last two decades to analyze empirically the impact of technology on employment with widely varying results. This section will explore three published studies and a working paper. Of the studies, the latter two build upon the first and demonstrate how uncertain economists are towards the impact of technology.

a) Robots and Jobs: Evidence from US Labor Markets (Acemoglu and Restrepo, 2017)

In this paper, Acemoglu and Restrepo empirically analyze the impact of industrial robots (appendix A) on US labor markets between 1990 and 2007. They perform their analysis on local labor markets in the US, which they proxy using commuting zones (Ers.usda.gov, 2019), and construct the measure of robot exposure on data from robot use in 19 industries. They analyze two different scenarios: one in which there is trade between the commuting zones and when where there is no trade between zones. They regress change in employment and wages on the exposure to robots and conclude that for every additional robot per thousand workers, the employment to population ratio falls by 0.18-0.34% and wages fall by 0.25-0.5%. Thus, they estimate around 360,000 and 670,000 jobs having been lost to robots. Their paper also acknowledges that there are relatively few robots in the US economy and thus their impact is limited. If estimates of robot growth over the next two decades materialize, then the impact could be more sizeable.

b) Robots at Work (Graetz and Michaels, 2018)

Graetz and Michaels analyze the industrial robots and empirically determine the effect of robot density (stock of robots per million hours worked) on labor productivity, wages and employment in 14 industries in 17 developed countries between 1993 and 2007. On average, robot density in these countries had increased over 150 times from 0.58 to 1.48, which they reason is due to falling prices of these robots. They note, based on IFR data, that the price of industrial robots, when quality adjusted, had fallen by about 80% relative their 1990 prices. They conclude, for robots, that industry-country pairs which saw greater increases in robot density from 1993 to 2007 experienced larger gains in labor

productivity. For labor market impacts, an increase in robot density between 1993 and 2007 resulted in a conservative increase of 0.36% annual growth in labor productivity compared to a mean growth of 2.4%. There is a positive correlation between robot density, productivity and wages. The regression showed no significant relationship between increased robot use and overall employment, yet robots may reduce the employment of low-skilled workers, implying a shift of employment towards high-skilled work. In conclusion, they caution that even in the developed countries, robots accounted for only 2.25% of the capital stock, which is relatively limited. If quality adjusted prices fall that the same rate, robots would be adopted at a greater scale and may have a greater impact.

c) Is automation Labor-displacing? Productivity Growth, Employment and the Labor Share (Autor and Salomons, 2018)

Autor and Salomons analyze the impact of automation on Total Factor Production (TFP) in 28 industries for 18 OECD countries since 1970. They argue that this measure is an omnibus measure that potentially overcomes the challenge for consistent measurement posed by the heterogeneity of innovation across sectors and periods (appendix E). The conclusion to this study is that while automation has not been labor-displacing, it has reduced the labor's share of value added. The models used estimate a labor share decline of 3.4-6.3 log points due to TFP growth between 1970 and 2007 and predict a 5.3 log points decline in the coming years. Note that the estimates indicate that labor share-displacing effects of productivity growth became substantial in the 2000s, whereas they were almost non-existent in the 1970s. This is consistent with the consensus that automation has become less labor augmenting and more labor displacing in recent decades. On the other hand, on average, productivity growth increased aggregate employment in by 5.92% between 1970 and 2007.

It is therefore fair to conclude that there is no clear answer as to the existence of long-term technological unemployment. To quote Pasinetti (1981), "For the time being, we may draw the important conclusion that the structural dynamics of the economic system inevitably tend to generate what has rightly been called technological unemployment. At the same time, the very

same structural dynamics produce counter-balancing movements which are capable of bringing macro-economic condition...towards fulfillment, but not automatically."

Job Guarantee Schemes (JGS) and Mahatma Gandhi National Rural Employment Guarantee Act (MGNREGA)

A Job Guarantee Scheme is an economic policy formulated with the purpose of providing a solution to the problems of inflation and unemployment by creating full employment and price stability. This is achieved by the state taking on the role of employer of last resort i.e. the state promises to make a job available for qualifying individuals seeking work (Wray,2009). Over the years, JGS has been called various names such Public Service Employment, Buffer Stock Employment or Employer of Last Resort Scheme interchangeably (Mitchel and Wray, 2005). To better explain JGS, this section will first explore the current economic policy paradigm. It will then present a popular model described by Mitchell and Wray (2005) and explain how JGS is the most logical employment-inflation policy that policymakers must implement. Finally, it will explore MGNREGA, the largest JGS in the world, both in monetary terms and scale of the project.

1. **How is current economic policy formulated? How did it get to this point?**

   Post-WWII, economic policy focused on ensuring low inflation and minimum unemployment. To this effect, policy-makers used two economic theories to stimulate growth and balance unemployment (William, 1998). First was the Philips curve, developed by A.W. Phillips, which stated that inflation and unemployment have a stable and inverse relationship (Andrew and Ohanian, 2001). The second was Keynesian demand-side economics, which states that the primary factor driving economic activity and short-term fluctuations is the demand for goods and services. Keynes maintained that unemployment was caused due to insufficient aggregate demand in an economy. He advocated for fiscal activism (the government intervene by altering interest rates or issuing bonds) to generate more demand and thus reduce unemployment.

   These key theories were questioned in the late 1960s and 1970s due to the stagflation that resulted from the oil shock and following recession. Policy makers now switched their

policy to a quest for balanced budgets and deregulation, with Non-Accelerating Inflation Rate of Unemployment (NAIRU) becoming a target for inflation-obsessed policymakers (William, 1998). NAIRU, formulated by Milton Friedman, states that inflation would rise if unemployment fell below the NAIRU level (Matthew, 2019). Thus, the case was formulated such that even in full employment, there is a subsection of unemployed people who are part of the natural rate of unemployment upon whose existence is the goal of low inflation. It is under this economic paradigm that JGS will be explained.

2. Is JGS a logical scheme? How will it impact inflation?

Advocates for JGS disagree on fundamental assumptions of the current economic paradigm. As William Vickery (1996) argued, the fiscal budget deficit is not an economic sin but is an economic necessity whose function is to convert purchasing power not spent on consumption or investment into purchasing power of the government (Mitchell, 1998). William Mitchell (1998) thus blames trends of high unemployment on highly restrictive fiscal and monetary policies of OECD governments.

In his 1998 paper, he characterizes a Buffer Stock Employment (BSE) model and how governments can use BSE to maintain price stability. The model is justified on two separate grounds. First, it is appealing from a social welfare perspective and second, it is a rational choice for a government that supplies a fiat currency and wants to maximize macro-benefits while having price stability (Mitchell, 1998). The model works as follows: The government continuously absorbs workers displaced from the private sector and employs them at minimum wage (appendix F) in socially useful activities (Mitchell, 1998). The minimum wage forms the price floor of the economy and the existence of the buffer stock of displaced workers would be continuously fluctuating, which would be accounted for by the type of jobs and functions available (Mitchell, 1998). Due to the price floor function, the BSE model would prevent any serious deflation and would define the wage structure of the private sector (Mitchell, 1998). As for inflation, the government would have to maintain a level of employment within the BSE sector to stifle excess demand and by extension, inflation. This leads to a new concept of the Non-Accelerating Inflation Buffer Employment Ratio (NAIBER), which, in the BSE economy, replaces the NAIRU as an

inflation control mechanism (Mitchell, 1998). In other words, minimum wage employment is used instead of unemployment as a control mechanism for inflation. Mitchell (1998) estimates that the cost of implementing a BSE model would range between 0.06-3.5% of an economy's GDP, making it cheaper in comparison to the Okun gap losses incurred due to unemployment (Mitchell, 1998).

There have been various critics of JGS. Mitchel and Wray (2005) condense the criticisms into 6 broad categories and respond to each claim individually. This section will summarize 5 of the criticisms and the arguments in defense (for greater analysis and for criticism 6, see Mitchel and Wray, 2005).

a) Criticism: JGS is a Keynesian demand expansion

   Response: The false assumption here is that JGS increases employment by raising aggregate demand. JGS offers basic wage to anyone willing to work and hires from the bottom of the economic spectrum, acting as a buffer stock program for the unemployed to maintain a 'loose' full employment. JGS is targets a small subsection of the labor market, provides jobs which are temporary in nature and is independent of demand levels as it does not depend on pumping-demand. Even if the criticism is accepted, all social programs are created with the aim to smooth consumption across periods, thus the criticism is more in favor of a JGS than against it.

b) Criticism: JGS is subject to a NAIRU constraint and can embolden higher wage demands in the private sector.

   Response: Inflation rises due to a rise in demand levels. As explained in part a, JGS is structured such that it neither depends on demand nor impacts aggregate demand. It can be conceded that there would be a one-time price instability at the introduction of a JGS, but the price floor mechanism ensures that cannot directly pressure prices above the floor.

   As for higher wage demands, this assumes that a worker in the private sector either prefers or is indifferent to the benefits and wages provided by the JGS compared to the benefits and wages in the private sector. This is only true in scenarios were the

wage in the private sector is below the legal minimum wage and is a further argument in favor of JGS (appendix G).

c) Criticism: JGS is a form of disguised unemployment

   Response: This criticism assumes that there is an immediate better alternative available to JGS workers. The JGS program is for people who are unemployed and cannot get immediate employment elsewhere. Their other option is to be unemployed with no productivity. The jobs provided are meant to be transitional, i.e. ensure that the worker has a minimum wage job until a job in the private sector is available.

d) Criticism: JGS is not operationally sustainable

   Response: The argument is that every worker who is unemployed, even in the short-term, will join the JGS workforce, thereby making it unsustainable in the long-term. But as argued in Wray (1998), the low pay will act as a disincentive for many to instead be full-time job searchers.

e) Criticism: JGS burdens the government budget constraint

   Response: The first claim is that a JGS would be funded fully by a budget deficit. But budgets usually move counter-cyclically as the deficit is determined endogenously by spending in the non-government sector. While true that in a slowing economy, the JGS pool grows and deficit rises but conversely, when the economy grows, the JGS pool shrinks and the deficit falls and may become a surplus. This remains true even if a larger pool of JGS remains as a growing economy means more private spending and consequently, less government spending in non-government sectors.

3. Mahatma Gandhi National Rural Employment Guarantee Act (MGNREGA)

In the backdrop of increasing inequality between urban and rural India, high rates of poverty and the seasonal unemployment in rural India, the government launched the MGNREGA 2005. The scheme made any adult of a household in rural India legally entitled to get a minimum of 100 days of employment from the government at minimum wage, if the person requests it. The work must be provided within 15 days of the request and if

the work is not provided, the scheme guarantees unemployment benefits to the person. The program has three broad goals (Shah, Mann and Pande, 2012: page 1):

a) Provide a social protection for the most vulnerable in rural India through provision of employment and empowerment of marginalized communities.
b) Improve the economy and livelihood in rural India through creation of durable assets, improved water security and by improving land productivity by strengthening drought and flood management.
c) Combine various anti-poverty and livelihood initiatives of the past to ensure better and transparent implementation.

The act was first implemented in 200 rural districts on 2nd February 2006. On 4th April 2007, an additional 130 rural districts were included and finally on 4th April 2008, it was extended to the remaining 295 rural districts in India (Ministry of Rural Development, 2009). The work provided by the scheme is basic unskilled manual labor, thus ensuring that anyone can be employed, irrespective of their qualifications. The majority of the funding for the scheme is provided by the central government but a small portion of the expenses are burdened by the state government (Ministry of Rural Development, 2009).

There were many expectations from the Act. The United Nations Development Program has highlighted the program as a way to achieve the Millennium Development Goal (MDGs) of tackling poverty and deprivation (The Times of India, 2011). This section will now explore how the program impacts wages, gender equality, consumption, seasonal migration and livelihood.

a) About 90% of India's labor force belong to the informal sector (Srija and Shirke, 2014). They are not protected by the strict labor laws and often work for less than minimum wage (strict labor regulation is often blamed for the existence of the informal sector on this scale). MGNREGA increased the opportunity cost of informal sector workers. With better pay, workers can reduce the number of hours they work in the informal sector, which creates a lack of labor supply. This forces the informal sector to raise wages to retain laborers and this also benefits persons who have not directly participated in the

scheme (Bose, 2017: page 246). A World Bank study has also found that participants in the scheme benefitted from sizable income gains relative to their opportunity cost wages (Ravallion, 2014). A study by Kareemulla et al. (2013) also found that in some districts, up to one-third of wage days for workers came from MGNREGA, which is testament to the impact of the scheme on wages.

b) A steady drop in male-female wage gap has also been observed since the scheme's implementation. Share of employment of women have risen in many states, in part due to the 33% requirement for women employment in the scheme. Although there are states where this condition has not been met, the trend of increasing gender inequality can be generally seen across all states and, on the national level, over 33% of rural laborers are female (Reddy et al., 2014).

c) A study conducted by Nayana Bose (2017) found that the program has increased household consumption between 6.5-10% in general, and by 12% for marginalized communities. The study also found that higher caloric and nutritional foods such as proteins and milk were also consumed more. The study shows that the intended beneficiaries of the program have had a marked improvement in income and livelihood. Also, historical discrimination against marginalized communities did not prevent them from accessing schemes and its related benefits.

d) The study by Reddy et al. (2014) conducted a survey to estimate the impact on migration and found that, largely, there was a decline in distress migration. Villages which saw massive migration towards richer towns and cities saw their residents return due to availability of job opportunities. Asset creation helped create many permanent jobs, which lured back workers. For example, farmers in Rajasthan who had migrated due to lack of proper irrigation infrastructure and general scarcity of water had returned to their native towns due to creation of water management assets under MGNREGA.

e) Kareemulla et al. (2013) found that the additional wages had improved the livelihoods of workers in rural India. Aside from increased consumption, the healthcare, education and debt repayment expenditure of household participating in the scheme had risen. If there

were surpluses beyond these expenses, households acquired durable assets and created amenities within their homes.

Overall, MGNREGA has had a positive effect on transforming the labor market of rural India. But there have been significant implementation issues as well. Natesan and Marathe (2015) found that there were major macro-economic problems for the scheme. The governance challenge has been immense with a large number of trained support staff posts being left vacant. Instead, junior level, untrained Block development officers were overseeing the projects, which affected their results. They also found that there were issues in matching demand and supply for the scheme. There is a lack of knowledge of the scheme among the population and thus, fewer people benefit from the scheme than required. States with bad implementation of the scheme are usually allotted smaller portions of the scheme's budget, which is allocated based on performance and outcomes. This makes the issues worse and the state is caught in a cycle of low performance and low funds.

In their report, Anderson et al. (2013) find significant corruption in the program. They found that too little demand for MGNREGA is registered and only 55% of their sample received official assistance in registering for the program. There were massive delays in receiving wage payments despite the two-week payment period of the program with up to 47% laborers waiting for over a month for their wages. There were also cases where the payment received by the laborers was lower than the amount they were supposed to received and the laborers suspected corruption by middlemen to be the reason. The report also found that the many of the sanctioned projects were not built or were left incomplete.

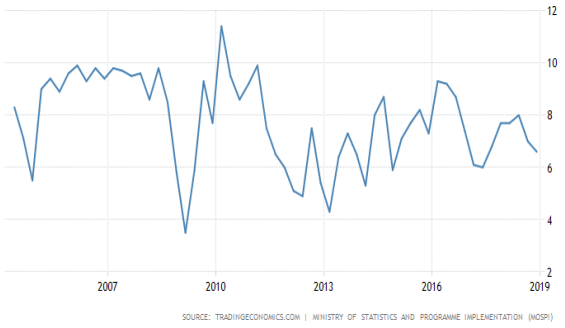
MGNREGA has been the largest and most ambitious implementation of a JGS with a large budget. There have been positive effects of the program on the rural labor market but there exist various implementation problems which reduce the potential impact of the scheme. Broadly, the program follows the JGS objective of creating a price floor, providing employment without raising inflation and improving livelihood to the most vulnerable in society and provides a strong basis for other countries to adopt similar programs to achieve the UN MDGs.

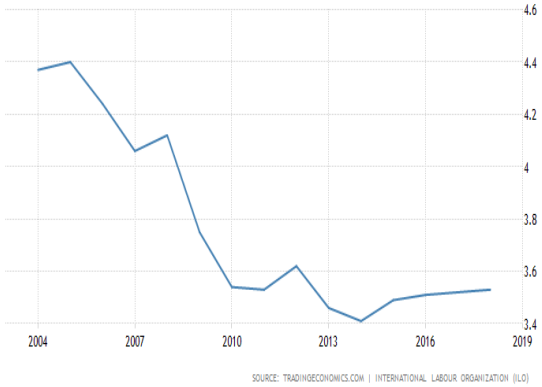
Gaps in literature

As can be seen above, a major portion of studies have taken place in developed nations, which have vastly different characteristics in their labor market relative to developing nations. This paper aims to provide a basis for further analysis of the impact of robots on the labor market of India. The paper also aims to understand the impact of the MGNREGA, when robots and population growth is accounted for, in a state that has implemented the scheme relative to if said state had not. Such an analysis would help provide a basic understanding whether current knowledge about both factors in India is in line with the ground realities and give a preliminary understanding about the extent of their impact on employment.

AUTOMATION, MGNREGA and EMPLOYMENT: A MODEL

In this section, we explain and define the model used for the regression analysis. The model uses a panel data set of 35 states and union territories for two years and analyses the average changes in WPR between 2004 and 2014. The regression analysis, which is a basic OLS regression (appendix, is run on 27 sectors of the Indian economy across all 35 states and union territories of India and uses micro-level data obtained from IPUMS International. Some important characteristics of the Indian Economy, as of 2014, is a low unemployment rate of 3.4%, a GDP growth rate of 7.4%. Over 80% of the population lives in rural areas, which is the target area for MGNREGA. Each state has a distinct economy of its own i.e. the dominant industry varies by state (appendix 8).





GDP growth (Data.worldbank.org, 2019) *Unemployment rate* (Data.worldbank.org, 2019)

In the economy, we assume that changes in employment is the result of the impact of automation, MGNREGA and population distribution across the 35 states and union territories in India. This is a very preliminary model, the purpose of which is to provide a basic understanding of the impact of these factors in isolation and in sync. The model framework broadly follows as below:

$$\mathbf{WPR}_{S,T} = \beta_0 + \beta_1 \mathbf{Automation\ Index}_{S,T} + \beta_2 \mathbf{MGNREGA}_{S,T} + \beta_3 \mathbf{X}_{S,T} + \beta_4 \mathbf{Year}$$

$$\mathbf{WPR}_{S} = f(\mathbf{Automation}_{S}, \mathbf{MGNREGA}_{S}, \mathbf{X}_{S,t})$$

I. *WPR* stands for Worker to Population ratio which, in this model, is defined as the number of employed persons per 1000 persons in the population. It is derived as seen in appendix 1.5. The total population by state has been taken from the Census 2001 and 2011 data run by the Indian government. The population for 2004 and 2014 has been estimated based on the average growth rate between 2001 and 2011. The number of employed have been taken from IPUMS. This variable is the dependant variable in the regression.

II. India, a middle-income country, lacks a reliable measure of robots in each of the 27 sectors explored in this paper[++]. This paper utilizes the data for robotization in the USA for these 27 sectors as a proxy to create a robot index. The index will be used to approximate the impact that robots would have had on employment in India under the assumption that the robotization in India is following similar, if not the same, pattern as the USA. Even if said assumption is voided, the index helps us identify the most vulnerable

states and industries to automation. This is vital to policy formulation considering reports from the International Federation of Robotics, which shows a rapid growth in the robots purchased starting 2009 and predicts faster growth in the coming years. The formula used to calculate the index is provided in appendix 1.6. The industry-wise breakdown of employment for both India and USA is taken from IPUMS International while the data for robots in the USA is taken from Acemoglu and Restrepo (2017: Table A1). Thus, the robots referred to in this regression are industrial robots (defined as in section 1.III.a in the literature review). The result coefficient can either be positive or negative but is expected to be very small as in line with the studies discussed above. The β_1 here is interpreted as the estimated change in employment for an increase in industrial robots per million workers in India.

III. To analyse the variable MGNREGA, a data set is constructed wherein the phased implementation of the scheme is used to create a weighted measure between 0 to 1 which is analysed to estimate the impact of the scheme on a state before and after the implementation of the scheme. The program began implementation on the 2nd of February 2006 and is analysed till the 2nd of February 2014 (eight years). Our measure for the 35 states and union territories is calculated as in appendix 1.7. The data for the duration of employment for each district is taken from Nrega.nic.in (2019). The coefficient is expected to be positive i.e. it is expected that the jobs scheme has had a positive effect on employment. The β_2 is interpreted as the impact of MGNREGA on a state's employment in 2014 compared to if the state did not implement the scheme.

IV. The variable X is the population of the state which is used as a control variable in the regression. The purpose of the variable is to provide a distribution of population by state and industry to properly understand how automation has affected each state and its employment. This is particularly important as each state in India has a varied economy and are characterised by different industries. So, the population of state with an industry that is highly susceptible to automation will be affected quite differently compared to other states. The data for population by state is taken from the Census 2001 and 2011 for India (appendix 2, 6). The coefficient is expected to be positive i.e. an increase in

population results in a general increase in employment. The β_3 estimates the impact on employment based on the change in population distribution across states.

V. The final variable Year is a dummy variable accounting for the year in question. For 2004, the variable is 0 and for 2014, the variable is 1. This is an important variable as the value of all MGNREGA inputs are 0 in 2004 and hence, the coefficient for 2004 and 2014 would vary.

++the only source of exhaustive sector data available for robots in India is from the International Federation of Robots, but the data is too expensive to access for the purpose of this paper.

Results and Analysis

In this section, the results of the regression analysis will be presented first. The first set of results will be without the control variable of population, which will be included in the second result. This is done to provide an analysis of the impact of MGNREGA and automation have on employment, ceteris paribus. Each variable's regression coefficient will then be analysed and explained with the purpose of providing the possible reasons for the results. It is to be noted that all P value references are taken regarding the P value for the 95th percentile confidence interval.

1. Automation

In a regression with just robots and employment, the results show that, ceteris paribus, for every 1% increase in robots per million workers, there is almost a 0.47% rise in employment. This result has a high significance at the 99% confidence interval (appendix 1.1). When other variables of MGNREGA and the dummy variable year is included, the regression results indicate that, ceteris paribus, for a 1% increase in robots per million workers, there is a likelihood of an average 0.16% fall in employment across all Indian states (appendix 1.3). When a further control variable of population distribution across the 27 sectors and states is included, the average fall in employment is likely to be on average 0.14%, ceteris paribus (appendix 1.4). Both these results cannot be stated with certainty due to the high p-value indicating a low significance. A likely reason for the high p-values in the latter two can be attributed to the low number of observations in the regression. But it can be observed that

the result shows that the impact of robots on employment is very low, which is in line with the empirical studies by Acemoglu and Autor. This can also be inferred in the scatterplot in figure 1, where it can be observed that, generally, robots do not affect employment. It must be noted that this result is not for a real-time analysis of India's robot-employment relation, as we use data from the USA to create an index for the regression. Nonetheless, this result provides us with an understanding of the potential impact that robots may have on employment in the future, when robot density in India begins to match those of the USA.

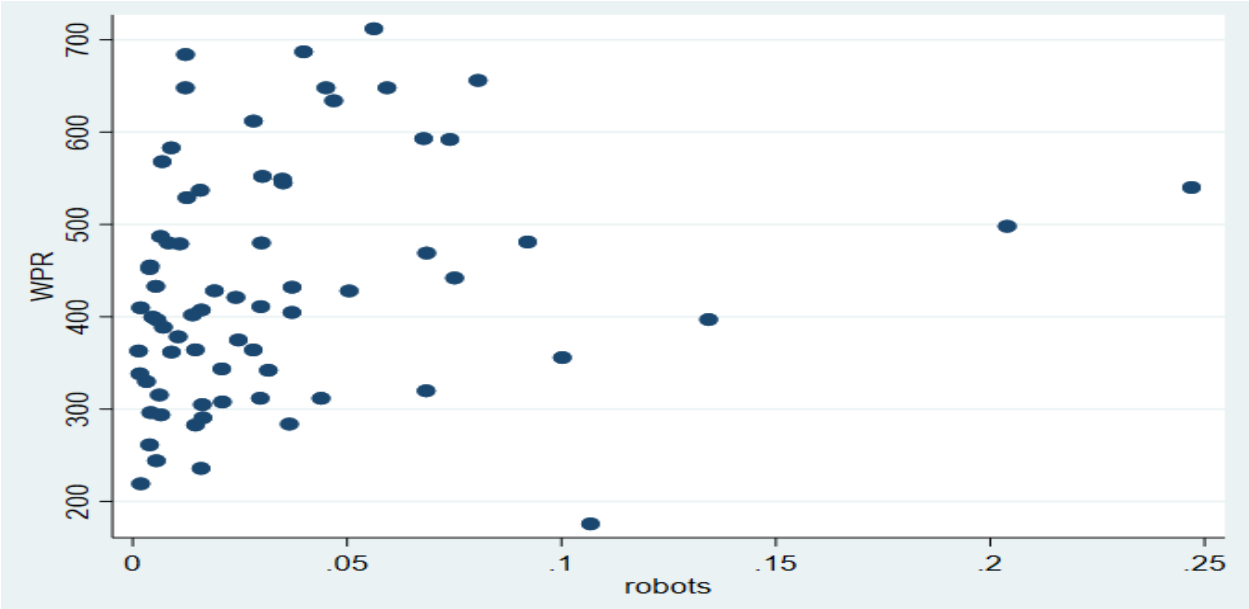
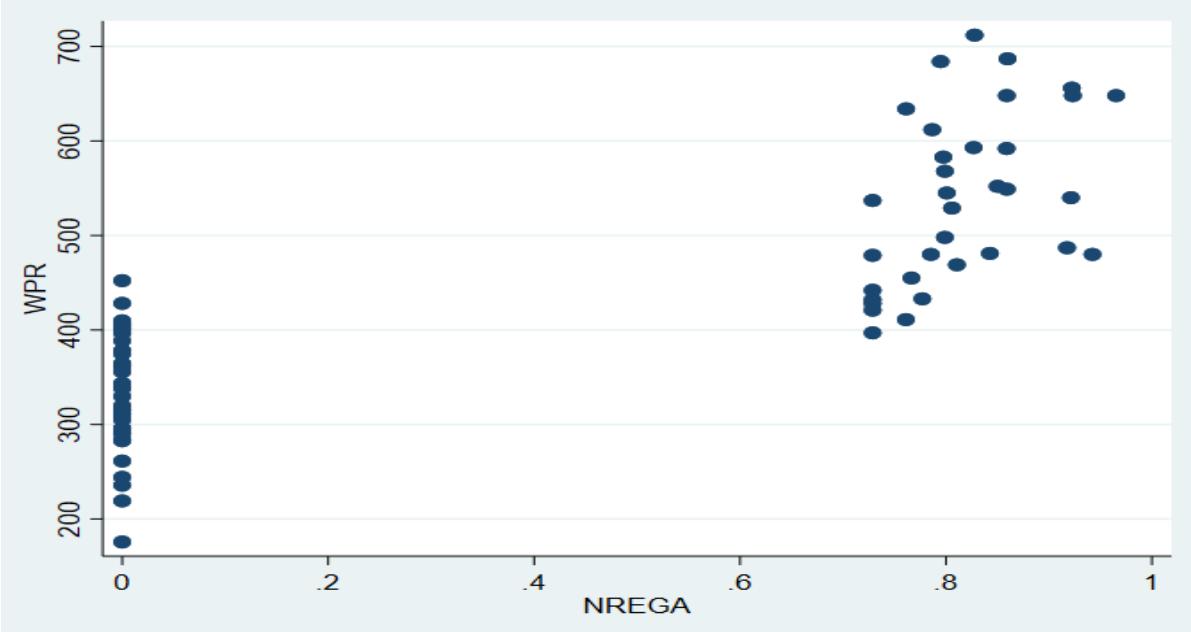


Figure 1

2. MGNREGA

The construction of the data set for the MGNREGA variable gives us an understanding of the impact of the scheme on a state's employment relative to if the state had not implemented it. When MGNREGA is regressed on employment in isolation, the result estimates, ceteris paribus, an average 59% rise in employment in a state that has implemented the scheme relative to if the state did not. This is a significant result at the 95% confidence interval with a low p-value (appendix 1.2). Once the robots and dummy variable of year is introduced, the result estimates, ceteris paribus, an average 14% rise in employment in a MGNREGA state relative to a non-MGNREGA state (appendix 1.3). A further introduction of control variable population distribution reduced the rise in employment to an average of 13% in a MGNREGA

state relative to a non-MGNREGA state, ceteris paribus (appendix 1.4). The latter two results are not significant and have a high p-value, but like the last section, it can be attributed to the low number of observations. The general trend observed is that MGNREGA has had a positive effect on employment across all Indian states and so it can be concluded that the scheme is succeeding in bringing more people into the workforce.



3. Population distribution

The coefficient for population density estimates that, ceteris paribus, for a 1% rise in population distribution, there is an average 0.34% fall in employment (appendix 1.4). This means that the rate of job creation in the economy is being outpaced by the population growth rate, despite positive effects of MGNREGA. This can be attributed to the earlier mentions and trends of jobless growth as the Indian economy has grown at an average rate of over 8% between 2004 and 2014. More analysis must be done to understand the underlying causes of jobless growth in India, especially as this result accounts for the impact of automation. It can be argued that robots have negative spill-over effects that could be the reason for this trend in jobless growth, but more in-depth empirical analysis must be performed to be certain.

Conclusion

Automation is poised to become an integral part of the world's economic order. From autonomous vehicles to artificial intelligence, it is reshaping the way humans do their everyday activities. Although there is concern that this will be accompanied by mass unemployment, there is little to no empirical evidence pointing to such. The regression analysis in this paper shows that the impact is very small despite the small number of factors considered. This result is in-line with empirical studies conducted elsewhere in the world and mentioned earlier in this paper.

Nonetheless, trends of increasing unemployment are common across the developing world. This paper analyses one of the prominently backed solutions to the issue, a JGS. It analyses the MGNREGA, the largest JGS program in the world run by India and finds that the scheme has contributed positively to employment trends in the country.

The results in this paper are not statistically significant when analysed together, potentially due to the small number of observations in our data set. Nonetheless, it provides us with the kind of impact these factors can have on the labour market and facilitates a solid basis for further research on this subject.

Appendix of descriptions and explanations

Appendix A

As per the definition of the Internal Federation of Robotics, industrial robots are fully autonomous machines that do not need a human operator and that can be programmed to perform several manual tasks (Ifr.org, n.d.).

Appendix B

The Venus Project proposes a system in which automation and technology would be intelligently integrated into an overall holistic socio-economic design where the primary function would be to maximize the quality of life rather than profits. The people working on it believe that mass technological unemployment is inevitable, but instead of being a problem, it will provide society with a new approach to work and income (The Venus Project, 2019).

Appendix C

In this point, a brief remark is needed. In Keynes view, prices are sticky, i.e., they adjust gradually. That idea alone, which is empirically validated (and intuitively sensible), justifies why this mechanism of adjustment is not valid.

Appendix D

Relative unemployment, here, is used to explain that although the percentage of unemployment may be low, the absolute numbers of unemployment is increasing. This is true of both developed and developing nations across the world (Monaghan, 2019).

Appendix E

TFP also has significant limitations as a measure of technological progress It is ultimately a regression residual and has an unspecified relationship to any specific technological innovation. Further, estimates of TFP may be confounded with business cycle effects, industry trends, and cross-industry differences in cyclical sensitivity (Basu and Fernald, 2001).

Appendix F

It must be noted that a minimum wage, especially in developing countries, is set with a goal of ensuring better worker protection while ensuring that it does not result in inflation. A JGS, in theory, is set up in a way that this minimum wage does not disincentivize job-search by the unemployed worker as the jobs provided are supposed to be temporary in nature.

Appendix G

Another criticism is that this may cause wages that are higher than the minimum wage to rise even further. This is untrue as the minimum wage, especially in developing nations where JGS is likely to be implemented, would be just enough to ensure that the worker is able to afford an extremely basic survival. Thus, as is intuitive, any wage that is above the minimum wage would be enough for workers to join the private sector workforce. Also, as the nature of the jobs in a JGS is supposed to be temporary, unskilled manual labor, there is an incentive to move towards a more better paying, secure job, usually found in the private sector.

Appendix of results and data

Appendix 1: Regression results and formulae used

1.1

```
. xi: areg lnW lnr , a(st)

Linear regression, absorbing indicators          Number of obs     =         70
Absorbed variable: state                         No. of categories =         35
                                                 F(   1,     34)   =     120.02
                                                 Prob > F          =     0.0000
                                                 R-squared         =     0.8396
                                                 Adj R-squared     =     0.6744
                                                 Root MSE          =     0.1739

------------------------------------------------------------------------------
       lnWPR |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
       lnrob |   .4690165   .0428117    10.96   0.000     .3820128    .5560203
       _cons |   7.893864   .1715527    46.01   0.000     7.545227    8.242501
------------------------------------------------------------------------------
F test of absorbed indicators: F(34, 34) = 4.693               Prob > F = 0.000

.
```

1.2

```
. xi: areg lnW NR , a(st)

Linear regression, absorbing indicators          Number of obs     =         70
Absorbed variable: state                         No. of categories =         35
                                                 F(   1,     34)   =     186.42
                                                 Prob > F          =     0.0000
                                                 R-squared         =     0.8879
                                                 Adj R-squared     =     0.7725
                                                 Root MSE          =     0.1454

------------------------------------------------------------------------------
       lnWPR |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
       NREGA |   .5883626   .0430918    13.65   0.000     .5007896    .6759356
       _cons |    5.79528    .024355   237.95   0.000     5.745784    5.844775
------------------------------------------------------------------------------
F test of absorbed indicators: F(34, 34) = 2.059              Prob > F = 0.019

.
```

1.3

```
. xi: areg lnW lnr i.year NR , a(st)
i.year            _Iyear_2004-2014    (naturally coded; _Iyear_2004 omitted)

Linear regression, absorbing indicators          Number of obs     =         70
Absorbed variable: state                         No. of categories =         35
                                                 F(   3,     32)   =      68.25
                                                 Prob > F          =     0.0000
                                                 R-squared         =     0.9018
                                                 Adj R-squared     =     0.7882
                                                 Root MSE          =     0.1403

------------------------------------------------------------------------------
       lnWPR |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
        lnrob |  -.1551245   .1510658    -1.03   0.312    -.4628354    .1525864
  _Iyear_2014 |   .5145395   .2518004     2.04   0.049     .001639     1.02744
       NREGA |   .1385105   .2255443     0.61   0.543    -.3209081    .5979291
       _cons |   5.099141   .6726281     7.58   0.000     3.729043     6.46924
------------------------------------------------------------------------------
F test of absorbed indicators: F(34, 32) = 2.317              Prob > F = 0.009

.
```

1.4

```
.  xi: areg lnW lnr i.year NR lnpop , a(st)
i.year            _Iyear_2004-2014    (naturally coded; _Iyear_2004 omitted)

Linear regression, absorbing indicators         Number of obs     =         70
Absorbed variable: state                        No. of categories =         35
                                                F(   4,     31)   =      51.07
                                                Prob > F          =     0.0000
                                                R-squared         =     0.9042
                                                Adj R-squared     =     0.7869
                                                Root MSE          =     0.1407

------------------------------------------------------------------------------
       lnWPR |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
       lnrob |  -.1435745   .1520912    -0.94   0.352    -.4537665    .1666175
 _Iyear_2014 |    .573506   .2610617     2.20   0.036     .0410672    1.105945
       NREGA |   .1257108   .2267071     0.55   0.583    -.3366614     .588083
       lnpop |  -.3429459   .3835766    -0.89   0.378    -1.125256    .4393637
       _cons |   10.59962    6.18904     1.71   0.097    -2.023012    23.22225
------------------------------------------------------------------------------
F test of absorbed indicators: F(34, 31) = 2.222               Prob > F = 0.014

.
```

1.5

WPR= (Number of employed/Total population) *1000 (see appendix 2, 6 and 7).

The subscripts *S* and *T* stand for state and year respectively.

1.6

Robot Index per million workers in India = 1,000,000* $\sum_{s=1}^{35}.\sum_{i=1}^{27}$.(Number of employed $_{I,S}$/Total Workers $_{S}$) *(Robots per 1000 in USA $_{I,T}$/ Number of employed in USA $_{I,T}$) (see appendix 2, 3, 4, 8).

The subscript *I* stands for industry/sector.

1.7

MGNREGA= $\sum_{i=1}^{35}$. (Number of districts of state $_{I}$ in phase J * Duration of J) (appendix 2, 5).

J stands for the phase of implementation and the duration is the number of months that *J* phase has run till 2nd February 2014.

Appendix 2

Data set for regression analysis

	A	B	C	D	E	F	G	H	I
1	State	WPR 2004	WPR 2014	2004 robot index	2014 robot index	NREGA 2004	NREGA 2014	POP2004	POP2014
2	Andaman and Nicobar Islands	294	537	0.065790117	0.157449361	-	0.72875	363,481	388,412
3	Andhra Pradesh	428	648	0.190761303	0.450764685	-	0.923125	78,721,238	87,367,837
4	Arunachal Pradesh	308	634	0.209095221	0.468846941	-	0.761328125	1,183,696	1,491,766
5	Assam	312	593	0.297322988	0.678542432	-	0.826851852	28,020,542	32,803,596
6	Bihar	236	480	0.159334602	0.300239429	-	0.942269737	89,328,792	112,039,100
7	Chandigarh	320	397	0.68439491	1.343211633	-	0.72875	947,080	1,109,878
8	Chhattisgarh	405	656	0.371345758	0.805348095	-	0.922291667	22,247,222	27,278,250
9	Dadra and Nagar Haveli	362	421	0.090347904	0.240507236	-	0.72875	257,456	401,333
10	Daman and Diu	283	432	0.146232152	0.371649113	-	0.72875	183,717	282,474
11	Delhi	261	402	0.039517396	0.139658264	-	0	14,731,737	17,856,064
12	Goa	244	479	0.055190865	0.109558678	-	0.72875	1,380,931	1,494,545
13	Gujarat	397	529	0.056749397	0.12640144	-	0.805769231	53,601,620	63,935,274
14	Haryana	363	455	0.013772895	0.040651383	-	0.766488095	22,406,633	26,864,631
15	Himachal Pradesh	452	684	0.039614125	0.123124038	-	0.794791667	6,313,911	7,131,161
16	Jammu and Kashmir	219	433	0.018715966	0.053841088	-	0.777102273	10,862,981	13,430,594
17	Jharkhand	296	648	0.0420448	0.122809112	-	0.965208333	28,758,521	35,207,302
18	Karnataka	410	568	0.018416181	0.068796764	-	0.798958333	55,323,983	63,954,573
19	Kerala	330	480	0.032203162	0.083383381	-	0.785357143	32,310,780	33,898,534
20	Lakshadweep	291	428	0.163536998	0.504766672	-	0.72875	61,797	65,692
21	Madhya Pradesh	364	592	0.28125174	0.739849082	-	0.8589	64,031,659	77,059,940
22	Maharashtra	389	552	0.071490678	0.302646506	-	0.850113636	101,527,339	117,766,605
23	Manipur	315	612	0.062128791	0.281659051	-	0.786666667	2,373,490	3,128,224
24	Meghalaya	407	687	0.160143379	0.398761723	-	0.859821429	2,513,242	3,215,646
25	Mizoram	344	712	0.207864197	0.562645592	-	0.8278125	951,163	1,174,492
26	Nagaland	176	498	1.06768614	2.039528263	-	0.798863636	1,986,576	1,975,062
27	Orissa	356	540	1.001908325	2.469572747	-	0.921375	38,355,527	43,742,919
28	Pondicherry	284	442	0.365270113	0.750735366	-	0.72875	1,056,427	1,353,085
29	Punjab	378	411	0.105864279	0.298766036	-	0.7610625	25,374,301	28,899,702
30	Rajasthan	364	545	0.146077948	0.350849824	-	0.800795455	60,119,563	72,930,581
31	Sikkim	375	648	0.246451031	0.593133045	-	0.8590625	561,769	634,192
32	Tamil Nadu	400	583	0.046601698	0.089912059	-	0.797379032	65,328,084	75,525,615
33	Tripura	305	549	0.162334705	0.349097119	-	0.8590625	3,341,617	3,837,463
34	Uttar Pradesh	312	481	0.439263559	0.92101741	-	0.842728873	176,282,247	211,936,276
35	Uttaranchal	342	469	0.316557641	0.685538332	-	0.810576923	8,968,432	10,655,496
36	West Bengal	338	487	0.016418504	0.064911951	-	0.917565789	83,506,172	95,067,106

Appendix 3

US industry breakdown of employment for 2005 and 2015 (IPUMS International)

	industry	2005	2015
2	Agriculture, forestry and fishing	3,054,102	3,494,217
3	Automotive	1,414,910	1,300,522
4	Basic metals	425,669	407,165
5	Construction	10,925,453	10,144,695
6	Education, research and development	13,806,648	15,977,305
7	Electricity, gas, water supply	1,154,632	1,305,292
8	Electronics	1,411,750	1,204,654
9	Financial Intermediation	7,044,925	7,067,169
10	Food and Beveradges	1,418,922	1,720,967
11	Glass and ceramics	424,422	345,211
12	Health and social work	16,041,874	20,390,478
13	Hotels and Restaurants	1,483,441	1,652,577
14	Metal machinery	1,797,578	1,653,078
15	Metal products	1,018,350	929,137
16	Mining and quarrying	560,535	896,058
17	Other community, social and personal service activities	9,650,995	10,919,043
18	Other manufacturing	3,058,056	3,170,421
19	Other vehicles	974,662	986,352
20	Paper	2,367,072	1,929,014
21	Plastic and chemicals	815,190	837,302
22	Public administration and defense, compulsory social security	8,080,957	8,578,287
23	Real Estate, renting and business activities	10,726,506	13,891,778
24	Textiles and apparel	754,981	509,291
25	Transport, storage and communications	6,507,770	7,075,796
26	Undifferentiated production activities of private households and of private households as employers	717,093	825,214
27	Wholesale and retail trade, repair of motor vehicles and personal and household goods	30,319,288	33,463,905
28	Wood and furniture	1,191,711	918,352

Appendix 4

Robots per 1000 workers in the US by industry (Acemoglu and Restrepo, 2017)

	industry	2004	2014
2	Agriculture, forestry and fishing	0.002	0.037
3	Automotive	69.007	117.72
4	Basic metals	0	7.17
5	Construction	0.003	0.02
6	Education, research and development	0.011	0.064
7	Electricity, gas, water supply	0	0.027
8	Electronics	5.713	13.109
9	Financial Intermediation	0	0
10	Food and Beveradges	2.906	6.169
11	Glass and ceramics	0.115	0.673
12	Health and social work	0	0
13	Hotels and Restaurants	0	0
14	Metal machinery	0	2.373
15	Metal products	7.487	8.289
16	Mining and quarrying	0.002	0.061
17	Other community, social and personal service a	0	0
18	Other manufacturing	0.838	8.288
19	Other vehicles	0.052	0.542
20	Paper	0.001	0.11
21	Plastic and chemicals	5.122	9.906
22	Public administration and defense, compulsory	0	0
23	Real Estate, renting and business activities	0	0
24	Textiles and apparel	0.002	0.048
25	Transport, storage and communications	0	0
26	Undifferentiated production activities of private	0	0
27	Wholesale and retail trade, repair of motor vehic	0	0
28	Wood and furniture	0.012	0.241

Appendix 5

MGNREGA implementation by phase (Nrega.nic.in. ,2019).

	State	Phase 1 (2.02.06)	Phase 2 (1.04.07)	Phase 3 (1.04.2008)	total	Ratios			Weights
2	Andaman and Nicobar Islands	0	0	3	3	0	0	1	0.72875
3	Andhra Pradesh	13	6	3	22	0.590909	0.272727	0.136364	0.923125
4	Arunachal Pradesh	1	2	13	16	0.0625	0.125	0.8125	0.761328
5	Assam	7	6	14	27	0.259259	0.222222	0.518519	0.826852
6	Bihar	23	15	0	38	0.605263	0.394737	0	0.94227
7	Chandigarh	0	0	1	1	0	0	1	0.72875
8	Chhattisgarh	11	4	3	18	0.611111	0.222222	0.166667	0.922292
9	Dadra and Nagar Haveli	0	0	1	1	0	0	1	0.72875
10	Daman and Diu	0	0	2	2	0	0	1	0.72875
11	Delhi	0	0	0	0	0	0	0	0
12	Goa	0	0	2	2	0	0	1	0.72875
13	Gujarat	6	3	17	26	0.230769	0.115385	0.653846	0.805769
14	Haryana	2	2	17	21	0.095238	0.095238	0.809524	0.766488
15	Himachal Pradesh	2	2	8	12	0.166667	0.166667	0.666667	0.794792
16	Jammu and Kashmir	3	2	17	22	0.136364	0.090909	0.772727	0.777102
17	Jharkhand	20	2	2	24	0.833333	0.083333	0.083333	0.965208
18	Karnataka	5	6	19	30	0.166667	0.2	0.633333	0.798958
19	Kerala	2	2	10	14	0.142857	0.142857	0.714286	0.785357
20	Lakshadweep	0	0	1	1	0	0	1	0.72875
21	Madhya Pradesh	18	13	19	50	0.36	0.26	0.38	0.8589
22	Maharashtra	12	6	15	33	0.363636	0.181818	0.454545	0.850114
23	Manipur	1	2	6	9	0.111111	0.222222	0.666667	0.786667
24	Meghalaya	2	3	2	7	0.285714	0.428571	0.285714	0.859821

25	Mizoram	2	2	4	8	0.25	0.25	0.5	0.827813
26	Nagaland	1	4	6	11	0.090909	0.363636	0.545455	0.798864
27	Orissa	19	5	6	30	0.633333	0.166667	0.2	0.921375
28	Pondicherry	0	0	2	2	0	0	1	0.72875
29	Punjab	1	3	16	20	0.05	0.15	0.8	0.761063
30	Rajasthan	6	6	21	33	0.181818	0.181818	0.636364	0.800795
31	Sikkim	1	2	1	4	0.25	0.5	0.25	0.859063
32	Tamil Nadu	6	4	21	31	0.193548	0.129032	0.677419	0.797379
33	Tripura	1	2	1	4	0.25	0.5	0.25	0.859063
34	Uttar Pradesh	22	17	32	71	0.309859	0.239437	0.450704	0.842729
35	Uttaranchal	3	2	8	13	0.230769	0.153846	0.615385	0.810577
36	West Bengal	10	7	2	19	0.526316	0.368421	0.105263	0.917566

Appendix 6

Indian Population (Censusindia.gov.in) *Note: 2004 and 2014 estimated based on average growth between 2001 and 2011.

	State	2001	2004*	2011	2014*
2	Andaman and Nicobar Islands	356,152	363,481	380,581	388,412
3	Andhra Pradesh	76,210,007	78,721,238	84,580,777	87,367,837
4	Arunachal Pradesh	1,097,968	1,183,696	1,383,727	1,491,766
5	Assam	26,655,528	28,020,542	31,205,576	32,803,596
6	Bihar	82,998,509	89,328,792	104,099,452	112,039,100
7	Chandigarh	900,635	947,080	1,055,450	1,109,878
8	Chhattisgarh	20,833,803	22,247,222	25,545,198	27,278,250
9	Dadra and Nagar Haveli	220,490	257,456	343,709	401,333
10	Daman and Diu	158,204	183,717	243,247	282,474
11	Delhi	13,850,507	14,731,737	16,787,941	17,856,064
12	Goa	1,347,668	1,380,931	1,458,545	1,494,545
13	Gujarat	50,671,017	53,601,620	60,439,692	63,935,274
14	Haryana	21,144,564	22,406,633	25,351,462	26,864,631
15	Himachal Pradesh	6,077,900	6,313,911	6,864,602	7,131,161
16	Jammu and Kashmir	10,143,700	10,862,981	12,541,302	13,430,594
17	Jharkhand	26,945,829	28,758,521	32,988,134	35,207,302
18	Karnataka	52,850,562	55,323,983	61,095,297	63,954,573
19	Kerala	31,841,374	32,310,780	33,406,061	33,898,534
20	Lakshadweep	60,650	61,797	64,473	65,692
21	Madhya Pradesh	60,348,023	64,031,659	72,626,809	77,059,940
22	Maharashtra	96,878,627	101,527,339	112,374,333	117,766,605
23	Manipur	2,166,788	2,373,490	2,855,794	3,128,224
24	Meghalaya	2,318,822	2,513,242	2,966,889	3,215,646
25	Mizoram	888,573	951,163	1,097,206	1,174,492
26	Nagaland	1,990,036	1,986,576	1,978,502	1,975,062
27	Orissa	36,804,660	38,355,527	41,974,218	43,742,919
28	Pondicherry	974,345	1,056,427	1,247,953	1,353,085
29	Punjab	24,358,999	25,374,301	27,743,338	28,899,702
30	Rajasthan	56,507,188	60,119,563	68,548,437	72,930,581
31	Sikkim	540,851	561,769	610,577	634,192
32	Tamil Nadu	62,405,679	65,328,084	72,147,030	75,525,615
33	Tripura	3,199,203	3,341,617	3,673,917	3,837,463
34	Uttar Pradesh	166,197,921	176,282,247	199,812,341	211,936,276
35	Uttaranchal	8,489,349	8,968,432	10,086,292	10,655,496
36	West Bengal	80,176,197	83,506,172	91,276,115	95,067,106
37	Total	1,028,610,328	1,083,283,723	1,210,854,977	1,275,903,419

Appendix 7

Employment by state India (IPUMS International)

1	State	2004	2014
2	Andaman and Nicobar Islands	106,779	208,577
3	Andhra Pradesh	33,705,228	56,614,358
4	Arunachal Pradesh	364,270	945,780
5	Assam	8,734,277	19,452,532
6	Bihar	21,061,335	53,778,768
7	Chandigarh	302,900	440,622
8	Chhattisgarh	9,002,827	17,894,532
9	Dadra and Nagar Haveli	93,141	168,961
10	Daman and Diu	51,942	122,029
11	Delhi	3,849,880	7,178,138
12	Goa	337,043	715,887
13	Gujarat	21,260,988	33,821,760
14	Haryana	8,132,943	12,223,407
15	Himachal Pradesh	2,855,505	4,877,714
16	Jammu and Kashmir	2,380,499	5,815,447
17	Jharkhand	8,518,909	22,814,331
18	Karnataka	22,667,979	36,326,198
19	Kerala	10,656,742	16,271,296
20	Lakshadweep	17,956	28,116
21	Madhya Pradesh	23,311,701	45,619,485
22	Maharashtra	39,459,125	65,007,166
23	Manipur	748,365	1,914,473
24	Meghalaya	1,023,746	2,209,149
25	Mizoram	326,779	836,238
26	Nagaland	348,989	983,581
27	Orissa	13,647,935	23,621,176
28	Pondicherry	299,810	598,064
29	Punjab	9,600,717	11,877,777
30	Rajasthan	21,897,106	39,747,167
31	Sikkim	210,551	410,956
32	Tamil Nadu	26,102,324	44,031,433
33	Tripura	1,018,780	2,106,767
34	Uttar Pradesh	54,943,263	101,941,349
35	Uttaranchal	3,067,422	4,997,428
36	West Bengal	28,250,775	46,297,680

Appendix 8

Employment by state and industry in India 2004 (IPUMS International)

	A	B	C	D	E	F	G	H	I	J
1	geo1_in2004	Agriculture, forestry and fishing	Mining and quarrying	Food and Beveradges	Textiles and apparel	Wood and furniture	Paper	Plastic and chemicals	Glass and ceramics	Basic metals
2	Jammu and Kashmir	1160658	11450	31147	214925	46691	6701	1389	0	2079
3	Himachal Pradesh	1796779	8879	20067	41326	23039	7450	11163	0	11625
4	Punjab	4859102	4388	111161	487303	88632	28509	42964	0	27132
5	Chandigarh	3780	0	7394	15323	1713	4196	4032	0	1519
6	Uttaranchal	1918232	248	21972	29085	32607	8202	5874	2920	0
7	Haryana	4195489	23826	59628	315478	50672	36248	66574	2000	20705
8	Delhi	31089	1448	16039	465420	23368	89574	47148	0	2241
9	Rajasthan	13024709	236075	163356	798135	154476	32440	45417	2231	10022
10	Uttar Pradesh	32752657	139063	915936	2705437	579254	196237	125867	200395	137768
11	Bihar	14996600	44823	183110	290314	242331	5285	9961	0	2894
12	Sikkim	114887	1561	1419	1723	675	193	521	0	0
13	Arunachal Pradesh	273335	3565	895	421	325	29	185	0	261
14	Nagaland	221556	0	1606	5627	1923	327	0	0	0
15	Manipur	447739	5224	4350	51498	5126	973	2154	0	699
16	Mizoram	227952	484	948	2361	634	368	0	0	68
17	Tripura	383797	675	13747	7110	16593	385	509	0	634
18	Meghalaya	747565	14895	4611	15732	6306	51	0	0	147
19	Assam	5785832	34267	44336	59189	85192	14142	2167	0	1497
20	West Bengal	12550482	146911	506754	1669717	457609	108114	171625	9339	112741
21	Jharkhand	4876554	206222	71258	130958	132063	4303	1942	1483	62993
22	Orissa	8147334	101330	171482	256673	498485	26063	9977	1780	76657
23	Chhattisgarh	6312810	94917	70071	63276	66025	10456	3268	19563	63182
24	Madhya Pradesh	15454763	265360	217952	350597	182279	28224	89968	2812	20186
25	Gujarat	12003414	149530	239000	1146295	176710	72193	346529	5216	85149
26	Daman and Diu	15981	0	648	962	0	392	7927	29	0
27	Dadra and Nagar Haveli	42833	0	571	5221	0	848	11320	0	3024
28	Maharashtra	21054405	194589	559476	1370862	285936	193899	340364	8829	63133
29	Andhra Pradesh	18917201	464508	620697	1217395	338885	69052	102195	2066	54591
30	Karnataka	14036992	104167	219780	789341	280284	106014	52662	0	27249
31	Goa	58977	5865	4550	3375	765	4815	8001	0	1476
32	Lakshadweep	5891	0	403	343	0	0	0	0	0
33	Kerala	3587247	130717	298151	516054	139689	64104	51336	0	4317
34	Tamil Nadu	11667569	101838	406652	2309257	347824	169043	498583	3507	45953
35	Pondicherry	83437	0	9801	20617	3899	3147	4609	2559	0
36	Andaman and Nicobar Island	30743	970	645	1583	619	815	0	0	0

	A	B	C	D	E	F	G	H	I	J	K
1	geo1_in2004	Metal machinery	Metal products	Electronics	Automotive	Other vehicles	Other manufacturing	Electricity, gas, water supply	Construction	Wholesale and retail trade, repa	Hotels and Restaurants
2	Jammu and Kashmir	1081	8242	4259	0	0	15871	29358	218339	201312	19791
3	Himachal Pradesh	5748	6026	0	7774	0	31071	48460	298183	141612	48976
4	Punjab	114008	90075	9415	15447	10956	202094	91852	746514	1096159	89215
5	Chandigarh	5546	4738	2780	29	0	7342	389	16959	42507	10695
6	Uttaranchal	10371	18857	6841	4782	0	16423	14020	233061	261521	41519
7	Haryana	70266	109619	16574	84095	6097	238591	52770	572557	926402	47448
8	Delhi	58681	62555	57702	7657	0	176430	3956	233495	928849	127319
9	Rajasthan	27026	118074	18753	3988	11392	782090	113677	2234145	1553517	228777
10	Uttar Pradesh	172530	351111	157545	34168	8557	1490450	92287	3037964	5550710	421864
11	Bihar	21024	19103	153	1697	3927	575451	20865	769849	1977272	184063
12	Sikkim	0	668	0	0	0	1549	2659	16706	18056	5645
13	Arunachal Pradesh	72	0	0	358	0	68	2981	16690	13927	654
14	Nagaland	72	78	111	0	0	1113	2367	6628	39033	6697
15	Manipur	7	594	0	0	0	8386	89	26017	70397	5691
16	Mizoram	0	459	0	0	0	2295	90	7321	31728	780
17	Tripura	42	875	77	0	0	15436	458	108909	129337	5682
18	Meghalaya	62	650	165	0	0	11959	4997	25485	56266	10329
19	Assam	2170	18966	2043	0	0	87276	33014	253757	956215	47662
20	West Bengal	67158	139039	73126	14403	41415	1751591	68474	1393304	3552940	399769
21	Jharkhand	15560	37093	1206	38032	0	383950	17946	928631	715888	67872
22	Orissa	12946	52282	1786	584	13094	468826	43667	881778	1176758	197173
23	Chhattisgarh	2591	37638	293	973	2099	216320	14240	639133	533091	114293
24	Madhya Pradesh	28364	73834	34429	36220	0	944949	53729	1120009	1846358	198285
25	Gujarat	100837	160134	38782	1965	806	1169934	56679	776291	1985040	190124
26	Daman and Diu	297	289	523	0	106	297	0	2362	6690	2122
27	Dadra and Nagar Haveli	1540	583	170	325	0	383	0	2451	5542	3166
28	Maharashtra	199974	366221	84116	159514	10250	1213142	120507	2012107	3958253	640448
29	Andhra Pradesh	62426	124346	30095	5383	23230	1226688	52132	1761419	3079817	611306
30	Karnataka	74189	98482	44191	29698	12603	610808	52413	896223	1984723	394432
31	Goa	1256	829	1097	221	1379	7268	6101	38184	51805	26678
32	Lakshadweep	0	0	0	0	76	0	931	4203	777	38
33	Kerala	24661	77217	13978	1721	11221	302781	47146	1178646	1360820	293939
34	Tamil Nadu	128648	224156	23821	112732	490	1110343	66681	1687825	2575011	607072
35	Pondicherry	1053	3875	3320	16	0	13859	3896	31027	45271	8159
36	Andaman and Nicobar Island	0	0	0	0	398	1351	3712	12341	14267	2369

	A	B	C	D	E	F
1	geo1_in2004	Transport,storage, communications	Financial Intermediation	Real Estate,renting,business activities	Public administration,defense,compulsory social security	Education, research and development
2	Jammu and Kashmir	105793	9391	4655	153929	78897
3	Himachal Pradesh	105474	7498	10502	65555	104721
4	Punjab	465607	81798	79109	222894	309057
5	Chandigarh	28061	16293	12862	64755	19667
6	Uttaranchal	105736	17393	14745	106102	121916
7	Haryana	405181	43623	95819	189770	217087
8	Delhi	319109	87210	218651	465097	163311
9	Rajasthan	677198	88532	184505	329275	494627
10	Uttar Pradesh	2029210	176563	357305	793065	1133305
11	Bihar	565477	48918	85371	176965	291536
12	Sikkim	8246	1052	18	16419	12769
13	Arunachal Pradesh	3343	54	2487	35133	4865
14	Nagaland	8129	1530	849	29058	13241
15	Manipur	18922	2016	1132	62668	25709
16	Mizoram	3804	545	1014	34669	9348
17	Tripura	39551	800	2315	58287	54074
18	Meghalaya	16950	1921	291	43285	35132
19	Assam	308313	17205	20768	197562	284422
20	West Bengal	1567026	244846	343617	553321	1048647
21	Jharkhand	288982	55286	33303	57064	225215
22	Orissa	427381	71702	70566	227163	370601
23	Chhattisgarh	209739	23619	20449	131528	163641
24	Madhya Pradesh	485550	76728	136754	514059	582428
25	Gujarat	890688	122974	155280	346204	508938
26	Daman and Diu	5499	86	1179	1262	3235
27	Dadra and Nagar Haveli	5947	110	1547	4885	1427
28	Maharashtra	1909159	441958	698295	838600	1041429
29	Andhra Pradesh	1564537	208825	267036	544195	711594
30	Karnataka	824220	177567	254170	356659	524871
31	Goa	47166	2437	5961	21462	11248
32	Lakshadweep	1370	0	109	2032	1202
33	Kerala	894107	188950	166143	191380	499386
34	Tamil Nadu	1176406	281141	451942	584603	575395
35	Pondicherry	21899	3806	3113	8156	11207
36	Andaman and Nicobar Islands	10490	288	1064	13469	4923

	A	B	C	D
1	geo1_in2004	Health and social work	Other community, social and personal service activities	Undifferentiated production activities of private households and of private households as employers
2	Jammu and Kashmir	17018	32252	6038
3	Himachal Pradesh	25350	20792	8607
4	Punjab	88007	177931	88534
5	Chandigarh	11341	8125	12852
6	Uttaranchal	32565	23551	17815
7	Haryana	74034	195861	44997
8	Delhi	64994	92270	150318
9	Rajasthan	206599	401167	63353
10	Uttar Pradesh	372296	1018315	113312
11	Bihar	111992	346373	102689
12	Sikkim	1951	1193	2642
13	Arunachal Pradesh	1439	2348	833
14	Nagaland	4964	3271	739
15	Manipur	1227	6853	741
16	Mizoram	840	553	582
17	Tripura	5791	128609	45090
18	Meghalaya	8268	4478	14201
19	Assam	38749	47785	391747
20	West Bengal	265966	470886	647414
21	Jharkhand	31306	116419	39757
22	Orissa	71645	201407	67022
23	Chhattisgarh	41664	97811	56012
24	Madhya Pradesh	118665	317844	140265
25	Gujarat	129073	261492	206303
26	Daman and Diu	98	1479	507
27	Dadra and Nagar Haveli	414	12	792
28	Maharashtra	420017	726639	660898
29	Andhra Pradesh	274651	1060423	342485
30	Karnataka	175364	366539	203221
31	Goa	9740	5082	11304
32	Lakshadweep	272	309	0
33	Kerala	177723	233899	209657
34	Tamil Nadu	261569	514988	319708
35	Pondicherry	2968	7955	6850
36	Andaman and Nicobar Islands	1756	2444	2533

Appendix 9

Industry Codes (industry unrecoded variable codes) (IPUMS International)

a) USA

	industry	USA
2	1. Agriculture, forestry and fishing	105/116/126
3	2. Mining and quarrying	206/216/226/236
4	3. Food and Beveradges	406/407/408/409/416/417/418/419/426
5	4. Textiles and apparel	436/437/438/439/448/449
6	5. Wood and furniture	306/307/309
7	6. Paper	456/457/458/459
8	7. Plastic and chemicals	468/469
9	8. Glass and ceramics	316/317/318/319
10	9. Basic metals	336/337/348
11	10. Metal machinery	356/357/358
12	11. Metal products	346/0
13	12. Electronics	367/0
14	13. Automotive	376/0
15	14. Other vehicles	377/378/379
16	15. Other manufacturing	326/338/386/387/399/429/467/476/477/478/488/489
17	16. Electricity, gas, water supply	586/587/588/596/597/598
18	17. Construction	246/0
19	18. Wholesale and retail trade, repair of motor vehicles and personal and household goods	606/607/608/609/616/617/618/619/626/627/636/646/656/657/658/659/667/668/669/679/686/687/688/689/696/697/698/699/816/817
20	19. Hotels and Restaurants	836/0
21	20. Transport, storage and communications	506/516/526/527/536/546/556/568/578
22	21. Financial Intermediation	716/726/736
23	22. Real Estate, renting and business activities	746/806/807/808
24	23. Public administration and defense, compulsory social security	906/916/936
25	24. Education, research and development	888/0
26	25. Health and social work	868/869/896
27	26. Other community, social and personal service activities	846/849/856/857/858/859/879/897/898/899
28	27. Undifferentiated production activities of private households and of private households as employ	826/0

b) India

	industry	IND
2	1. Agriculture, forestry and fishing	011/012/013/014/015/020/050
3	2. Mining and quarrying	101/102/103/111/112/120/131/132/141/142
4	3. Food and Beveradges	151/152/153/154/155
5	4. Textiles and apparel	171/172/173/181/182/191/192
6	5. Wood and furniture	201/202
7	6. Paper	210/221/222
8	7. Plastic and chemicals	241/242/252
9	8. Glass and ceramics	261/0
10	9. Basic metals	271/272/273
11	10. Metal machinery	291/292/293/300
12	11. Metal products	281/289
13	12. Electronics	311/312/313/314/315/321/322/323
14	13. Automotive	341/342/343
15	14. Other vehicles	351/352/353
16	15. Other manufacturing	160/191/192/223/231/232/233/243/251/269/331/332/333/359/361/369/371/37
17	16. Electricity, gas, water supply	401/402/403/410
18	17. Construction	451/452/453/454/455
19	18. Wholesale and retail trade, repair of motor vehicles and personal and household goods	501/502/503/504/505/511/512/513/514/515/519/521/522/523/524/525/526
20	19. Hotels and Restaurants	551/552
21	20. Transport, storage and communications	601/602/603/611/612/621/622/630/641/642
22	21. Financial Intermediation	651/659/660/671/672
23	22. Real Estate, renting and business activities	701/702/711/712/713/721/722/723/724/725/729/731/732/741/742/743/749
24	23. Public administration and defense, compulsory social security	751/752/753
25	24. Education, research and development	801/802/803/809
26	25. Health and social work	851/852/853
27	26. Other community, social and personal service activities	900/911/912/919/921/922/923/924/930
28	27. Undifferentiated production activities of private households and of private households as employers	950/0

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