

# **The Impact of India's Ease of Doing Business**

## **Program on the Manufacturing Sector**

by

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## **Abstract**

In September 2014, Prime Minister Narendra Modi announced his plans to make India a manufacturing hub of the world by cultivating a business-friendly environment. To accomplish this goal, the government developed a program that proposed custom-tailored reforms to states and awarded them with a yearly score that reflected their implementation efforts. Using data from 33 states and union territories in the time period from 2015 till 2017, this study performed panel data regressions to test the impact of the program on the manufacturing sector. The results indicated that an increase in a state's implementation score triggered an increase in their manufacturing sector's GDP. The composite nature of the score limited this study from identifying precisely which reforms affected manufacturing. In the attempt to overcome this limitation, the study explored the reforms attributed to the extraordinary increase of India's place in the World Bank EODB index in the same 2015-2017 time period as way of discerning specific reforms that conceivably affected the manufacturing sector.

## **Acknowledgements**

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## Table of Contents

<b>1</b>	<b>Introduction.....</b>	<b>1</b>
<b>2</b>	<b>Literature Review .....</b>	<b>4</b>
<b>3</b>	<b>India’s Ease of Doing Business Program .....</b>	<b>8</b>
<b>4</b>	<b>Data and Methodology .....</b>	<b>12</b>
4.1	<i>Recent Trends.....</i>	<i>12</i>
4.2	<i>Data Sources and its Limitations .....</i>	<i>15</i>
4.3	<i>Variable Definition and Summary Statistics.....</i>	<i>17</i>
4.3.1	Dependent Variable .....	18
4.3.2	Causal Variable.....	19
4.3.3	Control Variables (i.e. Confounding variables).....	20
4.4	<i>Empirical Strategy and Results.....</i>	<i>23</i>
4.4.1	Data Structure .....	23
4.4.2	Multiple OLS Regression .....	23
4.4.3	First Difference Estimator.....	26
4.4.4	Fixed Effect Estimator .....	28
4.5	<i>First Difference versus Fixed Effect: Which one to choose from? .....</i>	<i>31</i>
4.6	<i>Discussion of Results .....</i>	<i>35</i>
<b>5</b>	<b>Policy Discussion .....</b>	<b>36</b>

5.1	<i>The World Bank EODB Index</i> .....	38
5.2	<i>India's World Bank EODB Ranking</i> .....	39
5.3	<i>Regulatory Improvement since 2014</i> .....	41
<b>6</b>	<b>Conclusion</b> .....	<b>44</b>
<b>7</b>	<b>Bibliography</b> .....	<b>45</b>
<b>8</b>	<b>Appendix</b> .....	<b>52</b>

## List of Figures

Figure 1 - The 11-year old parallel trend between the manufacturing and industrial sector stops after 2016 .....	12
Figure 2 - In 2016 the manufacturing sector deviates from other sectors with which it had experienced a parallel trend for 5 years .....	12
Figure 3 - The average state-level DIPP-EODB score almost doubles from 32% in 2015 to 62% in 2017.....	13
Figure 4 – The DIPP-EODB score and FDI show an apparent correlation .....	14
Figure 5 – The histogram shows the distribution of the Manufacturing sector’s GDP .....	18
Figure 6 - The histogram shows the distribution of the DIPP-EODB Score (in %).....	19
Figure 7 - Distribution of Urban Population.....	20
Figure 8 - Distribution of Literacy Rates (0-100%).....	21
Figure 9 - Distribution of Electricity Transmission and Distribution Losses (0-100%).....	21
Figure 10 - Distribution of FDI.....	22
Figure 11 - Shows a positive correlation between the EODB Score and Manufacturing GDP ....	24
Figure 12 - India's place in the World Bank EODB ranking has seen an extraordinary increase since 2014 .....	37
Figure 13 - India's score in every indicator that constitutes the World Bank EODB Index has risen .....	40

## List of Tables

Table 1 - OLS regression results from regressing Manufacturing GDP on the EODB Score and progressively adding more control variables .....	25
Table 2 - First Difference (FD) regression of manufacturing GDP on the EODB score by progressively adding more control variables .....	27
Table 3 - Fixed Effect (FE) regression of manufacturing GDP on the EODB score by progressively adding more control variables.....	30
Table 4 - First Difference (FD) regression results .....	35
Table 5 - The improvement in India's World Bank EODB ranking in the 2014-2018 period .....	40
Table 6 - India's improvement in the World Bank EODB ranking from 2017 till 2018 .....	41
Table 7 - Simple OLS regression between FDI and the EODB Score .....	56

# 1 Introduction

In September 2014, Prime Minister Narendra Modi announced his plans to make India a manufacturing hub of the world with the implementation of a policy that coined the name ‘Make-in-India’ (MII). He called for entrepreneurs and industrialists both Indian as well as foreign to make India a global hub for their manufacturing activities in twenty-five economic sectors<sup>1</sup> so that the country could increase its share of manufacturing from a mere 16% of GDP in 2014 to 25% of GDP by 2022 (Nam, Nam, & Steinhoff, 2017). In an attempt to achieve such growth in the manufacturing sector, the MII policy heavily focused on attracting Foreign Direct Investments (FDI) and cultivating a business-friendly environment for foreign as well as domestic industrialists (Raghuram Rajan, 2015).

Since the implementation of the MII policy at the beginning of 2015, India has experienced a noticeable shift in trends among a variety of indicators. Most notably has been the disproportionate increase in the manufacturing sector since 2016. The manufacturing sector had been moving parallel to other sectors such as services, industry and construction for at least five years prior to that. The other noticeable shift has been with regards to India’s place in the World Bank Group’s Ease of Doing Business (EODB) ranking. The country’s ranking had never surpassed the 130 mark before 2014 (World Bank, 2018). This trend witnessed some miraculous improvements when the country climbed a whopping 53 spots between 2014 and 2018 (World

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<sup>1</sup> The sectors include: (1) automobiles; (2) automobile components; (3) aviation; (4) biotechnology; (5) chemicals; (6) construction; (7) defense manufacturing; (8) electrical machinery; (9) electronic systems; (10) food processing; (11) information technology and business process management; (12) leather; (13) media and entertainment; (14) mining; (15) oil and gas; (16) pharmaceuticals; (17) ports and shipping; (18) railways; (19) renewable energy; (20) roads and highways; (21) space and astronomy; (22) textiles and garments; (23) thermal power; (24) tourism and hospitality; and (25) wellness.



Bank, 2018). Such notable trends since Modi's implementation of the MII policy are certainly thought-provoking and their relationship is worthy of further exploration.

After deliberate evaluation of the aforementioned trends and reviewing the existing literature on this topic, I am led to believe that there could be a conceivable relationship between the programs implemented as part of the MII policy and the increase in the manufacturing sector's GDP. As part of the MII policy, the Department of Industrial Policy and Promotion (DIPP) launched a program (which I will from here on call the DIPP-EODB program) that proposed a number of regulatory reforms with the goal of making the country more conducive for doing business. This was intended to consequentially attract investments from industrialists both at home and abroad and contribute to making India a manufacturing hub of the world. Therefore, in this study, I will use state-level data from across the country to evaluate the extent to which the DIPP-EODB program triggered an increase in the manufacturing sector of India. The empirical strategy consists of panel data regressions using Fixed Effect (FE) and First Difference (FD). The results demonstrate that there is in fact a causal relationship between a state's compliance with the DIPP-EODB program and its manufacturing sector's GDP.

In 1937 Ronald Coase began to question the notion of costless transactions. Since then ample research has been done on the role of institutions and transactions costs in determining investment and economic growth. With the exception of a few studies, the prevailing view is that a conducive business environment creates the right incentive for individuals to engage in productive investments that cause higher economic activity. These conclusions have been drawn from a wide range of studies that explored everything from micro to country level data in both developed and less-developed parts of the world. Based on the literature, the positive correlation between business environment and economic activity has almost become conventional wisdom.

My study will contribute to the existing literature by expanding our understanding of the interdependence between business conduciveness and economic activity using Indian state-level data since the implementation of the MII policy. The study's outcome will also help Indian policymakers decipher whether the program has in fact reached its intended goal of boosting manufacturing.

The rest of this research paper is divided into five sections. In chapter 1, I will first start by exploring some the most prominent studies that explore the relationship between a country's business climate and economic activity. Chapter 2 will provide a comprehensive overview of the DIPP-EODB program whose goal has been to make India a manufacturing hub. It will review the mechanism with which the DIPP awards states and union territories with a yearly score intended to reflect their implementation efforts. This will be followed by Chapter 3 which consists of my empirical evaluation of the extent to which the DIPP-EODB program has triggered a variation in the country's manufacturing sector using panel data from 33 states and union territories from 2015 till 2017. The results demonstrate that a state's compliance with the DIPP-EODB program causes their manufacturing sector to increase. Chapter 4 will expose the study's inability to identify precisely which reforms effected manufacturing due to the composite measures provided by the DIPP-EODB program. In the attempt to overcome this limitation, the study explores the regulatory reforms that contributed to the extraordinary increase of India's place in the World Bank EODB in the same 2015 till 2017 time period. Finally, the conclusion will discuss the possibility of further studies that builds on the findings and overcome the limitations of this one.

## 2 Literature Review

In 1937, Ronald Coase began to question the notion of costless transactions. He argued that negotiations during business transactions incur costs such as carrying out inspections or writing up contracts. These costs were determinant in whether a transaction would take place or not. At a later point in his life he went on to succinctly say that “Business men in deciding on their ways of doing business and on what to produce take into account transaction costs. If the costs of making an exchange are greater than the gains which that exchange would bring, that exchange would not take place and the greater production that would flow from specialization would not be realized” (Coase, 1992, p. 710). Over the course of his lifetime, research that explores the role of institutions and transactions costs in determining investment and economic growth has gained significant traction among members of the academic community.

In the literature by Batra, Kaufmann, and Stone (2003), Dollar, Hallward-Driemeier, and Mengistae (2005), as well as Escribano and Luis Guasch (2005), a country’s investment climate is synonymous with a country’s ease of doing business climate.<sup>2</sup> They go on to argue that a conducive business environment is considered to create the right incentive for individuals to engage in productive investments that cause higher economic activity. More studies by Hall and Jones (1999), Bosworth and Collins (2003), Rodrik, Subramanian, and Trebbi (2004) have also discussed the importance of investment climate in determining the extent to which there is economic growth. Other studies including those of Gorgens et al. (2003), Djankov et al. (2006), and Dawson and Seater (2013), have found that there is a negative relationship between regulation that reduce investment climate and various measures pertaining to macroeconomic performance.

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<sup>2</sup> This is because a good investment climate is associated to reducing risks and increasing the conduciveness of doing business.

Some other studies by Kinda, Plane, and Véganzonès-Varoudakis (2011) have specifically explored the positive relationship that exists between the ease of doing business climate and firm growth while studies by Sekkat and Marie-Ange (2007) Jayasuriya (2011) and, Breen and Gillanders (2012) have shown the same positive correlation in relation to FDI and the increased economic activity that comes as a result of it.

At a macroeconomic level, many of these published studies use cross-country analyses that have shown that a conducive investment climate can promote FDI inflows (Sekkat and Marie-Ange 2007; Jayasuriya 2011), economic growth and productivity (Lucas Jr 1988; Hall and Jones 1999; Bosworth and Collins 2003; Djankov, McLiesh, and Ramalho 2006). Other empirical studies investigated this linkage based on firm-level data and established that a good investment climate does improve firm growth and subsequently economic growth as well. To draw on a more specific example, the earlier mentioned study by Batra, Kaufmann, and Stone (2003) explored data of 30,000 firms from around the globe and found that constraints on the investment climate created risk, extra costs and barriers to firm growth; and this resulted in lower economic activity.

Since this research paper explores the relationship between the ease of doing business environment and economic activity in India specifically, let me review some studies that investigate this relationship in countries with similar socio-economic characteristics. In a study by Korutaro and Biekpe (2013), the authors examined 29 developing countries from Africa, Latin America, and Asia (includes India) over a five-year period from 2003-2007. They found that decreased business regulation —as measured by the World Banks’s Doing Business Index— fosters a better investment climate. They go on to argue that the investment climate subsequently has positive effects on economic activity in the various countries. Similar research was carried out in developed countries in a study by Alestina et al. (2005) in which the authors examine the impact

of regulatory hurdles in transport, communication and utilities industries of 21 OECD countries over the years from 1975 to 1998. They found that regulatory hurdles lead to decreased investment and a fall in economic activity. Another famous study by Dawson (2006) found similar results in carrying out an analysis for a broader set of countries over the 1980-2000 period by using the regulatory index in the Economic Freedom of the World Index.

In addition to all the research from the academic community discussed thus far, the World Bank has also conducted numerous studies of its own which were aimed to develop a better understanding of the factors that make up a conducive business environment and how that effects economic outcomes. Their studies have also concluded that “a good investment climate addresses the local institutional, regulatory and policy environment in which firms operate and subsequently stimulates economic growth by providing firms with the incentive to invest and improve productivity” (World Bank, 2005, p. 14). With this it established the ‘Doing Business’ project to monitor and benchmark the business regulatory environment of countries around the world. It specifically developed the EODB index consisting of ten categories<sup>3</sup> that improve a country’s business environment. The organization intended to use these dimensions as a prescription for country’s striving to reach higher economic growth and also measure their steps taken. I believe that this is representative of the extent to which the causal relationship between business environment and economic growth have become universally accepted. A number of multilateral organizations now use these performance indicators as targets that developing countries must aspire to achieve higher economic growth.

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<sup>3</sup> The categories the constitute the EODB index are as follows: 1) Starting a business, 2) Dealing with construction permits, 3) Getting electricity, 4) Registering property, 5) Getting credit, 6) Protecting minority investors, 7) Paying taxes, 8) Trading across borders, 9) Resolving Insolvency, and 10) Enforcing contracts.

In summary, the accumulated evidence from the empirical literature suggests that a country's business regulatory environment is not only a relevant issue that has to be explicitly accounted and controlled for, but that it actually represents a particularly important and influential determinant in a country's economic growth levels. Despite all the research that has already been carried out in the field, there was not much that looked at manufacturing output specifically. Instead, most of them focused on economic growth in general without discerning a particular sector like manufacturing. The already discussed study by Kinda, Plane, & Veganzones (2011) was one instance where the manufacturing sector in the Middle East and North Africa were used as a case study to explore the positive relationship between firm productivity and investment climate in developing countries. With regards to literature on the effectiveness of the MII policy specifically, there was no academically credible literature to be found. This is understandable given the fact that it was only implemented four years ago and it being an ever-evolving policy with many facets being continually added since its initial launch in 2014. Given this information, I anticipate that the empirical analysis from this study will contribute to a deeper understanding of the extent to which India's attempts at improving business conduciveness triggered an increase in manufacturing output. The empirical results obtained from this case study will also contribute to the on-going debate on the relationship between factors that promote a good business environment and economic output.

### 3 India's Ease of Doing Business Program

The Department of Industrial Policy and Promotion (DIPP) in India spearheaded the entire program of improving the country's doing business environment. In the attempt to design the roadmap for this challenge, the DIPP policymakers considered two important factors. The first one is that given the country's federal structure, States and Union Territories (UTs) would play a pivotal role in promoting investor confidence. There would also be no one-size-fits-all reform due to India's structural, linguistic and cultural diversity. Therefore, the DIPP would propose yearly state-specific reforms. The second one is that compliance of proposed reforms among states would be a major impediment in policy implementation. Therefore, the DIPP also took on the exercise of assessing the implementation of the proposed state-level reforms and ensuring that the factors that enable ease of doing business are both measurable and comparable across states/UTs. This measurability and comparability of the state/UT's compliance was to promote "competitive and cooperative federalism" among the states/UTs. The competitiveness would enhance efficiency in reform implementation while cooperation would ensure that states/UTs learn from best practices.

With these considerations in mind, the DIPP launched the program on the 29<sup>th</sup> of December 2014 with a 98-Point Action Plan.<sup>4</sup> This plan was animated by the world bank's EODB index and comprised state-level regulatory reform proposals that targeted the following categorical areas: setting up a business, allotment of land and obtaining construction permits, complying with environmental procedures, complying with labor regulations, obtaining infrastructure related utilities, registering and complying with tax procedures, carrying out inspections, and enforcing contracts (DIPP, 2014). This first plan was subsequently followed by a report titled "Assessment

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<sup>4</sup> The 98-point action plan for states can be viewed on the DIPP's site under the following link: [http://eodb.dipp.gov.in/data/1\\_98point\\_action\\_plan\\_for\\_states\\_December\\_2014.pdf](http://eodb.dipp.gov.in/data/1_98point_action_plan_for_states_December_2014.pdf)

of State Implementation of Business Reforms” in September 2015 which evaluated the reforms implemented by states/UTs between the period of 1<sup>st</sup> January 2015 to 30th June 2015 (DIPP, 2014). In addition to assessing reform implementation efforts from the perspective of the state authorities, the DIPP also allowed for a business-to-government (B2G) feedback mechanism that measured the quality of reform implementation as seen in the eyes of the private sector. This was to ensure that the state/UT’s implementation assessment mechanism is comprehensive and impartial as it takes into account the businesses it is meant to serve (DIPP, 2014). Based on their findings, the DIPP then developed a four-step assessment cycle<sup>5</sup> that awarded states/UTs with a yearly score that would be a measurable reflection of their performance in implementing the proposed reforms. For the purpose of this paper, this score will be referred to as the DIPP-EODB score.

This first wave of regulatory improvements further created a need to sustain the momentum for more reforms (DIPP, 2015). Therefore, the DIPP then circulated a 340-Point Business Reform Action Plan (BRAP) for states/UTs in late October 2015 for further reform implementation. Unlike the initial plan which was inspired by the factors that make up the World Bank EODB index, this one was drafted in consultation with all states/UTs. Joint workshops were also conducted in partnership with the World Bank to help states/UTs better understand the essence of these reforms. Using the first two action plans as a foundation, the DIPP has been releasing yearly reform plans<sup>6</sup> that are both state-specific and measurable. This has been accompanied with yearly DIPP-EODB scores awarded to states/UTs based on their efforts at implementing suggested reforms. The score is intended to continue perpetuating “competitive federalism” as a roadmap towards an improved business environment.

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<sup>5</sup> The exact mechanism with which states/UTs are awarded a score using the four-step assessment cycle can be seen in Appendix B.

<sup>6</sup> These yearly state-level reform plans from the DIPP are called Business Reform Action Plans (BRAP).



To ensure that there is also “cooperative federalism”, the DIPP launched an online portal ([www.eodb.dipp.gov.in](http://www.eodb.dipp.gov.in)) in April 2016. The platform shares information on: a) real time ranking and tracking of the states/UTs based on the implementation of the recommendations, b) details of the good practices to learn and replicate, and c) provides information on current policies and practices across the state/UTs (DIPP, 2014). The portal has been a continuously evolving program of feedback and recommendations for reforms on regulatory processes, practices and procedures to states/UTs. Its aim is to have a continuous cycle of informed policy recommendations and result measurement based on the collective experiences and expertise from the World Bank, the DIPP, and of course states/UTs from across the country.

On the whole, this entire program can be summarized in two dimensions. The first dimension is that of the DIPP assessment cycle which can be summarized in the following four steps: capture, assess, collate, share. In the capturing phase, the DIPP obtains responses from the states on the implementation status of various factors suggested by the DIPP yearly Business Reform Action Plans (BRAP).<sup>7</sup> This is followed by the assessment step where the DIPP evaluates the implementation status for a given reform area and allocates a score between zero and one-hundred that reflects the percentage of proposed factors that were actually implemented by the state. The next step involves the collation of the state’s overall implementation status. The final step involves sharing the results and comparing the implementation status across states (DIPP, 2015). The details of the iterative process of this four-step assessment cycle can be viewed in Appendix B. This assessment cycle lays the foundation for the second dimension which is the ever-evolving exercise of undergoing an iterative process of state-specific policy suggestions by the DIPP, assessment of

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<sup>7</sup> BRAP is the list of yearly regulatory reforms proposed by the DIPP.

state-level implementation, impact evaluation and sharing of best practices in a continuous cycle targeted at ultimately creating a conducive business environment across the country (DIPP, 2014).

## 4 Data and Methodology

### 4.1 Recent Trends

Since the implementation of the DIPP-EODB program in early 2015, India has experienced a noticeable shift in trends among a variety of indicators. Most notably has been the disproportionate increase in the manufacturing sector since 2016. Prior to that, the manufacturing sector's GDP had

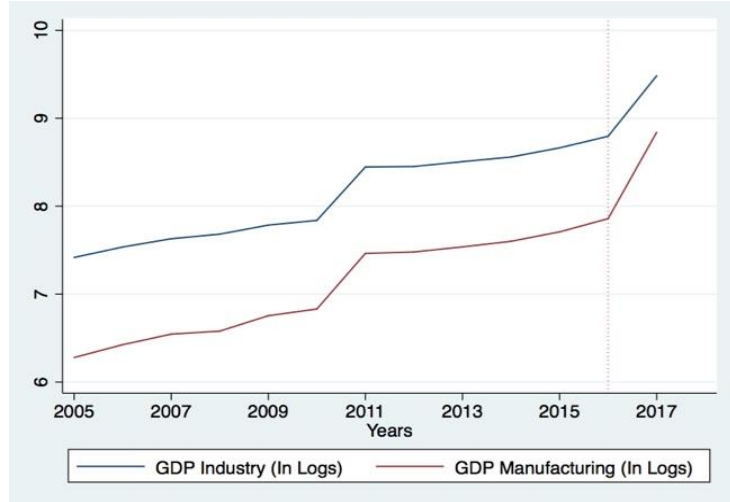


Figure 1 - The 11-year old parallel trend between the manufacturing and industrial sector stops after 2016

been moving parallel to the industrial sector's GDP for over ten years from 2005 till 2016. This trend witnessed an abrupt change in 2016 as demonstrated in Figure 1. In addition to breaking this

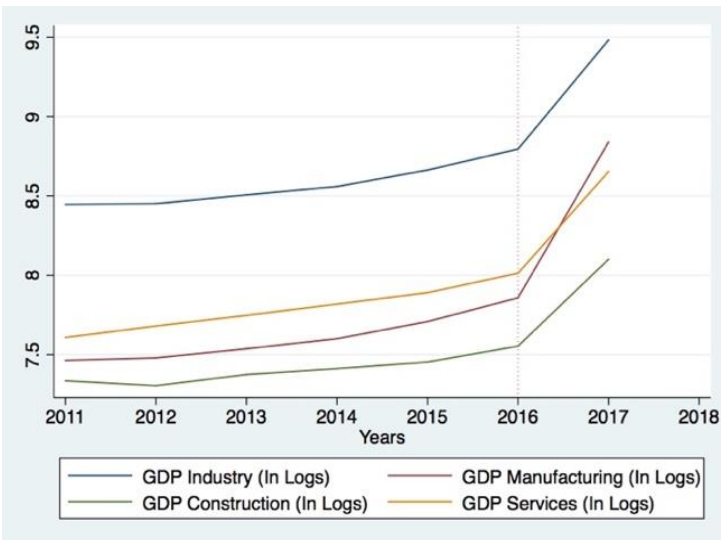


Figure 2 - In 2016 the manufacturing sector deviates from other sectors with which it had experienced a parallel trend for 5 years

over ten-year old trend with the industrial sector, the manufacturing sector's deviation also broke a five-year old parallel trend it had with other sectors such as construction, services and industry; it deviated away from construction and even overtook services as demonstrated in Figure 2. Such an isolated shift in the manufacturing sector in the years

since the MII policy's DIPP-EODB program was implemented is compelling. Therefore, the association between the increase in the manufacturing sector's GDP and the DIPP-EODB program is certainly worthy of further exploration.

In the attempt to examine whether DIPP-EODB program reached its intended goals, I need to evaluate if the DIPP-EODB score triggered the deviation in the manufacturing sector's output. Let us therefore now turn to the DIPP-EODB score and review its trend. In Figure 3, we can see that there appears to also be a steady increase in the EODB score in the years since the MII policy and its corresponding DIPP-EODB program were introduced. In every recorded year since 2014, the average DIPP-EODB score among states/UTs has risen and in fact almost doubled from an average of 32/100 in 2015 to an average of 62/100 just two years later in 2017 (Reserve Bank of India, 2019). The numbers essentially imply that states/UTs compliance with implementing the yearly reforms proposed by the DIPP-EODB program has on average been growing across the country. This indicator was introduced in association with the MII policy and therefore the data for that only exists since 2015. It is however not a problem because for my analysis I am

specifically interested in the variations that exist in state/UT's compliance of the DIPP-EODB program since its launch. Since this score is a composite measure and represents a myriad of factors, it is impossible to discern precisely which reforms are associated with this average increase in the DIPP-EODB score among states. I would

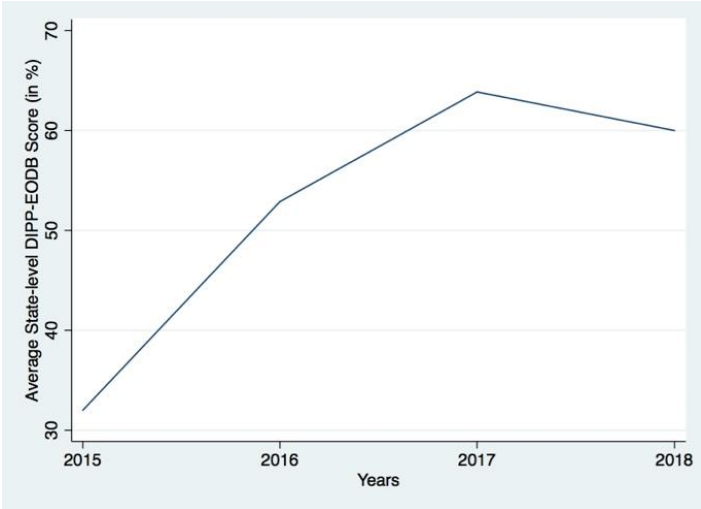


Figure 3 - The average state-level DIPP-EODB score almost doubles from 32% in 2015 to 62% in 2017

nonetheless like to point out the simultaneous increase in both the average DIPP-EODB score and the disproportionate increase in the manufacturing sector’s GDP as this essentially the relationship that makes up the crux of my analysis.

Finally, I would like to draw the attention to the FDI trend as wooing FDI into the country was one of core measures that was to complement the country’s improvement in business environment. Together they were expected to boost manufacturing, and therefore it is important to understand how much their movement align so the effect of only the DIPP-EODB score on manufacturing can be isolated. For the sake of trend comparability, both the FDI and the DIPP-EODB index were converted to logs. In Figure 4 below we can see that those two appear to be correlated. The simple OLS regression showcasing the exact correlation between FDI and the DIPP-EODB score is depicted in Appendix D. This trend is a noteworthy observation because attracting FDI was a part of the MII policy but could have also been indirectly influenced by the change in the country’s business environment. It is nonetheless important to keep in mind, so it can be controlled for in order to understand the association between the DIPP-EODB score and

the manufacturing sector more precisely. Much like the increase in the average DIPP-EODB score discussed earlier, the average FDI has also seen similar average increases over the years since the MII policy implementation as shown in Figure 4. The dip that we see in 2016 can perhaps be explained the so-called demonetization policy in

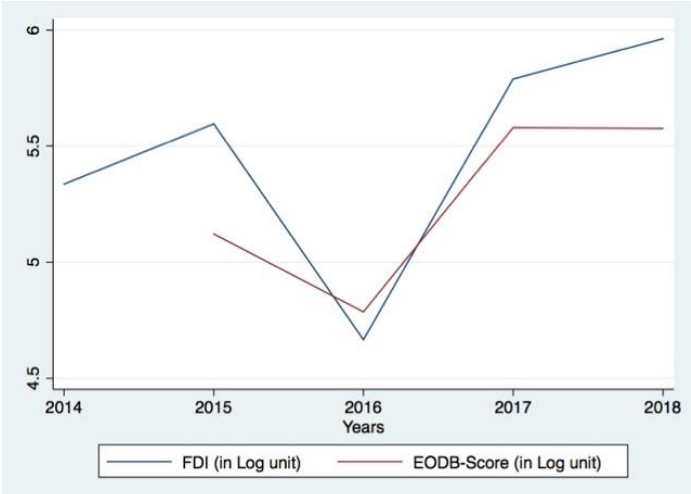


Figure 4 – The DIPP-EODB score and FDI show an apparent correlation

which 86% of all the cash in the economy became illegal tender with a surprise announcement by Prime Minister Modi on the eve of November 8<sup>th</sup>, 2016. The inadequate planning and chaotic implementation of the policy rocked the entire nation's economy and is presumably reflected in the dip depicted in Figure 4.

Now that I have reviewed the DIPP-EODB program in the last chapter and examined some notable trends in the years since its implementation, I am led to believe that there could be a conceivable causal relationship between the notable increase in the DIPP-EODB score and the disproportionate increase in the manufacturing sector. Therefore, I plan to evaluate if an increase in the DIPP-EODB implementation compliance score among states/UTs has in fact triggered an increase in the manufacturing sector's GDP of those states/UTs.

## **4.2 Data Sources and its Limitations**

All the numerical data used in my analysis stem from the Reserve Bank of India (RBI)<sup>8</sup> and the World Bank Group (WBG). Most of the data was available from the RBI on a yearly as well as on a state-wise level. These indicators include: the state-level DIPP-EODB scores, state-level manufacturing sector GDP, state-level industrial sector GDP, state-level construction sector GDP, state-level services sector GDP, state-level electricity transmission and distributional losses, state-level FDI and national interest rates. For indicators such as urban population and literacy rates I had to rely on state-level census data that was last released in 2011. Based on the historical trends and decadal growth rates, I predicted both state-level urban population and state-level literacy rates for all the years since the last census was released. The World Bank's databank provided me with aggregate country-level data of India and another 188 economies around the

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<sup>8</sup> The Reserve Bank of India (RBI) is India's central bank

globe. From their databank I was specifically able to acquire data associated to the their EODB index and the yearly variations in the 10 subcategories<sup>9</sup> that constitute the World Bank's composite EODB index.

After collecting yearly state-level data from the RBI, formatting and appending the various datasets so that it is in a workable layout, I was finally left with data for 33 states and union territories (UTs)<sup>10</sup> of India. The country is currently comprised of 29 states and 7 union territories; my dataset is therefore three short of the total 36 administrative divisions that make up the Republic of India. The missing UTs are Daman & Diu, Dadra & Nagar Haveli and Lakshadweep. In each of the missing cases, the data was either not available or very fragmented. This lack of data uniformity can be explained by shifting borders of the administrative divisions and emersion of new ones over the years. With my core analysis consisting of three years and 33 states/UTs, the overall dataset ultimately consisted of exactly 81 observations once it was transformed to panel data structure; the data structure that is required for me to execute regression analysis of many units (in this case states and UTs) over numerous time periods (in this case three years) using First Difference (FD) and Fixed Effect (FE). The number of observations is quite low by conventional standards and can be a hindrance to achieving significant coefficients if there is in fact a causal relationship.

In term of variables I had data for a different number of years. For some variables I managed to acquire data going back to the early nineties and for other variables the data went back

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<sup>9</sup> The categories the constitute the composite EODB index are as follows: 1) Starting a business, 2) Dealing with construction permits, 3) Getting electricity, 4) Registering property, 5) Getting credit, 6) Protecting minority investors, 7) Paying taxes, 8) Trading across borders, 9) Resolving Insolvency, and 10) Enforcing contracts.

<sup>10</sup> A union territory is a type of administrative division in the Republic of India. Unlike the states of India, which have their own governments, UTs are federal territories governed directly by the union government (central government); hence the name union territory.

till 2010. My causal variable (DIPP-EODB Score) only had data from 2015 onwards. This was however not a problem because the indicator was specifically created to measure the state's compliance in implementing the DIPP-EODB program suggested reforms and this exercise only came into existence in December of 2014. While this might lack overall uniformity, it was sufficient to carry out the intended analysis and attain a clear understanding of the aggregate trends of all the other variables included in my analysis. Ultimately my variables consisted of the causal variable (state-level DIPP-EODB Score), the dependent variable (state-level manufacturing sector GDP), and the control variables (state-level population, literacy rates, electricity transmission and distributional losses and FDI) from the 2015-2017 period.

Finally, it is important to note that the informal economy in India still accounts for roughly 81 percent of non-agricultural employment (International Labor Organization (ILO), 2018). This means that the aforementioned data is not entirely representative of the country because it doesn't factor in the informal economy. The results of the analysis are however still useful in understanding the causal relationship as long as one is aware of the data limitations. In addition to that, numerous economists both at home and abroad have questioned some of the economic statistics released by the Government of India (GoI) in recent years (Dutt, 2017). While this claim still lacks universal credibility, it is important to be aware that the data could have been compromised. Yet again, given the arms-length relationship that the central bank has with the government and the resulting independence that comes from it, this threat is perhaps not as alarming as it initially appears to be.

#### **4.3 Variable Definition and Summary Statistics**

Given the differences in the inherent nature of the variables, they were not all measured in the same unit. If the variable values ranged from 0 to 100, they were left in the original unit.



Otherwise they were converted to logarithmic values. This was done to ensure comparability in the aggregate trends (as demonstrated in the first section of this chapter) and to be able to better interpret the regression results. As part of evaluating each of my variables, I have run summary statistics and dropped extreme values that did not seem representative of the overall data. For the purpose of this paper research paper, I will carry out a more in-depth review of summary statistics of dependent and the independent variable. For more information regarding the summary statistics of the control variables, please review Appendix C.

### 4.3.1 Dependent Variable

As my dependent variable I have of course picked the state-level manufacturing sector's GDP since I am interested in understanding the abrupt increase that occurred since 2015. The unit in which this data was collected is in lakh<sup>11</sup> rupees (₹ Lakh) measured in constant prices using 2010 as the base year.

This was done to ensure that the values are

adjusted for the effects of inflation. For the purpose of visualizing the aggregate trend and enable a more intuitive interpretation of the regressions results, the variable was converted to logarithms.

This is demonstrated in Figure 5.

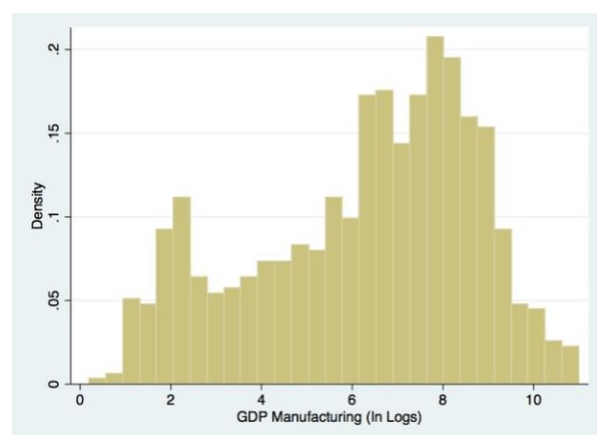


Figure 5 – The histogram shows the distribution of the Manufacturing sector's GDP

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<sup>11</sup> One lakh is one-hundred thousand.

### 4.3.2 Causal Variable

My independent variable is the DIPP-EODB score; the DIPP-EODB program's yearly compliance score that is given to the states/UTs. The score is a composite grade and reflects the extent to which states/UTs have succeeded in implementing reforms suggested by the DIPP to the states/UTs. In addition, the proposed reforms from the DIPP are context specific and vary from one state to the next. While the score may not tell me precisely which state-level implementation efforts are associated to its score level in a given year, it is still useful in understanding whether a variation in a state/UT's compliance affects its manufacturing output. I will be able to know how much the implementation compliance level as a whole is changing manufacturing on average without being able to point out specifically which reforms are responsible for it. This score ranges from 0% (no compliance to implementation of the proposed reforms) to 100% (full compliance to implementation of the proposed reforms). This variable was left in the original unit as a score from 0-100% because this range is ideal to visualize the trend shown in the first section of this chapter and more intuitive to interpret the regression results later in this chapter.

In reviewing the DIPP-EODB score, it appears to all be in line with the theory which states that it should range between 0 and 100. This is

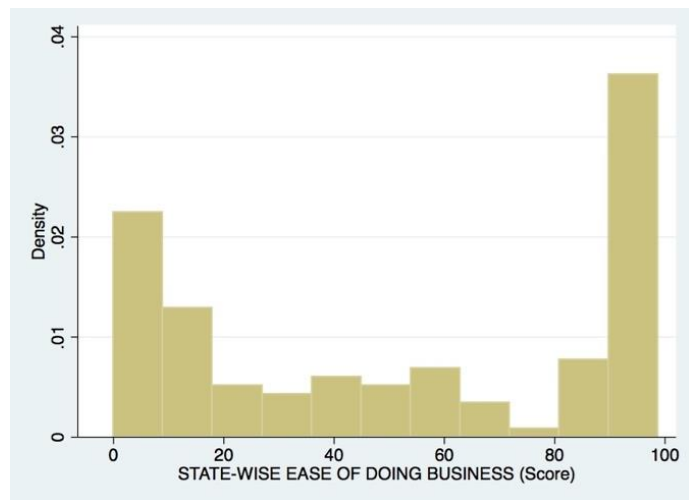


Figure 6 - The histogram shows the distribution of the DIPP-EODB Score (in %)

demonstrated in Figure 6 and in the summary statistics depicted in Appendix C. Therefore, no observations had to be dropped. From the histogram it is clear that a majority of the states fall into

either the very high levels of compliance category or the relatively low level of compliance category. One plausible explanation for this is that there is a high level of inequality in the resources required to implement proposed reforms.

### 4.3.3 Control Variables (i.e. Confounding variables)

The real world is very complex and there are many other variables that could correlate with the dependent variable and/or causal variable. These variables are also known as confounders. While it is impossible to account for all the confounders, I can get closer to estimating the relationship between my causal and dependent variable by controlling for confounders that are known to correlate with my causal and/or dependent variable. After reviewing relevant literature, I have decided to use the following control variables.

**Urban Population:** I control for urban population as a way of controlling for the total size of urban areas. Urban areas were specifically picked because manufacturing has a tendency to bring large amounts of workers to closer together and urbanize them. The level of urbanization would in a given state also affect the extent to

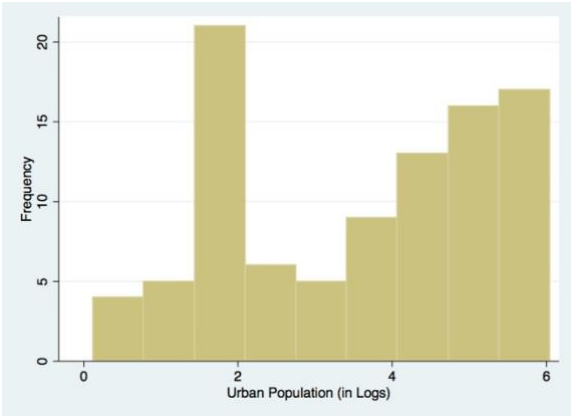


Figure 7 - Distribution of Urban Population

which manufacturing activities can take place. Therefore, it is plausible that a variation in the urban population can be associated with a variation in manufacturing. This is why it is being used as a control for the size of human capital that can affect the manufacturing sector. The variable unit was originally measured in thousands and has been converted to logarithmic values for the purpose

of having an intuitive interpretation of the regression results. The distribution is presented in Figure 7.

**Literacy Rates:** I control for literacy as an indicator for the quality of human capital. A state’s literacy rate is a good indication of how many of its citizens can quickly move between sectors. It is plausible that a variation in literacy will be associated with the extent to which citizens can be driven into and out of

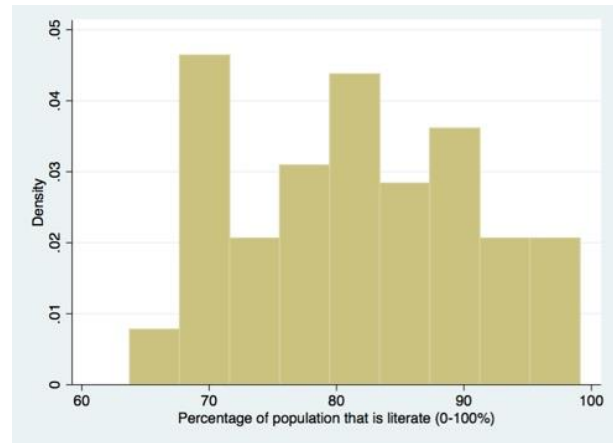


Figure 8 - Distribution of Literacy Rates (0-100%)

the manufacturing sector. The variable is measured in percentages ranging from 0% (for complete illiteracy in a state) to 100% (for complete literacy in a state). This variable was left in the original unit as a range from 0-100% is ideal to visualize the trend and more intuitive to interpret the regression results. The distribution is presented in Figure 8.

**Electricity Transmission and Distributional Losses:** This variable measures the extent to which there are losses in electricity transmission and distribution in a given state. I have included this variable as a proxy for infrastructure. It is by no means an ideal proxy but the closest I could find data for in the attempt to control for infrastructure.

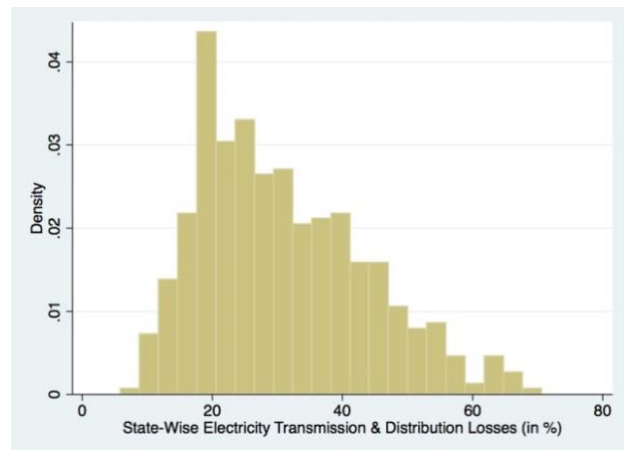


Figure 9 - Distribution of Electricity Transmission and Distribution Losses (0-100%)

It is important to control for the level of infrastructure between states because infrastructure is a core factors that influences economic activity. The variable is measured in percentages ranging

from 0% (for no distributional losses) to 100% (for complete distributional losses). For the sake of allowing a more intuitive interpretation of the regression results, this variable was also left in the original unit. The distribution is presented in Figure 9.

**FDI:** FDI has been added as a control variable because attracting FDI to the country was also a major component of the broader MII policy; it was expected to help boost manufacturing out and its allurements began the same time as the DIPP-EODB program was implemented. In the earlier section of this chapter I show a correlation between the FDI and the DIPP-EODB score. In order to get closer to isolating

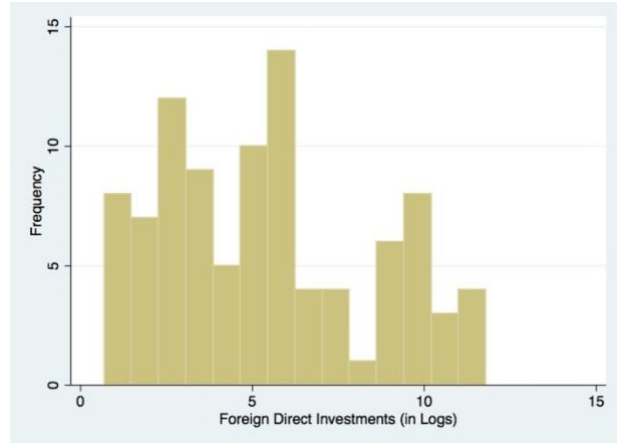


Figure 10 - Distribution of FDI

the effect of a variation in the DIPP-EODB score specifically, controlling for a strong known-correlator such as FDI becomes all the more necessary. The variable values are measured in crore<sup>12</sup> rupees (₹ Crores) and has been converted to logarithms. The distributed is depicted in Figure 10.

**Interest rates:** Economic theory states that there is generally an inverse correlation between interest rates and economic activity resulting from investments. It would therefore be important for me to control for interest rates. But since national interest rates affect the entire country without any state-level variations, I will not be able to use it as a control variable in my regression analysis. This is because due to the lack of variation, the values simply cancel out and are unable to be factored in. This is no doubt a limitation of this study.

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<sup>12</sup> One crore denotes ten-million.

## **4.4 Empirical Strategy and Results**

### **4.4.1 Data Structure**

For the purpose of finding a causal link between the DIPP-EODB score and manufacturing sector's GDP in India using state-level data over a certain time period, I have decided to resort to panel data structure. Panel data structure is a dataset where we observe the same units (in this case states) over more than one time period. Given this structure, the appropriate empirical strategy for my analysis could consist of one or both of the two models: one is the first-difference (FD) estimator and the other is the Fixed Effect (FE) estimator. I have picked these methods because they are a generalized version of diff-in-diff carried out on panel data structures. These estimators would also allow me to filter out any aspect of the data that is time-invariant; factors that could influence the analysis but do not change over time. It is in essence a solution to the problem of unobserved heterogeneity<sup>13</sup> in the context of panel data as I can control for aggregate trends using time and state fixed effect on both the models.

### **4.4.2 Multiple OLS Regression**

In order to identify the effect that I am after, I have estimated multiple OLS, first difference and fixed effect regressions. Before I dive into a causal analysis using the FE and FD estimators, it is important for me to understand if my variables are even correlated. Therefore, I will start with multiple OLS. The ordinary least squares (OLS) simply tells us if two variables are correlated with one another, and if there is a correlation it also tells us the extent to which a change in one variable is associated with the change in another variable. In other words, it helps me understand if there is

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<sup>13</sup> Unobserved heterogeneity is when a correlation between my observed variables and some other unobserved variables may be expected. A major motivation for using panel data has been the ability to control for the possibly correlated and time-invariant heterogeneity without observing it.

a statistically significant correlation between the DIPP-EODB score and the manufacturing sector's GDP. This correlation is a prerequisite for a potential causation between variables. In exploring the correlation between my causal variable (the DIPP-EODB score) and my dependent variable (manufacturing sector's GDP), I have used the year 2016 since that has the most

observations out of any of the years. Figure 11 gives a visual representation that there appears to be a positive correlation between the EODB score and manufacturing GDP. This leads the way into running an OLS regression on those two variables. The results from running an OLS regression of manufacturing GDP on the EODB score

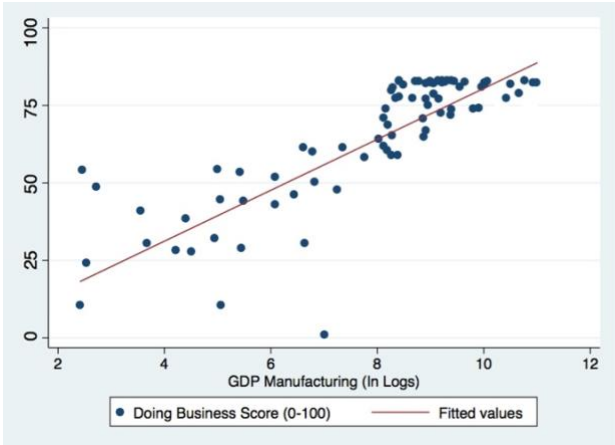


Figure 11 - Shows a positive correlation between the EODB Score and Manufacturing GDP

while progressively adding more control variables can be viewed in Table 1 of the next page. The results, as demonstrated in Table 1 show a Log-Level regression. This means that the dependent variable is represented in logarithms while the independent variable is represented in its original unit level. In interpreting it, we can say that 1-unit variation in a state's EODB score is associated with a 4% change in the manufacturing sector's GDP on average with a 99% statistical significance level when not controlling for any other factors. Once I control for all the other variables, the correlation coefficient falls and a 1-unit variation in a state's EODB score is now associated with a 2% change in the manufacturing sector's GDP on average still with a 99% statistical significance level.

VARIABLES	(1) Manufacture GDP	(2) Manufacture GDP	(3) Manufacture GDP	(4) Manufacture GDP	(5) Manufacture GDP
Business Score (0%-100%)	0.04*** (0.006)	0.02*** (0.007)	0.02*** (0.007)	0.02*** (0.009)	0.02*** (0.008)
Urban Population (Log Units)		0.66*** (0.199)	0.67*** (0.208)	0.54* (0.301)	0.58* (0.303)
Literacy Rate (0%-100%)			-0.01 (0.026)	-0.02 (0.025)	-0.02 (0.027)
Foreign Direct Investment (Logs)				0.08 (0.086)	0.05 (0.099)
Dist. Power Losses (0%-100%)					-0.01 (0.027)
Constant	5.51*** (0.535)	4.22*** (0.687)	5.38** (2.159)	5.49** (2.042)	6.31** (2.618)
Observations	32	31	31	31	31
R-squared	0.645	0.743	0.746	0.756	0.758

Robust standard errors in parentheses

\*\*\* p<0.01, \*\* p<0.05, \* p<0.1

*Table 1 - Demonstrates the OLS regression results from regressing Manufacturing GDP on the EODB Score and progressively adding more control variables*

This essentially means that comparing two states with the same urban population, same literacy rates, same FDI and same distributional power losses; a 1-unit higher increase in one state's EODB score (as compared to the other state) is associated with a 2% higher increase in the state's manufacturing GDP when compared to the other state.

Throughout all the regressions we can see that there most certainly is a positive correlation between the EODB score and manufacturing GDP that is statistically significant. The correlation coefficient and its statistical significance levels are stagnant after adding the first control, but the standard error (SE) shows some minor fluctuations. As the estimate falls, the SE appears to increase. The increase is however so small that it is negligible. Given that the OLS regression has clearly demonstrated a correlation between the EODB score and manufacturing, it is safe to move into the next step of figuring out whether a variation in one variable actually causes a variation in another variable.



My panel data structure allows me to use two models; Fixed Effect (FE) and First Difference (FD). Both the FD and FE estimates are obtained by running a multiple Ordinary Least Squares (OLS) estimation for a regression of  $\Delta y_{it}$  on  $\Delta x_{it}$ , where  $i$  indexes a particular unit and  $t = 1, 2, 3$  index the time period where each  $i$  unit is observed. In two time periods, first difference estimators are absolutely equivalent to fixed effect estimators. Therefore, there is no need to worry about a difference in results because there is none. However, my dataset has three time periods (2015-2017), and this will provide different results between FD and FE. I will therefore estimate both in order to attain a more comprehensive understanding of the relationship between my causal and dependent variable.

#### 4.4.3 First Difference Estimator

The FD estimator is used to compare units (in this case states) that experienced different changes in the causal variable  $x$  (in this case the DIPP-EODB score) between two years. It tells us that the dependent variables (in this case manufacturing GDP) would have changed the same way on average if both states had experienced the same change in the EODB score. In short, the FD estimator essentially measures the average change in manufacturing GDP (represented by  $y$ ) with a change in the EODB score (represented by  $x$ ) as demonstrated Equation 1.

$$\overline{\Delta y_{it}} = \alpha + \beta \Delta x_{it}$$

*Equation 1 - First Difference (FD) equation*

The Table 2 shown below demonstrates the regression results from carrying out a FD regression of manufacturing GDP on the EODB score while progressively adding more controls. From the estimates we can see that there appears to be a causal link between the EODB score and

VARIABLES	(1) Manufacture GDP	(2) Manufacture GDP	(3) Manufacture GDP	(4) Manufacture GDP	(5) Manufacture GDP
Business Score (0%-100%)	0.05*** (0.007)	0.03*** (0.007)	0.03*** (0.007)	0.03*** (0.008)	0.02*** (0.007)
Urban Population (Log Units)		0.58*** (0.180)	0.59*** (0.183)	0.50** (0.229)	0.68*** (0.231)
Literacy Rate (0%-100%)			-0.02 (0.025)	-0.02 (0.024)	-0.04 (0.027)
Foreign Direct Investment (Logs)				0.09 (0.075)	-0.02 (0.088)
Dist. Power Losses (0%-100%)					-0.04* (0.023)
Constant	5.75*** (0.499)	4.53*** (0.696)	5.89*** (2.024)	5.80*** (1.890)	8.56*** (2.608)
Observations	81	78	78	78	62
R-squared	0.567	0.682	0.687	0.698	0.717

Robust standard errors in parentheses

\*\*\* p<0.01, \*\* p<0.05, \* p<0.1

*Table 2 - First Difference (FD) regression of manufacturing GDP on the EODB score by progressively adding more control variables*

manufacturing sector's GDP that is statistically significant. The coefficient changes as I add more controls, getting us closer to the precise estimate. Moreover, the progression of the coefficient estimates resembles those of the OLS regression in Table 1 strikingly close. The coefficients strong resemblance to the OLS results is most likely because the OLS was measured in the year with the most observations. And since the total number of years used in the FD regression are only three years (with the year 2017 missing some observations), it is understandable that the three-year FD average will lean towards the year with the most observations (that being 2016) and therefore resemble the results presented by the earlier OLS regression.

What the coefficient estimates essentially imply is the following: comparing two states with the exactly the same characteristics in regard to the controls (same urban population, same literacy rates, same FDI, same electricity distributional losses), the manufacturing increased by

2% more in the states that experienced a 1-unit higher increase in the EODB score. The FD estimator also allows me to add lags in order to understand how a variation in the OEDB score in one year has an effect on the manufacturing GDP not just in that year but record the associated variation in manufacturing GDP in the subsequent years as well. Since I only have three years of complete data, I was only be able to add one lag as the FD estimator essentially shows the variation in the variables by differencing it from one year to the next. Given that I already have a small number of observations and I lost observations with each lag, that made the results both statistically and numerically insignificant. It will therefore not be discussed in further depth here. The results can however be viewed in the Appendix F.

Finally, despite the lack of a large amount of observations and only a three-year time period, the FD model was still able to acquire statistically significant results. One could argue that the significant results despite the meagre amount of observations is a robustness check on the validity of the FD estimates.

#### **4.4.4 Fixed Effect Estimator**

In the case of the FE estimator, when we compare two units or two time periods that have different levels of  $x$  relative to its mean in unit  $i$ ,  $y$  is expected to be higher by  $\beta$ , relative to its mean value in unit  $i$ , where or when  $x$  is higher by one unit. FE in other words is OLS on mean-differenced variables  $y - \bar{y}$  regressed on  $x - \bar{x}$ . The FE estimator is used to compare different units (in this case states) that experienced different trends in the causal variables  $x$  (in this case the EODB score) during a given time period. It tells us that the dependent variable (in this case the manufacturing sector's output) would have followed the same trend on average if both the states had experienced the same trend in the EODB score. In short, the FE estimator essentially measures

the average manufacturing sector's output (represented by y) at a given EODB score (represented by x) as demonstrated in Equation 2 below.

$$\overline{y_{it}} = \alpha_i + \beta x_{it}$$

*Equation 2 - Equation for the Fixed Effect (FE) estimator*

The Table 3 below demonstrates the regression results from carrying out FE regression of manufacturing GDP on the EODB score while progressively adding more controls and controlling for state fixed effect. I also estimated state and time fixed effect while controlling for no other variables and another one by controlling for all the other variables; those results can be found in the Appendix E. With regards to the state fixed effect results shown on Table 3, the correlation coefficients mean the following: comparing two states that have different EODB score relative to its mean in state i, but are the same in all other variables in that point in time (meaning same urban population, literacy rates, FDI and electricity transmission losses), the manufacturing GDP is expected to be higher by 0.04%, on average, relative to its mean value in state i, where or when the EODB score is higher by 1-unit than its long-term average in state i. Since FE takes the average over the entire time period and the time in this analysis only consists from three years (from 2015-2018), it is plausible that the full effect is not being captured and therefore the coefficient shown is extremely low. In other words, what it means is that the EODB score doesn't have a strong effect on the overarching trend in this short three-year period. Nevertheless, here it is important to point out that the result with controls has no statistical significance which means that the coefficient cannot be taken seriously. In other words, the coefficient number doesn't actually disprove or approve the existence of a causal relationship. Since the FE regression explores the trend over a very long time period, it also includes the average lagged effects that could show at a much later

VARIABLES	(1) Manufacture GDP	(2) Manufacture GDP	(3) Manufacture GDP	(4) Manufacture GDP	(5) Manufacture GDP
Business Score (0%-100%)	0.0023*** (0.000)	0.0008* (0.000)	0.0004 (0.000)	0.0003 (0.000)	0.0004 (0.001)
Urban Population (Log Units)		2.9146*** (0.646)	0.6810 (0.833)	0.7869 (0.771)	0.3983 (1.696)
Literacy Rate (0%-100%)			0.0681*** (0.019)	0.0650*** (0.019)	0.0658** (0.025)
Foreign Direct Investment (Logs)				0.0008 (0.007)	-0.0035 (0.008)
Dist. Power Losses (0%-100%)					0.0086 (0.052)
Constant	7.9666*** (0.017)	-3.9757 (2.638)	-0.2425 (2.587)	-0.4313 (2.227)	0.8538 (5.428)
Observations	81	78	78	75	60
R-squared	0.452	0.642	0.706	0.700	0.545
Number of States	33	32	32	31	31

Robust standard errors in parentheses

\*\*\* p<0.01, \*\* p<0.05, \* p<0.1

*Table 3 - Fixed Effect (FE) regression of manufacturing GDP on the EODB score by progressively adding more control variables*

point in time and may not be captured in the average trends demonstrated in the short three-year time span of this study. This could be a plausible explanation for why the coefficient estimates from the FE regression are very low. Under this assumption one can say that there is no short-term lag. This then appears to also align with the FD estimates showing no significant coefficients when attempting to capture a lagged effect. By this logic one could argue that the statistically insignificant coefficients demonstrated by the lagged FD and the numerically low coefficients demonstrated by the FE are a robustness check on both the models and enhances the validity of those results. If I had more years to carry this out, such a long-term change in the average would be more visible as some of the lags would get factored into the average effects that get exposed in FE. This lack of a longer time period is therefore clearly a limitation of this study.

#### 4.5 First Difference versus Fixed Effect: Which one to choose from?

With the different results attained from my regressions, it can be difficult to decide which one to choose from. Here it is important to point out that the estimates from the different models signify a different meaning and should therefore be interpreted differently. The result for FD essentially compares states/UTs with similar characteristics that experienced different changes in the EODB score between two years; had they experienced the same change in the EODB score, then the manufacturing GDP would have changed the same way, on average. The result for FE essentially compares states/UTs that experienced different trends in the EODB score across the entire time period; had they experienced the same trend in the EODB score then the manufacturing GDP would have followed the same trend, on average. While FD captures how manufacturing GDP changes from one year to the year with the change in the EODB score from one year to the next, FE shows the extent to which manufacturing GDP is higher in years when the EODB score is higher – while both control for aggregate trends.

That said, which estimate is more reliable, and worthy of further evaluation? In deciding which what criteria to use to evaluate the estimators, let me start by reviewing the assumptions that we have of both models: a) both have strict exogeneity. This means that the error term is not only uncorrelated with the explanatory variable in this time period but also uncorrelated with all the future values of the explanatory variable, b) both models have a random sample in a cross section, c) both have variance in variables across time (Angrist & Pischke, 2008). Given these assumptions, it turns out that the expected beta of FD is equal to  $\beta$  ( $\mathbb{E}[\hat{\beta}_{FD}] = \beta$ ) and expected beta of FE is equal to  $\beta$  ( $\mathbb{E}[\hat{\beta}_{FE}] = \beta$ ). This essentially means that both of their estimates are unbiased, and this cannot be used as a criterion for deciding which model to choose from. Under the same assumptions, both the FD estimator and the FE estimator are also consistent in circumstances

where the number of observations ‘N’ tends towards infinity (Angrist & Pischke, 2008). Now since they are similar in so many ways, we need other criteria to decide which one to choose. The criteria that we can use is to look at their relative efficiency. And it turns out that their relative efficiency depends on whether there is serial<sup>14</sup> correlation in the error terms of the original model. If the idiosyncratic error ( $u_{it}$ ) follows a random walk process (given that they are homoscedastic<sup>15</sup>), then its differences will be uncorrelated, and FD will be the appropriate estimator (Angrist & Pischke, 2008). But if the idiosyncratic error ( $u_{it}$ ) follows no random walk and then the error terms are in fact serially correlated, then FE will be the appropriate estimator (Woolridge, 2013).

My original model consists of Equation 3 where  $GDP_{it}$  represents manufacturing GDP of a given state ‘i’ at time ‘t’,  $\beta_0$  is the constant,  $\beta_1 Score_{it}$  represents the EODB score of given state ‘i’ at time ‘t’, and the same applies to the control variables all the way till the ‘N<sup>th</sup>’ control variable. Finally, we also have  $\alpha_i$  which represents the unobserved heterogeneity and the  $u_{it}$  which is the idiosyncratic error.

$GDP_{it} = \beta_0 + \beta_1 Score_{it} + \beta_2 Control (2)_{it} \dots \beta_N Control (N)_{it} + \alpha_i + u_{it}$
---

*Equation 3 - My original equation*

In transforming the equation to a FD estimated one as shown below in Equation 4, I remove the unobserved heterogeneity term ( $\alpha_i$ ); a characteristic of panel data that I have discussed earlier.

As a result, we are left with the idiosyncratic error ( $\Delta u_{it}$ ) as shown in Equation 4 below:

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<sup>14</sup> Serial correlation is the relationship between a variable and a lagged version of itself over various time intervals (Banton, 2019). If a variable's serial correlation is measured as zero, there is no correlation, and each of the observations is independent of one another. Conversely, if a variable's serial correlation skews toward one, the observations are serially correlated, and future observations are affected by past values (Banton, 2019). Essentially, a variable that is serially correlated has a pattern and is not random. In causal analysis we often may assume serially uncorrelated errors, but there is no reason why that condition will necessarily hold in the data.

<sup>15</sup> Homoscedasticity indicates that a dependent variables (DV) variability is equal across values of an independent variable (IV).

$$\Delta \text{GDP}_{it} = \beta_0 + \beta_1 \Delta \text{Score}_{it} + \beta_2 \Delta \text{Control (2)}_{it} \dots \beta_N \Delta \text{Control (N)}_{it} + \Delta u_{it}$$

*Equation 4 - FD estimated transformed equation*

For first difference estimator to be efficient we require this error term ( $u_{it}$ ) to also be serially uncorrelated. And if we assume that the idiosyncratic error is serially uncorrelated across time, then the covariance of the idiosyncratic error is equal to zero (that is  $\text{Cov}(u_{it}, u_{it-1}) = 0$ ) and the FD estimate is efficient and therefore appropriate. In testing whether there is serial correlation, I have found that there is in fact no serial correlation in my dataset. The test results for that are demonstrated in the Appendix A. Even if there was a serial correlation in my model, it might require more than just three time periods in order for a variable's lagged version of itself to become obvious. But since there doesn't appear to be serial correlation in the variables of my dataset, the FD model is more appropriate.

While the coefficient estimates for FD are more reliable in case there is serially uncorrelated idiosyncratic risks (that is  $\text{cov}(u_{it}, u_{it-1}) = 0$ ) in the original model, that is not the case with its standard error. In circumstances where we have serially uncorrelated idiosyncratic risks (that is  $\text{cov}(u_{it}, u_{it-1}) = 0$ ) in our original model, then the standard error of beta in Fixed Effect is less than the standard error of beta in First Difference (that is  $\text{se}(\hat{\beta}_{\text{FE}}) < \text{se}(\hat{\beta}_{\text{FD}})$ ). So, in those circumstances where we have serially uncorrelated idiosyncratic error, the standard error of fixed effect is better than the standard error of first difference. Alternatively, in circumstances where we have serially correlated idiosyncratic risks (that is  $\text{cov}(u_{it}, u_{it-1}) \neq 0$ ) in our original model, then the standard error of beta in Fixed Effect is more than the standard error of beta in First Difference (that is  $\text{se}(\hat{\beta}_{\text{FE}}) > \text{se}(\hat{\beta}_{\text{FD}})$ ). In those circumstances, the standard error of FD is a better estimate than the standard error of FE (Angrist & Pischke, 2008).



Another factor to consider in deciding which estimates are more reliable is by looking at the number of years in my time period. The sensitivity of the FE estimate falls as we reach a high number of time periods. This is because the strict exogeneity assumption (the assumption that the idiosyncratic error  $u_{it}$  was uncorrelated with the value of any of the explanatory variables ( $\text{cov}(u_{it}, X_i) = 0$ ) is more relaxed as the time period 'T' is large. In other words, in that case the FE is more robust to violations of the strict heterogeneity assumption than FD. By that logic the sensitivity of my FE estimates should be higher with the only three-year time period that I have in my dataset and therefore more inappropriate than the FD model. This aligns with the theory that FD is better than FE for short-run associations because it evaluates the change from one year to the other without looking at the long-term trends. Unlike in FD, FE strongly relies on long term trends in its estimates.

Finally, the FE estimator is effective in controlling for factors that do not change through time (time-invariant) for the various states. In other words, these factors are also known as time-invariant factors, they are state specific and fixed through time. Such factors include things like the different cultures, institutions, tastes and skills among the states. But in order to control for state-wide trends, account for serial-correlations and heteroskedasticity<sup>16</sup> in the FD estimator, I have ensured that the standard errors are clustered and that the regression also controls for both year Fixed Effect and state Fixed Effect. Given all the aforementioned considerations, the FD estimator appears to provide a more appropriate estimate for my study.

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<sup>16</sup> Heteroscedasticity refers to the circumstance in which the variability of a DV is unequal across the range of values of an IV that predicts it.

#### 4.6 Discussion of Results

The results from my FD analysis are presented in Table 4 below. From the results in the table it is clear that a change in a state's EODB score would trigger a subsequent change in the state's manufacturing sector's GDP. In other words, for Indian states this means that a higher EODB score attained from complying with implementing the yearly DIPP proposed reforms causes their manufacturing sector's GDP to increase. More specifically, a 1-unit increase in a state's EODB score from one year to the next causes their manufacturing GDP to increase by 2% on average.

<b>First Difference Model</b>		
<i>Log-Level Regression Estimates</i>		
<b>A state's DIPP-EODB Score</b> <i>(Units from 0-100)</i>	<b>Causes</b> - <b>Triggers</b> - <b>Effects</b>	<b>A State/UT's Manufacturing Sector GDP</b> <i>(Log Units)</i>
1-unit increase in the EODB Score (ex: 70 to 71)		2% increase (on average)
10-unit increase in the EODB Score (ex: 70 to 80)		20% increase (on average)

*Table 4 - First Difference (FD) regression results*

Similarly, a 10-unit increase in a state's EODB score from one year to the next causes their manufacturing sector's GDP to increase by 20% on average. This essentially means that a state/UT's compliance with the DIPP-EODB program triggers their manufacturing sector's GDP to increase.

## 5 Policy Discussion

In the last chapter my analysis has shown that a state/UT's compliance with the DIPP-EODB program certainly appears to have triggered an increase in their manufacturing sector's GDP. But since the score used in the program is a composite measure that only represents the extent to which states/UTs have complied with implementing the reforms proposed by the DIPP, I am unable to identify which specific reforms carried out by states/UTs actually contributed to an increase in the manufacturing output. All that I was able to summarize from my analysis is that a states/UTs overall compliance with the DIPP-EODB program was reflected in their score and an increase in a state/UT's score caused their manufacturing sector's GDP to go up as well. Given these data limitations, I was unfortunately not able to identify precisely with reforms corresponded to the increase in the manufacturing output. In this chapter I will attempt to overcome these limitations by using data from the World Bank EODB index to present a closer understanding of some of the regulatory changes that could have conceivably triggered the rise in the manufacturing sector.

Aside from India's notable trends from 2015 till 2017 which were discussed in the last chapter, the country also experienced a remarkable rise with regards to its place in the World Bank Group's Ease of Doing Business (EODB) ranking. When the World Bank first began to include India in its index in 2007, the country ranked 134 out of 189 economies (World Bank, 2018). Despite some slight improvements in the following years, India's ranking continued to dismally hover between 130 and 140 from 2007 till 2014 (World Bank, 2018). In the years since 2014 however, this trend has been witnessing miraculous improvements. For the first time since its inclusion in the World Bank EODB rankings, India climbed roughly 30 spots from its earlier

average and ranked 100<sup>th</sup> in 2017 (World Bank, 2018). It further climbed another 23 spots the following year and was ranked 77<sup>th</sup> in 2018. This is demonstrated in Figure 12. The country earned

the credentials of being a top global improver for two consecutive years (World Bank, 2018). Such a notable increase in India's rankings since the country's



Figure 12 - India's place in the World Bank EODB ranking has seen an extraordinary increase since 2014

implementation of the DIPP-EODB program is an intriguingly coincidental trend. Therefore, I think that the association between the DIPP-EODB program and India's dramatic rise in the EODB ranking is worthy of further exploration in my attempts to understand specifically which reforms are responsible for the rise in the manufacturing sector.

Since the World Bank data is provided on an aggregate level, I am unable to empirically prove a causal relationship between the reforms recorded by the World Bank and manufacturing output. This is because India's size and complexity makes the creation of a control group using another country for a difference-in-difference analysis too idealistic. But now that I have empirically proven a causal relationship between the DIPP-EODB score and manufacturing among states/UTs in India, and we have seen that the average DIPP-EODB score has risen in the 2015-2017 time period, I can get closer to understanding which reforms plausibly caused manufacturing to increase by looking at the reforms recorded by the World Bank in the same 3-year time period of my analysis. In essence, I believe that it is very plausible that the simultaneous increase in India's World Bank ranking, the increase in the average DIPP-EODB score and the increase in the

manufacturing sector's GDP that took place from 2015 till 2017 are attributed to the same regulatory reforms. Given the ever-evolving nature of the DIPP-EODB program and the resulting inability to identify how specific reforms caused an increase in manufacturing, I have decided to rely on the reforms attributed to India's World Bank ranking. This is because the World Bank has clearly listed the reforms that have been responsible in the extraordinary increase of India's global ranking. Before I dive into the regulatory reforms recorded by the World Bank, let us first get a better understanding of the World Bank EODB Index.

## **5.1 The World Bank EODB Index**

The World Bank EODB index is a ranking system that was first established by the World Bank. In this index, higher rankings (lower numerical value) indicate better for businesses and stronger protections of property rights (World Bank, 2018). The research carried out by the World Bank for this index represents data for 189 economies and aggregates information from 10 areas of business regulation (World Bank, 2018).<sup>17</sup> Each of the parameters are used to develop an overall EODB ranking. A high EODB ranking means the regulatory environment is more conducive for starting and operating of businesses. This is unlike India's EODB score which simply measures compliance towards implementing suggested reforms. "By gathering and analyzing comprehensive quantitative data to compare business regulation environments across economies and over time, the World Bank Doing Business reports encourages economies to compete towards more efficient regulation; offers measurable benchmarks for reform; and serves as a resource for

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<sup>17</sup> 1) Starting a Business, 2) Dealing with Construction Permits, 3) Getting Electricity, 4) Registering Property, 5) Getting Credit, 6) Protecting Minority Investors, 7) Paying Taxes, 8) Trading across Borders, 9) Enforcing Contracts, 10) Resolving Insolvency

academics, journalists, private sector researchers and others interested in the business climate of each economy” (World Bank, 2018).

That said, it is important to point out the flaws of the regulatory indicators provided by the World Bank. The most noteworthy flaw is the fact that the data mostly comes from the major metropolitan areas of a given country. In the case of India, the World Bank’s regulatory indicators are entirely collected from just two major cities in the country. Those two cities are New Delhi and Mumbai. It is already very problematic that the World Bank EODB index relies entirely on the biggest and most influential urban enclaves of every country. I think for India it is all the more problematic given the vast size and diversity of the country. Yet again, this is the only measure available and I believe still useful despite its limitation as long as those limitations are taken into consideration. Besides, the extensive usage of the index by multi-lateral organizations and governments worldwide can perhaps be considered reflection of its credibility.

## **5.2 India’s World Bank EODB Ranking**

In every recorded year prior to 2014, India had improved in only 1.3 out of 10 areas per year in the World Bank’s EODB index. This however began to shift in the years since 2014 when the country’s yearly average improvements jumped to around 5 out of 10 areas in the World Bank’s EODB index (World Bank, 2019). Moreover, in giving the years since the 2014 MII policy implementation a more in-depth look, the number of areas where India experienced doing business improvements increased from three in 2015 to a whopping eight three years later in 2018. Similarly, in the same time period, the average DIPP-EODB score among states/UTs has also risen and in fact almost doubled from an average of 32/100 in 2015 to an average of 62/100 just two years later in 2017 (Reserve Bank of India, 2019). There is clearly an upward trend in both the

## India's performance over the last four years

Indicator	2014	2016	Current Rank	Improvement in last 2 years	Improvement in last 4 years
Construction Permits	184	185	52	133	132
Getting Electricity	137	26	24	2	113
Trading Across Borders	126	143	80	63	46
Paying Taxes	156	172	121	51	35
Resolving Insolvency	137	136	108	28	29
Enforcing Contracts	186	172	163	9	23
Starting a Business	158	155	137	18	21
Getting Credit	36	44	22	22	14

Table 5 - The improvement in India's World Bank EODB ranking have been quite remarkable in the 2014-2018 period. The improvements in the specific sub-categories that constitute the overall rank are show in the table.

This figure was sourced from the DIPP (Department of Industrial Promotion and Policy (DIPP), 2018)

average DIPP-EODB score and the World Bank EODB index. In understanding which regulatory reforms caused both of these indicators to increase, we can rely on the discernable changes we have seen in the various business improvement areas of the World Bank EODB index. This approach is by no means an ideal strategy. But given the limitations of the DIPP-EODB score, it helps us get closer to differentiating which indicators in India's business environment have improved synchronously to the average increase in the DIPP score. All of those improvements from the 2014-2018 time period are depicted in Figure 13 in terms of the country's scores and Table 5 as well as Table 6.



Figure 13 - India's score in every indicator that constitutes the World Bank EODB Index has risen. This figure was sourced from the DIPP (Department of Industrial Promotion and Policy (DIPP), 2018)

in terms of the country's rank in the world. From the figures, it is clear that

India's place in every indicator that constitutes the World Bank EODB index has risen. Specifically, the regulatory measures that have seen major variations since the implementation of the DIPP-EODB program

are the following: getting electricity, starting a business, paying taxes, enforcing contracts, and to a lesser extent trading across borders and protecting minority investors. In addition to the change in rankings depicted

Indicator	2017	2018	Improvement
Construction Permits	181	52	129
Trading Across Borders	146	80	66
Starting a Business	156	137	19
Getting Credit	29	22	7
Getting Electricity	29	24	5
Enforcing Contracts	164	163	1

Table 6- India's improvement in the World Bank EODB ranking from 2017 till 2018 are listed in this chart as they are not depicted in the other table for those two years. This figure was sourced from the DIPP (Department of Industrial Promotion and Policy (DIPP))

thus far, the World Bank has also released a list of reforms that are attributed the rise in India's rank since 2014. The list gives us an idea of the reforms that were implemented in the various sub-categories that constitute the World Bank's composite score. While we cannot attain a definitive estimate of how much each reform contributed to the increase in manufacturing, it can still help us get a closer to understanding of some of the predominant reforms attributed to the the average increase in the DIPP-EODB score among states/UTs and the effect it ultimately had on their manufacturing sector's GDP.

### 5.3 Regulatory Improvement since 2014

With regards to the 'getting electricity' indicator, India has reduced the time taken to obtain an electricity connection from 105 to 55 days. This considerable fall in the time required to get an electricity connection is attributed to the enhancement of internal work processes and an online



platform to help streamline the procedures. The number of procedures decreased from 10 to 3.5 and the security deposit required for getting an electricity connection was also reduced. There was also the elimination of internal wiring inspection which helped expedite the process of getting electricity. Thanks to those reforms, the country's rank improved by a whopping 113 place in the 2014-2018 period (World Bank, 2019). On the 'starting a business' indicator, India made starting a business easier by considerably reducing the registration fees. It also eliminated the minimum capital requirement and the need to obtain a certificate to commence business operations (World Bank, 2019). Thanks in part to those reforms, India's place has increased by 21 spots in the 2014-2018 period (World Bank, 2019).

The other indicators have also seen changes, but to a lesser extent than the two discussed thus far. On 'protecting minority investors', India strengthened minority investor protections by requiring greater disclosure of conflicts of interest by board members, increasing the remedies available in case of prejudicial related-party transactions and introducing additional safeguards for shareholders of privately held companies. On 'paying taxes' the country made some small strides by introducing an electronic system for paying employee state insurance contributions; this resulted in India's rank to go up by 35 places the 2014-2018 period (World Bank, 2019). The country's 'trading across borders' ranking increased by 46 places in the 2014-2018 period thanks to its launch of a Customs Electronic Commerce Interchange Gateway portal (a digital filing system called eSanchit) which simplified border and documentary compliance procedures and made it easier to export/import across borders (World Bank, 2019). Finally, India also made enforcing contracts easier by creating dedicated divisions to resolve commercial cases resulting in its rank for 'enforcing contracts' to increase by 23 spots (World Bank, 2019).

By discussing the regulatory changes attributed to the World Bank EODB index, I hope to have revealed some of the reforms that are also conceivably attributed to the DIPP-EODB score and subsequently caused the manufacturing sector's GDP to rise. This was by no means an ideal approach in making an absolutely definitive connection between the World Bank listed reforms and the changes in the manufacturing sector. But given the data limitations of this study, I hope to have presented a closer understanding of the reforms that conceivably triggered manufacturing output.

## 6 Conclusion

This paper evaluated the extent to which India's DIPP-EODB program succeeded in boosting the country's manufacturing sector. Using panel data of states/UTs collected from 2015 till 2017, I have found that a state/UT's compliance with the program did in fact trigger an increase in their manufacturing sector's GDP. This suggests that the DIPP-EODB program has certainly met its goal of boosting manufacturing. However, the very nature of the score being a measure of a state/UT's compliance in implementing yearly DIPP proposed reforms hindered the possibility of discerning specifically which reforms triggered a variation in the manufacturing. This was a limitation of this study. In the attempt get closer towards understanding which reforms are to be held responsible, I have relied on the World Bank EODB index and explored the factors that caused the miraculous rise of India's ranking in the same time period. This was by no means an ideal approach and certainly another limitation of the study.

That being said, an opportunity for a further study could consist of constructing a control group for India in order to carry out a difference-in-difference analysis using World Bank data. This would allow us to specifically identify the extent to which each category that constitutes the World Bank index contributed to the increase in manufacturing. As a result, policymakers would attain a much better idea of the distinctive reform's contributions and cater their resources to those with the highest potential of boosting the manufacturing sector. One possibility would be to create a synthetic control group using weighted averages of similar countries from across South Asia. This method appears to not be very well developed yet and therefore it was not used in this study. But once its credibility gains traction, it could be a solution to overcoming the limitations of this study.

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## 8 Appendix

### Appendix A

#### Results from Testing for Serial Correlation

<pre>                 . xtgls rellngdp_manufacturing doingbusiness_score, igls                 Iteration 1: tolerance = 0                  Cross-sectional time-series FGLS regression                  Coefficients: <b>generalized least squares</b>                 Panels:      <b>homoskedastic</b>                 Correlation: <b>no autocorrelation</b>                  Estimated covariances   =      1      Number of obs   =      81                 Estimated autocorrelations =      0      Number of groups =      33                 Estimated coefficients   =      2      Obs per group:   min =      1   avg =  2.454545   max =      3                 Log likelihood          = -145.7026      Wald chi2(1)    =      89.41   Prob &gt; chi2     =      0.0000             </pre>						
rellngdp_manufact~g	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
doingbusiness_score	.0408355	.0043185	9.46	0.000	.0323713	.0492996
_cons	6.012317	.2728214	22.04	0.000	5.477597	6.547038
<pre>                 Cross-sectional time-series FGLS regression                  Coefficients: <b>generalized least squares</b>                 Panels:      <b>heteroskedastic</b>                 Correlation: <b>no autocorrelation</b>                  Estimated covariances   =      33      Number of obs   =      81                 Estimated autocorrelations =      0      Number of groups =      33                 Estimated coefficients   =      2      Obs per group:   min =      1   avg =  2.454545   max =      3                 Log likelihood          = -91.93979      Wald chi2(1)    =     167.75   Prob &gt; chi2     =      0.0000             </pre>						
rellngdp_manufact~g	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
doingbusiness_score	.0138305	.0010678	12.95	0.000	.0117376	.0159234
_cons	7.847346	.0664848	118.03	0.000	7.717038	7.977654
<pre>                 . xtserial rellngdp_manufacturing doingbusiness_score                  Wooldridge test for autocorrelation in panel data                 H0: no first-order autocorrelation                 F( 1, 16) = 15.037                 Prob &gt; F = 0.0013             </pre>						

## Appendix B

### The DIPP Iterative Cycle<sup>18</sup>

**Capture:** This step obtains responses from the states on the implementation status of various factors suggested by the DIPP yearly BRAP plans. The questionnaire allows states to respond “Yes”, “No” and in some cases “Not Application” depending on the implementation status of a proposed reform (DIPP, 2015).

**Assess:** This step deals with an evaluation of the implementation status for a given reform area. This implementation status reflects the percentage of proposed factors that were actually implemented by the state. That number is computed as:  $(\text{Number of questions in the area for which the response is “Yes”}) / *(\text{Total number of questions in the area}) - (\text{Number of questions in the area for which the response is “Not applicable”}) + * 100\%$  (DIPP, 2015).

**Collate:** This step involves that collation of the state’s overall implementation status. This is computed using the following method:  $(\text{Number of questions across all areas for which the response is “Yes”}) / *(\text{Total number of questions across all areas}) - (\text{Number of questions across all areas for which the response is “Not applicable”}) + * 100\%$  (DIPP, 2015).

**Share:** This step involves the sharing of results based on comparing the implementation status across states. It includes two things: a) an overall comparison of the overall implementation status across States and UT’s, and b) for various areas it also has a comparison of implementation status across States, specific to each area (DIPP, 2015).

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<sup>18</sup> This entire section is identical to the information provided on the official DIPP website as it was simply copied for the purpose of this appendix.

## Appendix C

### Summary Statistics of the Variables

<pre> .sum relngdp_manufacturing, detail  relngdp_manufacturing  ----- Percentiles      Smallest 1%      1.194344      .2009517 5%      1.790213      .8341851 10%     2.298714      .9004      Obs      841 25%     4.490666      .9829522      Sum of Wgt.      841  50%     6.736276      Mean      6.265474 Std. Dev.      2.446274 75%     8.149103      10.7769 90%     9.016254      10.84827      Variance      5.984259 95%     9.551839      10.92794      Skewness      -.4862058 99%     10.54604      11.00109      Kurtosis      2.263383 </pre> <p><i>Table C1 - Summary statistics of Manufacturing GDP (in Log units)</i></p>	<pre> .sum gdp_manufacturing, detail  Real GDP Manufacturing (₹ Lakh)  ----- Percentiles      Smallest 1%      2136      791 5%      3876      1490 10%     6445      1592      Obs      841 25%     57700      1729      Sum of Wgt.      841  50%     545044      Mean      2153135 Std. Dev.      4408784 75%     2238797      3.10e+07 90%     5328609      3.33e+07      Variance      1.94e+13 95%     9103642      3.60e+07      Skewness      4.343914 99%     2.46e+07      3.88e+07      Kurtosis      26.45534 </pre> <p><i>Table C2 - Summary statistics of Manufacturing GDP (in original units)</i></p>
<pre> .sum relnpopulation_urban, detail  relnpopulation_urban  ----- Percentiles      Smallest 1%      .0491326      -5.83e-08 5%      .6860844      .0283706 10%     1.41379      .0283706      Obs      320 25%     1.880614      .0491326      Sum of Wgt.      320  50%     3.936129      Mean      3.494735 Std. Dev.      1.720767 75%     5.02796      5.997186 90%     5.525453      6.021093      Variance      2.96104 95%     5.812487      6.045005      Skewness      -.294438 99%     5.997186      6.068925      Kurtosis      1.76291 </pre> <p><i>Table C3 - Summary statistics of Urban Population (in Log units)</i></p>	<pre> .sum population_urban, detail  population_urban  ----- Percentiles      Smallest 1%      146      139 5%      277      143 10%     571.5      143      Obs      320 25%     911.5      146      Sum of Wgt.      320  50%     7120      Mean      12983.35 Std. Dev.      14926 75%     21214.5      55919 90%     34889      57272      Variance      2.23e+08 95%     46493.5      58658      Skewness      1.234377 99%     55919      60078      Kurtosis      3.670075 </pre> <p><i>Table C4 - Summary statistic of urban population (in normal units)</i></p>
<pre> .sum fdi, detail  State-wise FDI (in Crore Rupees)  ----- Percentiles      Smallest 1%      0      0 5%      1      0 10%     4      0      Obs      286 25%     12      0      Sum of Wgt.      286  50%     174      Mean      5093.888 Std. Dev.      14538.55 75%     2073      62731 90%     13457      83288      Variance      2.11e+08 95%     37403      86244      Skewness      4.711889 99%     83288      131980      Kurtosis      30.71083 </pre> <p><i>Table C5- Summary statistics for the FDI (in original units)</i></p>	<pre> .sum relnfdi, detail  relnfdi  ----- Percentiles      Smallest 1%      0      0 5%      0      0 10%     1.386294      0      Obs      281 25%     2.484907      0      Sum of Wgt.      281  50%     5.159055      Mean      5.273207 Std. Dev.      3.048221 75%     7.636752      11.04661 90%     9.507255      11.33006      Variance      9.291649 95%     10.52951      11.36494      Skewness      .0810332 99%     11.33006      11.79041      Kurtosis      2.107485 </pre> <p><i>Table C6- Summary statistics for the FDI (in Log Units)</i></p>

. sum literacy\_rate, detail

Percentage of population that is literate

Percentiles	Smallest		
1%	40.74	37.49	
5%	47.84	38.35	
10%	54.86	38.44	Obs 890
25%	63.38	38.55	Sum of Wgt. 890
50%	71.78		Mean 71.56088
		Largest	Std. Dev. 12.64311
75%	81.2	97.73	
90%	87.72	97.87	Variance 159.8482
95%	90.77	98.49	Skewness -.305759
99%	96	99.12	Kurtosis 2.643632

Table C7 - Summary statistics for Literacy Rates (in original units)

. sum doingbusiness\_score, detail

STATE-WISE EASE OF DOING BUSINESS (Score)

Percentiles	Smallest		
1%	0	0	
5%	.3	0	
10%	.89	.13	Obs 129
25%	14.04	.14	Sum of Wgt. 129
50%	52.12		Mean 52.1562
		Largest	Std. Dev. 38.44699
75%	92.88	98.33	
90%	97.96	98.42	Variance 1478.171
95%	98.21	98.78	Skewness -.0760293
99%	98.78	98.78	Kurtosis 1.355648

Table C8 - Summary statistics of the DIPP-EODB Score (in Original Units)

. sum dpower\_losses, detail

State-Wise Electricity Transmission & Distribution Losses (in %)

Percentiles	Smallest		
1%	10.8	5.9	
5%	13.5	10.2	
10%	16.7	10.5	Obs 515
25%	20.3	10.7	Sum of Wgt. 515
50%	28.6		Mean 30.84485
		Largest	Std. Dev. 12.7778
75%	39.2	66.1	
90%	48.8	67.2	Variance 163.2723
95%	54.9	67.4	Skewness .648248
99%	63.6	70.6	Kurtosis 2.803963

Table C9- Summary statistics for Power Distributional and Transmission Losses (in original units)

## Appendix D

### Correlation between DIPP-EODB Score on FDI

	rellnfdi
rellnbusiness_score	<b>0.677</b> <b>(4.13)**</b>
_cons	<b>1.983</b> <b>(2.23)*</b>
R2	<b>0.16</b>
N	<b>92</b>

\* p<0.05; \*\* p<0.01

*Table 7 - Simple OLS regression between FDI and the EODB Score*

## Appendix E

### Time Fixed Effect Regressions With and Without the Control Variables

(1)		(1)	
VARIABLES	Manufacture GDP	VARIABLES	Manufacture GDP
Business Score (0%-100%)	0.0005 (0.000)	Business Score (0%-100%)	0.0005 (0.001)
2016.year	0.0659*** (0.020)	Urban Population (Log Units)	0.3448 (0.313)
2017.year	0.1323*** (0.021)	Literacy Rate (0%-100%)	0.0078 (0.027)
Constant	8.0063*** (0.013)	Dist. Power Losses (0%-100%)	-0.0002 (0.002)
Observations	81	Foreign Direct Investment (Logs)	0.0009 (0.008)
Number of state	33	2016.year	0.0434 (0.037)
R-squared	0.745	Constant	5.8830** (2.473)
Robust standard errors in parentheses		Observations	62
*** p<0.01, ** p<0.05, * p<0.1		Number of state	32
		R-squared	0.592
		Robust standard errors in parentheses	
		*** p<0.01, ** p<0.05, * p<0.1	



## Appendix F

### First Difference Regression with 1-Lag

	(1)	(2)	(3)	(4)	(5)
VARIABLES	Manufacture GDP	Manufacture GDP	Manufacture GDP	Manufacture GDP	Manufacture GDP
D.Business Score (0% -100%)	0.0006 (0.000)	0.0006 (0.001)	0.0006 (0.001)	0.0005 (0.001)	0.0004 (0.001)
D.Urban Population (Log Units)		-0.8544 (1.529)	-0.8308 (1.552)	-0.8195 (1.936)	-0.6082 (1.961)
D.Literacy Rate (0% -100%)			0.0063 (0.019)	-0.0002 (0.025)	0.0070 (0.026)
D.Dist. Power Losses (0% -100%)				-0.0002 (0.002)	-0.0005 (0.002)
D.Literacy Rate (0% -100%)					0.0001 (0.008)
Constant	0.0641*** (0.014)	0.0780*** (0.021)	0.0730*** (0.025)	0.0788*** (0.025)	0.0687*** (0.024)
Observations	48	46	46	30	29
R-squared	0.055	0.056	0.056	0.038	0.030

Robust standard errors in parentheses  
 \*\*\* p<0.01, \*\* p<0.05, \* p<0.1