Vol. 6

THE ECONOMICS REVIEW

AT NEW YORK UNIVERSITY

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Cover design by Garrett Boyce

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Letter from our Editor-in-Chief

The last two years have, without a doubt, been one of the most challenging times for our world, and especially for students. The pandemic did not stop the Economics Review's committed and passionate staff writers and editors from contributing to our publication and putting out interesting content. However, as our university guidelines were changing with the current events, we engaged in virtual learning, and our members connected with each other sitting in different countries and continents; we were unfortunately unable to publish our Print Publication due to administrative and budget issues because of COVID-19 for three semesters. On behalf of our team, I am extremely proud to now present our 2021-22 Print Publication volume that would not have been possible without relentless efforts from our team, our club advisers, the paper authors, and of course our supportive readers.

The Economics Review's Print Publication celebrates scholarship in economic research, global geopolitical topics, and most importantly, students' curiosity. I would like to thank every member of our club for their efforts and contributions in making our publications grow and reach larger audiences. I would also like to thank Avi Gupta and Martina Castellanos, our Managing Editors for the Print Publication, whose tireless efforts, coordination, and editing has made this print publication a success. Their careful curation and thoughtful guidance have ensured justice to the high scholarship and intellectual curiosity exhibited in these papers. Our team's accomplishments would be remiss without thanking our prompt and meticulous Webmaster Kairui Huang, who led the revampment of our website and has also kept our readers updated with our team's work. I am also very grateful to Roshni Rangwani, Will Rojas, and Anoushey Gajial, Co-Managing Editors of the Online Publication, for navigating our staff through tough times, keeping the spirit alive, and encouraging exceptional content despite being entirely virtual. I would also like to express my gratitude for the co-leadership and hard work of my co-Editor-in-Chief Kevin Lu, who has now graduated. A big thank you to the rest of our E-Board members including Garrett Boyce, Tom Jankowski, and Rodrigo Rowe.

The subjects covered in this volume cover a wide range of interesting and thought-provoking topics that promote economic inquiry and inspire research. On that note, I am pleased to present to you our 2021-22 Print Publication. I hope each piece provides you with an intriguing perspective and a new learning. Thank you to my predecessor Yasmine Deswandhy for her trust in our team's ability to grow and expand in the post-pandemic world. All of us at the Economics Review are extremely grateful to our readers for your encouragement, and we hope that you see the fruit of this team's efforts through this publication.

Happy Reading!

Sincerely,

Malvika Sriniwasan

Letter from the Managing Editors of the Print Publication

This past year, the tragedy of the COVID-19 pandemic has had a profound effect on the lives of millions of students around the world. The threat of the disease and its casualties destabilized our communities and caused significant fear in our households.

Whilst this crisis has brought unprecedented challenges for people in every sense of the word – financially, socially and most importantly, emotionally, we have been humbled by the wave of resiliency that is presented within our fellow writers. We commend them as even in what seems to be one of the darkest moments of the decade, they have demonstrated how to deal with adversity – with perseverance and tenacity. These authors are individuals who hold themselves responsible for a higher standard than anybody else expects them to. Their different walks of life, all exemplary in their own way, have all led them to this moment.

As a creative and passionate team of editors and writers, the Economics Review at New York University is an undergraduate organization aiming to provide New York University students with an informative, analytical, and inspirational source of economics-related articles and research papers. We would like to present to you, with great pleasure, the Editorial of the Economics Review at New York University.

The goal of the Economics Review is to encourage NYU students to conduct research and advance their career prospects by publishing their work. Our student-led editorial staff works with staff and freelance writers to produce content that will raise debate and awareness as well as improve research and writing skills among the NYU community. We encourage students from not only economics and related majors but also any interested personnel, regardless of their school or field of study, to contribute to the Review.

For the 2021-22 Academic Year Volume, the print publication committee selected five papers to present to our readers. The researchers discuss a wide array of issues related to the effects of the H-1B Visa Policy Change and its effect on foreign-born STEM workers in the U.S, TFP growth in group micro lending, the impact of urbanization in India’s agricultural sector and how competition drives technological innovation.

This publication would not have been possible without the comprehensive and thoughtful editing contributions of the Review Editors Chad Kim, Alexis Loh, Anika Pemmaraju, Cheryn Ryoo, and Jarred Xiong. We would also like to take this opportunity to give our sincere thanks to our Editors-in-Chief, Malvika Sriniwasan and Kevin Lu. Throughout this entire process, they have been diligent in their efforts to keep the Economics Review team centered and focused even when miles apart.

Happy Reading!

Sincerely,

Martina Castellanos & Avi Gupta

Academic Papers

Catch-Up Innovation in the Computer Chip Industry: A Case Study of Intel and AMD

By Zexuan (Amanda) Wang
Advisor: Daniel Waldinger

Abstract

The world of technology is filled with fierce competition among firms to put out the best innovation and the never-ending waves of innovation are largely motivated by that same competition. Two of the biggest players in the field are Intel and AMD, both specializing in chip designing and are directly behind the innovation of each chipset. This paper delves into the computer chip industry, which sits at the front and center of the tech sector, by studying the case of Intel and AMD, specifically on how one's innovation speed propels the other to innovate. This paper focuses on the dynamic relationship between innovation rate and technology gap between Intel and AMD using regression models. A key assumption made throughout the paper is that Intel and AMD consider each other to be a main competitor and that being the main drive to their respective chip innovation.

1. Introduction

This paper fundamentally studies how competition drives technological innovation. A lot of research has been done in this area across industries, and different industries have demonstrated very different relationships between the two variables. This dynamic relationship between competition and innovation is most important to be studied in the technology sector, where the market is very concentrated, and innovation happens extremely fast. With a higher demand for smaller and more advanced technology today, high performing computer chips that could meet and exceed consumer expectations have become the focal point in tech companies' race to dominate the chip market. The analysis run in this paper is concerned with the computer chip industry, with a focus on exploring the role played by the technology gap in inducing innovation in the CPU sector.

In almost all industries, there is always a leader: this company holds the most advanced technology as well as the fastest manufacturing speed, which leads to the most innovation output.. Take the computer chip manufacturing industry as an example: The leading firm Intel, which is one of the two companies being studied in this paper, dominates the global market with a 15.7% market share in 2019 alone, according to data from Gartner. Aside from Intel, the focus of the paper is on AMD, and more specifically, the innovation catch-up game Intel and AMD are playing. AMD's product quality has generally been trailing behind Intel. However, the introduction of AMD's Ryzen chip family in 2017 disrupted Intel's long-run dominance in the field, at least product quality-wise, according to PassMark Software, which offers CPU benchmark results.

It is interesting to look at how Intel would behave pre and post Ryzen's introduction in the product innovation front, to examine how tech firms change their innovative paces when there is an ever-changing technology gap between the leading firm and its competitors.

In this paper, the main focus is on how changes in the technology gap between Intel and AMD affect how Intel paces its innovation rate. The relationship between the technology gap and innovation for Intel and AMD is ambiguous since past research on this topic has shown different relationships between the two. Competition could be analyzed in two different ways, and they could both drive innovation in either direction. One is on the firm number level: On the one hand, having more competitors that offer similar products propels a company to innovate more to get the upper hand in the market; on the other hand, the rise in the number of competitions means a dampening in return of innovation, which could discourage a firm from continuing innovation at the current level. Another angle to study competition is looking at firms' technology level. Both proxies for competition are similar in terms of examining the level of competition that a firm faces. But it's more reasonable to approach competition from the technology level aspect when studying a market where consumer demand is more elastic and they are more likely to substitute similar products, like the computer chip industry. In this market, chip performance is the key characteristic in determining product quality and demand. Competition does not depend on the number of firms competing in the same market but the overall technological capabilities. This is also the reason that this paper only analyzes Intel and AMD. Various sources online including PassMark software, news outlets, and tech forums reached the consensus that AMD is the closest competitor Intel has in the product market. The competition landscape from either firm's perspective only consists of each other.

I approach this analysis by constructing a model under the assumption that Intel and AMD both consider each other the main competitor and the key that drives their respective innovation. This model takes the technology gap as the independent variable that helps explain innovation, the dependent variable. I use PassMark Software's CPU benchmark scores as a proxy for the technology level to measure both the innovation output and the technology gap between two firms. The analysis of the technology gap and innovation are constructed on both the proportional change rate and level difference to determine which method yields a more reasonable result. I hypothesize that Intel raises its innovation rate when AMD closes up the technology gap between the two.

The results are statistically imprecise, but one conclusion can still be drawn from the descriptive statistics: there's a negative relationship between the technology gap and innovation, which, under my assumption that Intel and AMD are each other's sole drive in innovation, implies that a more intense competition between Intel and AMD propels Intel to innovate faster. With access to more data on market share, R&D funding in CPU technology development, manufacturing cost, etc., a bigger sample that includes Intel's other competitors and data points that span a longer period, a statistically significant result could very well be obtained.

2. Literature

Goettler et al. (2008) studied the oligopoly of Intel and AMD during the years of 1993 and 2004. They state that, counter-intuitively, when Intel is a monopolist, the innovation rate for industry's frontier technology is higher than when Intel and AMD are in an oligopoly market. The underlying reason being 1) to induce consumers to upgrade, a monopolist is incentivized to innovate more, and 2) monopolists could attain more surplus from these upgrades, given its high pricing power. This paper provides big inspiration for this analysis, given the objects of interest are the same. But instead of studying whether the existence of AMD contributes to how motivated Intel is to innovate, my study focuses on the impact that the degree of competition intensity has on Intel's innovation pace. The time frame chosen by Goettler et al. is also different from this paper. Given that the technology level in the 1990s and early 2000s is far less advanced than that in the 2010s, and AMD only introduced Ryzen, the chip family that drastically changed the competitive landscape for Intel, in 2017, this analysis would probably show a different result.

One paper by Lee et al. (2011) directly examined the relationship between the technology gap and innovation. The paper's subjects were 10 LCD screen manufacturing firms that originated from Japan, Korea, Taiwan, and joint ventures. Lee and his colleagues found that firms that have an intermediate technology gap with the industry leader are more likely to make catch-up investments on their technology. This finding contributed to the area of the technological race of innovation by providing an empirical examination. My paper is fundamentally different from this one in that the specific sectors of the technology field we study are different. Nevertheless, the result of my analysis could be compared with Lee et al.'s paper to see if the contribution of the technology gap in inducing catch-up innovation is similar in a different technology sector.

The empirical paper by Hashmi (2013) alluded to a relationship between the technology gap and innovation. It suggested that the relationship between competition and innovation is different for each industry with a different technology gap. For industries like the ones in the U.K., where industries are more neck-to-neck when it comes to technological advancements, the relationship between competition and innovation is an inverted-U. At first, as competition increases, innovation rises but after reaching a peak at a certain point, innovation goes down as competition continues to rise. For industries in the U.S., the technology gap is wider and the relationship between the two parameters is mildly negative. It is not as obvious that the technology gap could be influencing the innovation rate, but the implication is clear. Instead of taking the technology gap as a given while studying how competition drives innovation output as Hashmi did in his, my paper uses the technology gap as a proxy for competition.

3. Institutional Details

Before getting into the analysis itself, it's necessary to define and clarify some technological terms. A CPU's clock speed is how many cycles a CPU executes in one second. A higher clock speed means a faster chip. Turbo speed is the maximum speed level a chip could run at. A CPU core is a hardware on the chip. Having more cores means a CPU can process more tasks at the same time, which makes the CPU faster. Threads are the virtual components in cores that tackle tasking. Threads allow the processor to perform multiple tasks at the same time. In other words, having more threads means that a CPU could process more tasks at a given time. Transistors measure the complexity of a chip, which can be translated as the processing power of a chip. The higher the transistor count, the higher the complexity of a chip, which results in higher chip processing power.

The quality of a single computer chip can be judged from different aspects. Even though each of the criteria, such as the number of cores, transistors, and threads as well as chip clock speed alone signals to a chip's capabilities of performing tasks and processing information, each parameter cannot be used on its own in comparison with another chip. A CPU with higher clock speed may be outperformed by another with lower clock speed equipped with more transistor count as a result of better manufacturing technology. That's why this paper uses an aggregated score that incorporates all the above specs of a chip and more from PassMark Software.

Moore's law states that the count of transistors on integrated circuit chips would double itself every 18 to 24 months. Figure 1 is an illustration of Moore's law. With Moore's law for transistor counts, it should be safe to deduce that the rate at which CPU cores and thread counts update would follow the same time frame. But according to the CPU benchmark website, both Intel and AMD put out "new" products nearly every quarter. Even though these products are just updated versions of older chip models, they are nonetheless faster and more advanced counterparts of their older versions, and therefore should be safe to be considered as a form of innovation.

In this analysis, I define frontier technology as the best chip, namely the chip with the best quality score, that each firm has put forward in a given quarter.

As mentioned earlier, Intel leads the global market with a 15.7% market share in 2019. The technology gap in this analysis is measured in terms of how far ahead Intel's technology is, compared to AMDs. Figure 2 shows Intel's global market share from 2008 to 2019.

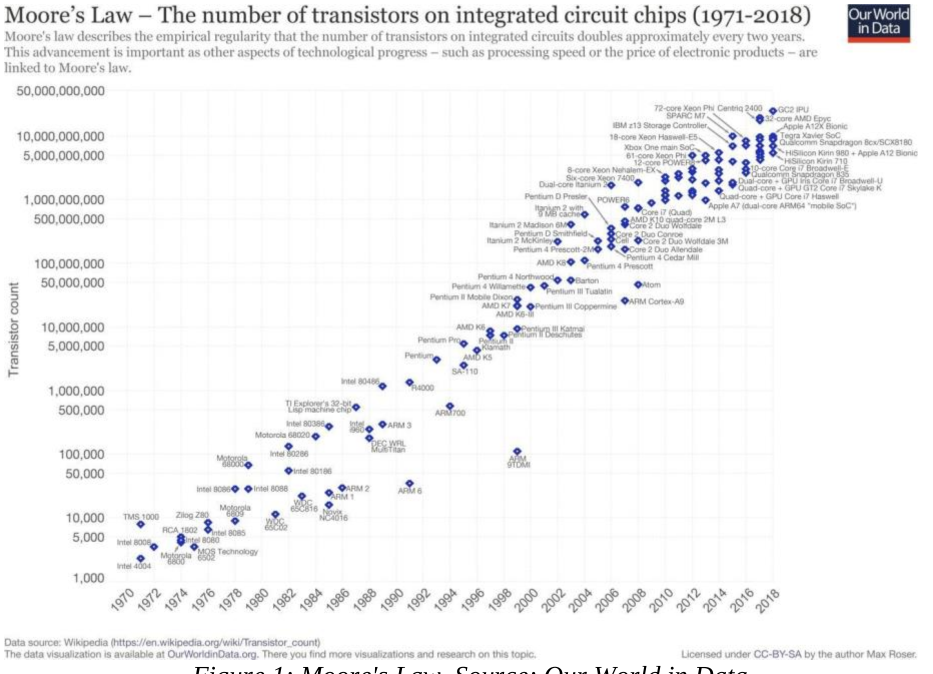

Figure 1: Moore's Law. Source: Our World in Data

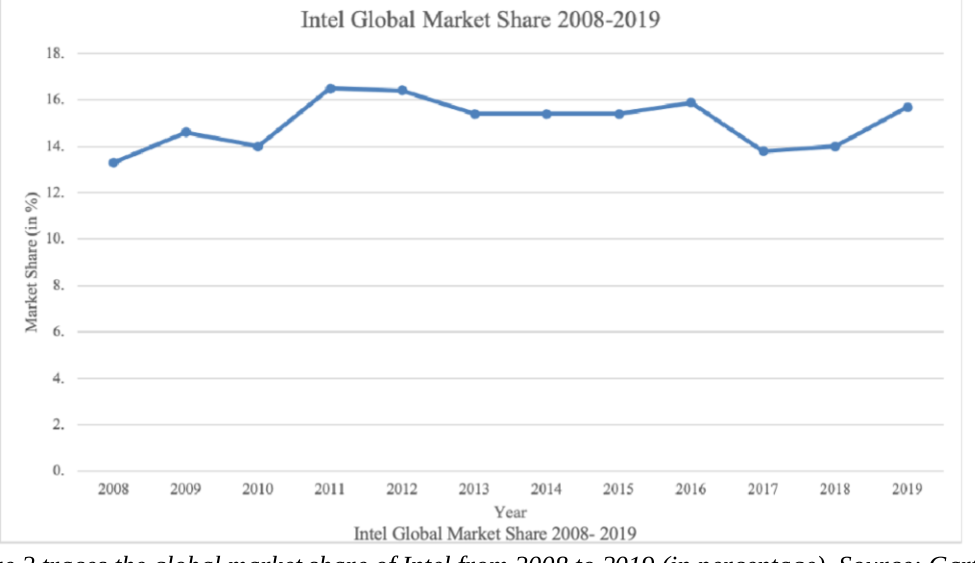

Figure 2 traces the global market share of Intel from 2008 to 2019 (in percentage). Source: Gartner.

4. Data

Using data from 2011-2019, I constructed a model studying the relationship between CPU innovation rate and the technology gap between Intel and AMD.

This paper uses CPU quality score data from PassMark Software, a resource that offers CPU benchmark results, to obtain a single index of CPU quality that could be used to compare chip models across different manufacturers of the industry and chip generations. This index of chip quality is calculated by taking a chip's transistors, cores, and thread counts into consideration, which only when combined, could truly speak for a chip's quality. The website tests each chip's compression, encryption, physics capabilities, etc. to determine the final score for a single chip. The market share data of Intel is taken from Gartner, a research firm which specializes in the IT industry.

The data points include the chip models Intel Core i3 to i9 from Intel, as well as the chip models AMD A8, A10, and Ryzen from AMD. Even though the data points included Intel's older chip models that were first introduced in 2010, Intel's frontier technologies (chips with best scores) that were compared with AMD's are only the Intel Core i7 and i9Since Intel released multiple chip models with different processing capacities in the same quarter, the higher quality chips are naturally the ones equipped with better technology that came from higher clock speed as well as more transistor and thread counts, i.e., the more technologically advanced chip models such as Intel Core i7 and i9.

The data points are constructed from Q2 of 2011 because there wasn't any score data available for AMD's chips in Q1 of 2011. The paper compares chip scores quarterly because both Intel and AMD are diligently updating their chip models and releasing new generations of the same model every quarter, likely in the hopes to beat their competitors. A quarter analysis provides a clearer look at how each company's product qualities move. More importantly, there was a quite big jump in AMD's score in 2017, as seen in Figure 3, which marks the introduction of AMD's most coveted and successful chip family so far, Ryzen. The introduction of Ryzen significantly closed up the technology gap between Intel and AMD, as seen in Figure 4, and even allowed AMD to take the lead in the quality scoreboard in early 2019. It is more interesting to take a closer look at the data right before and after Q1 2017, where AMD put Ryzen chips on the market.

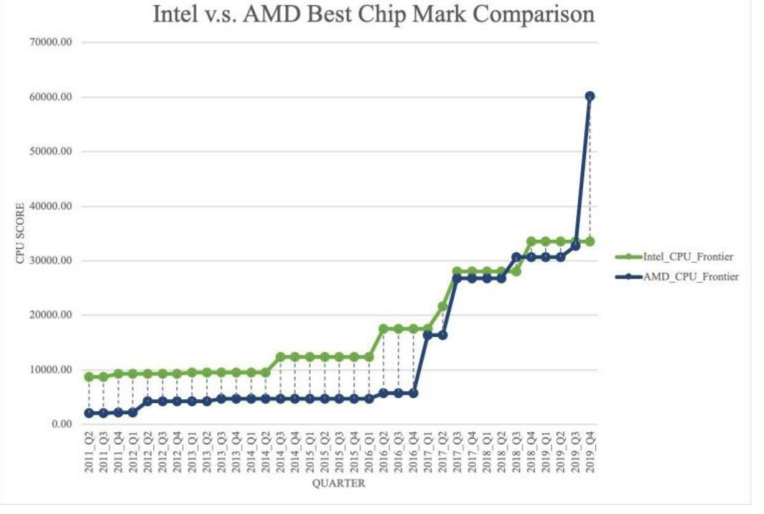

Figure 3: The graph is constructed from chip score data from PassMark Software, comparing Intel and AMD's frontier technology.

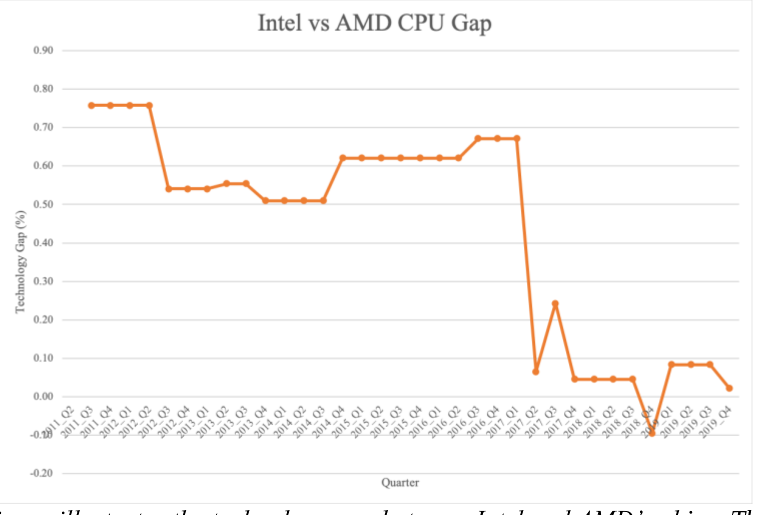

Figure 4: *The figure illustrates the technology gap between Intel and AMD's chips. The gap dropped below 0 in Q1 in 2019, which signals that AMD was taking the lead. Technology gap formula:* *Technology Gap*= $\frac{IntelScore_{t-1} - AMDScore_{t-1}}{IntelScore_{t-1}}$.

Another note for how the score data is constructed is that when the score of the next quarter (i.e., *t+1*) is lower than the current quarter (i.e. *t*), the score in *t* is also used for *t+1*in order to demonstrate that there's no technology advancement in this quarter. Because the lower score of the next quarter is sometimes a result of it being the score of a newer generation of an older chip model, i.e., a chip update, which doesn't signify a technology change because the updates only made the chip clock speed faster but utilized the same transistor, core and thread technology.

5. Method

I hypothesize that as the technology gap between Intel and CPU narrows, Intel would pick up its innovation speed and in turn, offer chips with better quality scores. The measurement of the technology gap is a measurement of how more technologically advanced Intel is, i.e. the difference between two firms' quality score in terms of Intel's.

I can test my theory by constructing the following model:

$$I_t = TG_{t-1}$$

Where I_t is the innovation rate of Intel in quarter *t*.

$$I_t = \frac{Q_t - Q_{t-1}}{Q_{t-1}}$$

Q_t is the quality score of Intel's best chip, i.e. frontier technology in quarter *t*, and Q_{t-1} is the quality score of Intel's best chip in quarter *t-1*.

The technology gap is defined by the equation below:

$$TG_{t-1} = \frac{INT_{t-1} - AMD_{t-1}}{INT_{t-1}}$$

Where TG_{t-1} is the technology gap between Intel and AMD in quarter *t-1*. INT_{t-1} and AMD_{t-1} stands for the quality score of the best chips produced by Intel and AMD in quarter *t-1*, respectively. I ran an OLS regression with the data I described in the Data section and the regression equation below:

$$I_t = \beta_0 + \beta_1 \times TG_{t-1} + \varepsilon_t$$

Where I_t and TG_{t-1} are defined as above, β_0 is the constant, β_1 is the coefficient of the variable technology gap and ε_t is the error term. I ran another OLS regression using level changes instead of rate changes on both sides of the equation, which measures innovation level and gap level respectively, to see if this tweak could bring a significant result. Innovation and technology are represented by equations below:

$$I_t = Q_t - Q_{t-1}$$

$$TG_{t-1} = INT_{t-1} - AMD_{t-1}$$

Where all notations still represent the same parameters. The regression equation remains the same. Table 1 summarizes both regression results, where column (1) shows the first regression result, and column (2) shows the second.

Table 1: Regression Results

	Dependent variable:	
	Innovation (1)	InnovationLevel (2)
Gap	-0.048 (0.067)	
GapLevel		-0.134 (0.092)
Constant	0.065* (0.035)	1,437.079** (570.799)
Observations	34	34
R2	0.016	0.063
Adjusted R2	-0.015	0.033
Residual Std. Error (df = 32)	0.107	1,749.211
F Statistic (df = 1; 32)	0.514	2.137
Note:	*p<0.1; **p<0.05; ***p<0.01	

Table 1

The P-value for the variable technology gap in the first regression is 0.4785, which unfortunately does not yield a statistically significant result. And again, for the second regression, no significant result was attained as the P-value for technology gap is 0.154, still above the significance threshold.

Plots of both regressions are shown in Figures 5 and 6. In both plots, we do see downward sloping lines, but since the regressions do not yield statistically significant results, we cannot say that the technology gap between Intel and AMD is negatively correlated with Intel's innovation rate. If significant results were obtained, the analysis would have rendered my hypothesis correct.

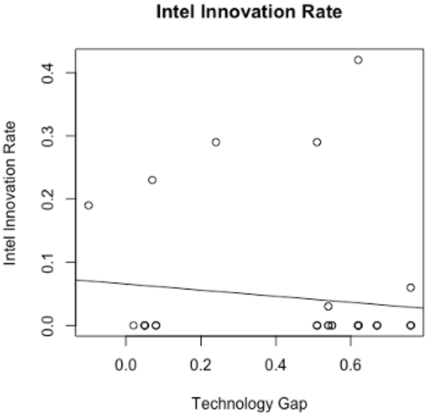

Figure 5: Regression 1 Plot

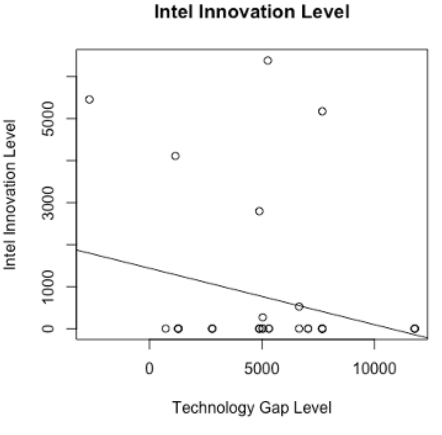

Figure 6: Regression 2 Plot

The proportional change in both variables used in regression 1 shows the rate at which the technology gap changes from time to time affects the rate at which innovation improves. The interpretation of the result could be that a ten percent increase in Intel's lead is correlated with a 0.48% decrease in the firm's innovation rate. The level change used in regression 2 shows the technology gap impacting the innovation level. The result can be interpreted as a one unit increase in the difference between the two firms' technology levels is correlated with a 0.134 decrease in Intel's innovation, which is represented by the chip quality score. Under the key assumption that Intel and AMD drive each other's innovation output, both regressions imply that a smaller technology gap between Intel and AMD induces Intel to innovate faster. But Intel's chip quality score, which is the base rate used here, is changing rapidly throughout time, using the proportional change method in regression seems to be a more convincing way to measure how much Intel is ahead of AMD as well as how fast Intel is innovating, having Intel's performance in the previous quarter as reference. For example, Intel's score was 1147 points higher than AMD in the second quarter of 2017, which seems like a very impressive gap, but knowing that Intel was only 7% more advanced than AMD at the time paints the real picture of how close the competition was. At the same time, Intel improved its quality score by 4112, which is a big jump on the surface, but it was only a 23% improvement from the first quarter of 2017. Having a point of reference in proportional change is a better indication for my analysis. There is undoubtedly an omitted variable bias that threatens the validity of the analysis by considering only one independent variable. There are certainly more factors that drive technology over time. Some omitted variables that could help explain innovation and the technology gap are discussed in the next section.

I considered putting thread count into the equation. However, as illustrated by Figure 7, thread count scores for Intel and AMD are at a similar level and move somewhat uniformly over the years, indicating that thread count is more of an industry-standard technology level signal that won't fit into my analysis of variants within each firm that contribute to innovation rate change.

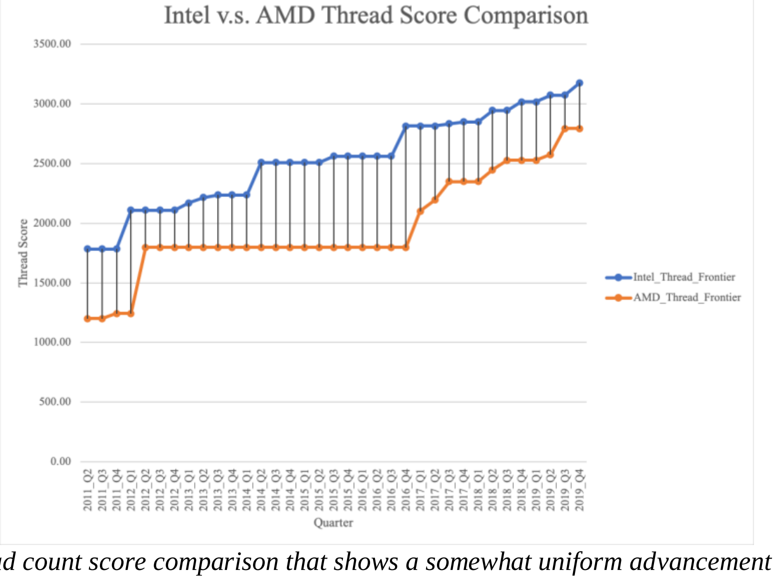

Figure 7: Thread count score comparison that shows a somewhat uniform advancement in technology in Intel and AMD.

6. Discussion

The limitation to the statistical precision mainly lies in omitted variable bias. There are a lot of factors not taken into consideration due to the lack of available data. Such data includes market share and historical pricing of each firm's CPU, each firm's funding in R&D used specifically for CPU technology development, overall competitive landscape in the CPU market (Intel may be trying to quicken its innovation pace to get ahead because of pressure from other firms, instead of AMD, or from all followers of the industry. And what propelled AMD to advance in 2017 might be pressure from other firms too), and manufacturing costs, etc. AMD outsources its chip manufacture so perhaps that's a factor worth being incorporated into the study, as this could affect the rate at which AMD's new CPU products are being introduced into the market.

Even though a statistically significant result was not obtained, and the null hypothesis couldn't be rejected, the point estimates are consistent with my hypothesis, where Intel's innovation rate picks up when the technology gap gets smaller between it and AMD. My regression results show that a one unit or ten percent increase in the technology gap is correlated with a 0.134 decrease in innovation level or a 0.48% decrease in innovation.

Under the key assumption that Intel and AMD alone drive one another's innovation output, a narrower technology gap between Intel and AMD signifies AMD's catching up with Intel, and it is correlated with a higher technology innovation rate in Intel. Intel's tendency to pick up its innovation speed when the technology gap decreases and even reverses indicates that when a leading firm starts to feel more pressure as a competitor comes close, or when it lags, the firm becomes more motivated to innovate more and faster to either maintain its leading position or return to that dominating position. In other words, a catch-up innovation phenomenon does exist in the competitive computer chip industry where firms try their best to catch up with leading competitors and not lag behind.

Another simple conclusion to be drawn from the insignificant result is that there is no relationship between the technology gap and innovation. Competition in the market could be happening in another way. This could help explain why different researchers reached different conclusions about the relationship between the two variables.

But adding more variables could change this result. If I had access to more data such as historical pricing, market share, and R&D spending on both firms' CPU models, which I would take as independent variables that affect Intel's innovation rate, I would have interpreted my result differently. Assuming coefficients on Intel's historical pricing, the share of CPU market and R&D spending (all data points relative to AMDs) are positive, my interpretation of the result would be that Intel is more motivated to pick up innovation pace when AMD comes closer in technology advancement and quality, and when Intel's relative price, market share and R&D spending are higher, since an industry-leading corporate like Intel would be incentivized to capitalize on its pricing and market power as well as R&D capabilities to strengthen its domination in the computer chip market. Nevertheless, it would also make sense if the coefficient of relative market share is negative. If Intel's relative market share is lower, the firm will be propelled to innovate faster to attain an upper hand in the market. But without actual data, all these are merely assumptions.

To further expand my analysis, I could also add one more decade worth of data points from both Intel and AMD, so I could study if there's a difference in the way the technology gap and potentially other factors I pointed out above affect innovation rate, between the short run and the long run.

The main assumption I made in the analysis is that Intel and AMD both consider only each other as the main competitor and the key that drives their innovation. Perhaps it isn't AMD's technology gap with Intel that explains Intel's innovation rate but rather that of other firms, and the same goes for AMD. If other data, such as CPU shipment data for the firms in the computer chip, exists and indicates that other firms are also key players in the field, it could very well threaten my analysis.

Even if this research did showcase a statistically significant result, it still paints a different picture from the study ran by Goettler et al. (2008), which shows Intel innovating slower as an oligopolist than as a monopolist. One reason this discrepancy exists could be because of the different periods where we run our analyses: Mine is of years 2011 to 2019, while their paper's analysis focused on 1993 to 2004, where the landscape of the computer chip industry was understandably very different from the recent decade. Demand for high technological performance of computer chips was not as high as now, where technology drives society and consumers' lives. Ryzen was not introduced to the market until 2017 and that chip family's birth is what propelled me to run this analysis. Another reason this discrepancy is here could be that I wasn't able to put the variables studied in their paper in my paper due to my restricted access to data that is licensed or proprietary.

As shown in Figure 3, AMD's shot up to a higher point than Intel in the last quarter of 2019, having data from 2020 and beyond could increase this analysis' statistical precision, and find out if the analysis holds under different circumstances and if it could be generalized to an analysis of a longer timeframe, especially with the COVID-19 pandemic early 2020 (and possibly into late 2020), where both firms' innovation output could be brought down drastically.

A possibility unrelated to variables themselves that contributes to the negative relationship observed in the results could be mean reversion. If Intel and AMD put out their products in alternating quarters, the increase in innovation level of one firm the following quarter is seemingly a response to the innovation put out by the other firm, but in fact a mere improvement of its product on its own pace regardless of what the competitor did. But as observed in Figure 3, the timeline in which each firm puts out new products does not necessarily follow the alternating pattern needed for this explanation to work – Intel seems to be innovating after AMD, but this observation is not definitive. Mean reversion probably does not come into play in this analysis.

7. Conclusion

Although my analysis could be improved and furthered by adding the missing variables mentioned in the previous section, it can be concluded that a narrower technology gap between two firms induces a quicker innovation rate in the leading firm, with the assumption that only Intel and AMD propel each other to innovate. When the leading firm feels the pressure from a fellow competitor, it is motivated to pick up its game to guarantee itself the dominating position in the market. That is a good thing for both firms and consumers. The competing firm sees the technology gap widen again due to the leading firm's faster innovation pace; it could be incentivized to pick up its technological development rate again to close up the gap.

This benign competition in the industry would mean products with better quality being produced at a bigger quantity as well as a shorter time frame. It doesn't just mean that the potential consumer surplus could be higher but that society as a whole would benefit through all these technological developments in computer chips. A better, faster and smaller chip does not just bring an edge to a smart computer, but also a technological revolution in all benefiting fields that rely on smart computers, which includes healthcare, transportation and education, industries that the evolution of a society depends on. The implication from this analysis extends much further than the computer chip industry itself.

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The Impact of Urbanization and Increased Production on the Agricultural Sector: An Econometric Time Series Analysis

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Abstract

Modern India is a rapidly developing country with per capita GDP rates following an upward trajectory over the past several decades. Intertwined with increased production rates are increased urbanization rates as well. However, given the significance of the agricultural sector in the Indian economy, it is worthwhile to investigate how the increased rates of production and urbanization impacted the agricultural sector and its workers. This paper first delves into the behavior of the growth rates of certain key macroeconomic variables pertaining to this context. Secondly, this paper investigates how the agricultural contribution to GDP in India has changed over time and how the workers of the agricultural sector have been impacted. The latter issue is analyzed using vector auto-regression models and instrumental variable regressions. We conclude by highlighting the effects of increased production and urbanization (as a function of time) on the workers in the agricultural sector and the economic implications of these effects.

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1. Introduction

The Republic of India, just as many of her counterparts in the developing world, has been subject to immense urbanization which prominently manifested during the later stages of the 20th century and further proliferated as the 21st century unfolded. More than half (approximately 67% to be exact) of modern India's output is attributed to her cities, which have been growing in size since the turn of the century. World Bank economists project that the approximately 282 million people living in Indian cities will more than double to 590 million people in the next two decades. In the midst of India's rapidly growing urban population and GDP, laborers in the agriculture sector, whose efforts have formed the backbone of the Indian economy for decades, are not necessarily reaping the benefits of India's surging economy. Statistics report the uncanny proliferation of farmer suicide rates from 1.4-1.8/100,000 in 1995-2005 to more than 10 suicides daily in 2017-2018. A study regarding how agricultural workers have been impacted throughout the course of time is worthy of consideration.

Although urbanization is an integral component of increased economic growth, it is a phenomenon which has its fair share of negative repercussions. Such negative attributes are especially prominent in a country such as India, where the population levels tend to exceed the capacity of resources provided. It is a necessity to heed the conditions of the workers in the agricultural sector and the ultimate outcome of their fate as time progresses and urbanization advances. Statistically, it is shown that the destitute areas of urban land, colloquially termed as slums, contribute to 26% of India's urban population (World Bank). This compels one to ponder whether an increase in the rates of rural-to-urban population migration, often termed as 'population urbanization,' translates to an increased percentage of residents who are actual residents, who now live in urban slums, and whether these residents would have been better off if their land was not subject to urbanization to begin with.

It is no secret that the agricultural sector is an indispensable component of India's economy, and an empirical and quantitative study on the effects of increased urbanization at the expense of impacting the agricultural sector is worthy of consideration. Specifically, we proceed with an empirical time series analysis on how a growth in Indian output and urbanization impacts the workers in the agricultural sector of the Indian economy. There have been many qualitative deliberations on the inadequacy of current mechanisms endeavoring to enhance the marginal productivities for agricultural workers (Goyal, Rai, Singh 2016). In this paper, we quantitatively analyze how marginal productivities in the agricultural sector are impacted by India's rise in GDP and urbanization. Sections 2 and 3 proceed with a literature review and a discussion of the variables respectively. Sections 4 through 7 elaborate on the analyses that were employed, and Section 8 concludes the study.

2. Literature Review

Reports regarding the positive impact of India's increased urbanization on her economic growth need to be heeded with caution. Although the benefits of urbanization definitely exist, the gap between India's land urbanization rate and the percentage of 'urban residents' who are able to reap the benefits of urbanization is not only quite significant but also increasing overtime. "Urbanization and Economic Growth in China - An Empirical Research Based on VAR Model" (Zi 2017) serves as a pivotal paper which separates the effects of population urbanization and land urbanization on economic growth in China. The paper proceeds by implementing a structured VAR in order to analyze how the endogenous variables (population urbanization, land urbanization and economic growth) have impacted each other throughout the course of time. The paper empirically showed a "unidirectional causality between resident population urbanization and China's economic growth, the former promoting the long-term growth of the latter" (Zi 2017). Although in the short term a negative impact on economic growth is observed, as time progresses and the population shifts from the rural market to the urban sector, economic growth is positively impacted in the long run. The paper also interestingly reveals the unidirectional causality between land urbanization and economic growth. However, in this case, it is economic growth which impacts land urbanization, and not the other way around. In the suggestions section of the paper, Zi emphasizes the need to increase population urbanization in China and the necessity of controlling land urbanization in an effort to bridge the gap between the two rates. Such suggestions are applicable to the Indian economy as well, perhaps with even greater relevance, due to the increase in the presence of 'urban slums' as a function of increased rates of land urbanization.

The use of monetary compensation to farmers in order to justify and make amends for unrestrained acts of land urbanization has also been heavily critiqued by several economic papers. As "Land Policy and Urbanization in the People's Republic of China" (Zhang and Xu 2016) succinctly states, "land expropriation without rational compensation drove farmers who had lost land into both homelessness and joblessness." The interesting thing to note is that monetary compensation is not necessarily equivalent to rational compensation. As stated in " The Neglected Political Economy of Eminent Domain" (Garnett 2006), "compensation-based reforms" are not "an alternative to constraints on the use of eminent domain," as high compensation levels may undermine political resistance to questionable projects and "private takings may generate instrumental harms that will persist even as compensation increases." Monetary compensation given to farmers and other laborers whose source of living was hinged on the agricultural sector is not enough to lift them out of the potential prospects of destitution that lies ahead. The negative impact that extensive land acquisition/urbanization has on the agricultural sector in India and subsequent farmer productivity/food production, is worthy of an empirical analysis.

3. Discussion of Variables

This paper extends gratitude to the World Bank, as all of the data values have been obtained from open source World Bank data. Following is a delineation of variable abbreviations and the ensuing explanations that have been employed in this paper in tabular form.

Variable Name/Abbreviation	Explanation/Significance
Y_{PC}	Per capita real GDP for both India and average global date
$Y_{PC\,Ag}$	Per capita agricultural contribution to GDP for India and average global data
N	Population variable
K	Agricultural machinery, tractors per 100 sq km of arable land. Used as a proxy for capital.

L	The number of laborers/workers in the agricultural/urban sector
MPL	Marginal product of labor. Calculated for both the agricultural and urban sectors
MPK	Marginal product of capital. Calculated for the agricultural sector assuming constant returns to scale.
NW	Nominal wages for workers in the agricultural and urban sectors
CPI	Consumer Price Index
RW	Real wages

4. Analysis of Growth Rates

We begin our analysis by exploring the growth rates of the variables under consideration. Growth rates of variables are analyzed for both India and average global data.

We establish the following definition:

$$\mu = \frac{\frac{Y_{PC\ Ag\ India}}{Y_{PC\ India}}}{\frac{Y_{PC\ Ag\ World}}{Y_{PC\ World}}} =$$ the relative density of agricultural contribution to GDP in India

We are interested in analyzing the growth rate of μ and hence we get the following:

$g(\mu) = (\ g(YPC\ Ag\ India\ ) - g(YPC\ India\ )) - (g(YPC\ Ag\ World) - g(YPC\ World))$ (Form A)

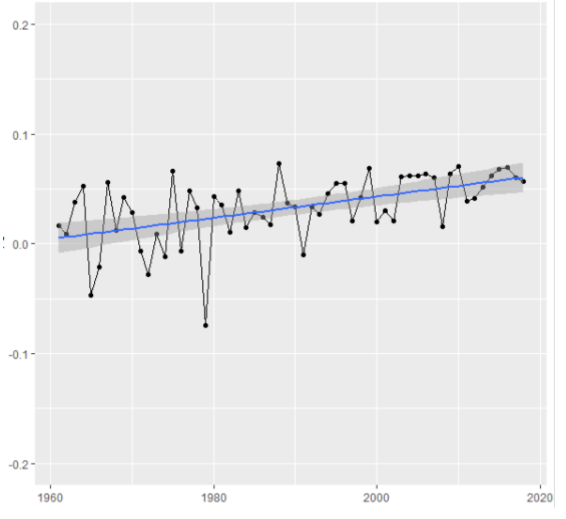
This equation can be rearranged to yield the following:

$g(\mu) = (\ g(Y_{PC\ \ Ag\ India}) - (g(Y_{PC\ Ag\ World})) - (\ g(Y_{PC\ India}) - \ \ g(Y_{PC\ World}\ ))$ (Form B)

The advantage of analyzing Form B is that it gives us the opportunity to inspect whether the direction of μ is mainly determined by the difference in growth rates of India's and the world's GDP or the difference in growth rates of India's and the world's agricultural contribution GDP. Preliminary Results: The following graphs (each with its respective title) have the years 1961-2019 on the x-axis and (-0.2 – 0.2)(growth rate) on the y-axis.

Growth rate in per capita GDP (India)

GR



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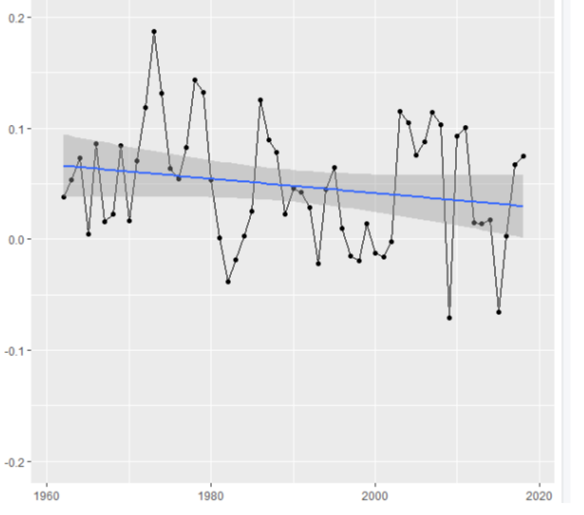
Per Capita GDP growth (Global Data)

GR



YR

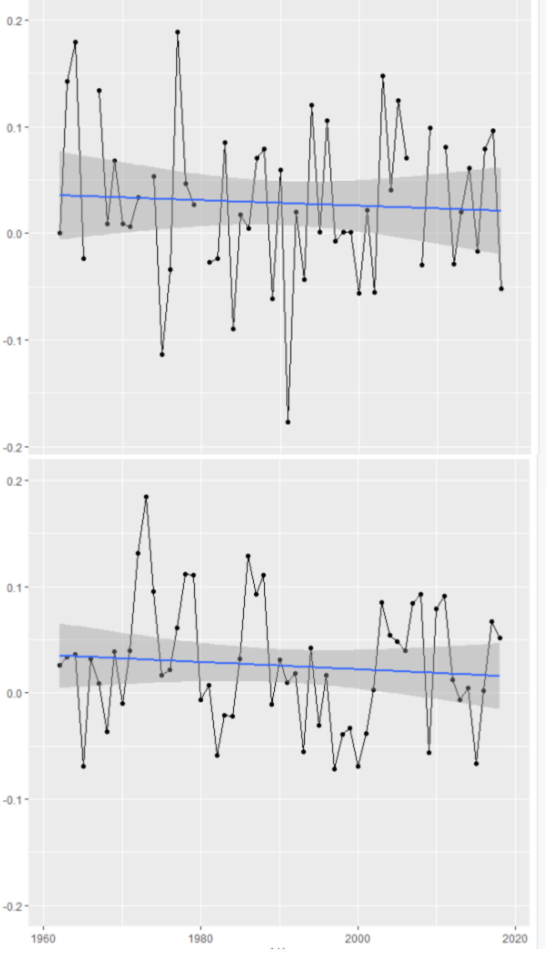
For India, we observe that the best fit linear model harbors a very slight negative slope (almost constant around the 0.07 growth mark) with a major contraction occurring around the early 1990s. Overall, we observe a wide dispersal of points around the linear model, most prominently from around 1970 to 2010. For the global data, we observe that the linear model is slightly more negative and the dispersal of points is not as pronounced.

Growth Rate of Per Capita Agricultural contribution to GDP (India)

GR

YR

Growth Rate of per capita Agricultural contribution to GDP (global data)



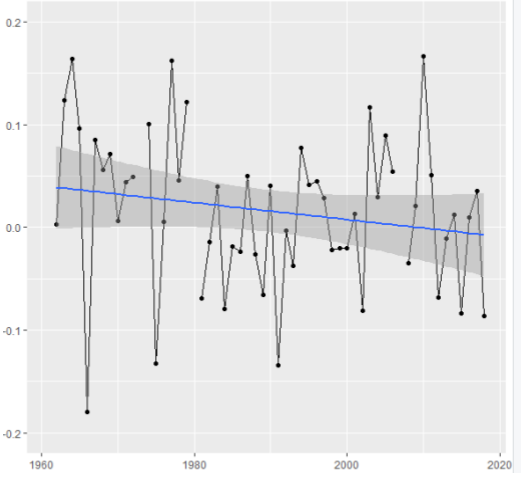
GR

YR

For India, we observe that once again the best fit linear model has a negligible slope and is fairly constant around the 0.03 growth mark, which is substantially less than the overall growth rate of the country's per capita GDP. We once again note the significant contraction which took place around the early 1990s.

Growth Rate in India's relative density of Agricultural contribution to GDP

GR



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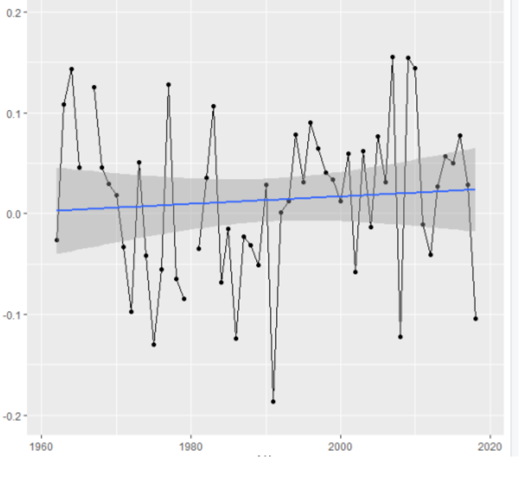
Overall, we notice a downward sloping trend line. We notice considerable variance around the trend line from about 1960 to 1980 with a major expansion around 1980. From 1980 to 2019 the dispersal minimizes considerably, with a significant contraction around the early 2000s.

Let us now revisit the formula derived earlier in order to analyze $g(\mu)$, and let us particularly pay attention to Form B $g(\mu) = (g(Y_{PC\ Ag\ India}) - (g(Y_{PC\ Ag\ World})) - (g(Y_{PC\ India}) - g(Y_{PC\ World}))$ (Form B). Following is the graphical representation of $(g(Y_{PC\ Ag\ India}) - (g(Y_{PC\ Ag\ World}))$

Difference between India's PC agricultural contribution to GDP and the World's

GR

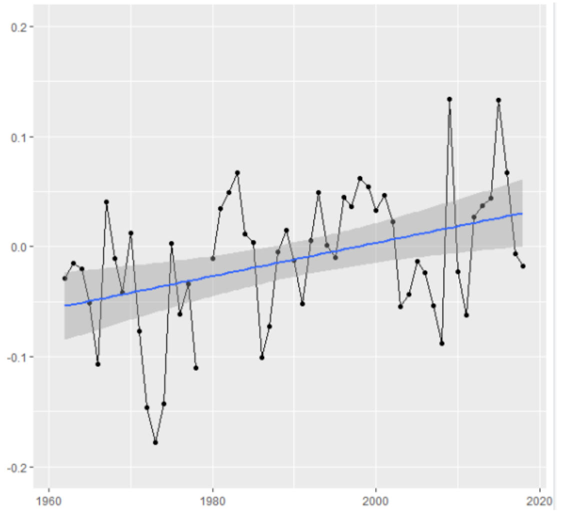


YR

Following is the graphical representation of $(g(Y_{PC\ India}) - g(Y_{PC\ World}))$:

Difference between India's growth rate of PC GDP and the World's

GR



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Although India's relative density of agricultural contribution to GDP is decreasing, we notice that the best fit trend line for $(g(Y_{PC\ Ag\ India}) - g(Y_{PC\ Ag\ World}))$ is slightly positive, although not quite substantial with severe dispersals around the line through the decades. We see however that the main trigger behind the decline of India's relative density statistic is the general positive difference $(g(Y_{PC\ India}) - g(Y_{PC\ World}))$ as indicated by the trend line. Therefore, referring back to Form B $g(\mu) = (g(Y_{PC\ Ag\ India}) - (g(Y_{PC\ Ag\ World})) - (g(Y_{PC\ India}) - g(YPC\ World))$, we observe that the latter part of the equation is more positive than the former, and hence $g(\mu)$ has a general negative trajectory. However, we have established empirically that the downward decline of $g(\mu)$ does not translate to a downward trajectory of $(g(YPC\ Ag\ India) - g(YPC\ Ag\ World))$, as the latter is still slightly positive.

Now, we will present the graphical representations of the growth rates of the marginal product of labor in the Indian agricultural sector. We can denote the marginal production of labor in the agricultural sector as follows:

$$MP_{L\ India} = B\frac{Y_{Ag\ India}}{L_{India}}$$

A major caveat lies in the appropriate selection of the value of *B*, which serves as a pivotal constant. Under the assumption of constant returns to scale, where we suppose that the sum of a, the constant associated with the marginal product of capital, and *B* is equal to 1, we can assume that the marginal product of labor is approximately equivalent to real wages given to laborers in the agricultural sector. Essentially, we abide by the following:

$$MP_{L\ India} \sim \frac{NW}{CPI}$$

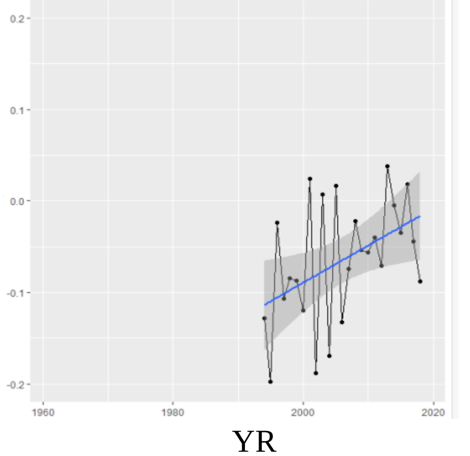
where *NW* is the nominal wage and *CPI* is the consumer price index (assuming a base year of 2010 in this context.) Given comprehensive data on India's nominal wages in the agricultural sector and the CPI (base year 2010), we have the following:

$$B = \frac{\frac{NW}{CPI} L_{India}}{Y_{Ag\ India}}$$

Of course, per capita values for Y and L were implemented. Based on the estimates of B, we arrived at the estimates of *a* by using *a = 1 – B*, by the assumption of constant returns to scale. Based on the deliberations above, we arrived at the following results. The graphs once again have the years 1961-2019.

Growth rate in the marginal product of labor in India's agricultural sector

GR



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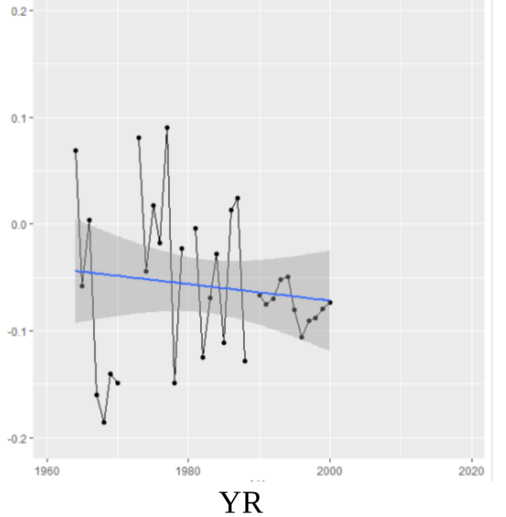
Growth rate in the marginal product of capital in India's agricultural sector

GR



YR

Unfortunately, due to data restrictions, the time periods for which there exists data for capital and labor in the agricultural sector have a negligible intersection. Hence the depictions for MPL_{India} and MPK_{India} cover different time intervals. However, the general trends as delineated by the trend lines can be used for analysis. We observe that the trend line for MPL_{India} is positive whereas that of MPK_{India} is negative. While it is likely that there will be a time when growth rate of MPL_{India} will embrace a downward trajectory, the current time period proves that adding more labor to the agricultural sector can potentially result in more productive yields. Therefore, workers being displaced from the agricultural sector as a consequence of urbanization could prove to be detrimental to the agricultural sector and the Indian economy as a whole.

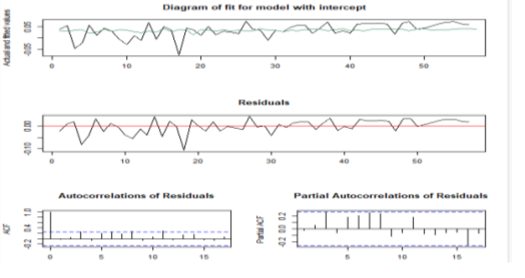
5. Analysis of Unit Roots/Structural Breaks

We will proceed to a structural break analysis where we test for the presence of unit roots in the time series progressions of our data. In other words, if the mean and the variance of our datasets are constant over time, we can confirm the stationarity of the data. Otherwise, we must label the time series progression as non-stationary.

We implement a Phillips and Perron structural break test in order to test for the presence of unit roots/structural breaks in the data. In terms of integrated order of processes, we are testing whether the time series progression is *I(0)* or *I(1)* (note that *I(k)* where k > 1 is very rare in real world processes and hence we will not consider them). Following are the results of the test when applied to time series progressions of the growth rates (for India).

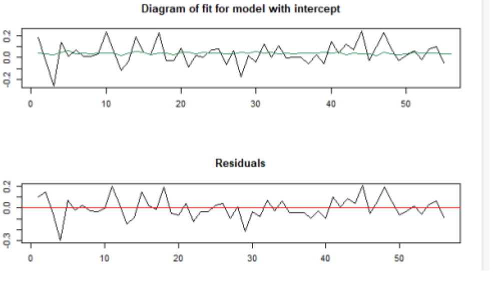
Test for growth rate in per capita GDP

```
####################################################
# Phillips-Perron Unit Root / Cointegration Test #
####################################################

The value of the test statistic is: -6.3014

>
> x@cval
                    1pct      5pct     10pct
critical values -3.547748 -2.912708 -2.593707
```



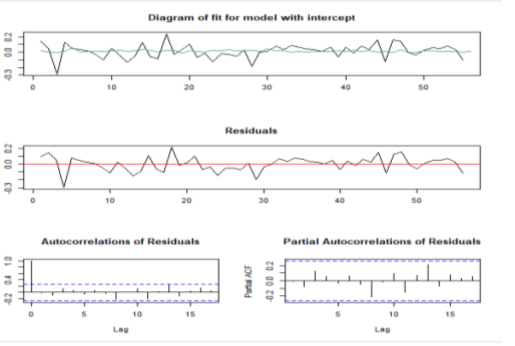
Test for growth rate in per capita agricultural contribution to GDP

```
####################################################
# Phillips-Perron Unit Root / Cointegration Test #
####################################################

The value of the test statistic is: -8.0144

> x@cval
                    1pct      5pct     10pct
critical values -3.549952 -2.913659 -2.594207
```



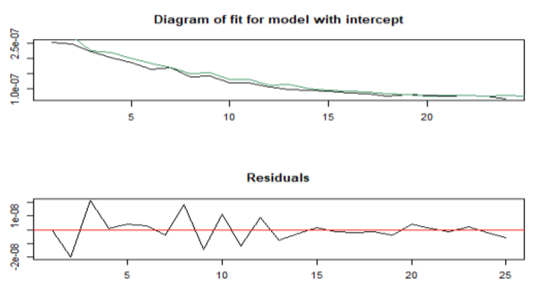
Test for the difference in growth rates of India's agricultural contribution to GDP and the world's

```
####################################################
# Phillips-Perron Unit Root / Cointegration Test #
####################################################

The value of the test statistic is: -8.3076

> x@cval
                  1pct      5pct     10pct
critical values -3.549952 -2.913659 -2.594207
```



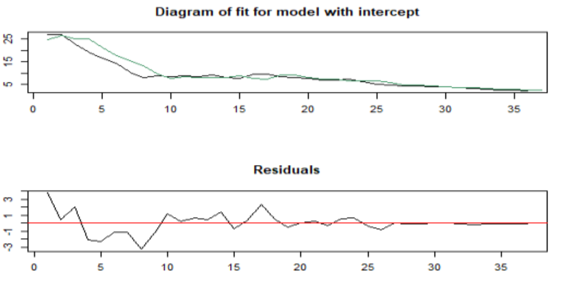
Test for the growth rate in $MPL_{Ag\ India}$

```
####################################################
# Phillips-Perron Unit Root / Cointegration Test #
####################################################

The value of the test statistic is: -9.3991
```



Test for actual values of $MPK_{Ag\ India}$

```
####################################################
# Phillips-Perron Unit Root / Cointegration Test #
####################################################

The value of the test statistic is: -2.3368
```



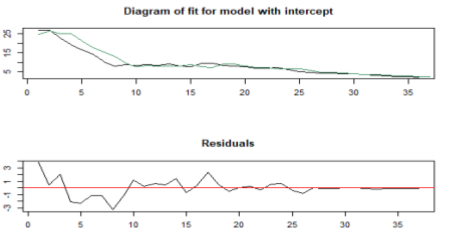
With the exception of the test for India's relative density statistic and $MPL_{Ag\ India}$, all tests failed to reject the null hypothesis and hence confirm the presence of a unit root. The first difference of the variable was tested as well to confirm that the processes are indeed *I(1)*. We note that India's per capita GDP values tend to embrace an upward deviation from its stationary trend as the 2000s unfold. It is important to note the downward stationary trend that the actual values of $MPL_{Ag\ India}$ embrace, although the progress of its growth rate hinted at a non-stationary process. Although the actual values are embracing a downward path, the general trend line for the growth rate is positive, as corroborated by a previously delineated graph. We posit that the marginal product values of factors of production in India are embracing a downward trajectory because we have used per capita values for output and since India's population is quite exorbitant the ratio $\frac{\frac{Y}{N}}{Factor\ of\ Production}$ tends to fall. This decline in $MPL_{Ag\ India}$, however, is still a matter of concern given the rise of India's overall output (and agricultural output). We posit that a more stable trajectory (instead of a persistent downward trend) for this statistic would correspond to a more substantial upward trajectory for the growth rate of this statistic which would be in accordance with the rise of India's overall GDP and the agricultural contribution to GDP.

Although we don't have enough modern data on capital in the Indian agricultural sector, we notice a sharp decline in the time series progression $MPK_{Ag\ India}$ in the early 1960s.

Additionally, there is a lack of evidence for any sort of revitalization in the trend all the way into the 1990s. Additionally, as we saw before, the trend line for the growth rate in $MPK_{Ag\ India}$ is negative. This corroborates the notion that investment in labor in the agriculture sector would result in more yields than investment in capital.

We can further substantiate the perpetual decline of $MPK_{Ag\ India}$ by using a Phillips- Perron test to test for the presence of a deterministic trend in our hypothesized model. That is, in addition to the random walk with drift model that we have proposed earlier, we can test if a model with a deterministic trend would be statistically relevant.

```
###################################################
# Phillips-Perron Unit Root / Cointegration Test #
###################################################

The value of the test statistic is: -1.659
```



We notice that the test statistic above the critical values and hence we fail to reject the null hypothesis, signaling that the model with a deterministic trend and drift is statistically relevant. By visual inspection we can see that B is negative and hence $E[MPK_{Ag\ India}]$ is forced to embrace a downward trend as time progresses (since the negative B is associated with the quadratic term t^2.) This further substantiates the notion that investment in capital would not result in significant agricultural productive yields as it has embraced a deterministic downward trend and hence investment in labor in the Indian agricultural sector should be heeded. The Indian agricultural sector has always been labor driven. A decline in the marginal contributions of labor (and ensuing labor compensation) in the climate of increased national productivity is an alarming phenomenon which warrants immediate attention.

6. Vector Autoregression Models

We proceed to the use of vector autoregression models in order to explore the bidirectional causal impact between a system of endogenous variables with respect to time lags. Let us initially consider the system of three endogenous variables delineated as follows:

Variable 1 - Growth rate in the Urban Population in India (g(Urban))

Variable 2- Growth rate in the per capita agricultural contribution to GDP in India ($\boldsymbol{g(YPC\ Ag\ India)}$)

Variable 3 - Growth rate in Marginal Product of Labor in the agricultural sector of India ($\boldsymbol{g(MPLAg\ India)}$)

We proceed with a model under the assumption that each endogenous variable is a function of itself at a lagged time period and a function of the other two endogenous variables at a lagged time period.

Reduced form VAR estimate

```
Estimation results for equation V1:
===================================
V1 = V1.l1 + V2.l1 + V3.l1 + const

        Estimate Std. Error t value Pr(>|t|)
V1.l1  1.0386786  0.0817845  12.700 4.96e-11 ***
V2.l1 -0.0028696  0.0015774  -1.819   0.0839 .
V3.l1  0.0035312  0.0021481   1.644   0.1158
const -0.0007839  0.0020180  -0.388   0.7018
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1


Residual standard error: 0.000567 on 20 degrees of freedom
Multiple R-Squared: 0.9079,	Adjusted R-squared: 0.8941
F-statistic:  65.7 on 3 and 20 DF,  p-value: 1.56e-10


Estimation results for equation V2:
===================================
V2 = V1.l1 + V2.l1 + V3.l1 + const

       Estimate Std. Error t value Pr(>|t|)
V1.l1  4.534116  12.022431   0.377    0.710
V2.l1 -0.008683   0.231877  -0.037    0.971
V3.l1 -0.299447   0.315775  -0.948    0.354
const -0.086443   0.296645  -0.291    0.774


Residual standard error: 0.08335 on 20 degrees of freedom
Multiple R-Squared: 0.09433,	Adjusted R-squared: -0.04152
F-statistic: 0.6944 on 3 and 20 DF,  p-value: 0.5663
```

```
Estimation results for equation V3:
===================================
V3 = V1.l1 + V2.l1 + V3.l1 + const

      Estimate Std. Error t value Pr(>|t|)
V1.l1 -24.6283     7.5749  -3.251  0.00400 **
V2.l1  -0.1361     0.1461  -0.931  0.36282
V3.l1  -0.5535     0.1990  -2.782  0.01151 *
const   0.5421     0.1869   2.901  0.00884 **
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1


Residual standard error: 0.05251 on 20 degrees of freedom
Multiple R-Squared: 0.4539,	Adjusted R-squared: 0.372
F-statistic: 5.542 on 3 and 20 DF,  p-value: 0.006183



Covariance matrix of residuals:
           V1         V2         V3
V1  3.215e-07 -1.698e-05 -8.276e-06
V2 -1.698e-05  6.947e-03  1.824e-03
V3 -8.276e-06  1.824e-03  2.758e-03

Correlation matrix of residuals:
        V1      V2      V3
V1  1.0000 -0.3593 -0.2780
V2 -0.3593  1.0000  0.4166
V3 -0.2780  0.4166  1.0000
```

In matrix form we have:

$$\begin{bmatrix} g(Urban)_t \\ g(Y_{PcAg})_t \\ g(MPL_{Ag})_t \end{bmatrix} = \begin{bmatrix} -0.00078 \\ -0.086443 \\ 0.5421 \end{bmatrix} + \begin{bmatrix} 1.0387 & -0.0029 & 0.00353 \\ 4.534 & -0.00868 & -0.299 \\ -24.6238 & -0.1361 & -0.5535 \end{bmatrix} \begin{bmatrix} g(Urban)_{t-1} \\ g(Y_{PC\,Ag})_{t-1} \\ g(MPL_{Ag})_{t-1} \end{bmatrix} +$$

$$\begin{bmatrix} 3.15x10^{-7} & 1.8x10^{-5} & -2.02x10^{-6} \\ -1.84x10^{-5} & 6.9x10^{-3} & 6.4x10^{-4} \\ -2.016x10^{-6} & 6.4x10^{-4} & 1.73x10^{-4} \end{bmatrix}$$

Due to the relatively small range in the data values for $g(Urban)_t$ compared to that of the other variables, we label $g(Urban)_t$ as the most exogenous variable in our system. We note that while urbanization in Western countries has been significantly explained by rural to urban labor migration, India's rapid growth in urban population is mainly attributed to a higher contribution of natural urban increase (Bhagat 2017). Specifically, according to the State of World Population 2007 report released by the UNPF, it was established from a component analysis of urban growth in India from 1961-2001 that urban natural increase accounted for 51%-65% of urban growth in that period (Chandran 2007). The discrepancy between urban access to electricity, drinking water, and sanitation, among other necessities, and rural access to the same necessities is quite substantial in India (Bhagat 2011b). Such a phenomenon plays a significant role in natural urban population increase. The order of $g(Y_{Pc\ Ag})_t$ and $g(MPL_{Ag}\ )_t$ will determine the exogeneity/endogeneity relationship between them. We claim that the specific order of these two variables would not change the primary results (namely the impulse response functions) considerably as both variables can potentially be endogenous relative to each other.

The lack of significant P values can be attributed to the fact that we used data only from 1993-2018 as those were the years with reported data for labor in the Indian agricultural sector. We acknowledge this as a limitation and focus on the general trend of the variables at time *t* as a result of increases/decreases in the lagged values of the variables at time *t-1*.

We notice that increases in $g(MPL_{Ag\ India})$ and $g(Y_{PC\ Ag\ India})$ in the previous time period have a positive and negative yet relatively nominal impact on *g(Urban)* respectively. A high *g(Urban)* at *t-1* will positively impact *g(Urban)* at time period *t* (positive coefficient 1.0387 with a significant p-value). Specifically, we claim that a 1% increase in $\frac{Urban^{t-1}}{Urban_{t-2}}$ is the urbanization rate in India at time period *t*. It is interesting to note, however, that a high value for *g(Urban)* in time *t-1* will have a significant positive impact for $g(Y_{PC\ Ag\ India})$ in time *t*.

Therefore, as time progresses, urbanization positively impacts India's agricultural contribution to its GDP, signifying that agriculture has continued to play an important role in the Indian economy throughout time even as the country seeks to urbanize. Therefore, a depletion in resources and investment towards the agricultural sector may belie economic growth. We further observe how all three variables in time *t-1* negatively impact $g(MPL_{Ag\ India})$ in time *t*. This highlights a pivotal discrepancy. Increase in the agricultural contribution to output is coupled with the decline in value and returns for laborers in the agricultural sector. The conditions and future of these workers, who are often not able to transition into work in the urban setting, must be taken into consideration.

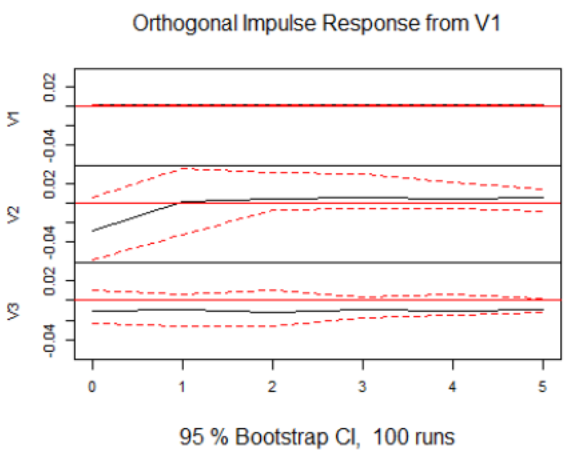
Following are the estimates of the structural form which have been solved analytically:

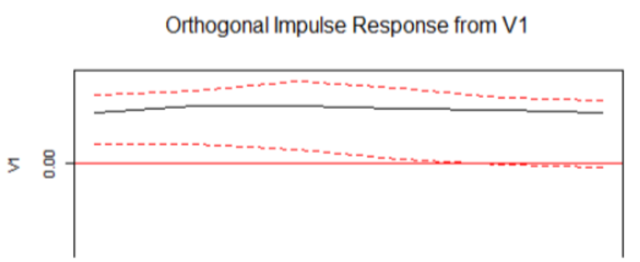
$$\begin{bmatrix} 1 & 0 & 0 \\ 58.4127 & 1 & 0 \\ 0.9822 & -0.09275 & 1 \end{bmatrix}\begin{bmatrix} g(Urban)_t \\ g(Y_{PcAg})_t \\ g(MPL_{Ag})_t \end{bmatrix}$$

$$= \begin{bmatrix} 1.0387 & -0.0029 & 0.00353 \\ 65.20727 & -0.178077 & -0.093 \\ -24.02412 & -0.138143 & -0.52228225 \end{bmatrix}\begin{bmatrix} g(Urban)_{t-1} \\ g(Y_{PCAg})_{t-1} \\ g(MPL_{Ag})_{t-1} \end{bmatrix}$$

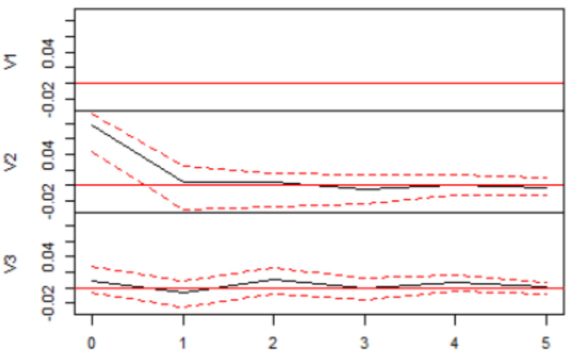
$$+ \begin{bmatrix} 3.15x10^{-7} & 0 & 0 \\ 0 & 6.9x10^{-3} & 0 \\ 0 & 0 & 1.73x10^{-4} \end{bmatrix}$$

Following are the impulse response functions delineating the response of the endogenous variables to a shock in our assumed exogenous variable. Predicted paths for the endogenous variables have been delineated for 5 years into the future with a specified 95% confidence interval. We note that the range of the values for *g(Urban)* is substantially less than that of the other variables and hence the range of the shock trajectory is less as well. In order to ‘zoom’ into this range, shock trajectories of *g(Urban)* have been reproduced below each set of impulse response functions. The range of the shock trajectories for ***g(Urban)* is (-0.001,0.001)** and has been delineated for the same 5 years. The justification for using 5 years stems from the limited amount of data we had at our disposal. Any effort to generate shock trajectories beyond 5 years yielded horizontal lines that were devoid of any significance.



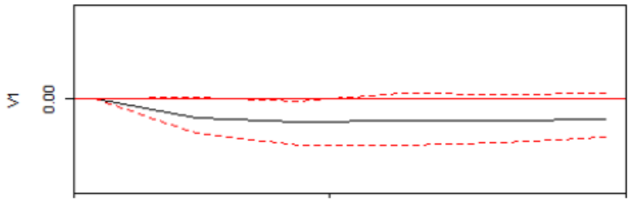


Orthogonal Impulse Response from V2

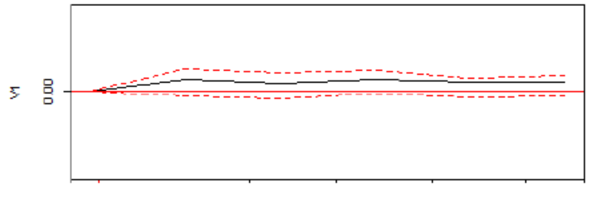


95 % Bootstrap CI, 100 runs

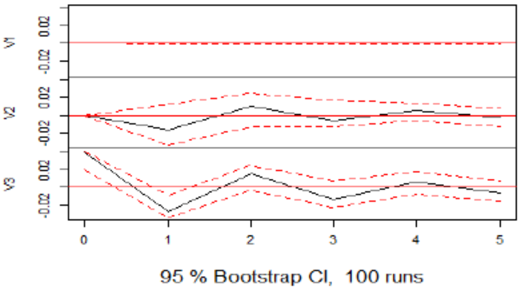
Orthogonal Impulse Response from V2



Orthogonal Impulse Response from V3



Orthogonal Impulse Response from V3



95 % Bootstrap CI, 100 runs

In the first graph, all paths are initiated by a positive 1%shock to *g(Urban).* A positive contemporaneous shock to *g(Urban)* initially results in a positive shock to itself which lingers for approximately 2 years before returning back to the steady state equilibrium. We note that the 95% confidence interval does not include 0 and is entirely in the positive realm. As for a contemporaneous shock to $g(Y_{Ag\ Pc})$ from *g(Urban),*we note that the 95% confidence interval does include 0 (as we can say with 95% confidence that a 1% shock to *g(Urban)* will contemporaneously result in a (-5% -1%) shock to $g(Y_{Ag\ Pc})$. However, the trajectory of this shock immediately embraces an upward trend in the subsequent time period before stabilizing to the steady state equilibrium. Moreover, the trajectory of the shock of *g(Urban)* to $g(MPL_{Ag})$ embraces a slight downward trajectory. This difference in the ensuing behavior of the shock to agricultural contribution to GDP and the shock to the rewards given to laborers in the agricultural sector as a result of a positive shock to India's rapid urbanization and GDP increase is one of the pivotal results of the paper. We note that the impulse response functions delineate the trajectory of a contemporaneous shock at time period t, and therefore it is expected for the shock to eventually wane and head back to the steady state value as time progresses.

Now, a 1% shock to $g(Y_{Ag\ Pc})$ slightly contemporaneously decreases *g(Urban)* (it can be argued that the decrease is negligible as the 95% confidence interval includes a change of (-0.05%,0%)) and leads to a massive positive shock to itself initially (the confidence interval is completely in the positive realm), after which the shock wanes significantly and stabilizes back to the steady state equilibrium as time progresses. The same shock leads to a positive increase in $g(MPL_{Ag})$ initially, after which the trajectory of the shock embraces an oscillatory path.

A 1% shock to $g(MPL_{Ag})$ leads to a positive increase to itself before the shock embraces an oscillatory path, eventually converging to the steady state equilibrium as time progresses. However, the same to $g(YAg\ Pc)$ initially embraces a negative trajectory.

The Indian economy has reached a stage where the productivity of the agricultural sector is not hinged on laborers in the sector and hence the importance of the work of these laborers has been neglected, ultimately resulting in the decline in welfare of these laborers. Most of these workers in the agricultural sector are only equipped with skills specifically pertaining to their trade and cannot afford to make the transition into the urban sector. Therefore, with the declining value of labor in the agricultural sector, workers are often confronting lower gains which readily pushes them into the realm of unemployment.

7. Instrumental Variable Regression

We conclude our analysis by performing an instrumental variable regression to see how urban population growth rates in India are impacting the growth rates of the marginal product of labor in the agricultural sector. Specifically, we are estimating the following:

$$g(MPL_{\ Ag}) = a + Bg(Urban) + Cg(Y_{PC\ Ag}) + e$$

However, we make the very crucial observation that our primary explanatory variable may be endogenous in nature and hence $Cov(g(Urban), e) \neq 0$. Therefore, it is liable that there are other factors, accounted in the error term e, which would be directly impacted by urbanization rates and would consequently impact $g(MPL_{Ag})$. Since we are not interested how those factors will impact our outcome variable, we introduce an instrument variable, $g(Urban_{t-1})$ (lagged growth rates in urbanization) such that $Cov(g(Urban_{t-1}), g(Urban)) \neq 0$ (this is corroborated by the VAR estimations) and $Cov(g(Urban_{t-1}), e) = 0$.

As an alternate instrument variable, we can use the lagged values of the marginal product of labor in the urban sector, namely $g(MPL_{Urban\ t-1})$ such that this instrument satisfies the conditions of relevance and exogeneity. Following are the results with $g(Urban_{t-1})$ as the instrument (left) and $g(MPL_{Urban\ t-1})$ as the instrument (right):

```
Call:
ivreg(formula = V3 ~ V1 + V2 | V2 + V6)

Residuals:
     Min       1Q   Median       3Q      Max 
-0.24552 -0.14474  0.01626  0.10271  0.29128 

Coefficients:
            Estimate Std. Error t value Pr(>|t|)
(Intercept)   2.5282    17.2360   0.147    0.885
V1         -101.7514   673.5126  -0.151    0.881
V2            0.2907     0.4358   0.667    0.512

Residual standard error: 0.1591 on 20 degrees of freedom
Multiple R-Squared: -4.043,	Adjusted R-squared: -4.548 
Wald test: 0.2227 on 2 and 20 DF,  p-value: 0.8023
```

```
Call:
ivreg(formula = V3 ~ V1 + V2 | V2 + V5)

Residuals:
      Min        1Q    Median        3Q       Max 
-0.091082 -0.042200 -0.008449  0.030965  0.110112 

Coefficients:
            Estimate Std. Error t value Pr(>|t|)  
(Intercept)   0.4540     0.1915   2.370   0.0274 *
V1          -20.7320     7.4546  -2.781   0.0112 *
V2            0.2553     0.1503   1.698   0.1043  
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 0.05761 on 21 degrees of freedom
Multiple R-Squared: 0.3339,	Adjusted R-squared: 0.2705 
Wald test: 5.102 on 2 and 21 DF,  p-value: 0.01563
```

In the results above, V3 is $MPLAg$, V1 = $g(Urban)$, V2 = $YPC\ Ag$, V5 = $g(Urban)t-1$, V6 = $g(MPLUrban\ t-1)$.

Estimation with $g(Urban_{t-1})$ as instrument:

$$g(MPL\ Ag) = 0.454 - 20.73g(Urban) + 0.2553g(YPC\ Ag) + e$$

Estimation with $g(MPL_{Urban\ t-1})$ as instrument:

$$g(MPL\ Ag) = 2.5282 - 101.75g(Urban) + 0.2907g(YPC\ Ag) + e$$

We notice that the former estimation yields more statistically significant results. This can be partially attributed to the fact that $g(Urban_{t-1})$ is a more relevant instrument than $g(MPL_{Urban\ t-1})$. Hence, $|Cov(g(Urbant-1), g(Urban))| > |Cov(g(MPLAg), g(Urban))|$ (as delineated in the VAR estimations) and the absolute value for the estimator for B is smaller and more statistically significant than the latter.

A 1% increase in $\frac{Urban^t}{Urban_{t-1}}$, explained solely by variation in the instrument employed, would result in an approximately 20% decline in $\frac{MPLAg_t}{MPlAg_{t-1}}$ where Urban$_t$, represents the population of India living in urban areas at time period t and MPL_{Ag} represents the marginal product of labor in the agricultural sector at time period t. Similarly, when we turn our attention to the exogenous variable, we can say that a 1% increase in $YPc\ Agt/\ YPc\ Agt{-}1$ will increase $MPLAgt.\quad / MPLAgt.$ 0.26% where $Y_{Pc\ Ag}$t is the agricultural contribution to GDP at year *t* essentially, growth rates in the agricultural contribution to GDP are accompanied by a lower magnitude growth to the marginal product of labor in the agricultural sector. The general implications proposed by both the estimations are fairly analogous. The effect of higher urbanization rates, explained by the variation in both lagged urbanization rates and lagged rates in the marginal product of labor (urban sector), is negative on the growth rate of the marginal product of labor in the agricultural sector. Additionally, a growth in the overall agricultural contribution to GDP does not result in the same magnitude (or higher magnitude) growth in the marginal product of labor in the sector, further insinuating the notion that laborers in the agricultural sector are not reaping the benefits of the increased importance and productivity of their sector.

8. Conclusion

India is a country which has undergone rapid expansion in economic output over the past several decades. This has driven the agricultural contribution to real GDP up as well, a testament to the important role played by the agricultural sector in the Indian economy. As we have established in our prior analysis, India's downward trend in the growth rate of its relative density of agricultural contribution to GDP is not a consequence of a decline in the agricultural contribution to GDP but rather due to the substantial positive difference between India's growth rate in real GDP and that of the world over the past several decades. However, using robust statistical analyses, we have shown that the workers in the agricultural sector are not reaping the benefits of the expansion their sector is experiencing. Increasing rates of urbanization and GDP are leading to increased rates of agricultural contribution to GDP but the ensuing depressed rates in the marginal product of labor in the agricultural sector is a matter of concern.

Workers not being able to embrace further economic opportunity as time progresses is an unfortunate byproduct of India's expansion. This unwanted trend can be the impetus behind the proliferation of suicides among Indian farmers which has been evident (this of course would warrant its own multidimensional analysis), especially over the past couple of decades (Pavuluri 2013). While the analysis conducted in this study highlighted the decline in the value of labor in the agricultural sector and the ensuing decline in welfare of agricultural workers India despite the growth of importance of the agricultural sector in the Indian economy (and the growth of the Indian economy in general), further studies regarding the welfare of displaced laborers in the agricultural sector amid urbanization and GDP increase in India can be conducted. Precisely, a quantitative analysis regarding how urbanization has led to the displacement of laborers in the agricultural sector and eventual outcome of such a displacement can be of considerable merit.

It is imperative to note that the results of this paper do not support the notion that agricultural laborers in India are toiling any less than they should. The efforts of the workers in this sector have been persistently high over the course of India's history and their hard work deserves more compensation and attention. MPL_{Ag} in India can only be boosted with the aid of the government. One way to bring forth change is to form more institutes and training programs which would further cultivate the talent and skills of agricultural workers. It is also important to ensure that agricultural workers are given the same access to fundamental conveniences (i.e. proper accommodations, electricity, clean water, etc.) that many urban workers enjoy. More governmental attention towards the development and welfare of agricultural workers will help bridge the positive gap between the supply of laborers and the demand (Vetrivel, Manigandan 2013). Given the tremendous ability and talent possessed by the agricultural labor force in India, adequate governmental attention towards their welfare will further increase the productivity of the agricultural sector. This in turn will have significant positive economic implications. In developing nations, it has been statistically shown that enhancements in agricultural productivity have a substantial contribution to the reduction of poverty (Thirtle, Lin, Piesse 2003).

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H-1B Visa Policy Change and Foreign-Born STEM Workers in the U.S.

By: Mengyue Sun

Abstract

The U.S. is a global leader in scientific and technological innovation. As a result, the U.S. attracts a significant number of highly-skilled foreigners to seek training and employment in the country annually. Under the U.S. immigration policy, the H-1B visa program provides a pathway for foreigners to work in the country for a fixed period of time. The visa is reserved for certain types of occupations only, the majority of which are related to Science, Technology, Engineering, and Mathematics (STEM). However, in 2004, the annual allotment of the H-1B visa was drastically decreased in order to limit the number of foreign-born workers in the country. While the policy succeeded in decreasing the number of foreign-born workers,, it also unexpectedly discouraged international students from seeking STEM education programs in the U.S. In this study, I investigate the unintended impacts of the policy change on foreign-born individuals' academic choices. Using individual-level data from 2003 to 2010 National Survey of College Graduates, I look at the change in propensity of Bachelor's and Master's degree holders to major in STEM due to the shift in their employment prospects. This study shows that foreign individuals are nearly 30% less likely to hold Master's degrees in the STEM field due to the discouraging effect of the visa reduction, while Bachelor's degree holders are not impacted. This study also shows that the decrease is mainly caused by people who pursue STEM degrees largely for employment purposes.

1. Introduction

The U.S. is a global leader in training and valuing its diverse bodies of workers, across specialized fields and demographics. Every year, millions of people around the world yearn for opportunities to pursue a degree and work in the U.S.. Similarly, the U.S. relies on capable foreign talent to buttress its global scientific and technological dominance. Foreign-born individuals have had an outsized impact on the U.S. labor market; they are responsible for countless contributions that have furthered American society. One of the most popular programs to encourage talented foreigners to train and work in the U.S. is the H-1B visa program. The H-1B visa is reserved for those who have "theoretical and practical application of a body of highly specialized knowledge" only. Among all the targeted specialty occupations under the visa, STEM (Science, Technology, Engineering, and Mathematics) jobs take up more than 90% of the requests for the visa, according to a research by Pew Research Center in 2017. Beneficiaries can work in the U.S. for up to three years, extendable to six years. However, the visa is limited; there is always a cap to the number of the visas that could be issued every year. Started under the 1990 Immigration and Nationality Act, the mandated annual issuance of the visa was capped at 65,000. In the years leading up to 2003, the cap was gradually raised to 115,000 in 1999, and 195,000 in 2001 in order to accommodate large volumes of foreign workers. However, in October 2003, as part of the H-1B Visa Reform Act of 2004, the cap was reinstated back to 65,000, creating a drastic shock for potential H-1B applicants. Until today, the cap has been kept at 65,000, and it has since become much harder to get an H-1B visa and work in the U.S.. More uncertainties arise when there are too many applicants and the visa has to be allocated on a lottery basis, meaning that whether one obtains the visa becomes a matter of probability.

When studying the effects of a H-1B policy change, one needs to account for both its intended and unintended consequences. Policymakers using the H-1B cap as a tool to control the flows of foreign-born workers in the U.S. may undershoot or overshoot their goals if they fail to lay out a comprehensive picture of factors that might affect people's decisions. Imposing such restrictions could, for example, influence people's longer-term expectation of their academic and career developments in the U.S., which may later be translated into changes in the quality and quantity of labor supply for the U.S.. Although policy changes may help reach certain short-term goals, changes in the number of H-1B visas granted annually can have long term impacts on foreign talent, thus curbing the competitiveness of the U.S. labor market in the long run.

To address the above issue, I investigate the consequences of the H-1B visa supply shock in 2004 with a special focus on the unintended consequences. I look at changes that international individuals with Bachelor's or Master's degrees might have made on their academic choices as a response to the policy change. Since H-1B, as an employment-based visa, is significantly associated with STEM-related majors and occupations, I test that the shock influenced international students' major choices due to the change of their beliefs on whether they could land a job in the U.S.. This topic is relevant to policy-makers since college students' academic choice shapes the labor supply in certain industries and determines U.S. global competitiveness in technology and innovation in the long term. I hypothesize that international students who come to the U.S. to major in STEM mainly for employment purposes will be deterred from doing so due to a more unfriendly labor market.

2. Literature

H-1B and Foreign-Born STEM Workers

Educating and retaining STEM workers are important goals for both U.S. science and technology communities as well as labor policy makers. An extensive amount of literature has shown that the H-1B visa program creates substantial economic benefits for the U.S.

Kerr and Lincoln (2010) documented that higher H-1B admissions increases total science and engineering employment and patenting through direct contributions of immigrants. They also found out that fluctuations in H-1B admissions significantly influence the rate of patenting by Indian and Chinese nationals. Given the fact that Indian and Chinese nationals have historically been the largest two beneficiary groups by ethnicity (more than 80% of all applicants from FY 2007 to 2017of the H-1B visa and pursue occupations in science and engineering) fluctuations of the H-1B admissions could also subsequently lead to fluctuations in the number of patents as they are heavily driven by these two nationals.

Studies on the broader classification of foreign-born individuals in the U.S., not just those who rely on H-1B but also on the alternatives such as permanent residence or naturalized U.S. citizenship, have also suggested that foreign-born individuals significantly boost U.S. technological innovation. Hunt and Gauthier-Loiselle (2010) reported that immigrants patent at a rate doubling the natives', and this is entirely due to the disproportionately large number of immigrant graduates holding degrees in the STEM fields. In follow-up research to Hunt and Gauthier-Loiselle (2010), Hunt (2011) further examined what type of immigrants is the "most innovative and entrepreneurial". She found that immigrants who first entered as temporary workers or students have a greater advantage over the natives in patenting. Whereas those who entered the U.S. as permanent residents already perform similarly to the natives.

Nevertheless, there has been increasing evidence that suggests U.S. employment is becoming less attractive to high-skilled foreigners who came to the U.S. for education. After training or education in the U.S., some individuals simply return to their countries of origin, a process called the reversal of brain drain. This creates concerns for many policy makers over the potential future loss of high-skilled workforce due to the higher return rates among these U.S.-trained individuals. Reports by the U.S. Citizenship and Immigration Services (USCIS) have shown that from FY 2007 to FY 2017, nearly all countries, except India and China, have experienced a reduced number of applicants for H-1B. Even for China and India, the relative application rates for the visa have slowed down over the decade. One explanation that Zeithammer and Kellogg (2013) offered was that students make job decisions based on the income differences in two locations. However, unlike before when wages in the U.S. were much superior compared to their home-country counterparts, nowadays the wage differentials are shrinking in certain industries. Less wage advantage in the U.S. might lead to an overall discount on the attractiveness of U.S. employment.

Foreign-born workers are an integral part of U.S. technology and innovation, and in turn the economy. A considerable amount of this benefit comes from the implementation of the H-1B visa program for those who are not U.S. natives. Yet, people who once decided to go to the U.S. for better employment and income would now have to reconsider if it is actually worth the investment: leaving their home country and families for a less attractive job and an uncertain future or pursuing a degree that they have little interest in. This is alarmingly serious since the administration has spent too much time on limiting workers' entry while dismissing the fact that the dynamic of global talent flow is already shifting.

The following section focuses particularly on the H-1B visa program and further elaborates on how people and institutions have reacted to the H-1B policy change.

H-1B Policy Changes and Institutional Reactions

There is not much literature that focuses on the specific types of labor that are affected by the policy change. Most existing micro-level studies examine the changes in the nature of the incoming international students, such as their academic choices as well as their career choices. A lot of these studies regard the 2004 shock as a point of drastic change and suggest that there were lots of unexpected consequences in the following two dimensions: (1) the quantity and quality of the foreign-born workers currently in the U.S. or expecting to enter the U.S. in the future, and (2) people's expectation on their educational and professional paths in the U.S.

Mayda et l. (2018) studied the effects of the shock on the hiring and selection of foreign-born workers. In addition to the intended reduction of the number of H-1B workers by the policy, there were consequences that were less intended. They found out that the H-1B hiring declines were concentrated at the lowest and highest ends of the wage distribution. This means that people who are the least qualified for the visa are filtered out, and yet, at the same time, those with the highest ability and most desired skills are also deterred from entering the market. The authors speculated that these workers of two ends have selected to work in countries that are less restrictive in terms of employment and immigration than the U.S.

On the quantity side, Shih (2016) conducted a study as a complement to Kato and Sparber (2013). The main difference between these two studies is that Shih replaced the dependent variable with college enrollment of international students and examined the causal relationship between the openness of the U.S. labor market and the number of international students in U.S. colleges. Shih discovered that the 2004 policy change reduced international enrollment by 10%! The impacts of labor policy on foreign-born students may occur through many ways unaccounted for by policy makers, as Shih argued in his paper. One way is that a more restrictive labor policy might be perceived as a less friendly climate of the U.S. labor market, which ultimately lowered incoming individuals' expected returns of working in the U.S. and, as a result, they did not even bother coming to the U.S. in the first place.

Amuedo-Durantes, Furtado, and Xu (2019) studied the effect of Optional Practical Training (OPT)[6]. Starting in 2008, all college graduates who are on the F-1 student visa with a STEM degree will have a 17-month extension on the allowed period of time to work in the U.S. This means a total of two years and five months of time allowance in the U.S. as a temporary worker. But for non-STEM students, the allowed time for them to work in the U.S. is still just one year. There are lots of benefits that come with the extension for STEM degree holders: longer-term employment for better training, developing professional contacts, and, perhaps the most tempting one, a maximum of three times to apply for the H-1B visa if an applicant did not get it in one shot. The article examined if this extension has led individuals more likely to declare a STEM major. The authors believed that the policy change might have triggered some sort of reaction in individuals who appear to be only "marginally" committed to pursuing a STEM major. These "marginal" individuals are, in fact, not truly interested in STEM, but they choose STEM because they expect more work opportunities associated with a STEM background; either they could earn more in STEM industries, or they could stay longer in the U.S. on OPT. They measured whether the policy change induced such a reaction by looking at Bachelor's degree holders with double majors and individuals with two Master's degrees. They assumed that those with a non-STEM first major / degree are not as committed to STEM as those with a STEM first major / degree. In theory, the effect of the OPT extension is the strongest for those who have a non-STEM first major / degree but also have some experiences or conditional interests in STEM. While they found no OPT extension influence on undergraduate students, they did find that for graduate students with two Master's degrees, the extension increased their likelihood of choosing the second Master's degree in STEM given a first Master's degree in non-STEM by 11%. Following the same rationale, this paper also believes that some students make their educational decisions not because they are truly interested in the subject but because of the expected employment returns that a STEM credential brings them.

3. Data

The principal data come from the National Science Foundation's National Survey of College Graduates (NSCG) (Appendix B, C). NSCG is a biennial survey that provides demographic and career information about individuals holding degrees in diverse academic fields. NSCG's respondents are all recent graduates from different years and degree types, which allows me to effectively track post-education outcomes, compared to surveys in which respondents graduate in the same year as the survey. In this study, I focus on non-U.S. individuals aged 16-50 who received degrees in the U.S. in or after 1991 to 2010, with 2004 being the point of policy change. However, it should be mentioned that the access to full data of NSCG is limited to the public due to protection of private information of the survey respondents. The effect of such limitation extends to some key variables that need to be controlled, so I have to adopt some assumptions as well as some conservative approaches to keep the effect of this data limitation to the minimum. These assumptions and approaches will be explained. change in 2004.

Demographic characteristics between the control group and treatment group vary drastically. Table 1 shows that Asian people represent around 63% of all the foreign students, nearly 6 times as large as their counterparts in the treatment group. Whereas there are fewer other-minority individuals, presumably including Hispanic and Black people and others, from foreign countries compared to their U.S. counterparts. These foreign students are also more likely to be male compared to local students. However, Table 2 and 3 show that in the post-policy period, the mean age of both the control group and the treatment group dropped by nearly 5 years compared to that in the pre-policy period. This is because the post-policy samples are individuals who obtained the most recent degree after 2004, whereas the pre-policy samples include individuals whose most recent degree could be obtained anytime between 1990 and 2004, which makes the pre-policy samples "older" than the post-policy samples. Major choices between the control group and the treatment group also differ from each other. In general, over three quarters of all foreign graduates hold a STEM degree, compared to 62% of local graduates. Table 2 and 3 also show that, after the policy in 2004, there was a 18% drop in the percentage of foreign-born individuals holding a STEM degree. This drop in people participating in STEM resonates with the results from Kerr and Lincoln (2010) that with a given change in the H-1B policy, the fluctuation in the number of patenting is the biggest for the Chinese and Indian nationals, two major ethnic groups in the international student pool. It also makes sense when viewed together with the results from Shih (2016) that since there was less enrollment in international students, who tend to pursue degrees in STEM, it is natural that there was less participation in STEM like the data suggests. All these characteristic differences point to the need for them to be controlled in the model as potential explanations for differences in choice of major.

The following section will detail the key variables extracted from the public-use data sources and how they are used in the study. These variables are: (1) most recent degree, (2) field of study / major of the most recent degree, (2) age, (3) gender, (4) citizenship status, and (5) race. Again, due to data restriction, some of these variables are not the most ideal choices for the model, yet they suffice to produce reliable and effective results.

Table 1: Descriptive Statistics: All individuals

	Full Sample			
	Non-U.S. Citizens		U.S. Citizens	
	Mean	S.D.	Mean	S.D.
STEM Major	0.76	0.43	0.62	0.49
Age	34.49	5.58	35.11	6.57
Male	0.63	0.48	0.54	0.50
Asian	0.61	0.49	0.12	0.33
Other Minority	0.16	0.37	0.24	0.43
Bachelor's	0.36	0.48	0.59	0.49
Master's	0.64	0.48	0.41	0.49
Most Recent Degree Year	1997	4.97	1997	4.85
Observations	7,205		65,300	

Table 2: Descriptive Statistics: Pre-policy individuals

	Pre-Policy			
	Non-U.S. Citizens		U.S. Citizens	
	Mean	S.D.	Mean	S.D.
STEM Major	0.78	0.41	0.64	0.48
Age	35.05	5.38	35.61	6.43
Male	0.63	0.48	0.54	0.50
Asian	0.62	0.49	0.12	0.33
Other Minority	0.15	0.36	0.23	0.42
Bachelor's	0.38	0.48	0.62	0.49
Master's	0.62	0.48	0.38	0.49
Most Recent Degree Year	1996	4.02	1996	4.00
Observations	6,267		58,337	

Table 3: Descriptive Statistics: Post-policy individuals

	Post-Policy			
	Non-U.S. Citizens		U.S. Citizens	
	Mean	S.D.	Mean	S.D.
STEM Major	0.60	0.49	0.48	0.50
Age	30.81	5.49	30.85	6.25
Male	0.57	0.49	0.48	0.50
Asian	0.59	0.49	0.13	0.34
Other Minority	0.22	0.41	0.33	0.47
Bachelor's	0.26	0.44	0.39	0.49
Master's	0.74	0.44	0.61	0.49
Most Recent Degree Year	2006	0.00	2006	0.00
Observations	938		6,963	

STEM or Non-STEM Major

NSCG collects information on up to 142 majors, from which I created two types of major: STEM and non-STEM. Since the classification of STEM and non-STEM degrees are slightly different from year to year, I refer to a common standard to categorize these two types for my study. The categorization is according to the 2008 STEM Designated Degree Program list provided by the U.S. Immigration and Customs Enforcement[7] as it is the closest to the standard that individuals in my study might have referred to. While public-use data does not contain detailed observations on all 142 majors, it allows me to track an individual's field of major in a broader sense. There are 20 main fields of major, 13 of which are STEM and the rest non-STEM, as shown by Table 4.

Table 4: Choice-of-majors by 2008 Designated STEM list

Field of Major	Type
Computer and mathematical sciences	STEM
Biological sciences	STEM
Other biological, agricultural, environmental life sciences	STEM
Chemistry, except biochemistry	STEM
Physics and astronomy	STEM
Other physical and related sciences	STEM
Chemical engineering	STEM
Civil engineering	STEM
Electrical, electronics and communications engineering	STEM
Mechanical engineering	STEM
Other engineering	STEM
Health-related fields	STEM
Other science and engineering-related	STEM
Economics	Non-STEM
Political and related sciences	Non-STEM
Psychology	Non-STEM
Sociology and anthropology	Non-STEM
Other social sciences	Non-STEM
Management and administration	Non-STEM
Other non-science and engineering	Non-STEM

Figure 1 shows the proportion of people studying each choice-of-major in a given experiment group in a given time period (each row adds up to around 100% due to rounding errors). The upper two panes show the control and treatment group before 2004, and the lower two panes show the control and treatment group after 2004. From both panes, we can see that a few fields of major are particularly popular among international students. These majors include computer and mathematical science, electrical engineering, psychology, management and administration. For popular majors that are STEM-related, the policy change seems to have decreased their proportions in the total count of all choice-of-major studied. For example, 29% of the treatment group individuals studied computer science before 2004, whereas it was almost 10% less after 2004. The proportion of the treatment group individuals studying electrical engineering also dropped by 5% after the policy. It should be noted that there were less control group individuals studying STEM majors as well, but the overall magnitude of their decrease is not as drastic as the treatment group individuals. In addition, more people shifted to non-STEM majors after the policy, with a 12% increase in management and administration by the treatment group, and a 11% increase in other non-STEM majors by the control group. This figure suggests that there may be some mechanical causes that lead to a common decrease in the number of STEM degree holders and a common increase in the number of non-STEM degree holders for both U.S. and non-U.S. students.. Despite the common trend, I believe that H-1B as a program targeting non-U.S. citizens has a distinct impact on non-U.S. individuals, which may have generated some spill-over effects onto U.S. individuals.

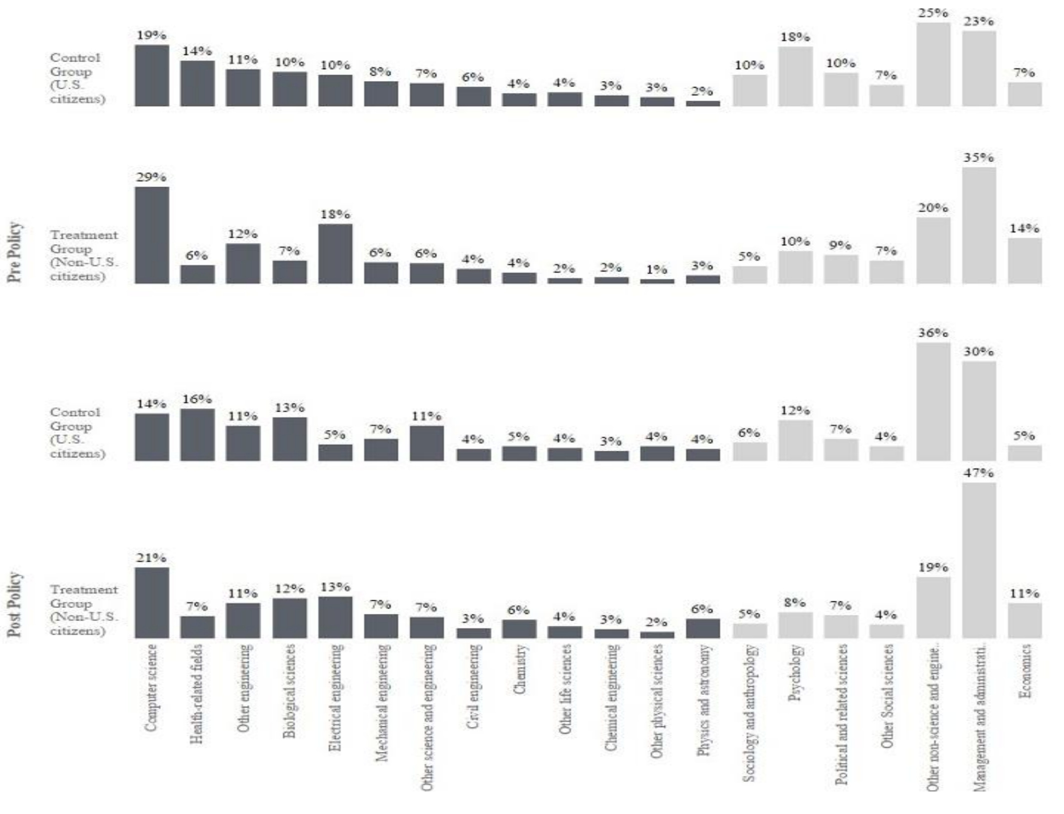

Figure 1: Choice of Major Composition

Citizenship Status - Treatment and Control Group

NSCG collects detailed information on an individual's citizenship, specific to country, and visa statuses. The principle line between the treatment group and control group is that people who are dependent on the H-1B visa in order to work in the U.S. are considered the treatment group, and people who are independent of the visa are the control group. U.S. citizens do not need a work visa to be domestically employed, which means that they face little to no employment constraint when considering college major. In rare cases with non-U.S. citizens from the five free trade countries (see footnote 5), alternative work visas are available for them in a luxurious amount, hence, they are presumed independent of H-1B as well. Therefore, these two types of people are categorized into the control group. Anyone who does not fit in with these two types will be considered as a treatment-group individual. By knowing individuals' citizenship and visa statuses, it is easy to generate the treatment and control group with the above sorting method.

However, this is only possible with full data access. I was only able to retrieve individual-level information on whether one is a U.S. citizen on a binary-value basis. The question now is how to account for permanent residents, or green card holders. One of the benefits of a green card is that even if one is not a U.S. citizen, he or she may still be employed without having to apply for a work visa. Although one could have a green card at the time of the survey, I assume that it is very likely that he did not have one during school time, which means that he still needed to take the employment constraint into account when making his choice of major. Therefore, all non-U.S. citizens, with either temporary visa or green card, are treated as treatment-group individuals in this study, including the immune individuals from the five free-trade countries, since they take up only around 1% of the total sample size in each monitored survey so their effect on the final result is assumed unsubstantial. The control-group individuals are 100% U.S. citizens.

Other Demographic Information

Gender, age, and race are essential characteristics as mentioned before, so they are collected as well. However, race is also one of the classified information. The available data only show three options that profile an individual's race: "White", "Asian", and "Other Minorities", which presumably includes Hispanic and Black. Figure 2 indicates that Asian students in both time periods took up around 60% of all international students, six times of their U.S. counterpart. A more interesting demographic characteristic is age. Figure 3 indicates that the age distribution of international students has a higher kurtosis and skinnier tails compared to that of U.S. students. While both student groups have a similar average age[8] of around 35, there is less variation of age within international students. This implies that international students' characteristics are more uniform, making them a collective group of people whose goals of pursuing a U.S. degree are quite similar to each other's. This distinctiveness in characteristics may also imply that international students are likely to be very sensitive to a particular type of external influence, such as changes in labor policy.

Figure 2: Race Composition

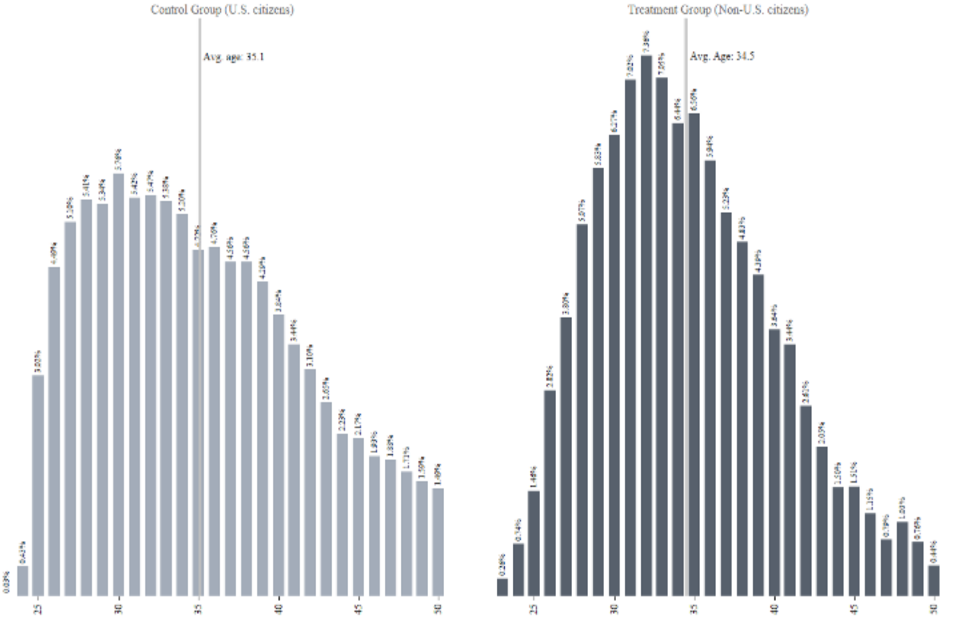

Figure 3: Age Distribution

4. Empirical Strategy

Our data allows a Difference-in-Differences regression strategy that is based on limited individual-level information. Given the range of the obtained factors that might be responsible for any observed patterns in educational choice changes and whether the time of interest is before or after the 2004 policy change, this paper attempts to explore the effects of the exogenous variation in the lowered H-1B visa quota on the probabilities of foreign-born individuals to pursue STEM / non-STEM degrees in U.S. colleges by estimating a probability model as shown by Equation 1:

$$STEM_{i,t} = \alpha_0 + \beta_1 Policy_{i,t} + \beta_2 T_i + \beta_3 Policy_{i,t} T_i + \beta_4 Gender_i + \beta_5 Age_i + \varphi Race_i + \psi Race_i T_i + E_{i,t} \quad (1)$$

in which the dependent variable $STEM_{i,t}$ equals to 1 if a student i whose most recent degree obtained in year t is in the STEM field, otherwise 0. The result of the regression will give a measure of the change of propensity of international students to major in STEM before and after the H-1B policy change. On the right hand side of the equation, $Policy_{i,t}$ is the policy time indicator which equals 1 if the individual is in the post-policy period, and 0 if the individual is in the pre-policy period. T_i is the treatment / control group indicator, which equals 1 if the individual is a non-U.S. citizen, and 0 otherwise. The key estimator is the interaction term between the policy time indicator and the treatment / control group indicator: $Policy_{i,t}T_i$. This term's coefficient will tell us how the policy change might have impacted the likelihood that international students in a constrained setting would hold a STEM degree compared to domestic students who are not constrained. Individual characteristics such as $Gender_i$, Age_i, $Race_i$, and $Race_iT_i$ are included as well.

5. Results

Table 5 presents the results of the main regression that tests the effect of the key predictor on the likelihood of an international student's educational decision on whether or not pursuing a degree in the STEM field. The regression is run separately for undergraduate and graduate students. The main findings are the following. The policy does not have a statistically significant impact on undergraduate students, while the sign of the main coefficient is negative, indicating a possibly slight negative impact of the policy on the likelihood of them choosing STEM. By contrast, the policy has a strong and negative differential impact on graduate students. Column 2 shows a material decrease of 28.5 percentage point in the likelihood of holding a STEM degree by non-U.S. students compared to U.S. students. That means that, while it was 78%[9] likely for a non-U.S. individual to hold a master's degree in STEM before the policy change, now it is half-and-half. The result is not surprising given the study by Amuedo, Furtado, and Xu (2019) that graduate degree holders are the most sensitive to the OPT extension while undergraduate degree holders are indifferent to the policy.

Demographic characteristics play significant roles in influencing the likelihood of holding a STEM degree as well. Specifically, male students are more likely to pursue STEM degrees than female students, with 67.7% more likely for a given Bachelor's degree holder, and 28.4% more likely for a given Master's degree holder. Also, older individuals are less likely to hold a master's degree in STEM, whereas age does not seem to matter for deciding on a Bachelors' degree.

Table 5: Main regression results

	Dependent Variable: STEM	
	UG (1)	GR (2)
Treatment	0.073	0.393***
	(0.087)	(0.072)
Policy	-0.070	-0.800***
	(0.044)	(0.037)
Treatment*Policy	-0.062	-0.285***
	(0.173)	(0.095)
Age	0.004**	-0.027***
	(0.002)	(0.002)
Gender	0.677***	0.284***
	(0.022)	(0.024)
Asian	0.276***	0.611***
	(0.039)	(0.037)
Other Minority	-0.245***	-0.192***
	(0.026)	(0.031)
Asian*Treatment	0.620***	0.394***
	(0.126)	(0.091)
Other Minority*Treatment	0.423***	0.276**
	(0.131)	(0.118)
Constant	0.416***	0.920***
	(0.065)	(0.076)
Observations	41,442	31,063
Log Likelihood	-24,237.200	-20,307.890
Akaike Inf. Crit.	48,494.410	40,635.770

Note: *p<0.1; **p<0.05; ***p<0.01

Results on race suggest that, with White students as the benchmark population in this model, Asian students are, in general, more likely to hold a STEM degree, whereas other-minority students are less likely to hold a STEM degree. It is worth noticing that a given Asian individual with a Master's degree, regardless of his / her nationality, is twice as likely to pursue a STEM degree than a given Asian individual with a Bachelor's degree. This difference indicates that a STEM Master's degree is somehow particularly attractive to Asian students, which may be associated with the significant influence of the policy change only seen on Master's individuals but not Bachelor's individuals. The last two variables measure the differences of a given race in the control group and treatment group. Results indicate that non-white, non-U.S. individuals are more likely to participate in the STEM fields than their U.S. counterparts, with Asians in Bachelor's degrees as high as 62% more likely than Asian Americans, and Other-minority individuals 42% more likely than their U.S. counterparts. This high level of STEM-participation from non-U.S. minorities is consistent with Hunt and Gauthier-Loiselle (2010) that STEM degrees are disproportionately held by immigrants, mostly of racial or ethnic minorities, who are highly skilled and motivated to pursue better education and career development in the U.S. Going-abroad is by itself already a selected process that produces only the most capable, intellectually or financially, individuals from other countries. These selected individuals constitute a collective body gravitated toward very distinct goals compared to U.S. individuals, and based on the results, these goals seem to be even more influential in decision making for Master's degree holders. To sum up, the result shows that, one, foreign students have high proclivity to pursue Bachelor's and Master's degrees in the STEM field, and, two, a more restrictive H-1B policy has caused an overall discouraging effect on the students' likelihood to choose STEM majors, and three, the impact of the H-1B restriction is the largest for Master's students.

Additional Tests

Next, to further establish the relation between policy change and the educational choice that an individual makes as a response to the policy, I re-estimate Equation 1 solely on Master's degree holders, in a slightly different context.

Table 6 shows the regression results of this test. The Marginal Group (column 1) refers to the group of people whose Bachelor's degree is non-STEM related, while the Committed Group (column 2) refers to the group of people whose Bachelor's degree is STEM related. The results indicate that it is almost 100% less likely for non-U.S. students who are marginally committed to STEM to hold a STEM Master's degree given the H-1B restriction! Even for those whose primary educational interest is STEM-related, the fact that there are less visas available has also discouraged them from holding a STEM degree by 22%. I should acknowledge that comparing one's Bachelor's and Master's degrees is not the most rigorous way to conjecture one's academic and professional intentions. Nevertheless, the strong results have shown that the H-1B policy change is overall disruptive to international students' tendency to both work and specialize in the STEM field in the U.S. It also means the change in likelihood of pursuing a STEM degree is largely driven by these very "marginal" individuals.

Table 6: Additional regresson results

	Dependent Variable: STEM	
	Marginal (1)	Commited (2)
Treatment	0.089	0.144
	(0.161)	(0.108)
Policy	-0.342***	-1.184***
	(0.073)	(0.049)
Treatment*Policy	-0.996***	-0.223*
	(0.290)	(0.121)
Age	0.020***	-0.061***
	(0.004)	(0.003)
Gender	0.230***	-0.212***
	(0.047)	(0.034)
Asian	0.248***	0.353***
	(0.085)	(0.048)
Other Minority	-0.419***	-0.050
	(0.060)	(0.044)
Asian*Treatment	0.439**	0.663***
	(0.205)	(0.128)
Other Minority*Treatment	0.103	0.340**
	(0.298)	(0.164)
Constant	-1.938***	3.247***
	(0.146)	(0.110)
Observations	11,003	19,218
Log Likelihood	-5,823.615	-11,100.830
Akaike Inf. Crit.	11,667.230	22,221.660

Note: *p<0.1; **p<0.05; ***p<0.01

Robustness Checks

Some may argue that the samples in the study may not be representative enough. For example, I included people who obtained the most recent degree in the 1990s. The concern of doing so is that the annual H-1B cap before 1999 was also 65,000; the high cap was only temporary. This means that people in the 1990s may also be subject to a restrictive H-1B policy, so treating them as pre-policy individuals defies the definition of "pre-policy". Table 7 column 1 and 2 present results from running the same regression in Equation 1 but excluding individuals whose most recent degrees were obtained from 1990 to 2000. According to the results of the main coefficients, the policy still significantly discouraged Master's students from pursuing STEM majors, while, again, no effect is found for Bachelor's students. my principal finding. Column 1 shows a slight change of the key coefficient from -0.062 to 0.065, statistically insignificant, and still cannot reject the null hypothesis that the effect of the policy is zero. Interestingly, the coefficient in column 3 is 8.156, but with an incredibly large standard deviation. This is likely caused by the fact that, after dropping individuals graduated from 2008 to 2010, there are only around 2,200 observations, among which only 45 individuals are undergraduate students. Given the result in Table 4 that graduate students are the main driver for a negative coefficient, a predominant presence of graduate students in this robustness test may have radically skewed the outcomes. Despite these extraordinary values, the negative sign of the key coefficients remains as a primary indication of the effect of the policy that is consistent with the main result in Table 4. These robustness checks results are overall convincing evidence that support the main finding that the policy discourages international individuals from pursuing STEM Master's degrees.

6. Discussion and Mechanism

How Did the Policy Affect Major Choice

Lowering the annual allotment of the H-1B visa was a response to the need to prioritize hiring American workers and limit international individuals' access to the U.S. labor market. While the restriction has worked effectively to decrease the number of foreign workers in the U.S., it has also created a less expected repercussion that international students were "scared away", especially those who may excel in highly technical and specialized fields. This study shows that international students are less likely to participate in the STEM field due to the policy, which may be concerning according to the literature that have demonstrated the key role that high-skilled foreign workers have played in the U.S. economic and technological communities.

Arguably, a restricted H-1B policy would, instead, cause either no impact on international students' educational choice or even stimulated their STEM participation rate. When an application is submitted to USCIS and entered the lottery, whether one wins the lottery or not does not depend on whether the associated occupation type is STEM or non-STEM related. So, even after lowering the cap, the probability of winning the visa lottery is the same for every applicant, regardless of the major type. Therefore, no matter how the policy changes, it would not make a difference on an individual's choice of major, and the key coefficients for both undergraduate and graduate degree holders should be close to zero, or statistically insignificant. Or, in another case, some individuals may believe that holding STEM degrees, by itself, increases the likelihood of winning the visa in the lottery[11]. While this belief is not true, when facing a more competitive hiring environment, these individuals would be, in fact, even more motivated to pursue a STEM degree by rationality since they think it will increase their chance of winning the lottery. Contrarily, this study has shown that the policy has negatively impacted international students' participation in the STEM field, which further demonstrates that, although the goal of the policy was to simply push the number of foreign workers to a lower limit, the policy has also unexpectedly discouraged international students from pursuing STEM degrees.

Consistent with Amuedo-Durantes, Furtado, and Xu (2019), this study also reaches the conclusion that Master's degree holders are most sensitive to labor policy changes. According to their study, a possible explanation is that accessing the U.S. labor market is often the primary goal for a foreign individual who is considering a Master's degree in the U.S., given U.S.'s industrial expertise and superior wages compared to their home countries'. Since the opportunity costs – such as time cost, switching-major cost – of a Master's degree are comparatively lower than those associated with a Bachelor's degree or a Ph.D., a Master's degree is considered the most efficient and fastest way to achieve that goal. Therefore, Master's degree holders are the most responsive to the H-1B policy change. In contrast, the primary goal for undergraduate students is more straightforward and education-oriented, which explains their indifference to the changes in labor policies. Plus, given the vast time cost of each major (usually 2 academic years) and a total time of 4 years required to finish the entire degree, it is hard for an average undergraduate student to change to, or even add, another major /degree in the middle of their time in college. This stickiness leaves even less room for undergraduate students to respond to the policy.

The "Marginal" Individuals

Another question remains which is why people switch from STEM to non-STEM at all? Why can't they continue on STEM and simply ignore the policy? To answer this question, I further examine the role and behavior of the "marginal" individuals mentioned before. While conducting behavioral studies or surveys is beyond the scope of this study, I developed a model that could represent a "marginal" individual's decision making process given the policy change.

Equation 2 shows a model that is similar to a cost and benefit analysis with which a "marginal" individual *i* weighs between the expected utilities of studying STEM and non-STEM majors / degrees: $E(U_{STEM,i})$, $E(U_{nSTEM,i})$. The main theory is that a "marginal" individual would only choose to hold a STEM degree when $E(U_{nSTEM,i})$ is strictly less than $E(U_{STEM,i})$; otherwise, in a situation of either $E(U_{nSTEM,i}) = E(U_{STEM,i})$, or $E(U_{nSTEM,i}) > E(U_{STEM,i})$, the individual will choose to hold non-STEM degree instead.

$E(UnSTEM,i) < E(USTEM,i)$ (2)

Next, I decompose these two expected utilities. In a very short time window after an international student's completion of degree in the U.S., he or she will generally face two outcomes: employed or unemployed (which is immediately followed by either repatriation or proceeding to another degree). The utilities of an individual getting employed and unemployed based on the major type $X \in \{nSTEM, STEM\}$ are respectively captured by U and U^u, and the probabilities of getting employed and unemployed based on the major type are respectively captured by $P(e|X)$ and $1 - P(e|X)$. Now, let's say the individual successfully lands a job in the U.S., there are two additional outcomes as the employer will need to file the H-1B application in order for the individual to stay and work beyond the limited time granted by OPT: win the visa lottery or not. If the individual wins, he or she will stay as employed, otherwise, repatriation or pursuing another degree will make this individual unemployed as the final outcome. If the individual does not manage to find a job at the beginning, he or she will not even have the chance to enter the lottery and the final outcome for this individual will be unemployed as well[12]. So in short, as shown by Figure 4, there are in total three possible final outcomes after an individual graduates: (1) initially employed and win the visa to stay employed, (2) initially employed but lose the lottery and become unemployed, (3) initially unemployed.

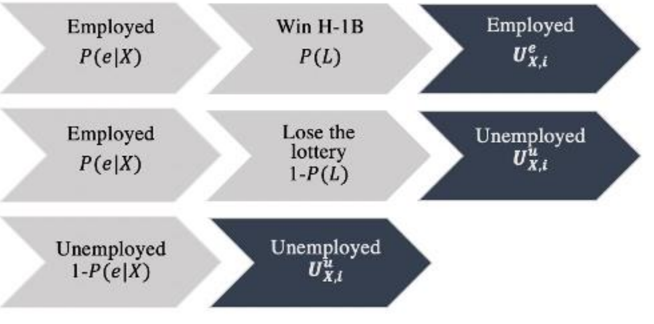

Figure 4: Post Graduation Outcomes

The probabilities of winning and losing the visa lottery are captured by $P(L)$ and $1 - P(L)$, which are basically determined by the visa cap - the lower the cap, the lower $P(L)$[13]. In the end, the expected utility of this individual to have a X degree is the sum of the expected utilities of the above three possible outcomes as Equation 3:

$$E(U_{X,i}) = P(e|X)P(L)U^e_{X,i} + P(e|X)[1 - P(L)]U^u_{X,i} + [1 - P(e|X)]U^u_{X,i}$$

which could be simplified to Equation 4:

$$E(U_{X,i}) = P(e|X)P(L)(U^e_{X,i} - U^u_{X,i}) + U^u_{X,i}$$

The individual will now have to weigh between $E(U_{nSTEM;i})$ and $E(U_{STEM;i})$ based on Equation 4. Since the policy's goal is to limit the number of international workers, not firms' ability to hire, $P(e|X)$ is presumably unchanged before and after the policy. In contrast, the lowered H-1B cap reduces P(L). Assume one's $U_{eX;i}$ and $U_{uX;i}$ remain constant before and after the policy, the overall change of the equation decreases both $E(U_{nSTEM;i})$ and $E(U_{STEM;i})$. However, it is very likely that $U_{eX;i}$ and $U_{uX;i}$ vary from one individual to another. For a \marginal" individual who has greater joy from winning the visa under a non-STEM occupation than under a STEM occupation, while feelingless “disappointed” if losing the visa under a non-STEM occupation than under a STEM occupation, the reduction in the visa cap will likely render the value of E(UnSTEM;i) larger than E(USTEM;i), which will eventually lead this individual to switch from STEM back to non-STEM.

7. Conclusion

Using data from the National Survey of College Graduates, I found that the H-1B visa policy reform in 2004 that greatly reduced the annual allotment of visas has decreased the likelihood of international individuals holding Master’s degrees in the STEM field from 78% to 50%, while no impact of the policy is found on Bachelor’s degree holders. The result is statistically significant and convincing given the additional regressions that are run to check my theory and the robustness of the main result. First, I test if individuals who are “marginally interested” in STEM play a role in this result by running the regression on Master’s degree holders with observable Bachelor’s degree history. The result shows that people who are “marginally” interested in STEM are swayed away from pursuing a STEM Master’s degree after the policy change. Even for individuals whose primary education interest is STEM-related, a more restrictive employment rule has also discouraged them from furthering on the path. Second, I run robustness checks by dropping samples that could be sources of concern for accurately defining the timeline cutoff in my framework. Results turn out to be congruent to the main result, with no change of sign for the key variables.

I should mention that this study is far from being ideal, or at least from what I envisioned from the beginning. Restricted access to lots of other potential factors that might influence individuals’ academic choices is a major challenge and drawback of my study. For example, an individual’s financial condition (e.g. whether or not the individual is on student loan, or family income level) might be critical to influencing his or her choice. It is also widely believed that an individual’s high school performance and parents’ education background also impact the individual’s academic and career paths. Moakler et al. (2014) found that individuals are more likely to choose STEM in college if they had strong confidence in mathematics from pre-college education and had parents with STEM occupations. Bound et al. (2016) also mentioned four key factors that could drive international student’s educational decision or even whether or not coming to the

U.S. in the first place, such as the affordability of U.S. institutions, the home country’s educational preparation of the student, the availability of quality education in the home country etc. A lot of relevant information such as the above are, in fact, collected by NSCG but unfortunately cannot be reached. This study still has lots of space to improve. Should the restricted data be obtained, I believe the results will be even more informative and credible than the ones presented in this study.

Lastly, in an address regarding boosting the U.S. STEM workforce, President Obama said:“Reaffirming and strengthening America’s role as the world’s engine of scientific discovery and technological innovation is essential to meeting the challenges of this century”[14]. The recent COVID-19 crisis has also confirmed the importance of foreign-born individuals in the U.S. health-care system who represent nearly 20% of the entire medical workforce, according to Zallman et al. (2019). With the world increasingly dependent on science, the need to continuously develop the STEM workforce is a priority for any country that aims for lasting competitiveness. And in a country like the U.S. that is founded on talented immigrants, cutting foreigners’ opportunities is the near equivalent to erasing the very strength that the U.S. has been relying on to thrive on the world stage. Policy makers need to make prudent calculations on matters related to talent development rather than simply focusing on short-term needs, political or economic, and it is imperative to reconsider policies that are clearly countering the rising demand for STEM workers.

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To What Extent is Group Lending in Microcredit an Effective Strategy to Improve Economic Well-being of Consumers?

By: Pranad Gandhi

Abstract

Microcredit has received significant widespread attention from economists and more recently, popular media and politicians, as a revolutionary tool to combat poverty. Its maverick status relative to other, primarily state-sponsored, credit lending policies has emerged due to the nontraditional approach adopted initially by Grameen Bank founder Mohammad Yunus, who pioneered group lending practices to allow for greater incentive and accountability amongst clients. The essay investigates the effectiveness of group lending strategies as a tool to accomplish goals of microcredit organizations by examining relevant theoretical and experimental frameworks. The theoretical concepts examined include informational and incentive constraints arising from economic inefficiencies in rural credit markets as well as the need for group lending mechanisms as tools to correct such market failure. A model is constructed to identify and predict the effects of group lending strategies, following which it is applied to a case study(a randomized control trial in Mongolia) to evaluate its efficacy by measuring impacts on household income, consumption and asset creation, money transfers and repayment rates.

1. Introduction

An accurate assessment of the nature of the informal credit markets is crucial for identifying inefficiencies in the operations of moneylenders and providing a vantage point to gauge the efficacy of substitutes such as microcredit. The informal credit market in most developing countries is characterized by **significantly high interest rates for very small loans** which are granted to borrowers possessing very little (if any) collateral. Interest rates, reportedly ranging from 134 to 159 percent in rural Punjab as found by Singh (1968) and 18 to 200 percent in Chambar, Pakistan as reported by Aleem (1990). Evidence regarding such practices has led to the belief that moneylenders are usurpers who assert their monopoly power to charge exploitative interest rates to the poor, a view seconded by economists in literature as well[4]. Contrarily, claims from several other empirical investigations in recent decades such as Braverman and Guasch (1989) and Aleem (1990) have attributed inflated interest rates to high administrative and screening costs incurred by the moneylender amidst the informational asymmetries endemic to informal credit markets. The paper thus begins with an expository review of relevant literature to model market failure in informal credit markets. The theoretical framework used is a simplified version of Stiglitz and Weiss (1984); it examines inefficiencies resulting from adverse selection and moral hazard while emphasizing their impact on strategic measures taken by lenders to earn profits.

On the other hand, microcredit has shown itself to be an effective substitute for traditional lending in informal markets across different parts of the developing world. The evolution of the mechanisms employed by current microfinance institutions have found their roots in co-operative institutions (ROSCAs and ASCAs) that have flourished in rural areas. Such cooperatives allowed for saving money in a circulating pot that provided households access to lump sum investments to increase productivity and earn higher profits in their businesses[8]. The microcredit movement in Bangladesh, helmed by Yunus' Grameen Bank, pioneered the group lending strategy that has shown great promise in solving informational constraints experienced by lenders. The second section thus seeks to demonstrate that microcredit is a powerful substitute for traditional informal credit lending strategies due to its effectiveness in remedying incentive-based and collateral constraints. To facilitate this, the 'Classic Grameen' group lending mechanism is deconstructed and its theoretical impacts on increasing market efficiency are examined.

Microfinance has seen widespread support from policymakers and multinational organizations throughout its development from a largely subsidized infant industry to what is presently reported as a flourishing business that can juggle societal needs and profit maximization. While there has been significant anecdotal evidence to display its benefits, the empirical literature measuring impacts of microcredit is still developing an adequate hypothesis on the effectiveness of microcredit. The third section of the paper thus presents an argument for the difference-in- difference approach for measuring microcredit impacts and introduces the case study of a field experiment to determine impacts of group vs. individual lending in Mongolia. The paper discusses impacts of group lending on several economic characteristics including business creation and growth, consumption and asset management, default rates and informal transfers.

2. Usurers or victims: Market Failure in informal money lending markets

In early literature, the lack of collateral and the resulting limited liability for the borrower in repaying loaned funds was considered the cause for the moneylender to implement higher interest rates as a strategy to reduce the risk of lending. In theory, if a given fraction of the borrowers are likely to default and the lender is neither able to seize collateral nor enforce obligations through other means, he is forced to grant loans at a higher interest rate to compensate for the inevitable lack of repayment. However, evidence from field experiments by Guasch (1989) and Aleem (1990) dispel the notion of higher interest rates as a coping strategy for potential default and highlight that default rates amongst the rural poor are in fact significantly lower compared to their urban and wealthier counterparts. Empirical work by Guasch (1989) investigating costs for moneylenders finds that a substantial portion (estimated 18 to 45 percent) of the interest levied on a loan is charged to repay the screening and administrative costs that the lender incurred to vet the borrower. This has several implications. First, for small loans, which are often the case for amounts lent to the poor (households living below 1.90 USD a day), the average fixed cost is higher. Second, it is likely that higher interest rates may contribute to a multiplier effect wherein a loan granted at high interest rates prompts increased screening for fear of the borrower defaulting, which in turn propels the interest rates even higher. Thus, the increased interest rates primarily serve to compensate for high screening and administrative costs, while small loans are provided due to the lack of collateral and weak enforcement mechanisms.

Note that a market is considered inefficient if there is remaining surplus that can be utilized by either the producer or consumer. Hence, inflated interest rates, while serving to combat informational constraints in the informal credit market are inefficient relative to a market where the size of the pie can be increased further; a market where screening is costless, where both the lender and borrower have equal information and where assets other than collateral can be leveraged to enforce loan requirements. An in-depth analysis of how such constraints compromise market efficiency is undertaken in the following paragraphs.

Credit rationing, which stems from problems of adverse selection and moral hazard, is a significant consequence of informational constraints endemic to the informal credit market. To examine the impact of credit rationing on market efficiency, consider a bank that lends in a competitive market and seeks to earn normal profit. The model of adverse selection and moral hazard presented in this paper is a simplified version of the original literature by Stiglitz and Weiss (1984). Allow the marginal cost of the bank to be k, that is, it costs the bank k dollars to lend an additional \$1, where $k > 1$, since the bank must repay the depositors some level of interest along with compensating for its administrative costs. Assume that a farmer with negligible wealth wishes to borrow \$1 to purchase working capital for production. The investment is sure to yield an output valued at y, where $y>k$. Thus, in order to make normal profits the lender would charge a gross interest rate (principal + interest) of k. The population of borrowers consists of a second borrower type, one that is riskier in his investments relative to the 'safe' borrower that receives y dollars for certain. The second borrower is a risk taker, such that he is less conservative in his spending or prefers investing in a crop that is more profitable but at the same time more vulnerable to the weather. He thus receives increased returns y' on his investment ($y' > y$) with a probability p but is also likely to receive no returns at all with complementary probability (1-p). The expected returns in both cases remain the same, that is $p\,y' = y$.

Now, for the lender to fully recover his costs, he must charge a higher interest rate to the risky borrowers given that there is a probability p of defaulting on the loan. This is proven by simple arithmetic. Given $p = 0.9$, one in every ten borrowers would default with zero returns on his loan while the rest of the nine borrowers successfully earn y'. Thus, recovering the costs of lending to ten borrowers would require that the nine profitable risk takers pay higher gross interest. Assume that the lender is aware of a proportion q of the borrowing population that is going to repay with certainty while the remaining population has risk involved. The lender will inevitably have to charge an interest rate higher than k. This results in some safe borrowers dropping out of the market until the lender reaches the required interest rate R such that normal profits resume. Let us quantify R given that the borrower wishes to earn normal profits[25]. The gross interest rate *R* must be such that it allows the lender to recover all costs. Hence, since the denominator in the above expression is greater than 1, the interest rate *R* has a value larger than *k*. After some algebraic manipulation, the interest rate can be written as '*k+A*'.

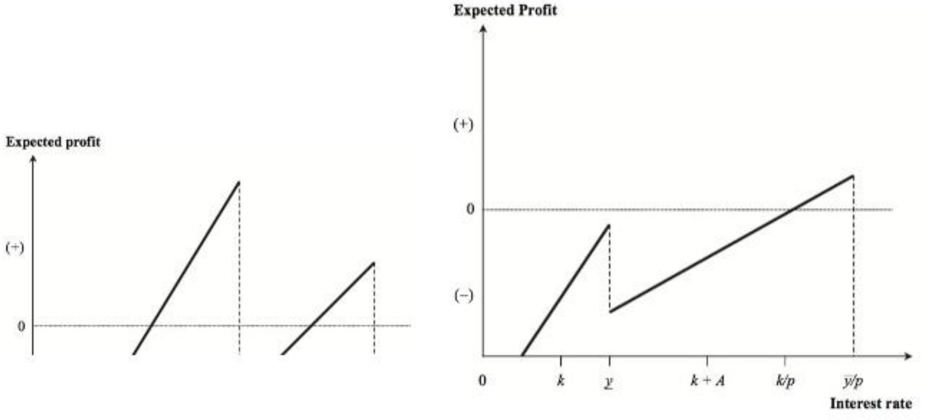

Figure 1(a) and (b): Relationship between interest rate and expected profits with heterogenous borrowers

Let us consider the impacts of increasing interest rates to compensate for the presence of risk taking borrowers on expected profits earned by banks. Figure 1(a) represents the range of interest rates the bank can charge to extract profits given the nature of the market. At interest rate *k*, while the maximum number of both safe and risky types are willing to borrow, the bank achieves negative profits. Normal profits arise when the bank charges the increased interest rate *k+A* to compensate for the risky borrowers in the market. The profits by the bank are maximized at interest rate *y* since the surplus extracted from the safe borrower is maximized by charging an interest rate equal to their investment return while, at the same time, risky borrowers continue to demand credit. After this point, the profits once again turn negative since all safe borrowers exit the market. Figure 1 (b) presents a scenario with a greater probability of default '1- *p*' for the risky borrowers. The increased risk from the greater likelihood of default from uncertain borrowers results in negative profits until interest rate *y*. Safe borrowers are entirely negated by the bank because lending at an interest rate suitable for the safe borrower would not adequately compensate for the risk of lending to the risky borrower type in the market. It can be inferred from a comparison of expected profits in both Figure 1(a) and 1(b), that the profits made by the moneylender loaning funds at a lower interest rate (Figure 1(a)) are greater relative to expected profits by lending to very risky borrowers at high interest rates of *y*. Hence, it is likely that the bank will lend at interest rate *y* which in effect offers a subsidy to the risky borrowers at the expense of safe borrowers in the market. Ideally, the bank would be able to finance both ventures by charging different interest rates but the informational asymmetry in the market prohibits this and causes economic inefficiency.

There are other informational constraints that emerge in further stages of the lending process. Problems of moral hazard, both ex ante and post ante, that is, before lending and after lending, fall into this category. Ex ante moral hazard arises from the inability to ensure that the borrower will put effort into production given he faces limited liability for his loans (there is no collateral, hence a default leaves the lender helpless). Consider the scenario where the borrower needs $1 to finance working capital and he can yield a result of *y*, where $y>1$. There is a cost of lending, *k* for the lender and there is a cost of effort for the borrower (let this be a non-monetary cost such as his opportunity cost of working as a wage laborer),*c*. If the borrower chooses not to expend the effort *c* the venture having no additional cost apart from the gross interest repayment, he can yield output of *y* with probability *p*. Hence, preventing the lender from shirking and incentivizing him to expend effort would require the cost of repayment to be lesser than the cost of shirking.

$$(y-R)-c>p(y-R)$$

The above expression shows the return for the borrower from repayment, which includes the cost of effort *c.* The right side of the expression shows the returns when the borrower chooses not to exert effort and leaves the profits to chance.

Hence, the bank's gross interest rate is effectively capped as a result of the lender's inability to ensure proper use of the loaned funds. The interest rate must be set so that it incentivizes the borrower to repay the loan as opposed to shirking. Hence, ex ante moral hazard precludes the moneylender from charging the optimal interest rate due to incentive constraints endemic to the informal credit market.

Similarly, ex-post moral hazard concerns the issue of ensuring repayment after the loan has been financed by the bank. The borrower may claim losses which cannot be verified due to lack of enforcement mechanisms or simply decide to run away with the money. Let us suppose that the borrower has some amount of collateral *w*, that can be seized upon default. The borrower is thus confronted by the scenario of either repaying the loan or refusing to pay (which would result in the loss of collateral). The second scenario can be further said to consist of the fleeing borrower being apprehended and collateral being seized (suppose this occurs with probability 1-*p*) and the borrower fleeing without detection (which occurs with probability *p*) if the borrower is too incentivized. Hence, to incentivize the borrower to repay we must compare the returns to the borrower depending on his course of action.

$$y-R+w>(1-p)(y+w)+py$$

If the bank is to incentivize the borrower to repay the loan the interest rate must be reduced to a value such that post repayment, the value of the output from the venture and the collateral exceed the potential value gain by feeling. This in turn results in the bank having to reduce interest rates. Usually, the value of the collateral offered is negligible and seeing room for ex post moral hazard, most banks decline to lend to very poor households.

3. Demystifying the miracle: Modelling the functioning of an MFI

Let us demonstrate how group lending schemes as practiced by a traditional MFI following the "classic" Grameen Model (this model has been subject to revision and improvement through supplementation with other schemes, but for simplicity, here we consider the group lending policy independently) solves problems described in the previous section.

The group lending mechanism pioneered by the Grameen Bank allows the microcredit organization to bridge informational gaps by utilizing pre-existing social ties between the borrowers. This occurs in spite of the bank's inability to distinguishing between risky and safe borrower types and resolve other such informational constraints. Given that joint liability requires that the group take responsibility for repaying funds owed by the defaulting individual and that borrowers are aware of the nature of each other's inherent risk, there arises an organic grouping of similar risk types. The "safe" borrowers join other "safe" borrowers to maximize certainty of repayment while the "risky" types are forced to join groups consisting of the remaining members who are also inevitably "risky" themselves.

This can be illustrated by using an example of an MFI lending to a group comprised of two borrowers. Consider similar parameters to the previous section. It costs the bank k dollars to lend \$1, where $k>1$, at a gross interest rate of R. The bank, while unaware of the nature of an individual borrower, is aware that q percent of the population is safe while "*1- q"* is risky. Moreover, a safe borrower is able to generate an output of y dollars with certainty *(y>1)*, while a "risky" borrower generates y' dollars with probability p and no return with complementary probability. Note $y' > y$ such that $p\,y'=y$. Since we have established that pairs will be formed with two borrowers of the same type, we know that the bank obtains returns $2R$ with certainty from the safe types. Note that q percent of the population is safe while returns from *(1-q)* percent of the population are susceptible to default. If we consider the pair comprising of two risky borrowers the probability with which both borrowers default is:

$$(1-p)^2$$

Hence the complementary probability with which the bank will receive some return, in scenarios where both "risky" types are profitable or one of them is lucky and profitable while the other is not, is:

$$1-(1-p)^2$$

The gross interest rate thus charged by the bank in order to earn normal profits must compensate for the chance of default. Given the probabilities of earning profits from both types of groups, the following is an algebraic representation of the gross interest rate,R, in relation to the cost of lending, k.

$$(q+(1-q)(1-(1-p)^2)R=k$$

As can be inferred from the expression, **group lending facilitates a lower interest rate for the bank relative to individual loans as charged by moneylenders**. This is because the risky borrowers are successful in repaying the loans with a far greater likelihood of $1-(1-p)^2$ relative to '*p'* if the loan was granted on an individual basis.

Intuitively, group lending is effective in combating adverse selection due to eliminating the cross subsidization experienced previously by the risky borrowers. If the lender were to choose to increase interest rates to earn normal profits, it would result in safe borrowers dropping out. If the percentage of risky types '*q'* was made inherently riskier due to economic shock, the lender's scope for profit would be further reduced (Figure 1(b)). Contrarily, group lending no longer allows the presence of safe borrowers in the market to allow for lower interest rates to be charged to risky borrowers (cross-subsidization) and the segmentation results in increased chance of recovering costs and hence, a lower interest rate overall.

Microfinance has also gained a firm footing in urban areas where the borrowers are significantly more diverse and increased worker mobility is observed. In such an environment, using microcredit to leverage social ties as demonstrated in the earlier paragraph may prove untenable. However, the same concept holds in principle and can be used to show the potential for gains from group lending practices. While deriving the mathematics of group lending in environments of borrower anonymity will steer us further from our central concern in this investigation, group lending is shown to allow for efficiency gains even when groups consisting of (safe,safe), (safe,risky) and (risky,risky) are formed randomly.

Group lending is pivotal in reducing ex ante and ex post moral hazard constraints by utilizing joint liability. Given that both parties to the group (let us continue to think of a group as a pair of borrowers) want to maximize the overall return, the individual not exerting appropriate effort and prone to shirking will be sanctioned by her partner. Consider similar parameters as in the previous section to demonstrate our claim. The borrower, choosing to expend effort is able to generate a return of *y* and successfully repays at gross interest rate *R.* If the borrower chooses to leave the returns off to chance, she can generate *y* dollars worth of output with a probability *p*, while with a complementary probability '*1-p'* she obtains no returns. As previously mentioned, the individual borrower is incentivized to expend effort when the returns from repayment are greater than the returns for shirking: $(y-R)-c>p(y-R)$

Consider a similar scenario for group lending where both borrowers face a choice to either shirk or not. Given the obligations of joint liability, the repayment due from the borrower who decided to shirk and was unlucky will be extracted instead from the partner who expended effort. This creates an incentive for the borrower to ascertain that her partner is always expending effort for her ability to retain surplus on her loan return is contingent on her partner repaying. On the other hand, there are positive returns to shirking only when both parties collude and decide to shirk. Thus, in order to prevent collusion of this kind the interest must be set such that the borrowers generate less returns by collectively shirking as opposed to expending effort: $(2y-2R)-2c>p^2(y-R)$. After some algebraic manipulation, the interest rate *R* with group lending is $y - \frac{c}{(1-p^2)} > R$ and is **larger relative to the interest rate constraint due to ex post moral hazard on individual loans**. Therefore, group lending incentivises the borrowers part of the group to preclude each other from shirking and reduces the in-built incentive in the interest rate that is required to preclude collective shirking via collusion.

$$y - \frac{c}{(1-p)} > R$$

4. Measuring Impacts: Designing empirical investigations and introduction to case study

The emphasis on anecdotal evidence by proponents of microcredit including several policymakers and MFIs has served to sideline systematic empirical reviews of microcredit impacts on the average consumer. Anecdotal evidence, while necessary, is not sufficient in providing a holistic view of the impact of microcredit. In order to establish microcredit as an effective tool in combating poverty, its impact on households must be considered in isolation to other economic factors. If one were to investigate the impact of access to microfinance on household income, perhaps hypothesizing increased productive investment from cheaper credit, it would be insufficient to use a single variable to account for changes in income. Consider an increase in income for a household. All else being equal, it is likely to result in a corresponding increase in demand for children, health expenditure etc. But it is also likely that there is a substitution effect caused by self-employment hours having greater value for the household. This in turn may give rise to higher opportunity cost for domestic activities like child-rearing resulting in a child (most likely the eldest) having to stay out of school to help out at home. A holistic inquiry into the impacts of microcredit is thus essential to understanding its long-term impact on household variables and thereby, its efficacy as a tool in alleviating poverty.

In line with the above reasoning, an experiment designed to measure the impacts of microfinance on the average client will aim to isolate impacts of all other variables to identify the existence of a causal relationship. The methodology of any such experiment will thus involve a baseline measurement accounting for all relevant economic characteristics of the sample before allowing sample households any access to microcredit. Subsequent measurements after a suitable time period to record economic changes experienced by households post acquiring microcredit loans will also be required. In spite of this, significant problems arise in adhering to this simple methodology.

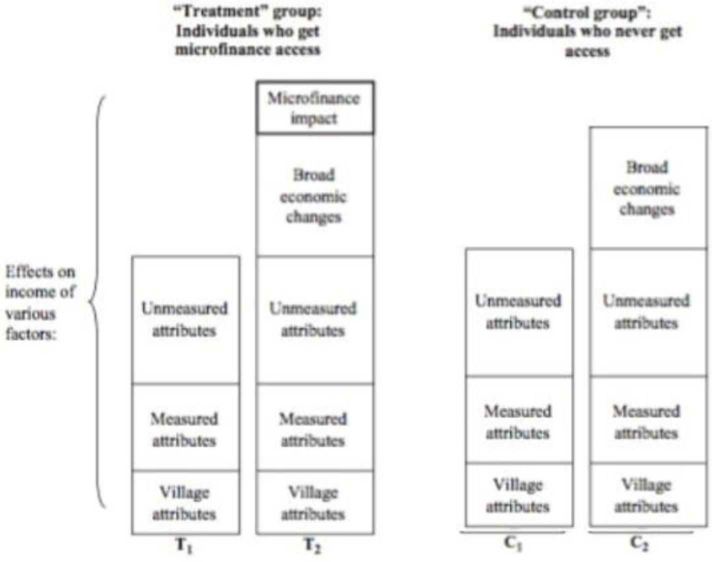

Figure 2: Difference-in-difference approach for measuring impacts of microfinance

The assumption that ‘fixed variables’ as measured by the baseline do not undergo any notable changes independent of microcredit proves to be untenable. Characteristics such as the borrower’s education, skills and social networks are all capable of improving in the time period of the experiment, thus skewing the results to overestimate the impact of microcredit. Moreover, the sampled households would inevitably be subject to impacts of broad macroeconomic changes in the economy taking place over the time frame of the experiment. Thus, counteracting the potential effects of such changes on the results necessitates the creation of a control group. A control group is a sample of households (given the present context of microfinance, most studies measure household impacts) similar in economic characteristics to those in treatment but without access to microcredit. As can be seen in Figure 2 , the broad economic changes experienced over the same time frame by both the control and treatment groups are relatively similar and thus a comparison between the changes occurring in both groups over the same time frame will successfully isolate the impact of microcredit. This approach to measuring and isolating the impact of microcredit where (T_2 - T_1) is compared to (C_2 - C_1) is known as the difference-in-difference approach. Hence, measuring baseline and ‘endline' characteristics of the control group identifies a measurable impact of macroeconomic changes to be negated from the measured ‘endline' results of the treatment group.

The empirical investigation serving as a case study for this paper was published by the European Bank for Reconstruction and Development in December 2011 as a working paper co-authored by *Attanasio, Augsburg, Haas, Fitzsimons and Harmgart*. The field experiment was conducted in partnership with *XacBank,* one of the largest MFIs in Mongolia. As part of the experiment, *XacBank* expanded its operations into areas consisting of both treatment groups (group and individual loan areas) which comprised an estimated two thirds of **the forty villages located across five provinces**

in rural Mongolia. Microcredit in rural Mongolia has been traditionally provided in the form of individual loans through official MFI programs since the shallow population density (people/km^2) of rural areas is believed to have compromised the social networks of the households. In spite of this, there is evidence of the occasional self-help group that provides small loans to groups that do not have significant social collateral in the form of borrower information (refer to section 2 to review potential incentive and cross subsidization benefits of group lending even when borrowers have informational constraints).

The targeted demographic of the investigation was less-well off women ('poorest of the poor') due to previously experiencing systematic exclusion from credit sources relative to richer (less poor) male counterparts. Before *XacBank* started operations, eligible villagers were informed that as part of the MFI's program two thirds of the population of all households in the villages will be receiving microcredit and interested women were asked to provide personal information along with relevant socio-economic data. This formed the baseline characteristics as measured by the study. The information measured included outstanding loans, economic characteristics of any enterprises operated etc. These are discussed in detail in the following section. After the preliminary data collection, two thirds of the interested clients were randomly assigned to treatment groups while the remaining did not receive any microcredit from *XacBank* (all three groups had previously experienced limited access to microcredit). The randomisation was executed across villages such that 15 villages had access to group loans, 15 villages had access to individual loans while the remaining 10 were used as control groups and no microcredit was provided by *XacBank*. This method was preferred by the organization for managerial and administrative purposes while it also allowed for minimizing spillovers in the form of informal transfers to people within the same village. Hereafter, group formation occurs independently of *XacBank* in the 15 villages where group loans were extended. As discussed in prior sections, in theory, the self-selected formation of groups is likely to contribute to increased efficiency for the micro lender and borrower both.

A comprehensive description of the methodology and estimation procedure of the experiment is beyond the purview of this essay, but a summary of the relevant information shall be provided. As part of the data collection prior to assigning potential clients into control or treatment groups, the study found that the control and treatment households were similar in almost all significant economic characteristics. These included "size, number of inhabitants, distance to the nearest province center and the nearest paved road, and the prices of various consumption goods " and "household structure, informal transfers, self- employment, wage earnings, the value of the dwelling or consumption patterns". It is important to note that a significant proportion of households measured in both groups had an outstanding loan but they were not using it to finance female-led entrepreneurial initiatives. This observation calls for a revaluation of the assumptions about microcredit. Subsequent to cheaper access to credit, poor households can experience greater savings (they do not pay as much interest on loans anymore) it can be safely assumed that poor households would choose to invest productively in businesses or durable assets. Contrary to this argument, most outstanding debt in sampled households were directed towards consumption and the purchase of non-business durables. In baseline control, group and individual treatment groups the proportion of households that had directed loan funds towards female owned enterprises were 15, 10 and 11 percent respectively. The randomization process of the study allowed for consideration of a variety of variables across which no significant differences were found and thus the study proceeded with extending microcredit.

As part of the micro-lending process by *XacBank*, group loans and individual loans were extended to treatment groups at interest rates between 1.5 to 2 percent with a decrease of 0.1 percent after every loan cycle (progressive lending). The extension of the second loan was conditional on repayment of the first group loan and allowed the bank to take advantage of joint liability. Credit would be withdrawn from the entire group if repayments were not made as scheduled. The MFI also provides dynamic incentives such as increasing the loan amount and/or maturity after each successful repayment made by the borrower. Moreover, borrowers were required to deposit 20 percent of the requested loan amount from their own funds into a joint savings account. This could be compensated for by pledging collateral however savings were

This table describes the main characteristics of the individual and the group loan products. Average loan size is calculated conditional on having a loan. Average loan size of group loans refers to loans per borrower not per group. Loans were disbursed in tögrög not US$. Source of data on maturities and loan size: XacBank.

	Individual loans	Group loans
Progressive?	Yes: larger loans, lower interest rate, and longer maturity after each successfully repaid loan	
Monthly interest rate	1.5% to 2%	
Grace period	One or two months depending on loan maturity	
Repayment frequency	Monthly, no public repayment meetings. In case of group loans, the group leader collects and hands over repayments to the loan officer	
Liability structure	Individual	Joint
Collateral	Yes but flexible approach	Joint savings (20% of loan) sometimes supplemented by assets
Available maturity	2 to 24 months	3 to 12 months
Average maturity 1st loan	224 days	199 days
Average maturity 2nd loan	234 days	243 days
Average size 1st loan	US$ 411	US$ 279
Average size 2nd loan	US$ 472	US$ 386

Figure 3: XacBank's loan product and relevant information

advised by XacBank due to the belief that it would install greater financial discipline. There were no mandatory meetings regulated by the MFI and the responsibility of cooperating to ensure repayment was with groups. Relevant information on the loan product is provided in Figure 3.

6. Business Creation and Growth

Business creation as a result of access to microcredit is shown to have increased significantly in group lending areas. This increase can be seen in the *Base Effect* row for group lending (G). The base effect shows the percentage difference (increase or decrease) in the changes experienced by the treatment group relative to the changes in control group. Figure 4 shows an 8% increase in the probability of any type of businesses in group lending treatment areas relative to control counterparts. There is a significant impact on female entrepreneurship largely driven by **the increase in female enterprise creation from the less educated demographic: 10% and 29%**

respectively (**row II column II (G)).** Note that the base effect was calculated using measurements from the follow up survey that took place almost 18 months after the first baseline survey. Hence, the changes are a result of several loan cycles. To measure the relevance of time

This table presents the results of difference-in-differences ITT regressions to measure the impact of group (G) and individual (I) loans on business creation and growth. *Base effect* refers to the basic difference between the treatment and the control villages. *High education* refers to an interaction term between a dummy for highly educated women and the base effect. *Intensity: Months* refers to an interaction term between intensity measure *Months* and the base effect. *Intensity: Number* refers to an interaction term between intensity measure *Number* and the base effect. Regressions also include a standard set of unreported pre-treatment covariates (see Table A1). The standard errors are clustered by village and reported in brackets. ***, **, * denote significance at the 0.01, 0.05 and 0.10-level. Table A1 provides the definitions and sources of all variables.

		Probability of any type of business		Probability of female business		Profit of any businesses combined		Profit of female business	
		G	I	G	I	G	I	G	I
		(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
I.	Base effect	0.080	-0.028	0.105*	-0.018	-2,125	-8,169	-2,125	-24,569
		(0.055)	(0.061)	(0.063)	(0.060)	(118,787)	(89,233)	(118,787)	(40,061)
II.	Base effect	0.284***	-0.001	0.289**	-0.105	-277,351*	-110,834	-88,405	-21,485
		(0.090)	(0.123)	(0.141)	(0.137)	(161,751)	(98,292)	(80,372)	(61,399)
	High education	-0.277**	-0.031	-0.186*	0.106	316,773	122,015	80,882	-2,933
		(0.124)	(0.126)	(0.110)	(0.143)	(221,398)	(129,769)	(113,427)	(89,685)
III.	Base effect	0.079	-0.029	0.103	-0.019	-7,658	-10,137	-20,514	-25,505
		(0.055)	(0.061)	(0.063)	(0.059)	(118,932)	(89,197)	(55,142)	(40,222)
	Intensity: Months	0.007	0.021**	0.014**	0.017	41,503**	26,255***	25,894***	10,428***
		(0.007)	(0.010)	(0.006)	(0.012)	(15,874)	(9,629)	(7,740)	(3,539)
IV.	Base effect	0.008	-0.028	0.103	-0.019	-6,018	-10,028	-19,855	-25,325
		(0.056)	(0.061)	(0.063)	(0.059)	(118,719)	(89,031)	(55,095)	(40,130)
	Intensity: Number	0.005	0.102	0.058*	0.010	201,679**	136,893*	135,560***	24,564
		(0.047)	(0.103)	(0.033)	(0.126)	(81,670)	(75,678)	(38,970)	(46,477)
	Observations	2,055	2,055	2,055	2,055	2,052	2,052	2,054	2,054

Figure 4: Impact on business creation and growth

period over which the client obtained loans and the number of loan cycles to the propensity of business creation the base effect was estimated (rows III and IV). There are significant positive impacts in group lending areas over time (rows III and IV) for female business creation. Contrarily, for individual loans there is no systematic increase in the probability of new business creation as a result of XacBank microcredit access. **The base effect for female owned businesses is negative in row I but the probability for a new business starts to improve given time and repeated loans (rows III and IV).** Another representation of the intensity of borrowing seeks to show impacts on business creation over time (Figure 5).

This chart shows the probability of enterprise ownership by an average respondent in the individual lending villages (left-hand side) and group-lending villages (right-hand side) as a function of the number of months respondents in a village borrowed on average from XacBank. The top two graphs show the probability of female-owned businesses whereas the two graphs at the bottom show the probability that the average household operates any type of business (operated by the respondent, her spouse, or jointly). The blue lines indicate the expected probability while the white lines indicate a 95 per cent confidence interval.

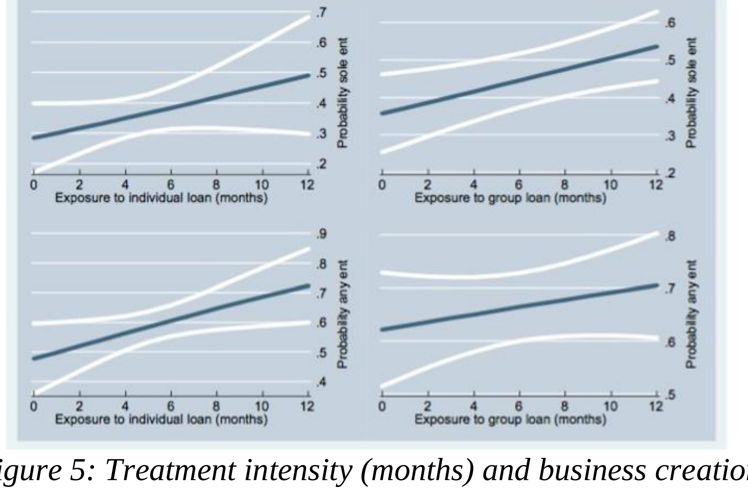

Figure 5: Treatment intensity (months) and business creation

The graphs in Figure 5 show the relationship between exposure to microcredit loans (in months) and its impact on the probability of starting a new business overall and with the targeted demographic of female entrepreneurs. The confidence intervals are narrowest for graphs showing the impact of individual loans on creation of any enterprise and the impact of group loans on female owned solo enterprises. As can be inferred from the graph in the top right, **the likelihood for a female client having been exposed to a group loan for a few days to start an enterprise is the same as the control group at 36 percent.** Whereas a repeated **borrower in treatment for 12 months is 52 percent more likely to start a new business.** This conclusion parallels that made from assessing profits measurements as shown in column (5) and (7) in group lending villages as shown in Figure 4. **Yearly profits for the business in group loaned treatment areas increase to 200,000 *MNT* (Intensity: *Number*).**

The above results support the claim that group lending is able to assist poor households in starting and sustaining profitable entrepreneurial ventures. However, it is necessary to take into account the scale and specialization level of these businesses. Evidence on such characteristics of the business across relevant literature such as Banerjee (2015) suggests that the poor run business on a very small scale and have very little specialization. These businesses are also likely to have negligible business assets and no employees. The concern for such growing businesses as shown by the increasing profits in the span of year to 200,000 MNT (USD 72) is that they will reach a point of production where the benefits of their production technology have exhausted. Banerjee and Duflo (2015) show the presence of different production technologies for businesses — one that has increasing marginal returns over a shorter range of production quantities while another that not only has greater returns on the margin but also has a broader range of production quantities over which the increasing returns occur. The difference between two technologies is where they start on the production quantity continuum. The first technology occurs with low levels of investment and thus models the output of credit constraint poor households while the other yields results only at higher quantities of production. While microfinance provides cheaper credit relative to informal moneylenders, its inability to provide lump sum investments (the yearly loan size of an average household in a treatment area was USD 300) precludes businesses from poor households to jump to the second production technology when marginal returns from the first technology start to taper off.

7. Informal Transfers

The expansion of formal credit in the form of microfinance can change the informal credit landscape in significant ways given its ability to influence consumer habits and divert household spending to small businesses. In theory, it is likely that microfinance will enable additional borrowing from informal sources as clients seek to use microfinance loans for business creation. It is also possible that microfinance compels households to substitute their borrowing from informal sources, thereby crowding out the insurance arrangements based on reciprocal lending. Consider the impact of group loans and individual loans on exchanging funds with friends and family (for the complete table, refer p. 34 *Attanasio, Augsburg, De Haas, Fitzsemos, Harmgert*). The field experiment finds those having provided access to group loans for at least six months from baseline are: 5 percentage points less likely to receive informal transfers from friends, 14 percent less likely to receive transfers from family and 8 percentage points less likely to lend to their friends. Contrarily, for clients provided access to individual loans, increasing loan size and loan cycles, there is an increase in the probability of making and receiving transfers to friends and families in the past year and past month respectively. Figure 6(a) and 6(b) show the relationship between treatment intensity in months to the likelihood of making/receiving transfer for group treatment households and individual treatment households respectively.

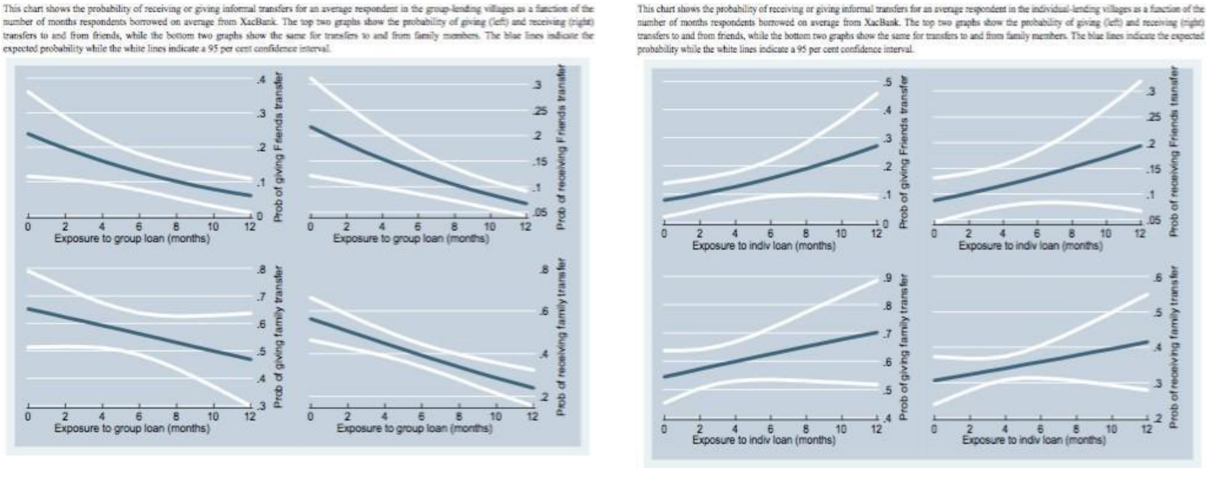

Figure 6(a) and 6(b): Treatment intensity (months) and informal transfers in (a) group lending and (b) individual lending treatment areas

There are likely to be several factors impacting the decreasing informal financial interaction of group lending households over time. Group lending households are likely to be relatively more risk averse compared to their individual lending counterparts due to joint liability. This behavior must translate to the financial interactions that the households undertake with their friends and family. Moreover, the financial collateral requirement (20% of savings) is of significance in instilling a pattern of saving and financial discipline, one that group ending households must consider more effective assets than lending sporadically with expectation of the same behavior.

8. Consumption and Asset Ownership

Households consumption was measured by the study at both disaggregate and overall levels to find a positive trend in group lending villages where there was an increase in the use of consumer goods (for the complete table, refer p. 30, 32 *Attanasio, Augsburg, De Haas, Fitzsemos, Harmgert*) These include dairy, fruits and vegetables and non alcoholic drinks, each showing an increase of 8, 10 and 14 percent respectively. While the increase in the consumption of dairy products can be attributed to increased household production, the other goods demonstrate an increase in household spending. In terms of an aggregate increase in consumption for households within treatment groups relative to their control counterparts, spending on consumer goods is 17 percentage points higher. The average treatment household had a loan of USD 300 and the spending on consumption goods pre-treatment in both control and treatment villages was an estimated USD 108. The spending on consumption goods has thus increased by USD 19 in treatment groups over the time frame of the experiment (6.3% of the loan size). On the other hand, temptation goods such as cigarettes showed a negative trend as consumption decreased over the time frame of the study (base effect/ intensity).

In terms of durables, there were significant increases in the consumption of non productive durable goods such as VCR's, radios and other large household appliances. The likelihood of owning a VCR/radio was 17 and 14 percentage points higher in group and individual treatment villages respectively while the likelihood of owning large household appliances increased by 9% and 7% in group and individual. Investment in other assets such as business durables (tools) and property (houses, *gers*) showed the following trends: less educated women in group lending zones were likely to disinvest in houses while likely using obtained funds to purchase tools for their business *(Base effect: High education (17)).*

9. Repayment

The impact study finds no significant evidence of the liability structure influencing the repayment patterns. The study measures the impact of several other characteristics in lenders and the corresponding probability of default. While the size of the loan does not influence the likelihood of repayment, there is a negative impact (at the 10 per cent S.L.) of the amount of outstanding debt at the time of the baseline survey. Thus, borrowers who had outstanding debt at the time of the baseline survey are more likely to repay. In addition, several factors are responsible for increased defaults for first time loaners. A first-time borrower with TV/VCR is more likely to default possibly due to the nature of spending on nonproductive durables. Similarly, this that owned land or enterprise at the time lending were less risky. Overall, repeated borrowers are much less risky than first time borrowers (Column 4) and across both first time and repeated borrowers, the likelihood of default increased as loans neared maturity.

	First loan		All loans	
	(1)	(2)	(3)	(4)
Group loan	0.029	-0.144	0.289	0.387
	(0.398)	(0.144)	(0.339)	(0.360)
Loan amount		-0.790		0.444
		(0.636)		(0.584)
Debt at baseline		-0.200*		-0.200*
		(0.140)		(0.117)
No. prior loans with XacBank				-0.161***
				(0.040)
Months since disbursement		0.096***		0.109***
		(0.024)		(0.021)
Owns land		-0.590***		-0.263
		(0.222)		(0.208)
Owns TV		1.262**		0.152
		(0.643)		(0.318)
Owns enterprise		-0.403*		-0.093
		(0.221)		(0.153)
Grade VIII education		-0.858***		-0.370*
		(0.297)		(0.218)
Vocational education		-0.809***		-0.359
		(0.325)		(0.225)
Age		-0.088		-0.023
		(0.090)		(0.066)
Age squared		0.001		0.000
		(0.001)		(0.001)
Buddhist		0.465		0.178
		(0.390)		(0.262)
Hahl		-0.763**		-0.707**
		(0.377)		(0.329)
Married		0.192		0.034
		(0.266)		(0.188)
Natural disaster		0.752*		0.300
		(0.404)		(0.277)
Observations	327	302	638	612
Pseudo R-squared	0.009	0.321	0.009	0.29

Figure 7: Factors affecting Loan repayment

A significant argument for promoting group lending as a pivotal microfinance strategy was to ensure high repayment with low screening and administrative costs for lenders. The field investigation in Mongolia finds no evidence that group lending clients are more likely to repay their loans than the individual lending clients. There is prevalent evidence to both support and refute the findings of the investigation, however this essay will attempt to analyze the impacts given the specific context of the experiment. As discussed previously, rural Mongolia is sparsely populated and leveraging social ties between community members is a hard task. In addition to this, the *XacBank* program did not require regular meetings between group members in public and thus, no record other than repayment rates can quantitatively suggest the effectiveness of their social interactions.

There have been significant analyses on the costs of group lending precluding the lender from fully leveraging joint liability. Among these costs are increased risk aversion of the borrowers and high costs of monitoring the effort exerted by other group members. Relative to risk neutral counterparts, borrowers who are highly risk averse will find monitoring costs to be higher in their increasingly stringent methods of screening fellow group members. Furthermore, monitoring costs are a function of loan size and progressive borrowing over time would result in high monitoring costs for risk averse group members There is strong evidence, as developed in the relevant literature, to demonstrate borrower's preference to opt for individual loans as the scale of their business rises and joint liability becomes too costly. In the case of the Mongolian field experiment however, loan size seems not to affect the repayment rate. It must be noted that repayment rate does not necessarily provide an accurate reflection of consumer behavior. Clients in both group and individual lending zones could have found alternative methods of financing - be it borrowing from competing MFIs or selling assets. There is also the constraint of imperfectly imposed social sanctions to combat moral hazard. In the theoretical model, the threat of social sanction is sufficient to avoid moral hazard from the borrower but in practice, social sanctions are never enforced to the point where they cause significant economic distress to preclude others from shirking.

10. Conclusion

The essay has successfully examined the varying theoretical models that support economists' understanding of the rural credit market and the role microcredit has to play as an effective tool to combat poverty. As evident from the analysis of the data collected from the test group after administering microcredit loans in Mongolia, the effectiveness of the group lending as an essential feature of microcredit programs is questionable. The factors examined in this paper, namely business growth, informal transfers, repayment and consumption and asset ownership, all contribute to a holistic understanding of the effectiveness of group lending as a tool to facilitate targeted objectives. As demonstrated in the analysis on repayment, there is no significant improvement in the repayment rate i.e., the percentage of loan amount repaid on time, between individual and group lending treatment groups. While the discussion in the previous sections assesses the validity of the result and suggests the need for further research on relevant areas such as the costs of group lending to borrowers, including risk aversion and the high cost of monitoring the effort of other group members. On the other hand, while there is significant improvement experienced in business creation and enterprise, especially for female entrepreneurs, it cannot be satisfactorily concluded that their businesses would experience such benefits over the long run if the terms of the loan did not undergo change, as discussed with reference to Banerjee and Duflo. Still, group lending appears to be a useful tool in fostering businesses by the poor. Asset ownership and consumption did not differ significantly between individual and group lending treatment groups, and hence, no relevant conclusion can be drawn about the effectiveness of group lending. Contrarily, group lending appears to make the borrower more financially responsible given the observed improvements in the reduction of informal transfers amongst the group lending population. Overall, the outcomes of a group lending scheme are severely dependent on the economic context and relevant economic characteristics of rural populations. While there are similarities in the economic lives of the poor throughout the world, there are also factors, as discussed earlier, that are significantly dependent on the role of the government and private institutions in rural credit markets.

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Total Factor Productivity Growth in the European Union

By: Jonas Oliver Piduhn

Abstract

This paper presents an analysis of total factor productivity (TFP) growth in the European Union in the period of 2006-2017 using two different methods to calculate estimates of TFP growth, the Solow-Törnqvist and Direct Substitution method, as well as the Denison- Hall-Jones decomposition across space to calculate relative TFP levels across nations. Despite catch-up TFP growth in the Central and Eastern European parts of the European Union, the overall average TFP level gap vis-à-vis technology leader Germany even slightly widened. That is why this paper closes by focusing on areas of improvement and TFP growth enhancing policies.

1. Introduction

As of today, the European Union consists of 27 member states, in this paper's timeframe of 2006 to 2017 still 28, varying among others in economic performance and the state of economic development. Thirty years after the fall of the Berlin Wall, those differences are still immense and spark discussions over the distribution of benefits from European Integration all across the European Union (EU). In this paper, I will examine the progress of European Integration using the indicator of total factor productivity (TFP) growth. Following the analysis by Burda and Severgnini (2009) of the period between 1994 and 2005, in which the Eastern European transition economies experienced higher TFP and GDP growth rates than countries formerly westwards of the iron curtain leading to economic convergence, I will analyze the development of TFP growth in the EU in the period between 2006 and 2017.

Most of the differences in cross-country and cross-time variation in GDP growth rates and thereby states of economic development are due to differences in growth of total factor productivity (Easterly and Levine (2001), Caselli (2005)). Admittedly, TFP growth can be seen as a rather narrow measure that is potentially vulnerable to measurement errors as conventional economic measures do not measure intangible assets very well. Using the broad definition by Spence (2011), TFP in general influences how much you can produce with a given set of inputs. As Kendrick shows in his 1976 paper, the growth rates of inputs such as capital and labor are not sufficient for explaining the growth rates of output. So, there has to be something else that influences this process. This "something else" (Easterly and Levine (2001)) is total factor productivity, a measure of technological progress, technical efficiency and innovation. TFP growth is the determinant of sustainable economic growth and improvements in standards of living.

Methodologically, this paper uses three econometric measurement approaches: Due to well-known difficulties in the measurement of capital stock not only in developing economies, additionally to the standard Solow-Törnqvist method I will apply the Direct Substitution method (Burda and Severgnini (2008)) to calculate estimates of the residual cross-country TFP growth rates. In order to compare the relative TFP levels across EU member states, I will use the Denison-Hall-Jones decomposition across space with Germany as the frontier and reference country. Applying these three methods to the data of the Penn World Tables Mark 9.1 revision (Feenstra, Inklaar and Timmer (2015)) this thesis addresses two main questions using the EU-cross section of countries:

- What is the TFP growth situation in the EU during the observation period?
- What are areas of improvement and related policies that could enhance higher future TFP growth rates in the EU?

The paper is organized as follows. Section 2 develops the basic framework of European integration. Section 3 focuses on drivers of TFP growth in general, in frontier as well as in laggard countries. Section 4 presents and discusses three different methods of measuring the TFP residual and TFP levels. Section 5 uses them to analyze the TFP development in the EU. Section 6 focuses on possible areas of improvement and TFP growth enhancing policies in the European Union. Section 7 provides some concluding remarks.

Overview of European Integration Process

For a more complete understanding of TFP growth in the European Union, one first of all needs to be familiar with the fundamentals of European Integration. Two definitions of European integration are used in order to describe the economic integration process in the EU: The efficiency definition and the equality definition. The efficiency definition refers to a process of integration in which two or more regions achieve an efficient production pattern due to their union (Eichengreen (1999)). In contrast, the equality or fairness definition focusses on the convergence of some indicator or set of indicators like GDP or consumption per capita. Keeping Eichengreen's definition in mind, I will now examine ways that lead to economic integration. In economic theory, there are several forces that lead to economic integration between countries and regions in the sense that less developed countries grow faster than developed ones. The most important factors leading to economic integration are the following (Rivera-Batiz and Romer (1991), Barro and Sala-i-Martin (1992), Easterly and Levine (2001), Burda and Severgnini (2009)): the neoclassical economic growth, factor mobility, Heckscher-Ohlin trade, acquisition of technological expertise and experience and efficiency gains through improvements in the economic environment.

All those factors contributed to the integration process we have seen in the European Union over the last decades. Table 1 shows the respective average real GDP growth rates of EU member states. In order to recognize regional differences, I subdivided the countries into geographical groups1. Recognizing that the choice of sub periods is subjective, I chose three four-year periods for my analysis of the years 2006 to 2017 in order to get a better understanding of the respective developments in the time period during the global financial crisis, the Eurozone crisis and the recovery afterwards. When not stated otherwise, all data I use including national income, product account and labor force data of all 28 analyzed countries is taken from the Penn World Tables Mark 9.1 revision (Feenstra, Inklaar and Timmer (2015)). The data for 2017 is the most current data available in the PWT 9.1. I decided on using the data from the PWT as it provides an internationally acknowledged data set with a useful and diverse panel nature.

Table 1: Average GDP growth rates, 2006-2017 (% per annum)

	2006-2009	2010-2013	2014-2017	2006-2017
"Western EU"	1.1	1.5	2.0	1.5
Austria	1.2	1.4	1.6	1.4
Belgium	1.1	1.2	1.5	1.3
France	0.6	1.3	1.4	1.1
Germany	0.6	2.2	2.1	1.6
Luxembourg	2.0	2.7	3.0	2.6
Netherlands	1.3	0.5	2.3	1.3
"Northern EU"	0.3	1.5	4.0	2.0
Denmark	-0.1	1.1	2.2	1.0
Finland	0.4	0.8	1.2	0.8
Ireland	0.5	1.6	11.7	4.6
Sweden	0.6	2.4	3.0	2.0
United Kingdom	0.1	1.7	2.2	1.3
"Southern EU"	1.1	-1.3	2.3	0.7
Croatia	1.2	-1.2	2.2	0.8
Cyprus	2.9	-1.7	2.4	1.2
Greece	1.1	-6.3	0.4	-1.6
Italy	-0.8	-0.6	0.9	-0.1
Malta	1.7	3.0	7.4	4.0
Portugal	0.3	-1.3	0.2	-0.2
Spain	1.4	-1.4	2.8	0.9
"CEE EU"	2.5	1.9	3.4	2.6
Bulgaria	4.2	0.9	3.3	2.8
Czech Republic	2.6	0.7	3.7	2.3
Estonia	-0.5	4.0	2.9	2.1
Hungary	-0.4	0.7	3.5	1.3
Latvia	1.0	2.2	2.9	2.0
Lithuania	1.6	3.8	3.0	2.8
Poland	5.1	2.9	3.8	3.9
Romania	4.3	1.0	4.7	3.3
Slovakia	4.9	2.8	3.3	3.6
Slovenia	2.0	-0.5	3.3	1.6
EU-28	1.5	0.9	3.0	1.8

Source: Penn World Tables 9.1. Author's calculations.

The results of Table 1 can be described as follows: The European Union as a whole saw a V-shaped development of average GDP growth rates over those three periods. This development is shared by the Central and Eastern European as well as the Southern European countries. Western and Northern member states saw accelerating average GDP growth rates from period to period. The performance of Northern Europe was particularly influenced by Ireland's noteworthy economic performance as the country saw double digit growth rates in the last sub period. Overall, Central and Eastern Europe had the highest average GDP growth rates in every period, continuing the catch-up process that started in the 1990s (Burda and Severgnini (2009)).

2. Key Drivers of TFP Growth

The key drivers of TFP growth can be subdivided into general drivers and those of particular importance for technology leaders and laggard countries respectively. A technology leader is a country that has the highest level of total factor productivity.

In general, knowledge and thereby technological advancements are accumulated by devoting resources to research (Romer (1986)). Yet, frontier research does not need to take place in every country (Prescott (1998)). Usually, it happens in frontier countries. This frontier research is useful to every country as the non-rivalry of ideas should lead to increasing returns to scale (Romer (1990)). Through research, innovations such as new products, processes and markets can be developed. Nevertheless, the stock of technological knowledge, usable knowledge (Kuznets

(1966)), is not the only factor that determines relative TFP levels at a point in time (Prescott (1998)). Differences in usable knowledge in different countries nowadays cannot explain differences in productivity as borders are no boundary for the diffusion of information anymore, but the amount of knowledge used can be influenced by the strength of resistance towards the adoption of new technologies (Prescott (1998)). The necessary willingness underlying productivity growth, the willingness of a society to transform itself with the confidence that technological progress will improve people's lives (Ferguson and Wascher (2004)), can be hindered by policies and societal constraints defending the status quo.

A country that is not the technological leader can find it easier to achieve higher TFP growth rates as they in part reflect imitation and implementation of already existing knowledge. In contrast, TFP growth rates of a technological leader are a sign of growth at the frontier of knowledge (Romer (1986)). Through a certain degree of imitation, the laggard countries can start the catch-up growth process, in some cases achieve 'growth miracles' that are only possible as the country is far behind the industrial leader (Prescott (1998)). Nevertheless, problems can arise with the implementation of already existing technologies: Technological knowledge is usually specified on a country's circumstances.

3. Methodologies

In order to estimate the TFP growth rates of EU member states, I employed two methods: Using the **Solow model** (Solow (1957)), the Solow residual is given by

$$\left(\frac{\Delta A}{A}\right)_{SOLOW,t} = \frac{\Delta Y_t}{Y_{t-1}} - \omega \frac{\Delta K_t}{K_{t-1}} - (1-\omega) \frac{\Delta L_t}{L_{t-1}}$$

where Y_*, K_* and L_* are real GDP, capital input and labor input in period t and ω is the elasticity of output with respect to capital. I will generally implement in the **Solow-Törnqvist (ST) form**

$$\left(\frac{\Delta A}{A}\right)_{SOLOW,t} = \frac{\Delta Y_t}{Y_{t-1}} - \omega_{t-1} \frac{\Delta K_t}{K_{t-1}} - (1-\omega_{t-1}) \frac{\Delta L_t}{L_{t-1}}$$

with ω_t being estimated as a Tornqvist index with $\omega_{t-1} = \frac{(s_{Kt}+s_{Kt-1})}{2}$, and s_{Kt} being the

capital share in income share in period t. In order to specify the factor labor in this as well as the following method for calculating TFP growth rates, I use human capital

(Hc), the number of persons engaged (Emp) and average annual hours worked by persons engaged (Avh) to calculate $L^4: \frac{\Delta L_t}{L_{t-1}} = \frac{\Delta Hc_t}{Hc_{t-1}} \times \frac{\Delta Emp_t}{Emp_{t-1}} \times \frac{\Delta Avh_t}{Avh_{t-1}}$. I subdivided labor into its different components, as on their own they provide a better understanding of the underlying economic processes. The role of human capital is particularly important, as growth of physical capital and population growth have a greater effect on income when the state of human capital is taken into account (Mankiw, Romer and Weil (1992))5. The main weakness of this approach is that it relies on the capital stock data estimated by a statistical agency like the PWT. Even though substantial improvements regarding the measurements of capital stock have been made in the PWT 9.1 (Inklaar and Woltjer (2019)), there are known general problems with estimating the capital stock (Burda and Severgnini (2008), Diewert and Nakamura (2013), Chen and Plotnikova (2014)): presumption of correct measurement of initial condition, distinction between utilized and idle capital and appropriate depreciation rate for certain sectors or types of capital cannot or can only hardly be found.

4. Contribution of intangible assets is often not included in measured capital

Given those problems with measuring the capital stock, Burda and Severgnini (2008) propose alternative methods for estimating TFP growth. I decided to employ the proposed **direct substitution method (DS)**. In this approach, κ is the rental rate of capital in time t. The substitution of the capital stock eliminates it from the TFP calculation. Only the depreciation rate is left in the equation as δ varies over time and is better measurable. The estimate of TFP growth is given by the following equation:

$$\left(\frac{\Delta A}{A}\right)_{DS,t} = \frac{\Delta Y_t}{Y_{t-1}} - \kappa_{t-1}\frac{I_{t-1}}{Y_{t-1}} - \omega_{t-1}\delta_{t-1} - (1-\omega_{t-1})\frac{\Delta L_t}{L_{t-1}}$$

The second part of my calculations focuses on the comparison of relative TFP levels of EU member states. Therefore, I use the **Denison-Hall-Jones (DHJ) decomposition across space** (Denison (1962), Hall and Jones (1999)). This model shows the TFP gaps vis-à-vis a benchmark country, usually the technology leader, using the GDP per hour gap as well as the capital intensity gap to the reference country. The leader's variables are marked with *. The model is based on the assumption of identical constant returns production technology and an appropriate benchmark. The fundamental equation is

$$\ln\left(\frac{Y_t}{H_t}\Big/\frac{Y_t*}{H_t*}\right) = \frac{1}{1-\alpha}\ln\left(\frac{A_t}{A_t*}\right) + \frac{\alpha}{1-\alpha}\ln\left(\frac{K_t}{Y_t}\Big/\frac{K_t*}{Y_t*}\right)$$

This implies that the TFP gap to the technology leader is given by

$$\frac{1}{1-\alpha}\ln\left(\frac{A_t}{A_t*}\right) = \ln\left(\frac{Y_t}{H_t}\Big/\frac{Y_t*}{H_t*}\right) - \frac{\alpha}{1-\alpha}\ln\left(\frac{K_t}{Y_t}\Big/\frac{K_t*}{Y_t*}\right)$$

5. TFP Growth Rates and TFP Levels in the European Union and Growth Accounting

After describing the theoretical basis of all three methods used for evaluation of TFP growth in the European Union, I will now turn to the analysis of my results.

First, the Solow-Törnqvist (ST) as well as the Direct Substitution (DS) method both lead to the same ranking of European regions by average TFP growth rates (Table 2). Over the entire observation period, the group of Central and Eastern EU member states had the highest average TFP growth rate, which is consistent with the economic theory of catch- up growth (Aghion and Howitt (2004)). They were followed by Northern and Western European member states. Southern EU member states showed the lowest average TFP growth in both measurements. All methods display an acceleration of average TFP growth in every regional group and the EU-28 over the course of the 12-year period, especially in the years of economic recovery in 2014-2017 following the end of the Eurozone crisis. These findings are particularly robust because they are the results of both methods with the DS method being the most robust one (Burda and Severgnini (2009)). TFP growth rates appear to have a pro-cyclical character in the EU during this period, even though the cyclicality of TFP in general can be questioned and varies between different industries (Wang (2014)).

Second, it is noteworthy to compare the degree of heterogeneity in each regional group with regard to average TFP growth. In Western and Northern Europe, all countries' average TFP growth rates constantly increased from period to period or stayed at the same level over the last two periods in both measures. Outliers are Luxembourg and Ireland: their TFP growth rates are much higher than their group's average. Both countries are strongholds of financial institutions. Ireland became a stronghold particularly in the last sub period after the sovereign debt crisis which can be seen in its jump in average TFP growth in the last period that outperformed every other EU member state.

Table 2: TFP estimates: Solow-Törnqvist (ST) and Direct Substitution (DS), growth rates, average % per annum

2006-2009			2010-2013		2014-2017		2006-2017	
	ST	DS	ST	DS	ST	DS	ST	DS
"Western EU"	-0.4	0.7	0.3	1.2	0.5	1.6	0.1	1.2
Austria	0.2	1.0	0.3	1.0	0.7	1.3	0.4	1.1
Belgium	-0.2	0.7	0.2	0.8	0.2	1.1	0.1	0.9
France	-0.8	0.1	0.2	0.8	0.2	0.8	-0.1	0.6
Germany	-0.1	0.3	1.3	1.8	1.3	1.8	0.8	1.3
Luxembourg	-1.3	1.5	-0.4	2.3	0.0	2.7	-0.6	2.2
Netherlands	-0.5	0.6	0.1	0.4	0.9	1.7	0.2	0.9
"Northern EU"	-1.1	0.0	0.8	1.3	2.0	3.3	0.6	1.5
Denmark	-1.0	-0.5	1.0	1.0	1.1	1.5	0.3	0.7
Finland	-1.1	-0.1	0.0	0.6	0.1	0.8	-0.3	0.5
Ireland	-1.8	0.6	1.4	1.9	7.0	10.6	2.2	4.4
Sweden	-0.6	0.0	1.1	1.7	1.4	2.2	0.6	1.3
United Kingdom	-0.9	-0.2	0.4	1.1	0.5	1.5	0.0	0.8
"Southern EU"	-1.1	0.4	-0.6	-0.7	0.8	1.6	-0.3	0.4
Croatia	-1.8	-0.3	0.2	0.0	1.3	1.8	-0.1	0.5
Cyprus	-0.9	1.6	-1.0	-0.9	1.0	1.8	-0.3	0.8
Greece	-0.6	0.6	-3.9	-5.3	0.1	0.0	-1.5	-1.5
Italy	-1.8	-1.0	-0.2	-0.3	0.2	0.6	-0.6	-0.2
Malta	-1.4	0.9	1.2	2.6	3.2	6.1	1.0	3.2
Portugal	-0.7	0.0	-0.1	-0.4	-1.2	-0.7	-0.7	-0.4
Spain	-0.6	1.0	-0.5	-0.5	0.7	1.8	-0.1	0.8
"CEE EU"	0.5	1.9	1.1	1.7	1.7	2.6	1.1	2.0
Bulgaria	-1.7	3.4	-0.1	1.3	1.6	3.0	-0.1	2.6
Czech Republic	1.6	2.1	0.4	0.5	2.5	3.0	1.5	1.9
Estonia	-0.3	0.5	1.8	3.2	1.0	2.0	0.8	1.9
Hungary	-0.8	-2.4	0.4	-0.9	1.0	0.5	0.2	-0.9
Latvia	0.4	0.9	2.0	2.2	3.0	3.0	1.8	2.0
Lithuania	0.9	1.6	3.1	3.7	1.1	2.5	1.7	2.6
Poland	1.2	3.6	1.2	2.8	1.1	3.0	1.1	3.1
Romania	1.3	4.0	0.5	1.3	2.8	4.3	1.5	3.2
Slovakia	2.6	3.9	1.8	2.5	1.3	2.5	1.9	3.0
Slovenia	-0.1	1.1	0.1	0.0	1.9	2.3	0.6	1.1
EU-28	-0.4	0.9	0.4	0.9	1.3	2.3	0.4	1.4

Source: Penn World Tables 9.1. Author's calculations

This is consistent with Beck, Levine and Loayza (2000) as they discovered a positive link between financial intermediary development and TFP growth. Innovations in the financial sector have already been an important complementary driver of TFP growth during past productivity booms (Ferguson and Wascher (2004)). While

Western and Northern Europe only showed negative average TFP growth rates in years 2006 to 2009, most countries in Southern Europe remained in the negative also in the period from 2010 to 2013. Part of the explanation for this weak performance is the severe damage done in those countries by the financial as well as sovereign debt crisis.

Third, Tables 3 to 6 show the country and regional group respective growth accounting in further detail. They present Solow-Törnqvist and Direct Substitution TFP estimates together with a detailed breakdown of GDP growth into its other components such as capital and labor, subdivided into human capital (Hc), the number of persons engaged (Emp) and average annual hours worked by persons engaged (Avh). In contrast to the ST approach, the DS method is based on investment data instead of capital stock. That is why the contribution of capital growth in column 8 is estimated as a residual. There are no big differences in EU countries with regard to their respective growth rates of average annual hours worked by persons engaged and human capital. The number of persons engaged grew most in Western Europe, but these three labor related growth rates only slightly contributed to overall GDP growth as they were constantly close to zero over the observation period. The relative contribution of capital and TFP growth heavily depends on the methods used to estimate it. Whereas in the DS method the contribution of TFP growth to GDP growth is much higher than in the ST method, the opposite is true for the capital growth rate.

Table 3: Growth accounting using the two methods, 2006-2009 (% p.a.)

					Solow Törnqvist		Direct Substitution	
	Y	Emp	Avh	Hc	ST	K (ST)	DS	K(DS)
"Western EU"	1.1	0.8	-0.3	0.3	-0.4	0.8	0.7	-0.3
Austria	1.2	0.7	-0.7	0.3	0.2	0.7	1.0	-0.1
Belgium	1.1	0.7	-0.2	0.1	-0.2	0.7	0.7	-0.1
France	0.6	0.3	-0.1	0.3	-0.8	0.7	0.1	-0.1
Germany	0.6	0.6	-0.4	0.1	-0.1	0.4	0.3	0.0
Luxembourg	2.0	1.4	-0.2	0.5	-1.3	1.6	1.5	-1.2
Netherlands	1.3	0.9	-0.1	0.2	-0.5	0.8	0.6	-0.3
"Northern EU"	0.3	0.3	-0.3	0.3	-1.1	1.1	0.0	0.0
Denmark	-0.1	0.4	-0.4	0.3	-1.0	0.5	-0.5	0.0
Finland	0.4	0.5	-0.3	0.4	-1.1	1.0	-0.1	-0.1
Ireland	0.5	-0.1	-0.5	0.3	-1.8	2.7	0.6	0.2
Sweden	0.6	0.3	0.0	0.3	-0.6	0.6	0.0	0.0
United Kingdom	0.1	0.3	-0.3	0.3	-0.9	0.7	-0.2	-0.1
"Southern EU"	1.1	0.6	-0.1	0.5	-1.1	1.3	0.4	-0.3
Croatia	1.2	1.1	0.0	0.7	-1.8	1.2	-0.3	-0.3
Cyprus	2.9	1.4	0.2	0.4	-0.9	1.8	1.6	-0.7
Greece	1.1	0.5	-0.4	0.4	-0.6	1.1	0.6	-0.2
Italy	-0.8	0.2	-0.3	0.4	-1.8	0.8	-1.0	-0.1
Malta	1.7	0.8	0.1	0.3	-1.4	1.9	0.9	-0.4
Portugal	0.3	-0.3	-0.1	0.7	-0.7	0.6	0.0	-0.1
Spain	1.4	0.1	-0.1	0.4	-0.6	1.5	1.0	-0.1
"CEE EU"	2.5	0.1	-0.2	0.3	0.5	1.8	1.9	0.4
Bulgaria	4.2	0.8	-0.1	0.3	-1.7	4.8	3.4	-0.3
Czech Republic	2.6	0.5	-0.3	0.1	1.6	0.7	2.1	0.2
Estonia	-0.5	-0.9	-1.4	0.3	-0.3	1.8	0.5	0.9
Hungary	-0.4	-0.7	-0.2	0.6	-0.8	0.7	-2.4	2.2
Latvia	1.0	-1.0	0.4	0.2	0.4	1.0	0.9	0.5
Lithuania	1.6	-1.0	-0.1	0.3	0.9	1.5	1.6	0.9
Poland	5.1	1.7	-0.2	0.4	1.2	2.0	3.6	-0.5
Romania	4.3	-0.5	0.1	0.3	1.3	3.1	4.0	0.4
Slovakia	4.9	0.7	0.1	0.4	2.6	1.1	3.9	-0.2
Slovenia	2.0	0.9	-0.2	0.4	-0.1	1.0	1.1	-0.1
EU-28	1.5	0.4	-0.2	0.3	-0.4	1.3	0.9	0.0

Table 4: Growth accounting using the two methods, 2010-2013 (% p.a.)

					Solow Törnqvist		Direct Substitution	
	Y	Emp	Avh	Hc	ST	K (ST)	DS	K(DS)
"Western EU"	1.5	0.4	-0.1	0.3	0.3	0.7	1.2	-0.2
Austria	1.4	0.7	-0.4	0.2	0.3	0.5	1.0	-0.2
Belgium	1.2	0.3	0.1	0.1	0.2	0.5	0.8	-0.1
France	1.3	0.2	-0.1	0.4	0.2	0.5	0.8	-0.1
Germany	2.2	0.6	-0.1	0.1	1.3	0.3	1.8	-0.1
Luxembourg	2.7	0.9	-0.1	0.5	-0.4	1.8	2.3	-1.0
Netherlands	0.5	-0.2	0.0	0.2	0.1	0.4	0.4	0.0
"Northern EU"	1.5	0.1	-0.1	0.3	0.8	0.5	1.3	0.0
Denmark	1.1	-0.4	0.1	0.3	1.0	0.2	1.0	0.1
Finland	0.8	0.1	-0.2	0.3	0.0	0.6	0.6	0.0
Ireland	1.6	-0.3	-0.6	0.3	1.4	0.9	1.9	0.4
Sweden	2.4	0.7	0.0	0.2	1.1	0.4	1.7	-0.2
United Kingdom	1.7	0.5	0.3	0.2	0.4	0.4	1.1	-0.3
"Southern EU"	-1.3	-1.2	-0.4	0.4	-0.6	0.4	-0.7	0.5
Croatia	-1.2	-2.3	-0.1	0.8	0.2	0.3	0.0	0.5
Cyprus	-1.7	-1.3	-0.5	0.4	-1.0	0.6	-0.9	0.6
Greece	-6.3	-2.4	-0.1	0.4	-3.9	-0.2	-5.3	1.2
Italy	-0.6	-0.6	-0.4	0.3	-0.2	0.3	-0.3	0.3
Malta	3.0	1.3	-1.0	0.3	1.2	1.2	2.6	-0.2
Portugal	-1.3	-1.6	-0.2	0.5	-0.1	0.1	-0.4	0.5
Spain	-1.4	-1.7	-0.2	0.4	-0.5	0.6	-0.5	0.5
"CEE EU"	1.9	-0.3	-0.1	0.3	1.1	0.9	1.7	0.3
Bulgaria	0.9	-1.1	0.0	0.2	-0.1	2.0	1.3	0.6
Czech Republic	0.7	0.0	-0.1	0.1	0.4	0.4	0.5	0.3
Estonia	4.0	0.6	0.3	0.3	1.8	0.9	3.2	-0.4
Hungary	0.7	0.0	-0.3	0.4	0.4	0.2	-0.9	1.5
Latvia	2.2	-0.1	-0.2	0.2	2.0	0.2	2.2	0.0
Lithuania	3.8	-0.1	-0.1	0.2	3.1	0.7	3.7	0.1
Poland	2.9	-0.3	-0.1	0.4	1.2	1.7	2.8	0.1
Romania	1.0	-1.0	-0.4	0.3	0.5	1.5	1.3	0.7
Slovakia	2.8	-0.1	-0.1	0.4	1.8	0.8	2.5	0.0
Slovenia	-0.5	-0.9	-0.2	0.4	0.1	0.1	0.0	0.2
EU-28	0.9	-0.3	-0.2	0.3	0.4	0.6	0.9	0.2

Source: Penn World Tables 9.1. Author's calculations.

Table 5: Growth accounting using the two methods, 2014-2017 (% p.a.)

					Solow Törnqvist		Direct Substitution	
	Y	Emp	Avh	Hc	ST	K (ST)	DS	K(DS)
"Western EU"	2.0	0.5	0.0	0.3	0.5	0.7	1.6	-0.3
Austria	1.6	0.3	-0.2	0.2	0.7	0.5	1.3	-0.1
Belgium	1.5	0.7	-0.1	0.1	0.2	0.6	1.1	-0.2
France	1.4	0.3	0.0	0.4	0.2	0.5	0.8	-0.2
Germany	2.1	0.4	-0.1	0.0	1.3	0.4	1.8	-0.1
Luxembourg	3.0	0.8	0.1	0.5	0.0	1.7	2.7	-1.1
Netherlands	2.3	0.5	0.1	0.2	0.9	0.5	1.7	-0.3
"Northern EU"	4.0	0.6	0.0	0.2	2.0	1.2	3.3	-0.1
Denmark	2.2	0.7	-0.3	0.3	1.1	0.4	1.5	-0.1
Finland	1.2	0.0	0.2	0.3	0.1	0.5	0.8	-0.2
Ireland	11.7	0.7	0.2	0.2	7.0	3.7	10.6	0.0
Sweden	3.0	0.8	0.0	0.2	1.4	0.6	2.2	-0.2
United Kingdom	2.2	0.9	0.0	0.1	0.5	0.6	1.5	-0.3
"Southern EU"	2.3	0.8	-0.1	0.4	0.8	0.5	1.6	-0.4
Croatia	2.2	0.3	-0.6	0.8	1.3	0.3	1.8	-0.1
Cyprus	2.4	0.8	-0.2	0.4	1.0	0.4	1.8	-0.3
Greece	0.4	0.6	-0.3	0.4	0.1	-0.4	0.0	-0.3
Italy	0.9	0.3	0.0	0.3	0.2	0.1	0.6	-0.2
Malta	7.4	1.4	0.2	0.3	3.2	2.2	6.1	-0.7
Portugal	0.2	1.1	0.0	0.4	-1.2	-0.1	-0.7	-0.5
Spain	2.8	1.2	-0.1	0.4	0.7	0.5	1.8	-0.5
"CEE EU"	3.4	0.7	-0.1	0.3	1.7	0.8	2.6	-0.1
Bulgaria	3.3	0.1	0.0	0.2	1.6	1.4	3.0	0.0
Czech Republic	3.7	0.6	0.1	0.1	2.5	0.4	3.0	0.0
Estonia	2.9	0.9	-0.1	0.3	1.0	0.7	2.0	-0.3
Hungary	3.5	1.7	0.1	0.3	1.0	0.5	0.5	0.9
Latvia	2.9	-0.1	-0.4	0.3	3.0	0.2	3.0	0.2
Lithuania	3.0	0.7	0.0	0.3	1.1	1.0	2.5	-0.4
Poland	3.8	0.7	0.0	0.4	1.1	1.6	3.0	-0.3
Romania	4.7	0.1	0.0	0.3	2.8	1.5	4.3	0.0
Slovakia	3.3	1.0	-0.2	0.4	1.3	0.8	2.5	-0.4
Slovenia	3.3	1.1	-0.1	0.4	1.9	0.1	2.3	-0.3
EU-28	3.0	0.7	-0.1	0.3	1.3	0.8	2.3	-0.2

Table 6: Growth accounting using the two methods, 2006-2017 (% p.a.)

					Solow Törnqvist		Direct Substitution	
	Y	Emp	Avh	Hc	ST	K (ST)	DS	K(DS)
"Western EU"	1.5	0.6	-0.1	0.3	0.1	0.7	1.2	-0.3
Austria	1.4	0.6	-0.4	0.2	0.4	0.6	1.1	-0.1
Belgium	1.3	0.5	-0.1	0.1	0.1	0.6	0.9	-0.1
France	1.1	0.3	0.0	0.4	-0.1	0.6	0.6	-0.1
Germany	1.6	0.5	-0.2	0.1	0.8	0.4	1.3	-0.1
Luxembourg	2.6	1.0	-0.1	0.5	-0.6	1.7	2.2	-1.1
Netherlands	1.3	0.4	0.0	0.2	0.2	0.6	0.9	-0.2
"Northern EU"	2.0	0.3	-0.1	0.3	0.6	0.9	1.5	0.0
Denmark	1.0	0.2	-0.2	0.3	0.3	0.4	0.7	0.0
Finland	0.8	0.2	-0.1	0.3	-0.3	0.7	0.5	-0.1
Ireland	4.6	0.1	-0.3	0.3	2.2	2.4	4.4	0.2
Sweden	2.0	0.6	0.0	0.2	0.6	0.5	1.3	-0.1
United Kingdom	1.3	0.5	0.0	0.2	0.0	0.6	0.8	-0.2
"Southern EU"	0.7	0.1	-0.2	0.4	-0.3	0.7	0.4	-0.1
Croatia	0.8	-0.3	-0.2	0.8	-0.1	0.6	0.5	0.0
Cyprus	1.2	0.3	-0.2	0.4	-0.3	0.9	0.8	-0.1
Greece	-1.6	-0.4	-0.3	0.4	-1.5	0.2	-1.5	0.2
Italy	-0.1	0.0	-0.2	0.3	-0.6	0.4	-0.2	0.0
Malta	4.0	1.2	-0.3	0.3	1.0	1.8	3.2	-0.4
Portugal	-0.2	-0.3	-0.1	0.5	-0.7	0.2	-0.4	0.0
Spain	0.9	-0.1	-0.1	0.4	-0.1	0.9	0.8	0.0
"CEE EU"	2.6	0.1	-0.1	0.3	1.1	1.1	2.0	0.2
Bulgaria	2.8	-0.1	0.0	0.2	-0.1	2.7	2.6	0.1
Czech Republic	2.3	0.3	-0.1	0.1	1.5	0.5	1.9	0.1
Estonia	2.1	0.2	-0.4	0.3	0.8	1.1	1.9	0.1
Hungary	1.3	0.4	-0.1	0.4	0.2	0.5	-0.9	1.6
Latvia	2.0	-0.4	-0.1	0.2	1.8	0.5	2.0	0.2
Lithuania	2.8	-0.2	-0.1	0.2	1.7	1.1	2.6	0.2
Poland	3.9	0.7	-0.1	0.4	1.1	1.8	3.1	-0.2
Romania	3.3	-0.4	-0.1	0.3	1.5	2.0	3.2	0.4
Slovakia	3.6	0.5	-0.1	0.4	1.9	0.9	3.0	-0.2
Slovenia	1.6	0.4	-0.1	0.4	0.6	0.4	1.1	-0.1
EU-28	1.8	0.2	-0.1	0.3	0.4	0.9	1.4	0.0

Source: Penn World Tables 9.1. Author's calculations.

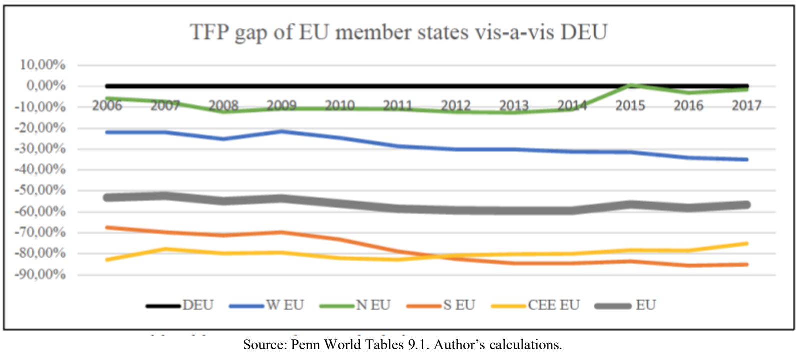
Using the Denison-Hall-Jones growth decomposition with Germany as the reference and frontier country to calculate the relative TFP levels in the EU, the following trends can be observed (Table 7, Graph 1). The Western parts of the EU have constantly lost ground to Germany, overall 10.3 percentage points to a 33 % gap. The biggest widening of the gap occurred from the first four years to the second four years during the Eurozone crisis. A similar trend can be observed in Southern Europe. The gap to the German TFP level grew by 15 percentage points to a gap of 84.7 % on average over the years 2014-2017. In contrast to the Western and Southern member states, the Northern and Central and Eastern European member states narrowed their TFP gap to Germany. The most important driver of this development in Northern Europe was Ireland that as the only country in the EU had a higher TFP level than Germany. Over the last period, Ireland's TFP level was 66% greater than the German level. In Central and Eastern Europe, the TFP gap shrank by 2 percentage points over the entire period after growing in the second four years. Ever since 2012, the TFP gap of the Central and Eastern EU member states to Germany is smaller than the one of Southern EU member states. Northern EU member countries narrowed their TFP level gap to Germany by 5.1 percentage points over the entire twelve years to a 3.9 % gap. The TFP gap to Germany increased in the period of 2010-2013 in all regional groups. As a whole, the European Union's average TFP level gap to Germany has widened by 4.2 percentage points to 57.7% over the course of the entire period. After an initial strong increase from the first to the second four years, the gap slightly narrowed over the third four years.

Table 7: TFP gap vis-à-vis Germany using Denison-Hall-Jones Decomposition across space

	2006-2009	2010-2013	2014-2017	2006-2017
"Western EU"	-22.7%	-28.4%	-33.0%	-28.0%
Austria	-24.9%	-26.8%	-30.3%	-27.4%
Belgium	-14.9%	-17.2%	-23.5%	-18.5%
France	-8.2%	-11.9%	-15.4%	-11.8%
Luxembourg	-62.3%	-78.3%	-85.0%	-75.2%
Netherlands	-3.2%	-7.7%	-10.7%	-7.2%
"Northern EU"	-9.0%	-11.7%	-3.9%	-8.2%
Denmark	-4.4%	-6.4%	-6.6%	-5.8%
Finland	-20.3%	-27.7%	-36.8%	-28.3%
Ireland	14.0%	16.7%	66.1%	32.3%
Sweden	-12.3%	-13.8%	-12.3%	-12.8%
United Kingdom	-22.1%	-27.1%	-30.0%	-26.4%
"Southern EU"	-69.5%	-79.7%	-84.7%	-78.0%
Croatia	-80.1%	-89.3%	-89.8%	-86.4%
Cyprus	-66.0%	-73.7%	-83.2%	-74.3%
Greece	-82.9%	-115.6%	-134.4%	-111.0%
Italy	-43.4%	-51.4%	-58.3%	-51.0%
Malta	-67.0%	-68.3%	-49.7%	-61.7%
Portugal	-103.0%	-109.3%	-122.5%	-111.6%
Spain	-44.1%	-50.4%	-55.2%	-49.9%
"CEE EU"	-79.9%	-81.4%	-77.9%	-79.8%
Bulgaria	-62.3%	-68.5%	-77.4%	-69.4%
Czech Republic	-106.6%	-107.0%	-103.6%	-105.7%
Estonia	-89.7%	-94.0%	-91.3%	-91.7%
Hungary	-85.8%	-91.0%	-92.8%	-89.9%
Latvia	-129.0%	-141.0%	-122.6%	-130.9%
Lithuania	-74.7%	-69.1%	-64.6%	-69.5%
Poland	-40.6%	-27.3%	-27.0%	-31.6%
Romania	-81.7%	-90.1%	-74.5%	-82.1%
Slovakia	-60.9%	-53.6%	-50.0%	-54.9%
Slovenia	-67.7%	-72.9%	-75.3%	-72.0%
EU-28	-53.5%	-58.3%	-57.7%	-56.5%

Source: Penn World Tables 9.1. Author's calculations.

Graph 1: TFP gap vis-à-vis Germany using Denison-Hall-Jones decomposition across space



Source: Penn World Tables 9.1. Author's calculations.

6. TFP Growth Enhancing Policies

The results of section 5 indicate that more decisive steps are needed in order to stimulate TFP growth and TFP level convergence in the European Union. It requires policies and investments by the government to improve the foundations for TFP growth (El-Erian and Spence (2008)) as national policies are strongly linked with TFP growth (Beck, Levine and Loayza (2000)). First, I have to note that there is not one single measure that on itself could increase TFP growth rates and encourage TFP level convergence in the European Union but a bundle of different policies is needed. This policy bundle involves changes within each member state as well as on the European level, on the supply as well as demand side. In parts, those policies do not even primarily have to focus on TFP growth itself but contribute to the creation of an innovation encouraging environment. Having said that, in the following I will outline policies in three areas of improvement that I identified as particularly important:

Research & development and human capital

The importance of the role of R&D and human capital in fostering TFP growth is indisputable (Sachverständigenrat zur Begutachtung der gesamtwirtschaftlichen Entwicklung (2019)). The best policy to encourage research and thereby technological progress is the implementation of direct subsidies to increase the research incentive (Romer (1990)). This could occur by significantly increasing the funding for research and researchers at European universities. In 2017, EU-28 countries on average spent 2.06% of their GDP on R&D, less than the OECD average R&D spending of 2.34% of GDP, with the long run target being a spending of 3% (OECD, Eurostat). Spending more money on R&D on the EU level is the right path forward, as in general on the EU-level projects with a European added value should be financed (Franco-German Council of Economic Experts (2020)).

The second-best policy according to Romer (1990) is subsidizing the accumulation of total human capital, which has the following two effects: First, investing in human capital is necessary in order for the labor force to bring the potential created by new innovations and technologies to fruition (Ferguson and Wascher (2004)). Second, educated people are good potential innovators. Thereby, education - including the learning to change and adapt - and research increases the progress of technological innovations as well as its spreading (Nelson and Phelps (1966)). Close to the technological frontier, it is very important to increase years of higher education because the rate of return to education is greater the more technologically advanced an economy is (Nelson and Phelps (1966)).

Labor and product market regulation

The third area of improvement refers to labor and product market related policies. Those policies have to find a balance between under- and overregulation as the overall effect of competition of aggregate innovation and TFP is an inverted U-curve (Aghion and Howitt (2004), Aghion et al. (2014)). First, productivity increases with further competition, as incumbents are challenged by new companies to be more productive. But at a certain level, more competition can hinder TFP growth e.g. due to a low level of patent protection that lowers the profitability of investments in R&D (Sachverständigenrat zur Begutachtung der gesamtwirtschaftlichen Entwicklung (2019)). On the sectoral level, innovation reacts positively to more product market competition in sectors in which companies are close to the technological frontier and/or compete neck to neck, whereas a negative reaction can be expected in sectors with firms that are farther away from the technological frontier (Aghion and Howitt (2004), Aghion et al. (2014)). With regard to the European Union, the greater rigidity of the product and labor market regulation in certain countries has lowered their TFP growth rates over the last years (Burda and Severgnini (2009), King (2016)). The rigidity of regulation influences the strength of resistance to adopt new technologies, which is one of the main causes for different levels of TFP between countries (Prescott (1998)). Indicators on labor and product market regulations are provided by the World Bank (Doing Business) and the OECD. Table 8 shows the development of four indicators in the EU: EPL (strictness of dismissal regulation for workers on regular contracts (both individual and collective dismissals)) from the OECD as well as PROC (number of procedures necessary to start a business), DUR (time in days needed to start a business) and COST (cost of starting a business measured in percent of annual GNI per capita) from the World Bank. The last three indicators show a positive development over the observation period in every EU region caused by noteworthy product market reforms, particularly in Central and Eastern Europe. These three measures have significant effects of TFP growth (Burda and Severgnini (2009)), so their advancement should be a priority for TFP growth enhancing policies. EPL basically remained constant over time, with some improvements in Southern EU member states, and seems to have no significant effect of TFP growth (Burda and Severgnini (2009)). Despite those developments described in Table 8, there is still room for improvements in labor and product market regulation to further spur TFP growth. Especially laggard regions still need to catch up to regions that are better positioned on those indicators and their TFP level such as Northern EU member states.

Table 8: Product and labor market regulation

	EPL			PROC		
	2006-2009	2010-2013	2014-2017	2006-2009	2010-2013	2014-2017
W EU	2,5	2,4	2,5	6,5	6,3	5,5
N EU	1,7	1,7	1,7	4,2	4,2	4,0
S EU	3,2	2,9	2,6	9,5	8,8	7,1
CEE EU	2,7	2,5	2,4	8,1	6,1	5,5

	DUR			COST		
	2006-2009	2010-2013	2014-2017	2006-2009	2010-2013	2014-2017
W EU	17,2	12,8	10,7	6,1	4,0	4,1
N EU	14,3	13,8	10,5	0,8	0,6	0,4
S EU	26,8	20,8	15,5	15,1	12,2	8,4
CEE EU	31,5	18,9	16,1	8,0	4,6	3,7

Source: OECD, World Bank; EPL: Range of indicator scores: 0-6 (as this measure is provided by the OECD, there are no numbers on BGR, HRV, CYP, MLT, ROU)

7. Conclusion

In conclusion, a broad agenda is needed to achieve higher future TFP growth rates in the EU than the ones we have seen over the period from 2006 to 2017. Over this period, both methods employed show that Central and Eastern EU member states had the highest average TFP growth rates followed by Northern and Western European member states. Southern EU member states had the lowest average TFP growth. Despite catch-up growth in Central and Eastern EU member states, the overall TFP level gap vis-à-vis technology leader Germany slightly increased. Three areas of improvement in order to enhance future TFP growth and TFP level convergence in the EU are the current misallocation of resources across the economy, research and development and human capital as well as labor and product market regulation.

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