The Implications of Artificial Intelligence: Considerations for the Labour Market

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ABSTRACT

This paper aims to offer preliminary insights on the potential implications of artificial intelligence adoption for the Trinidad and Tobago labour market. Artificial intelligence (AI) usage has been both theorized and empirically shown to facilitate productivity gains for business and occupations. Contemporary literature suggests that these gains are largely concentrated among high skilled occupations, where individuals tend to perform non-routine cognitive tasks. Acemoglu (2024) postulates that the transformative nature of AI is reflected in its ability to facilitate automation, task complementarities, deepening automation, and new task creation, which manifests as growth in total factor productivity. On the basis of this assumption, this paper utilizes a vector auto-regression (VAR) model to trace the effects of shocks to total factor productivity on employment by skill level. It gives further considerations to the likely impact of AI on investments in areas likely to drive automation and task complementarities. Main findings suggest that while increased total factor productivity impacts all skill levels, employment of medium and low skilled workers appear to be most vulnerable.

JEL Classification: J08, O30

Keywords: Artificial Intelligence (AI), Occupational Skill Levels, Vector Auto-regression (VAR), Labour Market, Total Factor Productivity (TFP).

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Introduction

Artificial intelligence (AI) was first defined by John McCarthy (1956) as the science and engineering that manifest into the manufacture of intelligent machines[1] (especially intelligent computer programs). From inception, the term was viewed as broad in scope and subjective in nature. In the intervening years, several bodies of literature, such as OECD (2019), have noted that even with the emergence of a vast array of technological innovations, there is no singular, internationally recognised definition of what constitutes AI. Similar sentiments were subsequently offered by European Commission (2020) and Briône et al. (2023). Lane and Saint-Martin (2021) note that definitions are further complicated by the fact that artificial intelligence development and deployment did not occur in a vacuum. Resultantly, the concept of AI is often conflated with different new technologies that emerged alongside it, such as factory automation and robotics.

Given the general obscurity associated with a definition, the impact of AI on the economy is difficult to ascertain. Notwithstanding, it has the potential to act as a disruptive agent, particularly in the context of the labour market. Lane and Saint-Martin (2021) note that while developments in artificial intelligence have created fears associated with potential job losses, there is also the potential to complement and augment human capabilities. This can potentially facilitate higher productivity and improved job quality. However, Muhleison (2018) contends that trepidations surrounding issues created by technological advancements should be dismissed, since society tends to adapt to modern innovations and will likely do the same with the digital revolution.

Discussions on the relationship between technological advancements and the labour market are generally encased in Schumpeter's (1942) creative destruction, wherein technological advance is the main source of economic growth and improvements in the quality of life. Balsmaier and Woerter (2019) suggest that this process generally tends to be positive for the labour market as it creates new jobs, improves productivity, and increases the demand for labour. Acemoglu (2024) contends that the impact of AI can be modelled as an improvement in total factor productivity, via several channels. The disruptive nature of AI stems from its ability to reduce the cost of capital and act as an agent of labour substitutability.

The goal of this paper is to explore the extent to which the deployment of AI alters the dynamics of the labour market. The methodology utilizes a Cobb-Douglas production function to calculate total factor productivity. Using vector auto-regressive (VAR) techniques, impulse response functions are generated to measure the responsiveness of employment (classified by high, medium and low-skilled workers) and investments, to innovations in total factor productivity. The governing intuition is similar to that expressed by Acemoglu (2024), wherein AI will generate positive movement in total factor productivity in the coming decade. In the ensuing sections of the paper, a review of relevant literature on the topic will be undertaken, followed by a discussion of the stylized facts. This will be proceeded by a discussion of the methodology. The results of this model will then be reviewed, before concluding.

Literature Review

In 2021, the European Commission's Joint Research Centre acknowledged the immense literature and varying definitions of what constitutes AI. The report drew consensus on four common characteristics, which are shared by the numerous taxonomies and constructed definitions. Firstly, AI must possess the ability to perceive or observe the surrounding environment. Secondly, AI must be capable of processing

[1] https://hai.stanford.edu/sites/default/files/2020-09/AI-Definitions-HAI.pdf

vast amounts of information (data collection and interpretation). Further, decision-making and subsequent actions must occur with a particular level of autonomy (including adaptation or reaction to changes in the environment). Finally, AI can be identified by the capability to perform tasks with the objective of reaching a specific goal or outcome. These identified criteria highlight the goal-oriented nature of artificial intelligence, specifically relating to the domain of human performed tasks, at varying levels of complexity or skill.

Frank et al. (2019) identified three contrasting perspectives of the impact of AI on the nature of employment. The *"doomsayer's perspective"* suggests that while technology enhances human labour efficiency, it may also lead to negative employment effects. Herein, technological unemployment is prompted by labour obsolescence generated by readily substitutable artificial intelligence. Conversely, the *"optimist's perspective"* posits that efficiency gains from technology can offset transition costs for certain labour types. Resultantly, this creates new needs and opportunities through creative destruction, thus facilitating employment for workers not directly competing with AI. This perspective accounts for the evolution of skill requirements over time. Meanwhile, the *"unifying perspective"* proposes that technological change creates uncertainty about the future of work. Given that an occupation can be viewed as an abstract bundle of skills, technology may manifest as a disruptive force to specific skills of the occupation, rather than to its entirety.

Acemoglu (2024) provides insights into the medium-term macroeconomic effects of AI. This is accomplished via construction of a task-based model, where the production of a unique final good requires a series of tasks, which can be allocated to capital or labour. Employment of AI induces automation, which then expands the set of tasks produced by capital using digital tools and algorithms. Automation has the added effect of enhancing the productivity of labour if some cognitive tasks are assisted by AI. Productivity gains from AI can therefore be measured either as growth of average output per worker or as total factor productivity growth. These may emanate from various channels, namely, automation, task complementariness, the deepening of automation, and new task creation.

Acemoglu et al. (2020) utilised online job postings related to the field of AI to explore trends in adoption and implications for the United States labour market. This approach links measures of AI activity—through job postings outcomes—to AI exposure scores[2]. No significant relationship was found between AI exposure and employment or wages at the occupation or employment level. Notwithstanding, a noticeable surge in AI activity, particularly after 2015, was reported. This was on account of establishments with high exposures to task structures that are more suitable for AI applications. Despite the rise in AI usage, its impact on employment patterns was deemed insignificant, due to the size of the US labour market. This suggests that the positive productivity and complementarity effects appear minimal compared to its displacement consequences.

Task-based indicators of AI adoption measure capabilities linked to tasks performed by workers, often at the occupational level. A common finding is that some high-skilled occupations are among the most exposed[3] to artificial intelligence. Felten et al. (2019) note that jobs requiring advanced degrees were most exposed. Meanwhile, both Brynjolfsson et al. (2018) and Webb (2020) found that exposure was highest amongst those in occupations with a greater skill mix. OECD (2021) substantiated these findings, explaining that much of the recent innovations in the field of artificial intelligence—several of which are related to non-routine cognitive tasks—are now expected to primarily affect high-skilled jobs. Fossen and Sorgner (2019) note that this contrasts with the impacts of previous waves of automation

[2]An AI exposure index or score is built upon the works of Felten, Raj and Seamans' (2019); Brynjolfsson, Mitchell and Rock's (2018); and Webb's (2020) AI Exposure scores.

[3] AI exposure is an index that captures the degree of overlap between the capabilities of AI and the human skills and competencies for a given task (Pizzinelli,, et al. 2023)

technologies, which tended to primarily replace routine manual and low-cognitive tasks performed by lower- and middle-skilled workers.

The findings of Frey and Osborne (2017) are in line with those identified by Fossen and Sorgner (2019), as it relates to the impacts of earlier waves of automation technologies. They report, that computerization leads to a decline in employment for routine intensive occupations, which can be easily performed by sophisticated algorithms. Such findings are noted as far back as John Maynard Keynes's (1933) prediction of widespread technological unemployment, induced by the discovery of techniques to economise labour, which outpaces the rate at which new uses can be discovered. This is substantiated by the works of Acemoglu and Autor (2010), who found that routine tasks in middle-skilled cognitive and manual jobs follow precise procedures, easily codified in algorithms, making them easily performed by computers. Furthermore, Autor and Dorn (2013) reported a structural shift in the labour market, with workers reallocating their labour supply from middle-income manufacturing to low-income service occupations due to increased flexibility and adaptability.

Frey and Osborne (2017) found that wages and educational attainment exhibit a strong negative relationship with the probability of computerisation. These findings imply a discontinuity within the literature as pertains to the impact of capital deepening on the relative demand for skilled labour. While nineteenth-century manufacturing technologies were discovered to largely replace skilled labour by simplifying procedures[4], the influence of the twentieth-century "computer revolution (automation)" resulted in the hollowing out of middle-income jobs. Findings from Frey and Osborne (2017) suggest that technological progress within the twenty-first century would result in a truncation of the current trend in labour market polarisation, with automation being principally confined to categories of low-skill and low-wage workers. These type of workers, would therefore reallocate to occupations with tasks non-susceptible to computerisation—those demanding creativity and social intelligence.

OECD (2019) regards AI as a "general purpose technology" (GPT), a concept developed by Bresnahan and Trajtenberg (1992) for technologies with potential application across a wide range of sectors and occupations, as well as the ability to improve over time and generate complementary innovation. Brynjolfsson et al. (2017) note that the economic significance of the GPT label is that it adds depth and scale to the challenges and opportunities presented by AI (in particular machine learning) to the labour market.

Gao and Feng (2023) argue that despite AI enhancing productivity, global macroeconomic data shows a decline in total factor productivity, possibly attributable to a buffer period during which economies are restructuring and reorganizing production patterns, or observation biases due to statistical errors. To this end, the authors investigate the effects of AI on productivity using micro-level data from Chinese manufacturing firms over the period 2010 to 2021. Utilising the Cobb-Douglas function to calculate TFP[5], the empirical findings from baseline regression analysis revealed a significant positive effect of AI on the TFP of manufacturing firms. Results revealed that AI possesses the ability to enhance value-added products, increase output value, and boost productivity. Additionally, it drives skill structure adjustments within firms, as they hire more high-skilled employees. Heterogeneity analysis also revealed that the nature of property rights, industry concentration, and the structure of factor endowments could result in heterogeneous effects on the productivity impacts of AI. Specifically, AI significantly enhances the productivity of non-state-owned enterprises. Further, productivity gains from AI are particularly

[4] As seen in in the works of Braverman, 1974; Hounshell, 1985; James and Skinner, 1985; Goldin and Katz, 1998

[5] The Cobb-Douglas function is used to determine firm-level TFP using the LP approach: $lnY_{it} = \beta_0 + \beta_k lnK_{it} + \beta_l lnL_{it} + \beta_m lnM_{it} + \beta_i lnI_{it} + \omega_{it} + \varepsilon_{it}$

pronounced in highly concentrated industries, while firms in capital-intensive and technology-intensive industries experience significant productivity improvements because of AI.

Stylized Facts

1.1 Artificial Intelligence in Trinidad and Tobago

Georgieff and Hyee (2021) identified the need to examine the economic location in which AI is implemented in order to appropriately assess its influence on employment. Such datasets could not be appropriately developed for the domestic context. Presumably, this highlights the embryonic use of artificial intelligence in Trinidad and Tobago. Nonetheless, evidence of growing interest in the field has manifested via numerous conferences, research seminars, and exhibitions tailored toward local experts and innovators. Notable among these was the Tech Hub Islands Summit[6], hosted by the American Chamber of Commerce (AMCHAM); and the Trinidad and Tobago Big Data Forum[7], hosted by the United Nations Trinidad and Tobago.

Efforts are also being made to tighten cybersecurity nationally with the aid of AI technologies, as noted in the National Digitalisation Agenda/Strategy[8]. The successful implementation of the national digitalisation strategy would result in the digitalisation of a large proportion of government services and immense datasets being generated daily, recording the confidential or sensitive information of citizens. This reality has raised concerns domestically in the areas of cybersecurity, especially in the aftermath of cyberattacks launched within the country in recent years. To this end, in June 2024, the "Overwatch Cyber Fusion Centre"[9]' was launched as the Caribbean region's first cybersecurity centre. The Centre's operations reportedly leveraged applications in the areas of artificial intelligence (AI) to proactively monitor and assess cyber threats, identifying vulnerabilities before they are exploited.

Technology experts have noted that Trinidad and Tobago is lagging behind global trends in artificial intelligence.[10] It has been noted that AI has the potential to conduct high level tasks thus significantly reducing labour costs. Further, though the country may not be a leader in AI investments, much of the services brought on by its adoption globally can organically be utilized domestically. In this vein, though much discussion has been ongoing about AI adoption, equal - or greater- emphasis may need to be placed on the regulatory environment that will surround its usage. This remains unclear for the domestic setting. Policymakers have however noted the potential transformative nature of AI which has enhanced productivity while also displacing jobs, as it becomes further integrated into several sectors globally.[11] In this regard, a need to update and introduce new data laws has been touted as a way to protect citizens.[12]

[6] Held July 1st- 2nd 2024 - this initiative aims to establish a national tech ecosystem and marketplace, enabling local businesses to export tech services to international markets and cultivate a critical local talent pool. https://www.techislands.net/event/tech-hub-islands-summit-t-h-i-s-2024-618/page/introduction-tech-hub-islands-summit-t-h-i-s-2024.

[7] The Big Data Forum aims to strategize the future of Big Data in Trinidad and Tobago. https://www.bigdataforumtt.com/about

[8] A 3-year project (2023-2026) being executed by the Ministry of Digital Transformation in collaboration with the United Nations Development Programme (UNDP)

[9] Overwatch is a collaboration between 'Precision Cybertechnologies' and 'Digital Solutions' and the 'Inter-American Development Bank's (IDB) Lab'. The Cyber Fusion Centre employs advanced threat intelligence, advanced technologies, and skilled cybersecurity experts to provide 24/7 monitoring and rapid response to cyber threats.

[10] Christopher Boodoosingh was speaking at the Nordic Blockchain Conference in Copenhagen, Denmark. T & T Behind on AI, but can catch up – Trinidad & Tobago Chamber of Industry and Commerce

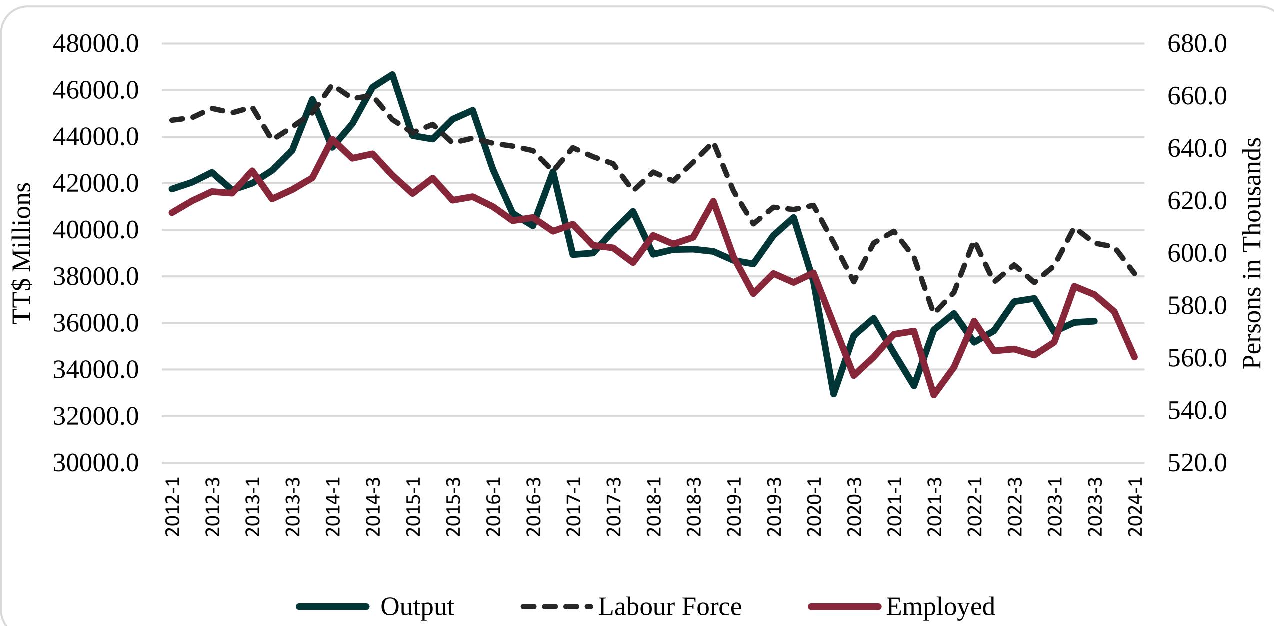
[11] Prime Minister Keith Rowley spoke about the potential effects of AI at his Labour Day Address. Rowley: AI redefining the nature of work in T&T - Trinidad Guardian

[12] Minister of Planning and Development Pennelope Beckles at the opening of the annual UN Big Data Forum. Planning Minister: Government will bring new data laws to protect citizens - Trinidad and Tobago Newsday

1.2 Factor Input Characteristics in Trinidad and Tobago

Labour market fluctuations largely mimic movements in domestic production. Over the period 2012 Q1 to 2024 Q1, employment (and the labour force) has followed a similar declining trend to output **(figure 1)**. Over the entire period under review, domestic employment contracted 8.9 per cent, moving from 615.4 thousand persons in the first quarter of 2012 to 560.4 thousand persons in the first quarter of 2024. However, in the intervening years, employment ballooned to 643.5 thousand persons in the first quarter of 2014 and fell to a low of 545.9 thousand persons in the third quarter of 2021. Relatedly, the labour force contracted 8.9 per cent, similarly reaching a high of 664.3 thousand persons in the first quarter of 2014, falling to a low of 576.9 thousand persons in the third quarter of 2021. The heights witnessed within the labour market during 2014 in part reflected momentum from the positive economic performance experienced during that period. As output fell over the first half of 2020, employment (and the labour force) followed a similar path. During this period, the government imposed restrictions on the movement of people to slow the spread of the COVID-19 virus (a global pandemic), resulting in disruptions to routine economic activity.

Figure 1: Output and Number of Employed Persons



Source: Central Statistical Office (CSO)

According to the International Labour Organization (ILO), an occupation is a group of jobs whose primary activities and duties are highly comparable[13]. The Dictionary of Occupations for Trinidad and Tobago (DOTT), published by the Ministry of Education, identifies a structure for occupational groupings[14], which is utilised by the Central Statistical Office (CSO) as part of its quarterly Labour Force Survey (LSF) Bulletins. The labour force is disaggregated into nine major categories (ten categories, if Not Stated is included) (**Appendix 1 & Table 1**).

[13] The International Labour Organisation's (ILO'S) International Standard Classification of Occupations (ISCO) provides a statistical framework under which occupational data can be made available for a country's labour market that is internationally comparable. ISCO-08 was published in 2008 and is the fourth iteration, following ISCO-58, ISCO-68 and ISCO-88.

[14] The Occupational Research Unit (ORU) of the Ministry of Education, produces and maintains the Dictionary of Occupations for Trinidad and Tobago (DOTT), which modifies the ISCO to produce a structure for occupational grouping based on the criteria of the work performed and the skill or ability necessary to carry out the necessary task (MOE 1992).

Groupings are based on worker skill levels and very general sectors of economic activity, and are a convenient means of grouping all occupations falling within these wide fields of work (MOE 2013). Among the ten occupational groups, the largest number of the employed persons belong to the Elementary Occupations (ELE) grouping, which on average, accounted for 18.7 per cent of total employment. Excluding the Not Stated (NS) group, the occupational group possessing the fewest number of persons employed was Agriculture, Forestry and Fisheries (AGRI), which accounted for approximately 2.8 per cent of the employed, on average, over the period. Occupational employment trended negatively for most of the nine major groupings, with the notable exception of those working in the Legislators, Senior Officials and Managers (LSOM) and Professionals (PROF) (as well as the NS) categories.[15]

Table 1: Summary Statistics on Occupational Groupings of the Employed

Occupational Groups	Employed Persons (000 s) between 2012 Q1 and 2024 Q1				
	Average	Maximum	Minimum	Range	% of average total employed
LSOM	61.5	74.0	50.3	23.7	10.3
PROF	34.6	41.7	24.2	17.5	5.8
TAP	81.2	93.9	69.3	24.6	13.6
CLERK	62.0	76.8	46.4	30.4	10.4
SERV	93.0	104.4	81.6	22.8	15.5
AGRI	16.5	29.1	9.5	19.6	2.8
CRAFT	87.3	102.7	65.0	37.7	14.6
PMAO	48.7	60.5	32.8	27.7	8.1
ELE	112.0	128.1	91.3	36.8	18.7
NS	2.2	4.4	0.7	0.7	0.4
Total	599.0				100.0

Source: Central Statistical Office (CSO).

The ILO (ISCO-08) [16] consolidates the nine major occupational groupings into four occupational levels based on skill level and skill specialization (ILO 2008). These levels are determined by the complexity and breadth of tasks and duties in an occupation, the level of formal education according to the International Standard Classification of Education (ISCED) (UNESCO, 1997[17]), and the amount of informal on-the-job training or previous experience required for competent performance of these tasks. These occupational skill levels are outlined in **Appendix 2**.

On average, the majority of the employed population falls into occupational skill grouping Level 2 (**table 2**) which accounted for an average of 57.3 per cent of the employed population. This represents employed persons that at a minimum have a secondary school level education. During the review period, the occupational skill Level 1 group, which represents the lowest level of specialist work, accounted for 18.7 per cent of total employment. At the highest end of specialised employment, skill levels 3 and 4, accounted for approximately 29.6 per cent of employment. Over the review period, occupational employment has declined in those occupations requiring elementary level education or training, whereas occupations requiring a high degree of specialised education and training have trended upward.

Table 2: Summary Statistics on Occupational Skill Levels of the Employed

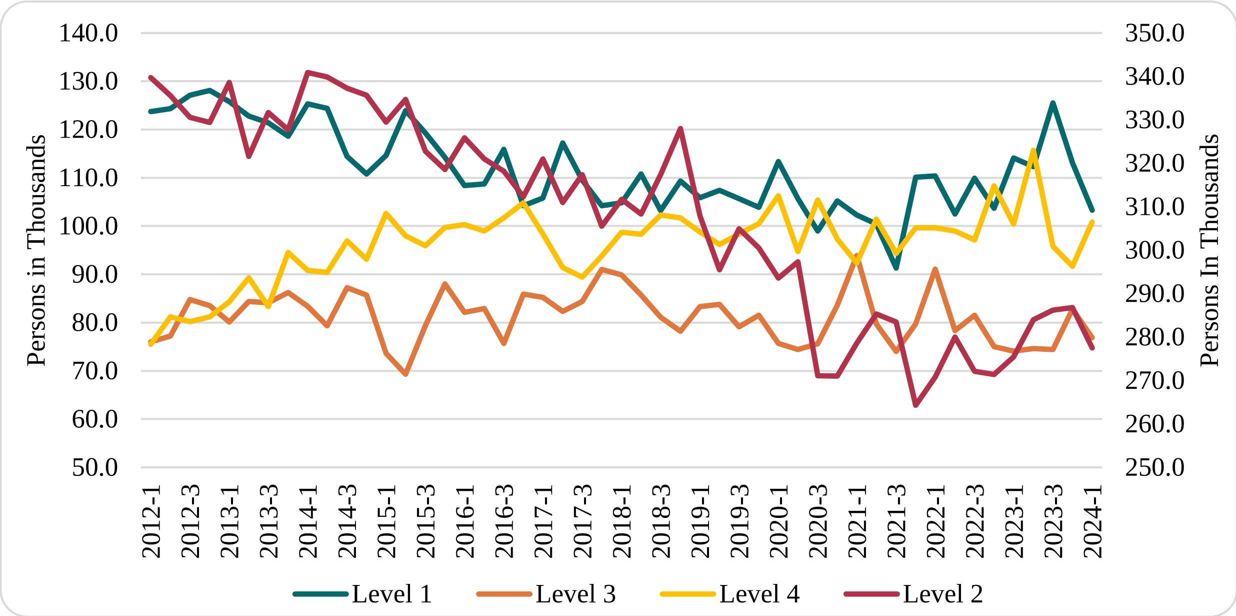
	Employed Persons (000s) between 2012 Q1 and 2024 Q1

[15] See Appendix 1 for a full breakdown of the individual groupings, their acronyms and associated definitions.
[16] https://ilostat.ilo.org/methods/concepts-and-definitions/classification-occupation/
[17] https://uis.unesco.org/sites/default/files/documents/international-standard-classification-of-education-1997-en_0.pdf

Occupational Groups	Average	Maximum	Minimum	Range	% of average total employed
Level 1	112.0	128.1	91.3	36.8	18.7
Level 2	307.5	340.9	264.3	76.6	57.3
Level 3	81.2	93.9	69.3	24.6	13.6
Level 4	96.1	115.7	75.5	40.2	16.0
Not Stated	2.2	4.4	0.7	3.7	3.7
Total	599.0				100.0

Source: Central Statistical Office (CSO), Groupings constructed based on ISCO-08, as explained in (MOE 2013)

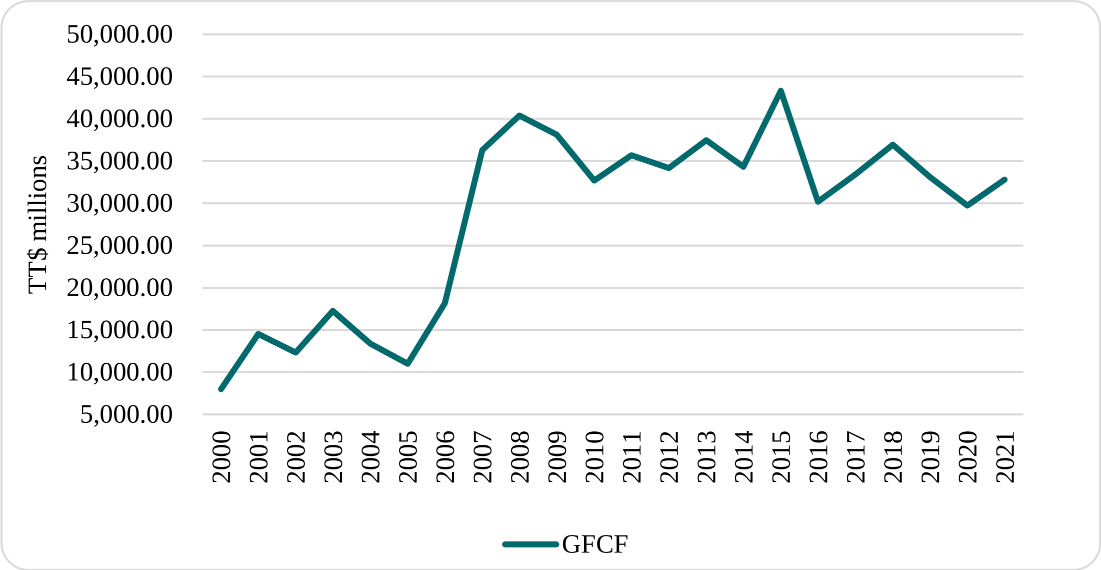
Figure 2: Occupational Employment by Skill Level (ISCO-08)



Source: Central Statistical Office (CSO), Groupings constructed based on ISCO-08, as explained in (MOE 2013)

Over the period 2000 to 2021, GFCF has trended upward, increasing from approximately $8.0 billion in 2000 to $32.8 billion in 2021 **(figure 3)**. Sizable growth in the value of GFCF is observed between 2006 and 2009, reflecting significant gains in the value of fixed assets within the Construction sector.

Figure 3: Annual Gross Fixed Capital Formation



Source: Central Statistical Office (CSO).

Data and Methodology

Total Factor Productivity

Acemoglu (2024) argues that productivity gains from artificial intelligence can be measured as either growth of output per worker or as growth in total factor productivity. This is facilitated via several distinct channels, namely automation, task complementarity, deepening of automation and creation of new tasks. In the absence of official data on artificial intelligence for Trinidad and Tobago, this paper utilizes these assumptions proposed by Acemoglu (2024). Artificial intelligence is assumed to affect the economy via a pass-through to total factor productivity. In this vein, we treat the domestic economy as possessing an aggregate production function of the neoclassical Solow-Swan form given by Dahal (2013) and shown in the Cobb-Douglas production function below:

$$Y_t = A_t K_t^{\propto} L_t^{\beta} \quad \textbf{(1)}$$

where Y_t is real GDP in time t, A_t is a measure of total factor productivity, also known as the Solow residual, K_t represents the stock of capital in time t, given by gross fixed capital formation, and L_t gives the labour force at time t. All data, with the exception of A_t is sourced from the CSO. GDP and labour force data are quarterly from 2012 to the third quarter of 2023. Capital data is annual from 2012 to 2021. The aforementioned is interpolated to generate a quarterly time series for the same period which is then forecasted seven periods ahead using ARIMA forecasting. The Solow residual (A_t), represents the part of output that is not explained by growth in traditional factors. It is meant to represent changes in efficiency related to the use of inputs and changes in technology.

From **(1)** above we can deduce that:

$$lnY_t = lnA_t + \propto lnK_t + \beta lnL_t + \varepsilon_t \quad \textbf{(2)}$$

This linear expression allows us to utilize ordinary least square (OLS) estimation, wherein our Solow residual (lnA_t) is estimated as everything not determined by labour and capital. All data used meets satisfactory stationarity criteria[18] (see **Appendix 3)**. Further, residual diagnostics indicated that our error term lacks both heteroscedasticity and serial correlation with other variables in model. This aligns with Masu et al (2020). Estimates of total factor productivity are then examined against other variables using a standard reduced form VAR.

Data

Consistent with the literature, and aligned with the research question, several indicators were utilized to evaluate the impact of increased total factor productivity on the labour market. Acemoglu (2024) also notes the need to consider the impact to capital, given the marginal rate of technical substitution for labour. Furthermore, artificial intelligence enables automation, which in turn drives investment. Stationary forms of all variables are used in order to avoid spurious regression.

The literature broadly speaks to the impact of artificial intelligence on employment across skill levels (high, medium and low). In order to dissect the labour market across similar classifications, reference is made to the Ministry of Education's National Occupational Classification of Trinidad and Tobago (NOCTT). The NOCTT groups workers by an International Standard Classification of Occupations (ISCO) skill level[19]. To buttress the classifications, use is also made of the mean income levels over the period 2014 to 2023.

High skilled workers (HIGH) are classified by a requirement of the third or fourth ISCO skill level. Medium skilled workers (MED) are classified as those requiring the second ISCO skill level. Low skilled workers (LOW) are classified by the requirement of the first ISCO skill level. Consideration was also given to occupations requiring the second ISCO skill level that were noticeably below the average income level over the past decade. The breakdown is shown in **table 3**.

Table 3: Occupational Breakdown by Skill Level

High Skilled ISCO-08 Levels 3 &4	Medium Skilled ISCO-08 Levels 2	Low Skilled ISCO-08 Levels 1
1. Legislators, Senior Officials and Managers 2. Professionals 3. Technicians and Associate Professionals	1. Clerical Support Workers 2. Services and Sales Workers 3. Craft & Related Trade Workers 4. Plant and Machine Operators & Assemblers	1. Agricultural, Forestry & Fishery Workers 2. Elementary Occupations

Source: Central Statistical Office (CSO)

Acemoglu (2024) highlights automation and task complementarities as pathways via which artificial intelligence can affect the production of an economy. For this reason, the model includes investments on intellectual property (IP) and machinery and equipment (ME). Both datasets were sourced from the gross fixed capital formation time series produced by the Central Statistical Office.

[18] For stationarity purposes we utilize the log transformations of seasonally adjusted GDP (Y) and gross fixed capital transformation time series (K).
[19] See Appendix 2

VAR Estimation

The model assumes that artificial intelligence affects the economy through improvements in total factor productivity. Therefore, by imposing one unit shocks to our total factor productivity variable (TFP), we can trace the effects to the other variables specified earlier, using the impulse response functions generated by our VAR. The imposition of this shock is meant to mimic the likely impact to total factor productivity stemming from artificial intelligence adoption, as posited by Acemologu (2024). The authors however note that while this is an empirically derived estimate of the impact to TFP, artificial intelligence is not to be considered as the sole contributory cause to improvements in TFP. This paper utilizes the accumulated generalized impulse response functions in order to avoid any sensitivities to variable ordering. The VAR is estimated in the following form:

$$\theta Y_t = \delta + \mu(L)Y_{t-1} + \varepsilon_t \quad \textbf{(3)}$$

From **(3)** above Y_t signals our vector of endogenous variables (*TFP, HIGH, MED, LOW, IP, ME),* which were earlier identified as the variables of the model's analysis. θ is an *n x n* matrix of contemporaneous coefficients of Y_t. Meanwhile, δ is a vector of constants, while $\mu(L)$ represents an *n x n* matrix of lag operator polynomials of Y_t. Our vector of error terms is denoted by ε_t.

Discussion of Results

A VAR of lag length 2 was chosen on the basis of overall model stability, normality, heteroscedasticity, and serial correlation tests (**Appendix 4.1)**. In line with Acemoglu (2024), it is assumed that any shocks from artificial intelligence will manifest as positive shocks to TFP. Analysis is thus undertaken on the impulse response functions of all variables in the model, as a response to shocks in total factor productivity. Further, the results are also discussed in the context of variance decomposition analysis. This highlights the decomposition of the variance of the forecast error into contributions from the various shocks.

Results of the econometric analysis (**Appendix 4.2**) highlight mixed implications for the labour market. Employment of high skilled workers responds favourably over the forecast period, despite a notable dip in the fourth period. Initial declines are noted in the employment of both medium and low skilled workers. Declines in the latter are more pronounced. Rebounds are noted in the employment of medium skilled workers by the third period, though this is short-lived. The response of employment levels in the medium and low skilled classifications are thus characterized by persistent declines over the forecast period. Among the three labour categories, high skilled employment appears least responsive to shocks to TFP. Greater vulnerability is displayed by the other categories, with total factor productivity initially accounting for 26.9 per cent of the variance in medium skilled employment. This contribution remains relatively steady, through to the outer periods. Low skilled employment meanwhile, appears to be relatively less affected, with 23.7 per cent of its movement accounted for by TFP in the first period. This marginally intensifies over the forecast period, as the contribution of total factor productivity remains noticeably pronounced.

Movements in high skilled employment are largely accounted for by itself. Noticeably, movements also appear to be increasingly informed by investments in intellectual property. In addition to movements in total factor productivity, medium skilled employment appears largely informed by movements in high skilled employment and investments. Low skilled employment is significantly less responsive to changes in investment but is more notably accounted for by movements in other labour categories. This may hint at the desire of labour participants to migrate from lower skilled jobs to higher skilled (and higher paying) jobs.

These results counter much of the common findings of the literature. Felten et al. (2019) asserted that jobs requiring advanced degrees were most vulnerable to the increased TFP brought on by AI. Fossen and Sorgner (2019) however note the vulnerability of medium and low skilled workers to automation technologies. These tend to replace tasks associated with such categories of workers. This result was largely associated with the first wave of automation technologies, which in turn may speak to the embryonic phase of adoption of artificial intelligence technologies locally. General results therefore suggest that increased TFP predominantly appears to trigger job displacement in the medium and low skilled categories. Meanwhile, the increased employment among high skilled labour reconciles with Gao and Feng (2023), thus offering implications for skill structure adjustments within firms as they hire more high-skilled employees. Conversely, it may speak to sentiments of Schumpeter's creative destruction, whereby job losses in the other categories may create new jobs, requiring higher skill levels. This potentially points to upskilling needs among medium and low skilled workers in order to maintain job market relevance in the aftermath of artificial intelligence adoption. Fatun and Pazour (2021) note that retraining needs vary based on the nature of jobs. As such consideration needs to be given to potential increases in structural and frictional unemployment.

While the results offer positive implications for high skilled employment, as defined within this study, consideration needs to be given to the unifying perspective proposed by Frank et al. (2019). Herein jobs are identified as a set of tasks. While AI may replace some of the tasks associated with a job it may not necessarily replace the job in its entirety. The surge in high skilled employment may actually reflect an increasing demand for certain skills associated with that employment classification as opposed to the jobs themselves. These occupations require high levels of literacy and numeracy, as well as excellent interpersonal communication skills. Embedded within these skills is an ability to understand complex written material and ideas communicated in various media (see **Appendix 2**). When juxtaposed to the scale of expenditure on the Government Assistance for Tuition Expenses programme (GATE) over the years, these results may suggest the potential alleviation of an underemployment issue, as opposed to the creation of an unemployment-related phenomenon. Clarity on this would however require future research.

Interestingly, improved factor productivity results in increased investment in intellectual property. Domestically, this category of investment has been solely accounted for by investments in mineral and petroleum exploration[20]. Productivity innovations therefore appear to elicit positive responses from the energy sector. Given the economic structure, this potentially reinforces sentiments of a Dutch disease effect. Further, it supports the notion of the higher general productivity of this particular sector in comparison to the rest of the economy. However, this discussion falls outside the scope of this paper and would therefore warrant further investigation by future works. Investment in machinery and equipment initially declines in response to productivity but persistently improves over the forecast period. Acemoglu (2024) argues that artificial intelligence potentially increases investments. This occurs through the reduction in the cost of capital for some marginal tasks or increased effectiveness of machinery or algorithms performing some marginal tasks. While the root cause is uncertain in the domestic case, the rise in investments is noteworthy. In this regard, it is useful to consider the impact of these investments on the labour market.

Investments in intellectual property appear to have an initial negative impact on high skilled employment. This temporarily improves but subsequently erodes. Herein, a short-lived relationship is established

[20] Other categories include Computer Software and Databases, Entertainment Literacy or Artistic Originals and Other Intellectual Property products. Over the period 2000 to 2021 no investments have been reported in these sub-categories.

between high skilled employment and investments from one of the more competitive sectors. Variance decomposition analysis shows that intellectual property investment increasingly accounts for movements in high skilled employment over the forecast period. Medium skilled employment generally responds negatively over the forecast period. Low skilled employment also poses an initial negative response to innovations in intellectual property investment, though a persistent positive response is noted beyond the fourth quarter. Given the sector driving this particular investment category, it is possible that some of the elementary occupations associated with the energy sector benefit from these investments. Innovations to investment in machinery and equipment largely elicit a response from the high skilled employment classification. Employment levels within the medium and low skilled classifications, though somewhat responsive, remains relatively muted. Investments into plant and machinery therefore appear to be a useful path to job creation among high skilled workers. This again perhaps speaks to sentiments of creative destruction, wherein automation displaces medium and low skilled labour, and create jobs among the more highly skilled.

Conclusion and Recommendations

In consideration of rapid accelerations in artificial intelligence developments, this paper aimed to examine the resultant impacts on the labour market. Consistent with the literature and in line with the structural dynamics of the domestic economy, consideration was also given to the resultant impact on investment. Several bodies of literature have advocated that artificial intelligence be modelled as positively affecting total factor productivity (Noy and Zhang 2023; Brynjolfsson et al. 2018; Acemoglu 2024). Accordingly, total factor productivity is derived from estimates of a Cobb-Douglas production function. Via VAR estimations, impulse response functions were generated to examine the responsiveness of economic variables to a positive one-unit shock on total factor productivity.

Results revealed that labour market responses countered the general narrative of the contemporary literature. Responses were in greater alignment to literature on the first wave of AI automation, likely reflecting the early stages of adoption in the domestic setting. Gains are noted in the employment of high skilled labour, while job displacements are evident among medium and low skilled workers. Job losses thus appear to create new jobs requiring more advanced skills. The net effect of this on the domestic labour market remains uncertain. In the event that job losses outweigh job creation, consideration needs to be given to the adequacy of the social safety net and the deployment of active labour market policies. Medium and low skilled employees, who appear more at risk to improvements in productivity may become reliant on the State for support as they transition through possible structural unemployment.

Further research is also required to ascertain the nature of jobs created, given the broad nature of labour classifications. Fatun and Pazour (2021) assert the need to align education initiatives and retraining needs to the evolving demands on skills of the workforce. Therefore, consideration should be given to a targeted reform of national education policy. A more reformed initiative could incentivize enrolment in programs that offer skills in line with jobs created among the more highly skilled. Such programs need not be implemented solely at the tertiary education level, but can be integrated into the curriculum as early as primary education. Notwithstanding, Cheung et al. (2012) noted the need to align tertiary education initiatives in Canada with long term growth, institutional incentives and policy priorities. Adoption of similar principles domestically, as a starting point, may therefore aid in offsetting potential labour market disruptions brought on by increased total factor productivity through the adoption of artificial intelligence.

By extension, consideration could be given to a potential regulatory framework to govern AI development and adoption in Trinidad and Tobago. Recent establishment of a Ministry of Digital Transformation has placed technology as an integral component in the process of economic development. Roopnarine and Spencer (2021) noted that the Government is the single largest employer domestically and further attribute the historically low unemployment rate to the prevalence of State-funded Social Sector Investment Programmes (SSIP). These programs generally target low-skilled individuals as a means of alleviating poverty and crime. The digitisation of services among the largest employer thus raises questions on where these persons will likely be employed, particularly given the implication for employment opportunities generated among high skilled occupations. A straightforward migration of employment would lend legitimacy to notions of underemployment. Alternatively, an inability to readily redirect these workers can create structural unemployment. Further, results point to the replacement of low skilled workers, which are generally targeted by the SSIP program. Consideration must therefore be given to alternative crime and poverty reduction initiatives. This may again be reconciled by a reformed national education policy.

Altered dynamics of labour demand will also pose implications for wages. Though this falls outside the scope of investigation, it can be reasoned that an increased demand for higher skilled workers will likely drive wages upward. The inverse can also be hypothesized for medium and low skilled workers. Future works should seek to bring clarity on such components of labour demand dynamics.

The generation of increased investment was also noted. This aligns with theories of artificial intelligence proposed by Acemoglu (2024), whereupon the performance of marginal tasks by labour is replaced by artificial intelligence on account of the reduced cost of capital or the increased effectiveness of machinery or algorithms. Increased total factor productivity stimulates investments in intellectual property, which are centred around the energy sector. Adams (2010) notes that increased intellectual property rights has a positive relationship with foreign direct investment (FDI). The Trinidad and Tobago energy sector is the predominant contributor to FDI. Thus, on the assumption of increased factor productivity via artificial intelligence, benefits may potentially accrue to the country's external position. However, this falls outside the scope of this paper and thus has not been explicitly modelled. Future research may be warranted to further investigate this concept. Increased investment is also noted for plant, machinery and equipment, which may signal efforts toward automation. Such investments also appear to have positive implications for job creation among high skilled workers and adverse implications for other labour classification. When coupled with direct effects from total factor productivity, this may indicate sentiments of creative destruction. It further alludes to the substitutability of labour brought on by capital investments.

This paper offers several macroeconomic considerations in the adoption of artificial intelligence. Domestic labour conditions display vulnerability, particularly among the medium and low skilled classifications. Job creation is noted among higher skilled workers. Consideration should be given to upskilling needs with the careful alignment of national education policy to national policy developments. Future works should also seek to bring clarity on the implications for wages and the implications for other structural dynamics of the labour market.

Appendices

Appendix 1: Major Occupational Categories of the Labour Force

Major Groups	Occupations	Description	
Group 1	Legislators, Senior Officials, and Managers	LSOM	Includes jobs that plan, direct, coordinate, and evaluate the activities of governments, businesses, and other organisations, as well as develop and review policies, laws, rules, and regulations
Group 2	Professionals	PROF	Includes vocations that need extensive professional knowledge and expertise, primarily requiring knowledge expansion, the application of scientific and creative concepts, systematic instruction, or a combination of these activities. Competent performance in these vocations is normally required at the fourth ISCO skill level, obtained by post-secondary education or a university degree.
Group 3	Technicians and Associate Professionals	TAP	Includes vocations that require technical skills, research, scientific or creative concepts, operational procedures, and government or commercial laws. The majority of jobs require skills at the third ISCO skill level, obtained through post-secondary education but is not equivalent to a first university degree.
Group 4	'Clerks' or Clerical Support Workers	CLERK	Includes occupations that involve information recording, organisation, storage, computing, retrieval, and clerical responsibilities. The majority of jobs demand skills at the second ISCO skill level (obtained through a five-year secondary education programme)
Group 5	Service Workers (including Defence Force) and Shop Sales Workers	SERV	Includes occupations that provide personal and protective services, such as travel, housekeeping, catering, personal care, fire prevention, and demonstrating items in retail stores, stalls, and marketplaces. Most vocations require abilities at the second ISCO skill level (gained during a five-year secondary school).
Group 6	Agricultural, Forestry, and Fishery Workers	AGRI	Do a variety of tasks such as crop cultivation, animal husbandry, forest conservation, fish breeding, and aquatic life gathering to provide food, shelter, and income for themselves and their families. Most vocations require abilities at the second ISCO skill level, (gained during a five-year secondary school).
Group 7	Craft and Related Workers	CRAFT	Employs specific knowledge and abilities to build and maintain buildings, mould metal, erect structures, and operate machine tools. They also manufacture, fit, maintain, and repair machinery, equipment, and tools, as well as print and process foodstuffs, fabrics, and handicrafts. They employ manual and hand-powered instruments to save physical labour and increase product quality. Most vocations require skills at the second ISCO skill level, (obtained through approximately five years of secondary-level education)
Group 8	Plant and Machine Operators and Assemblers	PMAO	Includes personnel that operate and supervise industrial and agricultural machinery, drive trains, motor vehicles, and mobile equipment, and assemble products to exact specifications. They demand equipment knowledge, an understanding of machine-paced activities, and the capacity to respond to technological advancements. Most vocations demand abilities at the second ISCO skill level, (obtained during a five-year secondary school).
Group 9	Elementary activities	ELE	Includes activities that require simple, routine operations with hand-held tools and physical exertion. The majority require primary education abilities at the first ISCO skill

Source (MOE 2013); Author constructed, summarising information on pages xi to xiii.

Appendix 2: ISCO-08 Occupational Skill Level

Occupational Skill Level	Occupational Group	Requirements	Educational Requirements
Level 1	ELE	Simple routine, physical or manual tasks. (Cleaning, digging, lifting, sorting, storing, assembling goods, operating non-motorized vehicles, and picking fruits and vegetables). Examples include office cleaners, freight handlers, garden labourers, and kitchen assistants	Basic literacy and numeracy skills may be required for some jobs. Completion of primary education or the first stage of basic education (ISCED-97 Level 1) may be required for competent performance in some occupations at skill level one.
Level 2	CLERK, SERV, AGRI, CRAFT and PMAO	Ability to read instructions, make written records, and perform simple calculations. Involves tasks such as operating machinery, driving vehicles, maintaining and repairing equipment, and manipulating information. Examples include butchers bus drivers, secretaries, accountants, clerks, sewing machinists, dressmakers, shop sales assistants, police officers, hairdressers, building electricians, and motor vehicle mechanics.	Requires advanced literacy, numeracy, and interpersonal communication skills. Knowledge and skills for competent performance are typically obtained through first-stage secondary education (ISCED-97 Level 2), with some requiring second-stage secondary education (ISCED-97 Level 3), which may include specialized vocational education and on-the-job training (ISCED-97 Level 4).
Level 3	TAP	Involve complex technical and practical tasks in specialized fields (such as ensuring health, safety, and regulatory compliance, preparing estimates for materials and labour, coordinating worker activities, and performing technical functions.) Examples include shop managers, medical laboratory technicians, legal secretaries, commercial sales representatives, diagnostic medical radiographers, computer support technicians, and broadcasting and recording technicians.	These occupations demand exceptional literacy, numeracy, and interpersonal communication skills, requiring the ability to comprehend complex written material, prepare factual reports, and communicate effectively in challenging situations. The knowledge and skills required for competent performance are typically obtained through higher education for one to three years after secondary education (ISCED-97 Level 5b).
Level 4	LSOM and PROF	Requires complex problem solving, decision-making, and creativity in a specialized field. (Tasks include analysis, research, disease diagnosis, knowledge imparting, and design of structures or machinery.) Examples include sales managers, civil engineers, secondary school teachers, medical practitioners, musicians, operating theatre nurses, and computer systems analysts.	These occupations require high levels of literacy and numeracy, as well as excellent interpersonal communication skills (understanding complex written material and communicating ideas in various media.) The knowledge and skills required for competent performance in these occupations are typically obtained through three to six years of study at a higher educational institution (ISCED-97 Level 5a or higher).

Source: ISCO-08.

Appendix 3: Cobb-Douglas Production Function Diagnostics

Appendix 3.1: Stationarity Statistics

Stationarity Statistics				
Variable	ADF		KPSS	
	Test Statistic	Level	Test Statistic	Level
ln Y	-4.5	I(0)	0.1	I(0)
ln K	-3.34	I(0)	0.05	I(0)
ln L	-4.85	I(0)	0.14	I(0)

Source: Authors and Eviews12

Note: Test statistics showed the presence of stationarity at the level of 5 per cent for the log transformation of all variables with the exception of lnK which was stationary at the 10 per cent level using the ADF test. This form of the variable was still used given overall model instability once differenced and also on account of the fact that the variable was forecast 8 periods ahead to complete the time series.

Appendix 3.2: Model Output

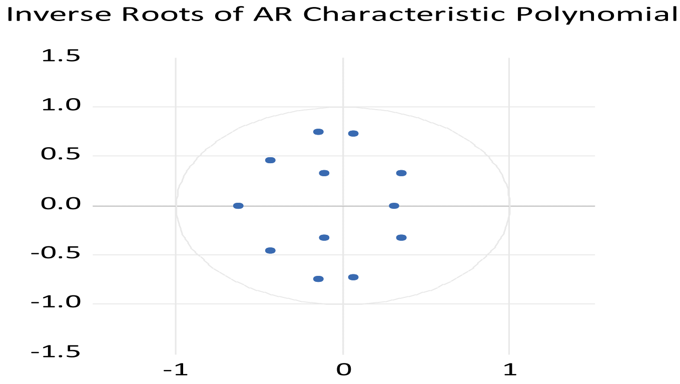
Model Output			
Variable	Coefficient	Test Statistic	p-value
ln K	0.166	3.3136	0.0018
ln L	1.949	14.2003	0.0000
ln A	-3.467	-3.9188	0.0003
R-Square		0.8519	
Prob(F-Statistic			0.0000

Source: Authors and Eviews12

Appendix 4: VAR Model Diagnostics and Results

Appendix 4.1: Diagnostics and Stability Tests

Appendix 4.1.1: Stability Test



Source: Eviews 12

Appendix 4.1.2: VAR Lag Length Criteria

Lag	LR Test Statistic	Final Prediction Error	Akaike Information Criterion	Schwarz Information Criterion	Hannon-Quinn Information Criterion
0	NA	**3.70e-15***	-16.20416	**-15.93206***	**-16.11260***
1	**54.78731***	4.14e-15	-16.12954	-14.22490	-15.48869
2	31.85362	9.41e-15	-15.54040	-12.00320	-14.35024
3	46.98279	5.82e-15	**-16.71450***	-11.54475	-14.97503

Source: Eviews 12
Note: Bold cells refer to the lag length selected by the respective criterion. Though most of the criteria specified a lag length of 0, a VAR was run with a lag length of 2 in order to avoid instances of heteroscedasticity

Appendix 4.1.3: Tests for Heteroscedasticity

Chi-sq	df	p-value
496.4364	504	0.5864

Source: Eviews 12
Note: Null hypothesis significant at 1, 5 and 10 per cent levels

Appendix 4.1.4: Test for Serial Correlation

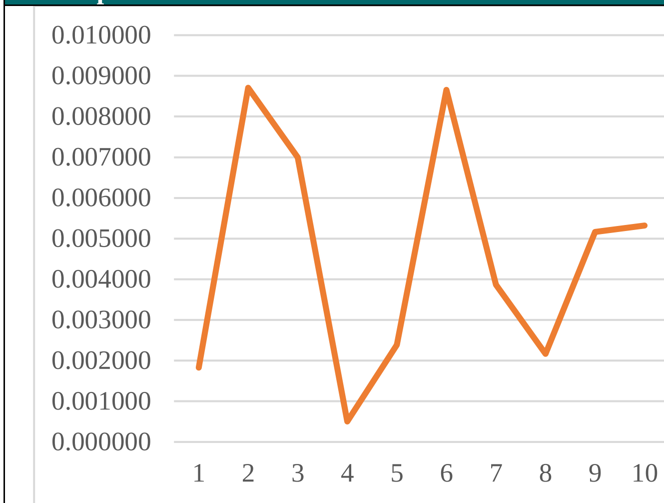
Lag	LRE Stat	Prob
1	31.83593	**0.6984**
2	32.13193	**0.6854**

Source: Eviews 12
Note: Bold cells refer to no serial correlaton at 1, 5 and 10 per cent levels

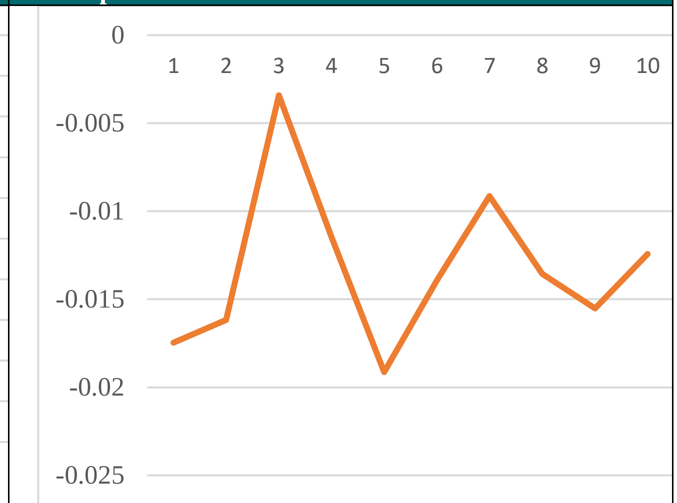
Appendix 4.2: VAR Results

Appendix 4.2.1: Standard Generalized Accumulated Responses to Total Factor Productivity

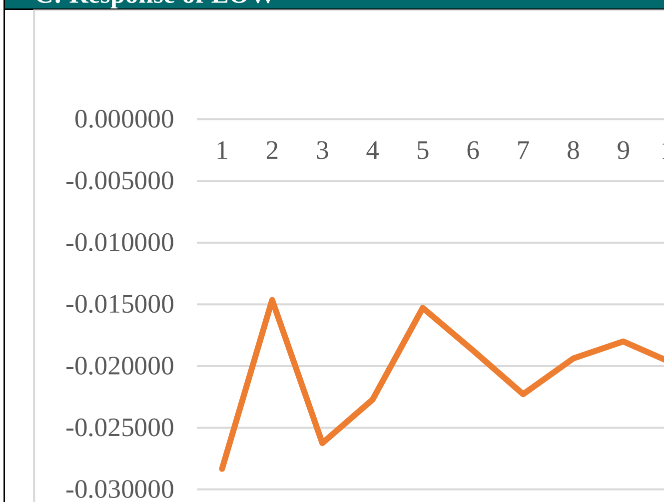
A: Response of HIGH



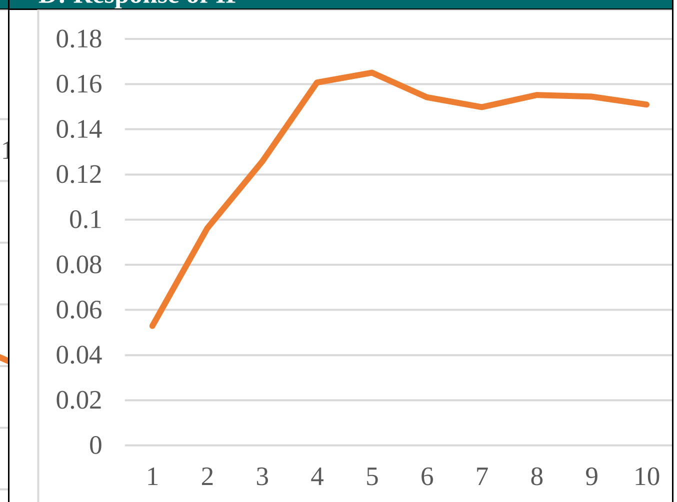
B: Response of MED



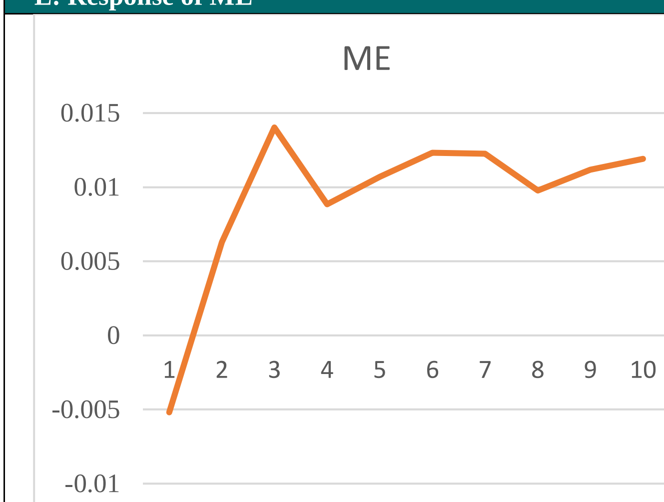
C: Response of LOW



D: Response of IP



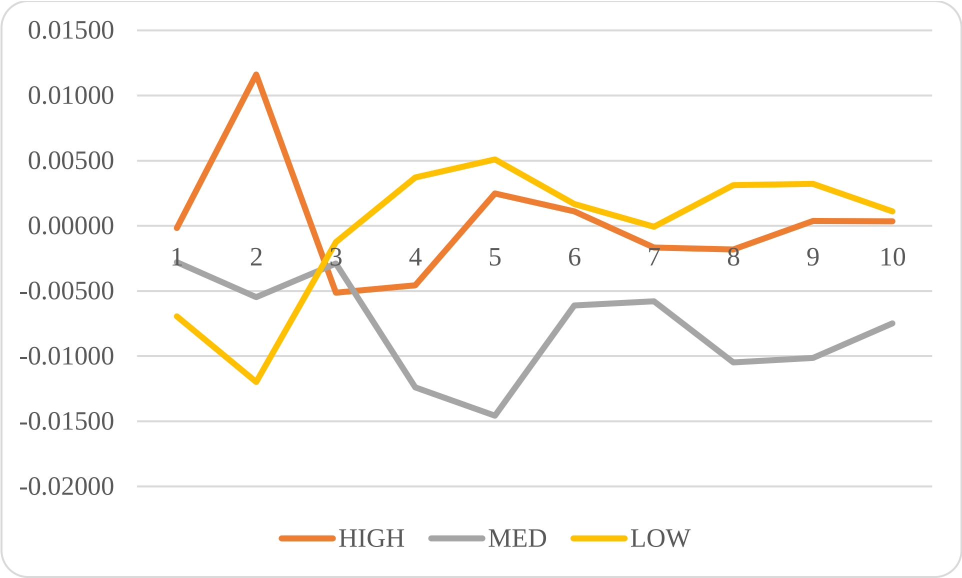
E: Response of ME



Source: Eviews 12

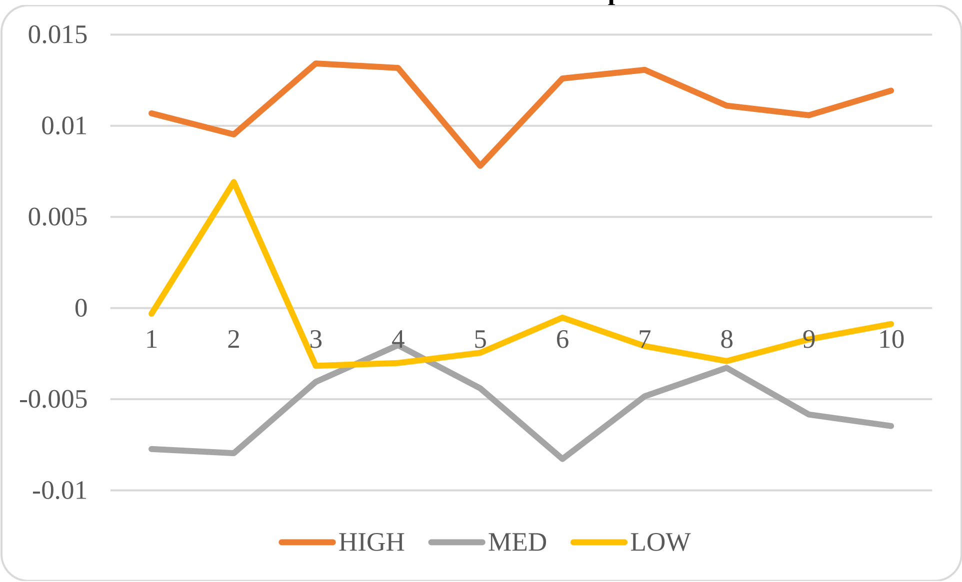
Appendix 4.2.2: Standard Generalized Accumulated Responses to Investment

Appendix 4.2.2.1: Standard Generalized Accumulated Responses of Labour to IP Investment



Source: Eviews 12

Appendix 4.2.2.2: Standard Generalized Accumulated Responses of Labour to ME Investment



Source: Eviews 12

Appendix 4.2.3: Variance Decompositions

Variance Decomposition of *HIGH*							
Period	***S.E.***	***TFP***	***HIGH***	***MED***	***LOW***	***IP***	***ME***
1	0.0	0.2	99.8	0.0	0.0	0.0	0.0
2	0.1	1.5	88.9	0.3	2.0	3.5	3.8
3	0.1	1.4	82.2	0.3	2.2	10.3	3.6
4	0.1	2.3	79.5	0.7	3.7	10.0	3.8
5	0.1	2.3	77.8	0.7	4.6	10.8	3.7
6	0.1	3.2	76.1	1.0	4.6	10.7	4.4
7	0.1	3.7	75.5	1.0	4.7	10.7	4.4
8	0.1	3.7	74.9	1.3	4.8	10.6	4.6
9	0.1	3.9	74.7	1.3	4.8	10.6	4.6
10	0.1	3.9	74.4	1.5	4.9	10.6	4.7

Source: Eviews 12

Variance Decomposition of *MED*							
Period	***S.E.***	***TFP***	***HIGH***	***MED***	***LOW***	***IP***	***ME***
1	0.0	26.9	1.5	71.6	0.0	0.0	0.0
2	0.0	20.5	18.5	55.0	4.8	0.3	0.8
3	0.0	25.3	19.0	45.0	6.4	0.3	3.9
4	0.0	26.6	18.2	41.6	6.2	3.8	3.6
5	0.0	26.9	17.8	38.4	7.8	3.6	5.5
6	0.0	26.7	17.2	36.4	8.4	6.1	5.2
7	0.0	26.5	16.5	35.8	8.8	5.9	6.6
8	0.0	26.7	16.2	35.1	9.2	6.5	6.5
9	0.1	26.3	15.9	35.1	9.3	6.4	7.0
10	0.1	26.5	15.8	34.8	9.4	6.5	7.0

Source: Eviews 12

Variance Decomposition of *LOW*							
Period	***S.E.***	***TFP***	***HIGH***	***MED***	***LOW***	***IP***	***ME***
1	0.1	23.7	26.4	14.9	35.0	0.0	0.0
2	0.1	24.9	25.9	12.8	34.5	1.7	0.2
3	0.1	25.5	23.6	13.6	31.2	5.3	0.9
4	0.1	25.6	23.4	13.5	30.9	5.7	0.9
5	0.1	26.5	23.1	13.3	30.6	5.6	0.9
6	0.1	26.5	23.1	13.2	30.4	5.8	0.9
7	0.1	26.5	23.0	13.2	30.3	5.8	1.3
8	0.1	26.6	22.9	13.1	30.2	5.9	1.3
9	0.1	26.5	22.8	13.2	30.2	5.9	1.4
10	0.1	26.5	22.7	13.2	30.2	6.0	1.4

Source: Eviews 12

Variance Decomposition of *IP*							
Period	***S.E.***	***TFP***	***HIGH***	***MED***	***LOW***	***IP***	***ME***
1	0.3	2.9	0.0	0.0	0.5	96.6	0.0
2	0.4	3.3	1.9	0.1	8.0	86.6	0.1
3	0.4	3.5	1.7	1.6	11.7	79.8	1.7
4	0.4	4.2	1.7	2.0	11.7	78.7	1.7
5	0.4	4.2	1.7	2.1	11.8	78.3	1.9
6	0.4	4.3	1.8	2.1	11.7	78.2	2.0
7	0.4	4.3	1.8	2.1	11.7	78.1	2.0
8	0.4	4.3	1.8	2.1	11.7	78.1	2.0
9	0.4	4.3	1.8	2.1	11.7	78.1	2.0
10	0.4	4.3	1.8	2.1	11.7	78.0	2.0

Source: Eviews 12

Variance Decomposition of *ME*							
Period	***S.E.***	***TFP***	***HIGH***	***MED***	***LOW***	***IP***	***ME***
1	0.1	0.9	6.4	8.7	0.4	4.3	79.3
2	0.1	4.3	6.5	7.9	6.7	3.6	70.9
3	0.1	5.5	9.4	7.7	6.6	3.9	66.8
4	0.1	5.9	11.1	7.7	6.4	4.2	64.7
5	0.1	5.9	11.1	7.8	6.5	4.2	64.5
6	0.1	6.0	11.1	7.8	6.7	4.2	64.2
7	0.1	6.0	11.1	7.8	6.7	4.3	64.1
8	0.1	6.1	11.1	7.8	6.7	4.3	64.0
9	0.1	6.1	11.1	7.8	6.7	4.3	64.0
10	0.1	6.1	11.1	7.8	6.7	4.3	63.9

Source: Eviews 12

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