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A BOOTSTRAPPED MALMQUIST FRONTIER ANALYSIS APPROACH

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Abstract

This paper attempts to examine productivity changes of insurance companies in Singapore as represented by bootstrapped Malmquist indices, generated from a data envelopment analysis (DEA)-based frontier analysis, and attribute these changes to an increasing investment in information technology infrastructure and equipment, and increasing investment in staff enhancement. Through this analysis, the author finds that there has been a general increase in productivity and efficiency from 2011 – 2017, as seen from changes in the kernel density functions of productivity change between the two periods. The author also finds, through running a panel tobit regression model, that there is a positive correlation between productivity change, and investments in IT equipment and staff enhancement. Admittedly, there are still limitations to the methodology used, in particular the lack of breakdown of IT investment data.

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1. Introduction

This paper attempts to highlight an increase in productivity of insurance companies operating in Singapore from 2011 – 2017, and to demonstrate that there is a positive relationship between productivity change, and technology adoption and employee enhancement, thus attributing the rise in productivity of insurers in recent times to increased technology adoption. With the rise of financial technology and increased abundance and accessibility to Insurtech applications within the industry, as well as the start of Industry 4.0 in recent times led to industry incumbents facing increased competition from smaller, more technology-savvy companies and increasing innovative insurance solutions. In order for incumbents to remain relevant within the industry, in the early 2010s (particularly in 2013-2014), an increasing number of said incumbents have taken steps to increase the incorporation of technology into their operations and improve efficiency (Accenture, 2017). This can be seen from the following statistics:

- Global IT expenditure by insurance companies has increased by 32% from 2013-2016 (Celent, 2017).
- Global IT spending by insurers on cognitive/AI technologies is expected to rise from USD76mil in 2016 to USD571mil in 2021 (Deloitte, 2019).

As such, there is a need to assess if current efforts in increasing technology adoption have borne fruit in raising the overall performance, in this case productivity, of traditional insurers. In this context, the paper attempts to make the following contributions:

- Draw some insights pertaining to the relationship between investments in technology and firm productivity, particularly in an industry where technology adoption is slow relative to not only all other industries in general, but also those within the same sector (finance), such as banking.
- Use data envelopment analysis (DEA) and the Malmquist Index as productivity change metrics in the context of the first contribution (since most literature use general firm performance metrics such as profitability ratios or capital growth

metrics), and test for robustness by substituting the productivity index for other productivity metrics commonly used in economic literature.

After reviewing prior literature pertaining to productivity estimation, we decided on using the Malmquist Productivity Index as the means of estimating productivity change in our paper. The Malmquist Productivity Index is a ratio calculated using distance functions derived from data envelopment analysis, as we will show later. The reason behind this is that this methodology does not assume any functional form for the production frontier, and there are no specifications for the mode of technology as compared to other estimation methods used in economic literature such as Ackerberg Caves and Frazer (2015) and Levinsohn and Petrin (2000). From our review of the literature pertaining to the relationship between IT investment and other firm performance metrics such as Francalansi and Gallal (1998) and Loveman (1994), we note that there is ambiguity in opinions about whether technology adoption has a positive, negative or insignificant impact on firm performance. However, the current literature does not take into account the effect on firm productivity from the perspective of the Malmquist Index, which is something this paper aims to address. From our review of productivity studies conducted by other researchers in other industries such as airlines, banks and agriculture, we note that there are a number of firm-level and industry-level variables that are significantly correlated with firm productivity change as well. As such, there is a need to control for these variables in any regression model regressing firm productivity change and technology adoption.

We later describe the methodologies used in quantifying productivity, namely the derivation of DEA distance indicators and the Malmquist Productivity Index, and noted that the index can be interpreted as the change in the Solow residual in the Solow production function. We also showed how the total factor productivity change as represented by the Malmquist Index could be further decomposed into a change in technical efficiency, which is represented by the relative distance from the output-input ratio of the firm to the relative production frontier of interest, and technology change, which is represented by the shift in the frontier over time. This allows us to examine if the effect of our variables of interest on the individual components of total factor productivity change is due more to efficiency changes or technological capability changes.

We mainly derived our variables of interest from the Monetary Authority of Singapore (MAS) Cadenza documents (for a full description, see section 4). For the variables constituting the Malmquist Index inputs and outputs, we note from the summary statistics that there has been an increase in both the values of both input and outputs, and attempted to determine if the increase in output is solely determined by the increase in inputs, or if there has been an increase in productivity. To show this, we constructed a kernel density function using the empirical distribution of the DEA indices in 2011 and 2017, and ran a Tobit fixed-effect regression by regressing the calculated productivity indices against our regressors (technology investment and staff investment) and a series of firm-level and industry-level control variables, to assess if technology adoption and staff enhancement have any significant relationship with productivity changes. From our results, we showed that there has been an increase in insurer productivity over the period of 2011-2017, and that there is some positive and statistically significant relationship between this productivity change and our variables of interest, which could indicate that the increase in productivity could be correlated with the increased IT and staff enhancement investments. In order to test the robustness of the results we derive, we ran the same regression setup, but with a different set of productivity indicators. For the first round of robustness checks, we used the Ackerberg, Caves and Frazer (2015) production function estimation method to derive an estimator for unobserved productivity change and used it as the dependent variable in the regression. In the next round of robustness checks, we use other firm performance measures such as return on equity, value-add per unit invested capital and value-add per unit human capital. From the results, we showed that the relationship between insurer productivity change and our variables of interest remain robust when we use different productivity metrics.

The paper is organized as per the following. Section 2 gives an overview of the Singapore insurance industry and trends, as well as some prior literature pertaining to similar areas. Section 3 introduces the sample data criteria and the data sources used. Section 4 describes the methodologies used in quantifying productivity and in assessing if investment in technology and staff has significant impact on productivity changes. Section 5 presents the results of the analysis carried out on the dataset. Finally, Section 6 concludes the paper.

2. Literature Review

2.1 The Singaporean insurance industry and Insurtech

Since its liberalization in 2000, Singapore's insurance industry has grown to be one of the top insurance and reinsurance hubs in Asia (InsuranceAsia, 2016), with total premiums collected rising from S$1.8bn in 2011 to S$3.3bn in 2017 (Monetary Authority of Singapore, 2017). This came in tandem with increased digitisation in the economy, which has resulted in the entry of high-tech startups, as well as the advancement of Singapore's advanced financial sector development. This resulted in the emergence of the financial technology (Fintech) sector. With the implementation of the Smart Nation Initiative by the Singapore government in 2014, which aims to leverage on digital technologies to improve competitiveness and productivity across all sectors, the development of the Fintech sector reached new heights, with the amount of Fintech investments and the number of Fintech deals in Singapore rising significantly from 2013 – 2017 (KPMG, Pitch, 2018).

Interestingly, despite the strong push for digitalization in the financial sector, the pace of technology adoption by insurance companies seems to be slower compared to that by other financial institutions (Business Times, 2018). Based on a global study by PwC in 2016, as many as 74 per cent of insurers predicted disruption of their businesses over the next five years. Yet only 43 per cent said they have Fintech at the heart of their corporate strategy. Less than a third were exploring partnerships with Fintech firms, and only 14 per cent invested in or supported Fintech incubation (PwC, 2016). While some of the incumbent companies have increased adoption of digital innovation in certain aspects such as customer engagement, product purchasing and claims processing, (Applied Innovation Institute, 2018 (see Appendix A)), there is still uncertainty in the industry as to how such investments have translated into tangible benefits for the insurers. As such, this paper attempts to address this issue by drawing some insights pertaining to the relationship between investments in technology and firm productivity.

2.2 Determinants of insurer performance

Based on the current literature, researchers have used different firm performance indicators pertaining to profitability and productive efficiency, and attributed changes in firm performance to different factors. In the case of productivity, most quantifiable measures used by organisations define it as a family of ratios pertaining to output quantity to input quantity. Francalansi and Gallal (1998) measured life insurer productivity using premium income per employee and operating expense per employee, and attempts to assess the combined impact of IT expenditure and worker composition (using managerial and professional intensity as proxies) on firm productivity of life insurers. Xiang, Kim, Lee, He (2010) derived several firm profitability indicators such as return on assets (ROA), return on equity (ROE), profit margin (PM), sales growth (SG) and earnings per share growth (EPSG), and regressed these variables against IT investment, along with other financial variables.

For the purpose of our paper, we focus on the productivity as the performance indicator of interest. According to Syverson (2011), simply put, productivity is efficiency in production: how much output is obtained from a given set of inputs. As such, it is typically expressed as an output–input ratio.

In terms of productivity estimation on the economics front, much work on deriving semi-parametric production frontiers has been done by Olley and Pakes (1996) and Levinsohn and Petrin (2000), whereby, in order to account for simultaneity issues caused by correlation between production inputs and random shocks, they introduce a non-parametric proxy for investments and intermediate inputs respectively within the production function equation. Ackerberg, Caves and Frazer (2006) attempted to account for potential collinearity of production inputs during production function estimation using Olley and Pakes (1996) and Levinsohn and Petrin (2000) by including the labour term in the non-parametric component of the regression equation.

Some researchers assume non-parametric methods to estimate a production frontier, and derived productivity change indices. Caves, Christensen and Diewert (1982) developed index number procedures for making productivity comparisons under very general circumstances, by defining Malmquist input, output and productivity comparisons for production structures with arbitrary returns to scale, substitution possibilities and biases in productivity change. Loveman (1994) assumes a theoretical parametric form for the production frontier (Cobb-Douglas function) determined by IT and non-IT capital. Biener, Eling, Wirfs (2014) conducted input-oriented data envelopment analysis (DEA) in order to extract Malmquist productivity indices (pertaining to total factor productivity and technical efficiency), and regressed the indices against measures of firm size, geographical diversification, intra-industry competition and other financial indicators.

After reviewing the methods proposed in the literature to measure firm performance and productivity, we conducted DEA analysis and derived the Malmquist total factor productivity index, along with its components, as a means to measure productivity change within firms (see section 3 for the complete methodology). DEA is, in fact, a mathematical model used for the evaluation of decision-making units' (DMU) productivity. This method uses several inputs and outputs to compare the productivity of relatively similar DMUs in a single time period (DMUs can refer to firms or countries). In this method, the efficient frontier curve is decided through a series of points that are designed via linear programing. The DEA of traditional data is regulated by the efficient (inefficient) frontier, which determines the best (worst) efficiency grade that can be assigned to a DMU. (Kaffash et al., 2013).

The Malmquist Index was introduced by Malmquist in 1953 in the context of consumer theory, and was later extended to other applications such as productivity change measurement. It is currently one of the most widely used methods that trace productivity over two periods of time. As we will show later in section 3, we can further decompose the Malmquist Index into technology change and efficiency change components. This is commonly used in research literature that conducts productivity estimation for insurance companies and other financial institutions (Leverty and Grace (2010), Weiss (1986), Eling and Luhnen (2010)).

The advantages of using DEA and Malmquist indices as the measures of productivity and productivity change are as follows (see Biesebroeck (2008), Grifell-Tatje and Lovell (1996) and Wang et al. (2012)):

- DEA does not assume a functional form for output or productivity.
- The underlying technology is entirely unspecified (unlike Ackerberg, Caves and Frazer and other similar literature that includes total factor productivity as a multiplier), and is allowed to vary across firms

- Each firm is considered a separate process that can be combined with others to replicate the production plan of the unit under investigation.
- After deriving the MPI from the DEA estimates, the index can be further decomposed into constituents pertaining to changes in efficiency and changes in technology (as we will show in section 3.

While we acknowledge the merits of the Malmquist index as a measure of productivity change, it is interesting to analyse if the relationship between productivity indicators and the variables of interest changes with the type of productivity indicator used. Furthermore, As such, we use other measure of productivity commonly used in industrial organisation literature, such the Ackerberg-Caves-Frazer framework and firm performance metrics, and study their relationships with our variables of interest as a means of robustness checks.

2.3 Productivity determinants in firms of other industries

For objectivity, we review literature on how Malmquist indices have been used as productivity measures and determinants of change in productivity in other industries. A. Assaf (2010) used bootstrapped Malmquist index methodology to measure and test the extent of efficiency and productivity changes in the UK airline sector. His results show that most airlines witnessed significant decreases in productivity, efficiency, technology and scale measures, and, by a second-stage Tobit regression, this was attributed to factors such as stage length, load factor and airline size. Hauner (2005) attempted to explain sources of efficiency differences between large German and Austrian banks, particularly in terms of cost-efficiency, scale-efficiency and productivity change. His results showed the following:

- State-owned banks are more cost-efficient (most likely due to cheaper funds), and cooperative banks are about as cost-efficient as private banks.
- Increasing economies of scale but decreasing economies of scope provide rationale for M&As among banks with similar product portfolios.
- Interbank and capital market funding is found to be more cost-efficient than deposits when the cost of retail networks is controlled for.

Latruffe, Davidova and Balcombe (2008) used a bootstrapped version of Malmquist indices (as per Simar and Wilson (1999)) to investigate productivity change in Polish farms, as well as its determinants. The latter was done by constructing a heteroskedastic panel regression with the Malmquist indices against land area, capital to labour ratio, share of commercialized output, and a binary variable for agricultural education, along with year dummies. The results showed, via the confidence intervals, that stagnation rather than productivity regress had occurred, and could be attributed to farming policies in Poland and high costs of land registration.

From the literature review done, the authors understand that many firm-level, industry-level and regional-level variables have significant relationships, both positive and negative, with firm performance. As such, in our analysis, we make a point to control for these variables. Some of the variables mentioned in the literature will be used as firm-level and industry-level controls in this paper.

2.4 Impact of technology adoption on general firm performance, or specific functions of insurance companies

Up to the point when this paper was written, there appear to be no means to quantify a variable like technology adoption as per the literature. As such, most papers use other observable variables as a proxy for technology adoption. One such example would be the amount of IT investment / expenditure incurred by the company. Interestingly, the literature diverges pertaining to whether technology adoption has positive or negative effects on firm performance. Francalansi and Galal (1998) found that the impact of IT expenditure was mixed at best, while the amount of IT expenditure tends to be higher in countries with greater managerial intensity. Loveman (1994) derived a negative relationship between IT capital and output, as well as no correlation between IT capital and labour productivity. Hu and Plant (2001) conducted a Granger causality test for return on equity (ROE) as a proxy for asset-normalized profitability and IT investment, and found that there was no statistically significant relationship between IT expenditure and firm profitability. They attributed it to the following reasons:

- Firms have failed to capitalize on IT investments over time.
- Overspending on IT infrastructure could have resulted in increased inefficiency instead.

Xiang, Kim, Lee, He (2010) published results indicating that IT investment has a statistically significant impact on only certain measures of firm performance measures such as profit margin and sales growth, but has a negligible relationship with others. Bazini (2015) conducted research based on collecting data from both primary (decision-maker (company management) surveys about ICT implementation within insurance companies in Albania.) and secondary (literature reviews of other studies), and found that a large proportion of managers (more than 80%) affirmed the increase in customer patronage after making the investment. Idson and Oi (1999) posit that workers are more productive in larger firms, which thus leads to higher wages. They attributed to larger firms tending to have better technologies, equipment and work organisations.

To the knowledge of the authors, the current literature does not include analyzing the impact of technology adoption/investment on firm productivity from a DEA/Malmquist Index perspective. As such, one contribution this paper makes would be to address this issue, and see if the impact, if any, remains robust when analyzing other measures of firm performance and economic productivity.

3. Productivity Measure: the Malmquist Productivity Index (MPI)

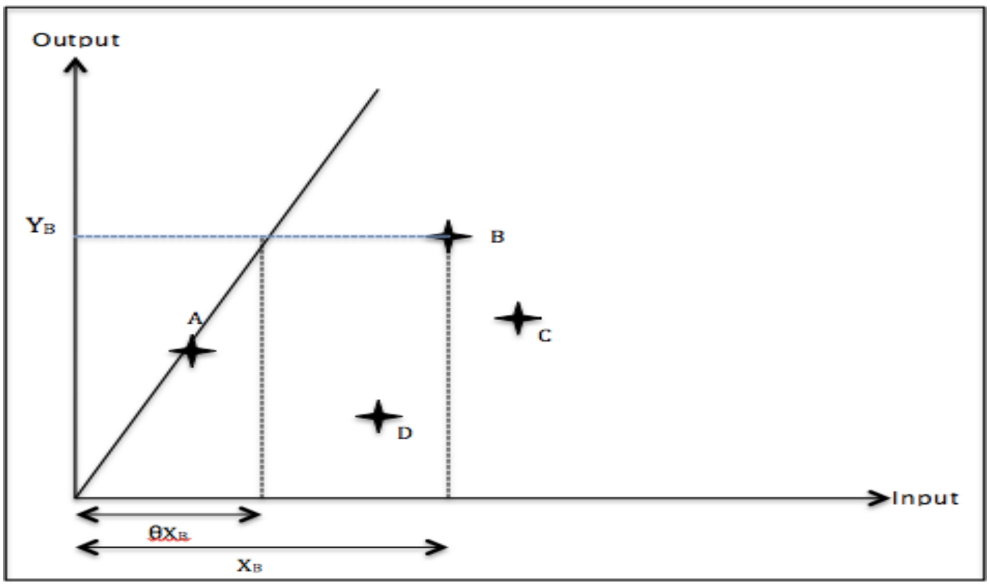
In the study, we carried out the analysis in two separate stages. The first stage involves estimating changes in productivity of Singaporean insurers via a bootstrapped Malmquist Index approach. In the second stage, we regress the derived productivity index in a panel Tobit regression to examine the relationship between productivity change (dependent variable), investment in technology and investment in employees (regressors), before and after controlling for other firm-specific and industry specific variables. The following section describes the computation and interpretation of the MPI, while section 5 specifies the regression model used.

3.1 Description

This study employs the MPI of DEA to quantify productivity changes of Singaporean general, life and composite insurers across several periods. By measuring changes in productivity, we can assess whether a change in efficiency has occurred. The MPI indices help us to better understand how benchmarking results change over time. The MPI was developed by Malmquist (1953), applied to frontier analysis with the creation of DEA, a non-parametric frontier estimation method created in Charnes et.al (1978). It was further developed by other authors such as Caves et al. (1982) and Fare et al. (1994), particularly as to its decomposition into its components. It essentially measures productivity changes across two periods of time, which result from changes in technical efficiency (also known as the catch-up effect), and changes in technology (also known as the frontier-shift effect). The catching-up effect defines how efficient a decision-making unit (DMU) transforms inputs into outputs, while the frontier-shift effect expresses technological improvement between the two time periods 1 and 2. These changes are in turn based upon a distance function approach. The reciprocal distance function is defined as the Farrell technical efficiency (as per Farell, 1957), whereas the input distance function is defined as the distance between the point of production and the ideal point near the minimum input level.

For simplicity of explanation, we assume a single input and output x and y respectively, as well as a constant-returns to scale technology. We also assume an input-based approach to evaluate the index. For the first part, the DEA index measures the distance of a decision-making unit's (DMU) input/output bundle from the production frontier given a technology at either time t or time t+1. This can be seen from the following:

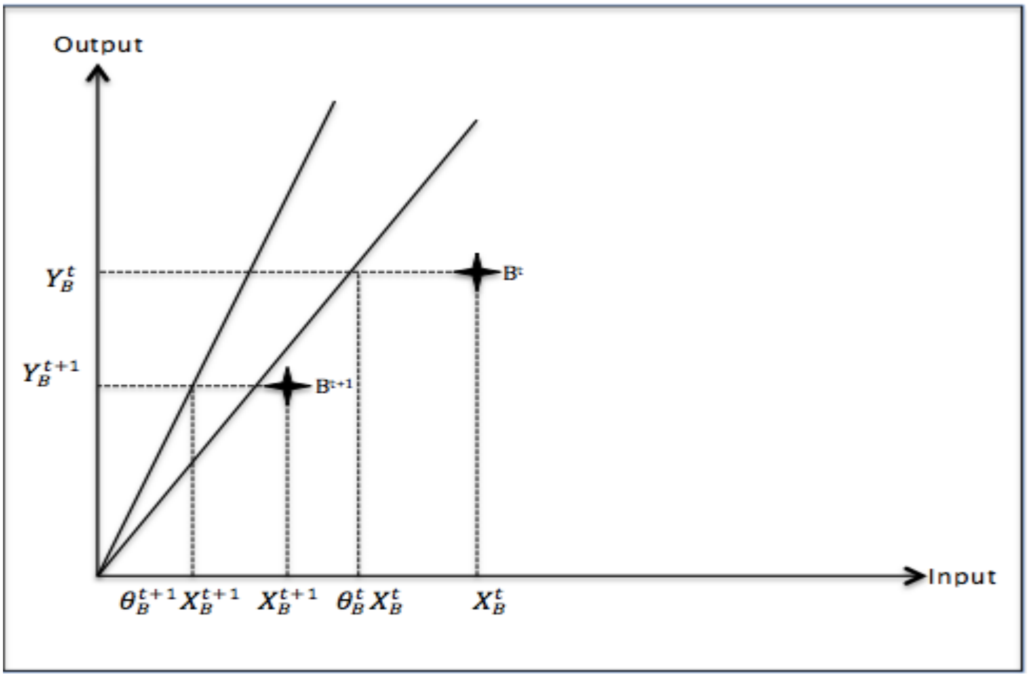
Figure 1: DEA Analysis



Source: Author's impression

As seen from Figure 1, the production possibility frontier at a time t was generated with the assumption that company A is the most productive among the sample firms, as seen from the fact that it has the highest output/input ratio. Observing firm B, we see that given an output Y_B, it uses X_B amount of input to generate said output. However, we can see from the frontier generated that to produce the same amount of output, only $\theta_B X_B$ amount of input is required. As such, θ_B, which is the distance function between company B and the frontier, represents the proportion that firm B can scale back its inputs used.

Figure 2: Frontier Analysis across time t and time t+1



Source: Author's impression

Figure 2 shows how this relates to productivity change over two periods of time. Suppose we have a firm B that produces at point B_t at time t and point B_{t+1} at time t+1. In order to derive the Malmquist Index, we must first denote a new distance function $d_0^{t_2}(x_{t_1}, y_{t_1})$, whereby $d_0^{t_2}(x_{t_1}, y_{t_1}) = {\theta_B^{t_2} X_B^{t_2}}/{X_B^{t_1}}$.

Taking technology at time t as reference.

$$M_0^t(x_{t+1}, y_{t+1}, x_t, y_t) = \frac{d_0^t(x_{t+1}, y_{t+1})}{d_0^t(x_t, y_t)}$$

Taking technology at time t+1 as reference

$$M_0^{t+1}(x_{t+1}, y_{t+1}, x_t, y_t) = \frac{d_0^{t+1}(x_{t+1}, y_{t+1})}{d_0^{t+1}(x_t, y_t)}$$

To prevent arbitrariness, we take the geometric mean of the 2 methods (as per Fare et Al. (1994)).

$$M_0^{t.t+1}(x_{t+1}, y_{t+1}, x_t, y_t) = \left[\frac{d_0^{t+1}(x_{t+1}, y_{t+1})}{d_0^{t+1}(x_t, y_t)} \times \frac{d_0^t(x_{t+1}, y_{t+1})}{d_0^t(x_t, y_t)}\right]^{\frac{1}{2}} \qquad (1)$$

By Caves, Christensen, Diewert (1982), we can further decompose the right hand side of the equation as shown below:

$$M_0^{t.t+1}(x_{t+1}, y_{t+1}, x_t, y_t) = \frac{d_0^{t+1}(x_{t+1}, y_{t+1})}{d_0^t(x_t, y_t)}\left[\frac{d_0^t(x_{t+1}, y_{t+1})}{d_0^{t+1}(x_{t+1}, y_{t+1})} \times \frac{d_0^t(x_t, y_t)}{d_0^{t+1}(x_t, y_t)}\right]^{\frac{1}{2}} \quad (2)$$

= TECHEFFCHANGE × EFFICHANGE

Equation 1 shows that the MPI is essentially the product of technical efficiency progress, which is the first ratio on the right hand side of the equation and technology change, which is the second ratio of the right hand side of the equation. A MPI score greater than one indicates productivity growth from period t to t+1, while a MPI score less than unity implies productivity regress over time. This applies to the scores of the catching-up and frontier-shift effects as well. The technical efficiency change can be further decomposed into pure technical efficiency change (i.e. relative to a variable returns-to-scale technology) and scale efficiency change, as shown below.

$$M_0^{t.t+1}(x_{t+1}, y_{t+1}, x_t, y_t) = \frac{d_v^{t+1}(x_{t+1}, y_{t+1})}{d_v^t(x_t, y_t)} \times \left[\frac{d_v^t(x_t, y_t)}{d_c^t(x_t, y_t)} \div \frac{d_v^{t+1}(x_{t+1}, y_{t+1})}{d_c^{t+1}(x_{t+1}, y_{t+1})}\right]$$

$$\times \left[\frac{d_c^t(x_{t+1}, y_{t+1})}{d_c^{t+1}(x_{t+1}, y_{t+1})} \times \frac{d_c^t(x_t, y_t)}{d_c^{t+1}(x_t, y_t)}\right]^{\frac{1}{2}} \quad (3)$$

= PUREEFFCHANGE × SCALEEFFCHANGE × TECHEFFCHANGE

Note that for the distance functions above, the subscripts c and v indicate the assumption on the type of returns to scale (constant VS variable respectively). The former is as defined as above, while the latter is similarly defined, but with the additional constraint on the distance function such that they sum to unity.

To formalize the generalisation of the distance function in DEA and MPI, we can express the formulation of the distance function as derived by Charnes, Cooper and Rhodes in 1978 (CCR), as shown below.

$$\min_{\lambda_j} \theta_0$$

$$s.t. \sum_{j=1}^{n} \lambda_j x_{ij} \ \leq \theta_0 x_{i0}$$

$$\sum_{j=1}^{n} \lambda_j y_{rj} \ \geq y_{r0}$$

$$\lambda_j \ \geq 0, \qquad j = 1, \dots, n$$

where x_{ij} and $y_{rj}$are the i_{th} and r_{th} input (out of m inputs) and output (out of s outputs) of firm j respectively, λ_j represents the intensity variable which serves to form the convex combinations of data to form the production frontier, and terms with a 0 index refer to the variables pertaining to the firm being evaluated. The first two constraints imply that any choice of x_{ij} and y_{rj} are bounded within an estimated production frontier, as defined below:

$$P = \left\{(x, y) \epsilon \ R_+^m \times R_+^s : (x, -y) \geq \sum_{j=1}^{n} \lambda_j \big(x_j, -y_j\big), \lambda_j \geq 0, j = 1, \dots, n\right\}$$

After deriving the estimates of θ_j, the Malmquist index can be defined as shown earlier.

3.1.1 Malmquist TFP change and Solow residuals

Fare et al. (2011) showed how the Malmquist index could be computed and interpreted as one form of the Solow residual, assuming that productivity change is only caused by technology change. Suppose we assume, as Solow did, that the technology at any time t could be represented by a production function i.e., we assume that a single output is produced by multiple inputs (for now we assume an output-based approach). This is as defined below:

$$A(t).F(x^t) = Max\{y^t : (x^t, y^t) \in P^t\}$$

Note that we can also relate this to the distance functions used to define the Malmquist index, as shown below.

$$A(t).F(x^t) = Max\{y^t : D_0(x^t, y^t) \leq 1\}$$

$$= Max\left\{y^t : D_0(x^t, 1) \leq {}^{1}/_{y^t}\right\}$$

$$= {}^{1}/_{D_0(x^t, 1)}$$

As such, the output distance function may be written as

$$D_0(x^t, y^t) = {}^{y^t}/_{A(t).F(x^t)}$$

which expresses how many times more output can be scaled up. We also assume, as assumed by Solow, that the technical change is Hicks-neutral, which means that the production function can also be written as:

$$y^\tau = A(\tau).F(x^t)$$

After substituting this equation into the definition of the MPI as in (1), we get the following:

$$M_0(x^t, y^t, x^{t+1}, y^{t+1}) = \left(\frac{{}^{y^{t+1}}/_{A(t+1).F(x^{t+1})}}{{}^{y^t}/_{A(t+1).F(x^t)}} \times \frac{{}^{y^{t+1}}/_{A(t).F(x^{t+1})}}{{}^{y^t}/_{A(t).F(x^t)}} \right)^{1/2}$$

$$= {A(t+1)}\Big/{A(t)}$$

From the final equation, we can see that in the single output case, the MPI is coincident to the Solow residual. Note that if efficiency change is present (firm does not produce at the frontier), we can simply treat y^t as a scalar multiple of $A(t).F(x^t)$, where the scalar multiple indicates the firm's output as a fraction of its production frontier.

3.2 Bootstrapping of Malmquist Indices

One issue that arises when directly computing and measuring MPI is that it does not differentiate between the underlying true distance functions and their estimates (Fare et al, 1994). In fact, certain literature on non-parametric efficiency measurement, such as Lovell (1993), stated that non-parametric, linear programming approaches to efficiency measurement should be counted as deterministic measures, indicating that such approaches may not be grounded on statistical methods. However, if one sees production data as having been generated from a distribution with bounded support over the true production set, then efficiency, changes in productivity and technology are always measured relative to estimates of underlying, true frontiers, conditional on observed data resulting from the underlying (unobserved) data generating process. This results in estimators that are downward biased, and the rate of convergence towards the true value falls as the number of inputs and outputs increases.

Simar and Wilson (1998) developed a bootstrap technique that estimates confidence intervals for distance functions used to measure technical efficiency, and showed that statistically estimating consistent confidence intervals involves replication of the unobserved data-generating process. Simar and Wilson (1999) further extends this to Malmquist indicators through a smoothed homogeneous bootstrap method, since they are constructed from nonparametric distance function estimates using data from different time periods.

The procedure is as follows:

1) Compute the technical efficiency, $\hat{\theta}$, of the sample general insurers using the equation below.

$$Min\left\{\theta \mid y \leq \sum_{j=1}^{n} \lambda_j y_j \,; \theta x \;\geq \sum_{k=1}^{m} \lambda_k x_k \quad \theta > 0, \lambda_j \;\geq 0, j = 1, \ldots, n, k = 1, \ldots, m\right\}$$

where θ is a real variable, x and y are input and output vectors, respectively, and λ_j and λ_k represent the weights for output j and input k respectively.

2) Generate a pseudo sample from $\hat{\theta}_j$ to obtain $\theta_1^*, \ldots, \theta_n^*$ by using the smoothed bootstrapping method.

3) Repeat step 2 B times to provide a set of bootstrap samples.

4) Measure the distance functions, $\widehat{D}_b^t(x^t, y^t)$, $\widehat{D}_b^t(x^{t+1}, y^{t+1})$, $\widehat{D}_b^{t+1}(x^t, y^t)$, $\widehat{D}_b^{t+1}(x^{t+1}, y^{t+1})$, between t and *t+1* to obtain bootstrap estimates for each insurer. From this, construct B bootstrap estimates for MPI.

5) Estimate the confidence intervals for each insurer. The MPI, catch-up effect and frontier-shift effect must be corrected for bias, which results in increased error variance, as shown in Simar and Wilson (2000).

4. Data

4.1 Description

For the purpose of this study, we constructed a panel dataset of insurance companies observed over 7 years. To start off, we collected data from the following sources, and did a round of filtering of sample observations as per the following:

For the raw data, sample insurers are all licensed insurers (general, life, composite) identified on the website of Monetary Authority of Singapore (MAS) with complete panels. We collect firm level and industry level data from the Insurance Company Returns Reports (Cadenza Reports) published on the MAS website. We excluded firms that reported certain essential financial variables as 0 or "-" (one such example would be staff expenses, since it does not make sense that companies do not incur such expenses since they pay out salaries). After this round of exclusion, we are left with 35 firms. All variables required for the analysis have been adjusted for inflation, using inflation data from the Department of Statistics data portal (Singstat).

4.2 Summary statistics

4.2.1 Inputs and Outputs for MPI Computation

Based on previous literature, we applied the value-added (production) approach as recommended by Cummins and Weiss (2013). We based the choice of inputs and outputs used on the three major functions of insurance companies as defined by most researchers, as per above.

- *Risk pooling and risk bearing*. Insurance provides a mechanism through which consumers and businesses exposed to losses can engage in risk reduction through pooling. The actuarial, underwriting, and related expenses incurred in risk pooling are important components of value added in the industry. Insurers also add value by holding equity capital to bear the residual risk of the pool.

- *Financial services pertaining to the insuring of insurable losses*. Insurers provide a variety of real services for policyholders including financial planning, risk management, and the provision of legal defence in liability disputes.

- *Intermediation*. For life insurers, financial intermediation is a principal function, accomplished through the purchase and sale of asset accumulation products such as annuities. For non-life insurers, intermediation is an important but incidental function, resulting from the collection of premiums in advance of claim payments. Insurers' value added from intermediation is reflected in the net interest margin between the rate of return earned on invested assets and the rate credited to policyholders.

As such, we selected the inputs and outputs for the MPI frontier as shown below:

4.2.1.1 Inputs

- *Operating expenses*. This follows the methodology as stated in Eling and Luhnen (2010) and Ennsfellner et al. (2004). This variable is simply calculated as the sum of expenses pertaining to the insurance company’s operations. For the case of this study, we define it as the sum of the insurer’s expenses pertaining to management and distribution. Traditionally, the literature suggests that the variables used should be labour, business services and capital as inputs. However, due to limited data availability, we aggregate and proxy them as operating expenses.

- *Surplus*. This follows the methodology as stated in Cummins and Rubio-Misas (2006), Cummins et al. (2004), and Jeng and Lai (2005), and is defined as the amount of capital owned as equity by the insurer. Equity capital is an important input in insurance because insurers must hold equity to ensure policyholders that they will receive payment if claims exceed expectations and to satisfy regulatory requirements. The variable was taken as recorded in the Cadenza documents.

- *Debt capital*. This follows the methodology as stated in Cummins and Rubio-Misas (2006), Cummins et al. (2004), Eling and Luhnen (2010), and is defined as the amount of capital owned as debt by the insurer. Debt capital is important since it provides an alternative source of funds from borrowed funds and deposits from reinsurance companies. The variable was taken as recorded in the Cadenza documents.

4.2.1.2 Outputs

- *Policy Benefits Claimed + additions to reserves*. This follows the methodology as stated in Barros et al. (2005), Cummins et al. (2004) and Ennsfellner et al. (2004), and is defined as the losses/claims paid out in year t added with reserves accumulated by the insurer in that year. Since transactions flow data such as the number of policies issued, the number of claims settled, etc. are not publicly available for access, we use this variable as a proxy for risk pooling and financial services. The variable was derived by summing up the variables 'Total claims made' and 'Reserves accumulated', which were as recorded in the Cadenza documents.

- *Total investment*. This follows the methodology as stated in Eling and Luhnen (2010), Ennsfellner et al. (2004) and Jeng and Lai (2005), and is defined as the total investments made into different asset classes. The total value of invested assets is treated as a proxy for financial intermediation, since it is derived from the inflow and outflow of asset purchases. The variable was derived by summing up the amount of investment to all asset classes as stated in the Cadenza documents.

Table 1:

Definition of input and output variables

Type	Variable	Definition

Inputs	Operating Expenses (x_1)	Sum of expenses pertaining to management and distribution.
	Surplus (x_2)	Amount of capital owned as equity
	Debt Capital (x_3)	Amount of capital owned as debt
Outputs	Policy Benefits Claimed + reserves (y_1)	Losses/claims paid out in year t added with reserves accumulated in that year.
	Investment (y_2)	Total investments made into different asset classes.

We calculated the growth rates of the input and output variables over the period of interest (2011-2017) as shown below:

Type	Variable	Growth Rate (%) (2011 – 2017)
Inputs	Operating Expenses (x_1)	62.11
	Surplus (x_2)	73.81
	Debt Capital (x_3)	49.37
Outputs	Policy Benefits Claimed + reserves (y_1)	86.53
	Investment (y_2)	45.00

From the results above, we see that not all output variables have necessarily grown at a faster rate than all input variables, or vice versa. As such, it can be shown that there is no clear indication whether inputs or outputs have grown at a faster rate than the other. An interpretation of this could be that, at this stage of the analysis, it is still uncertain whether there is any effects of productivity increases over the time period of interest on output changes. As such, the objective of our analysis becomes more well-defined by decomposing it into two parts: firstly, to observe how firm productivity changes over the stipulated time period, and how this change can be correlated with technology and staff investments.

4.2.2 Regressors

For this particular study, investments in technology, and investment in employees are the main variables of interest. Many researchers have attempted to derive the determinants of insurer productivity by directly regressing the bootstrapped MPI indices against different types of firm-level financial variables (see section 2 for details). Based on what the author knows about the current literature, there is no paper that attempts to examine the impact of technology investment on productivity change as measured by the MPI indices. We examine the following measure of technology investment: investment in information technology (IT) equipment.

4.2.2.1 Investment in information technology (IT) equipment ($ITINVEST_t$)

This variable essentially measures the amount of capital invested into information technology infrastructure and equipment, such as computer systems, telecommunication networks, etc. Due to lack of availability of data, the author uses this as a proxy for the degree of technology adoption, since it accounts for the fact that technologies incorporated into insurance operations such as big data management and digital direct-to-client interfaces require more sophisticated computing infrastructure to operate.

However, we note that any form of investment made into IT equipment at time t may not necessarily translate to a positive impact on productivity at time t. It could even translate to a negative impact on productivity, since technically it is considered a cost to the company at time t. Furthermore, the effects of the technology invested into the performance of the firm may require a certain period of time before they are felt. As such, we include lags of $ITINVEST_t$ at time *t-1*, *t-2* and *t-3* in the regression (as in $ITINVEST_{t-1}$ $ITINVEST_{t-2,}$ $ITINVEST_{t-3)}$, which would allow us to examine the duration needed for the productivity impacts of IT investment to be felt.

4.2.2.2 Investment in employees ($STAFFCOST_t$)

This variable measures the total expenses to the insurer pertaining to employees. The authors use this variable as a proxy for employee benefits and enhancement, since other than salaries, any additional expense to staff could be attributed to investments to improving the overall quality of the working environment for employees, such as through performance bonuses or skills retraining, which could help increase labour productivity, and hence general productivity, within the company.

Similarly to the case of investment in IT equipment, we include lags of $STAFFCOST_t$ at time *t-1*, *t-2* and *t-3* in the regression (as in $STAFFCOST_{t-1}$ $STAFFCOST_{t-2}$, $STAFFCOST_{t-3}$), which would allow us to examine the duration needed for the productivity impacts of IT investment to be felt.

4.2.3 Control variables

We follow the convention in prior literature in the sense that we include various control variables in the regression model to control for other factors that may affect productivity changes as discussed in the literature review, so as to ensure robustness of results pertaining to the effects of our regressors on productivity change. Furthermore, some of the control variables included were previously used in other literature as independent variables.

Table 2 summarises the above content pertaining to regressors and control variables. It also includes the expected sign of the regression coefficients should the MPI be regressed against these variables, as per the literature.

Table 2:

Definition of regressors and control variables

Type	Variable	Explanation	Expected Sign
Regressors	Investment in IT equipment (ITINV, SGD mil)	Represents amount invested into information technology equipment, computers, etc	(+)
	Investment in staff enhancement (STAFFCOST, SGD mil)	Represents amount of investment into staff enhancement and retraining	(+)
Firm-Level	Log of gross written premium and annuity revenue (*LPREANNREV*)	Represents revenue stream	(+)
	Log of total assets (*LTOTASSET*)	Represents company size	(+/-)

	Equity turnover (SOLV)	Represents company 's ability to generate revenue via equity	(-)
	Insurance leverage ratio (*ILR*)	Represents liquidity. Calculated by the ratio of technical provisions to surplus (equity)	(-)
	Expense revenue ratio (*EXPREV*)	Represents expense management. Calculated by total expenses over total revenue	(-)
	Equity Asset ratio (*EAR*)	Represents debt gearing. Calculated as total surplus (equity) over total assets	(+)
	Return on equity (*ROE*)	Represents the ability of company to generate returns	(+)
Industry Level	LIFE	Binary variable that takes the value 1 if, in year t, the insurer is in the life insurance business only, 0 if it is not.	(+/-)
	COMPOSITE	Binary variable that takes the value 1 if, in year t, the insurer is in both the life and general insurance businesses, 0 if it is not.	(+/-)

4.3 Descriptive statistics of variables

Table 4 (see Appendix C) presents the descriptive statistics of the independent variables and controls by year. From the table, it can be seen that on average, both IT investment and investment in staff have increased from 2011-2012 to 2016-2017. While this may point towards a possible link between both types of investment and productivity change, it is premature to conclude so. As such, we proceed with the panel Tobit regression.

5. Regression model

As highlighted in Banker (1993) and Banker and Natarajan (2008), the use of a two-stage DEA procedure followed by regressing the Malmquist estimates against other regressors will result in consistent estimators of the regression coefficients. Since we use panel data for the analysis, as well as the fact that the Malmquist indices have a lower limit of 0, we ran a panel Tobit regression using the regressors and control variables, as shown below.

Regression without controls:

$$Y_{i,t} = \beta_0 + \sum_{j=0}^{3} \beta_{j+1} ITINV_{i,t-j} + \sum_{j=0}^{3} \beta_{j+5} STAFFCOST_{i,t-j} + \alpha_i + \varepsilon_{i,t} \quad (3)$$

Regression with firm-level controls:

$$Y_{i,t} = \beta_0 + \sum_{j=0}^{3} \beta_{j+1} ITINV_{i,t-j} + \sum_{j=0}^{3} \beta_{j+5} STAFFCOST_{i,t-j} + FIRM_{it} + \alpha_i + \varepsilon_{i,t} \quad (4)$$

Regression with firm and industry-level controls:

$$Y_{i,t} = Y_{i,t} = \beta_0 + \sum_{j=0}^{3} \beta_{j+1} ITINV_{i,t-j} + \sum_{j=0}^{3} \beta_{j+5} STAFFCOST_{i,t-j} + FIRM_{it} + INDUSTRY_{it} + \alpha_i + \varepsilon_{i,t} \quad (5)$$

Where $Y_{i,t}$ represents the Malmquist index used,

$$FIRM_{it} = \sum_{j=1}^{6} \beta_{j+9} FIRM_{j,i,t}$$

$FIRM_{j,i,t}$ represents a firm level indicator of firm *i* as in Table 3 at time *t*, and

$$INDUSTRY_{it} = \beta_{16} LIFE_{i,t} + \beta_{17} COMPOSITE_{i,t}$$

α_i represents the time-invariant fixed effect.

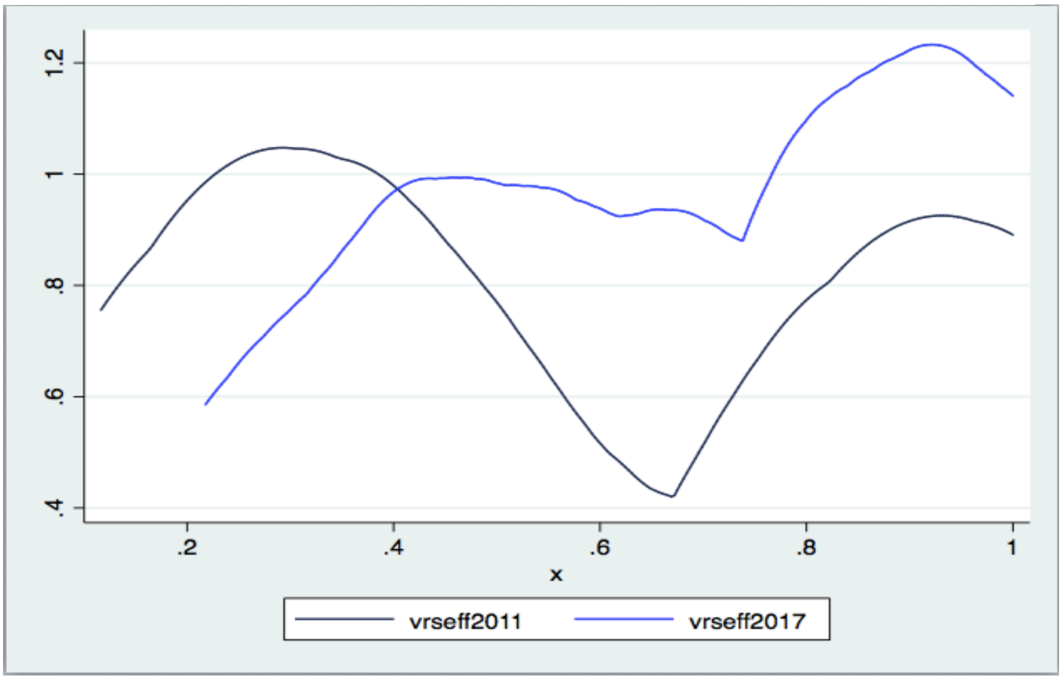
Examining the signs of β_1 to β_8 will not only give us a better understanding of the effect of IT investment and staff investment on productivity, but also how long does it take for productivity gains/losses arising from these investments to be realized.

6. Results

6.1 Productivity Distribution

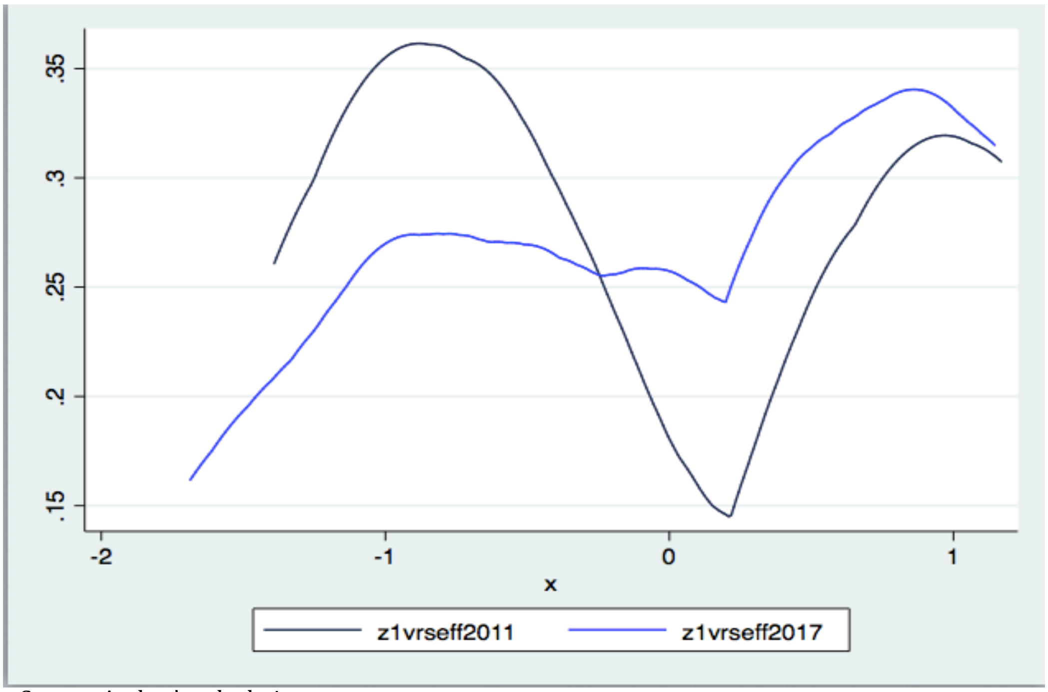
Figure 3 shows the distribution of insurers' DEA productivity index in 2011 and 2017. As shown, a larger proportion of insurers have DEA indices that are closer to unity (which indicates full efficiency) in 2017 than in 2011, both before and after standardizing the indices. This difference in distribution is statistically significant, as after conducting the Wilcoxon signed rank test (since sample data does not follow normal distribution). Since we also wish to examine whether the changes in productivity were significant, we examine the Malmquist index-based productivity change from 2011 – 2017, as shown in Table 4.

Figure 3: Productivity Distributions Before Standardisation, 2011 and 2017



Source: Author's calculation

Figure 4: Productivity Distributions After Standardisation, 2011 and 2017



Source: Author's calculation

Table 4:

Decomposition of MPI (2011 – 2017)

Insurer Name	TFP (MPI)	EFF	TECH	PUREEFF	SCALEEFF
AIA Singapore Private Limited	0.935	0.530	1.765	1.000	0.530
AIG Asia Pacific Insurance Pte. Ltd.	1.032	0.646	1.597	1.407	0.459
AXA Insurance Pte Ltd	1.135	0.500	2.269	1.449	0.345
Aviva Ltd	1.616	0.995	1.625	2.482	0.401
Axis Specialty Limited (Singapore Branch)	0.401	0.316	1.271	0.365	0.865
China Taiping Insurance (Singapore) Pte. Ltd.	1.587	0.765	2.074	3.990	0.192
Chubb Insurance Singapore Limited	1.038	0.819	1.268	0.982	0.834

Cigna Europe Insurance Co S.A.-N.V., Singapore Branch	0.691	0.366	1.889	0.464	0.789
Coface, Singapore Branch	0.121	0.119	1.022	0.289	0.411
Direct Asia Insurance (Singapore) Pte Ltd	0.927	1.000	0.927	1.000	1.000
EQ Insurance Company Ltd.	1.505	0.761	1.976	0.618	1.232
ERGO Insurance Pte. Ltd.	2.292	1.231	1.862	1.370	0.898
Etiqa Insurance Pte. Ltd.	1.408	0.782	1.800	0.790	0.990
Friends Provident International Ltd (Spore Branch)	1.172	1.000	1.172	1.000	1.000
Generali International Limited	5.431	2.815	1.929	1.000	2.815
Great Eastern Limited	2.968	1.125	2.638	1.000	1.000
HSBC Insurance	0.425	0.867	0.490	0.868	0.999
India International Insurance Pte Ltd	0.699	0.650	1.075	0.716	0.907
Liberty Insurance Pte Ltd	0.868	0.528	1.644	0.770	0.686
Lonpac Insurance Berhad	2.780	1.000	2.780	1.000	1.000
MSIG Insurance (Singapore) Pte. Ltd.	0.914	0.555	1.648	1.417	0.392
Manulife (Singapore) Pte. Ltd.	1.314	0.726	1.809	1.549	0.469
NTUC Income Insurance Co-operative Limited	1.148	0.709	1.619	1.000	0.709
Old Mutual Intl Isle Of Man Limited S'pore Branch	1.070	1.000	1.070	1.000	1.000

QBE Insurance (Singapore) Pte. Ltd.	1.807	1.199	1.508	1.330	0.901
Sompo Insurance Singapore Pte. Ltd.	0.109	0.102	1.075	0.145	0.702
Swiss Life (Singapore) Pte. Ltd.	1.057	1.000	1.057	1.000	1.000
Swiss Re International Se, Singapore Branch	1.259	0.613	2.053	0.901	0.681
Tokio Marine Insurance Singapore Ltd	1.981	1.375	1.441	4.029	0.341
Transamerica Life (Bermuda) Ltd. (S'pore Branch)	3.896	2.787	1.398	3.920	0.711
United Overseas Insurance Ltd	1.283	0.585	2.194	3.074	0.190
XL Insurance Company Se Singapore Branch	0.862	0.517	1.669	2.342	0.221
Zurich International Life Limited (S'pore Branch)	2.253	1.048	2.150	1.118	0.938

This table indicates the MPI, or total factor productivity change occurring from 2011 – 2017, as well as its components of technology change and efficiency change. Indices greater than 1 indicates productivity progress, while indices less than 1 indicates productivity regress.

As seen from Table 4, 22 out of 34 insurance companies in the dataset have an MPI score greater than 1. This indicates that most of the companies experienced an increase in total factor productivity (TFP) during the sample period 2011 to 2017. We conducted a Pearson correlation test on the MPI index and its components for the years from 2011 – 2017 (see Appendix B), and found that TFP change can be attributed to both improvements in technology and improvements in efficiency albeit to a slightly lower extent.

6.2 Regression results

Table 6 (see Appendix C) reports the results of the panel Tobit regression as in (3). To begin with, we note from the first column that the innovation readiness ranking, staff enhancement investment and IT investment are positively and significantly correlated with TFP change (TFPCHANGE). To go into specifics, however, we note that the coefficients are only positively significant for the following regressors:

- $ITINVEST_{t-2}$
- $STAFFCOST_{t-1}$

This could be interpreted as the following (before controlling for other variables):

- On average, for every additional 1 thousand dollars invested in IT two periods before, the insurer experiences additional TFP gain.

- On average, for every additional 1 thousand dollars invested in staff enhancement one period before, the insurer experiences additional TFP gain.

Column 2 of Table 6 indicates that technology investment at time t-2 and staff enhancement investment at time t-1 is positively and significantly correlated with technology improvement. Column 3 of Table 6 indicates that staff enhancement investment at time t-1 is positively and significantly correlated with efficiency improvement in insurers.

Table 7 reports the results of the panel Tobit regression, both before and after controlling for firm-level and both firm-level and industry-level variables respectively, particularly while setting TFPCHANGE and TECHEFFCHANGE as the dependent variables (for full details of regression results, see Appendix). Interestingly, after controlling for firm level variables, we note the following:

- The coefficients for $ITINVEST_{t-2}$, and $STAFFCOST_{t-1}$ in column 1 have now become more statistically positively significant.

- Interestingly, the coefficients for $ITINVEST_{t-3}$ and $STAFFCOST_{t-2}$ are negative and statistically significant when TECHEFFCHANGE is regressed against them.

6.3 Robustness checks

While the results shown in section 6.2 have generally indicated positive effects of IT and staff investments on insurer productivity, it is important to assess whether these effects are applicable to general firm performance, or at least other measures of firm productivity. Furthermore, we wish to see if the above results still hold in accordance with traditional economic measures of firm productivity. As such, we conduct panel regressions using the same regressors and control variables, but with other measures of firm productivity, as well as other measures of firm performance such as profitability.

For the first round of robustness checks, we will be utilizing the Ackerberg, Caves and Frazer (2006) (ACF) framework to estimate productivity. This is because not only does it incorporate the benefits of the methodologies described in Olley-Pakes (1996) and Levinsohn-Petrin (2000), but also accounts for some collinearity issues that could arise from them, as we will show later. A description of the ACF method can be found in Appendix E.

6.3.1 Results

Table 8 shows the results of implementing the Ackerberg-Caves-Frazer framework to the data. We observe that the coefficient for $STAFFCOST_{t-1}$ is still statistically significant before and after controlling for firm level and industry level variables. This implies that the positive relationship between staff investment at time t-1 and productivity measured by the Ackerberg-Caves-Frazer (2006) framework still holds after changing the productivity measure. However, we note that the coefficient for $ITINVEST_{t-2}$ is only statistically significant before including controls, and not statistically significant after controlling for firm level and industry level variables. This indicates that investment in IT equipment in time t-2 may not result in an increase in productivity in time t as measured by the Ackerberg-Caves-Frazer (2006) framework, once w take into account other firm-level and industry level variables. However, it is still to be noted that the coefficient is still positive, which could imply that the positive correlation still holds some merit.

6.3.2 Other performance measures

We also analyse the relationship between our variables of interest and other firm performance measures. Table 9 shows the results of the panel regression model conducted using return on equity (ROE_t) and value-add per unit intellectual capital ($VAIC_t$) as dependent variables. ROE is calculated as net profit over total surplus (equity) at time t, which can be interpreted as a profitability measure normalized by the total equity value held by the insurer. $VAIC_t$ is calculated as value-add (VA) over total invested capital, whereby VA is calculated by net profit plus staff costs, as shown by Pulic (2000). In other words, $VAIC_t$ can be interpreted as the production or value-add of the insurer per unit investment. Stahle et al. (2011) goes even further to posit that VAIC, rather having anything to do with intellectual capital as was originally intended, should be interpreted as the productive efficiency of the insurer's labour and capital investments.

From table 9, we note the following:

- The coefficient for $ITINVEST_{t-2}$ is positive and statistically significant, both before and after controlling for firm level and industry level variables. This indicates that investment in IT equipment in time t-2 results in an increase in productivity in time t as measured by VAIC.

  Coefficient for $STAFFCOST_{t-1}$ is still statistically significant before and after controlling for firm level and industry level variables. This implies that the positive relationship between staff investment at time t-1 and productivity measured by VAIC still holds after changing the productivity measure.

Table 7	Dependent Variables					
	(1) TFPCHANGE	(2) TECHEFFCHANGE	(3) TFPCHANGE	(4) TECHEFFCHANGE	(5) TFPCHANGE	(6) TECHEFFCHANGE
$STAFFCOST_{t-1}$	**0.00156** **(0.00127)**	**0.00281*** **(0.00122)**	**0.00368**** **(0.00110)**	**0.00272*** **(0.00132)**	**0.00688**** **(0.00223)**	**0.00314*** **(0.00149)**
$STAFFCOST_{t-2}$	-0.00228 (0.00195)	-0.00331* (0.00165)	-0.00186 (0.00192)	-0.00302** (0.00116)	-0.00329 (0.00185)	-0.00321* (0.00147)
$STAFFCOST_{t-3}$	-0.00212 (0.00161)	-0.000712 (0.00125)	-0.00167 (0.00150)	-0.000831 (0.00116)	-0.00218 (0.00162)	-0.000895 (0.00111)
$ITINV_{t-1}$	-0.00617 (0.00422)	-0.00155 (0.00461)	-0.00401 (0.00863)	-0.00125 (0.00718)	-0.00411 (0.00559)	-0.00125 (0.00641)
$ITINV_{t-2}$	**0.0260**** **(0.00862)**	**0.0253***** **(0.00660)**	**0.0239***** **(0.00648)**	**0.0251***** **(0.00696)**	**0.0281***** **(0.00589)**	**0.0256***** **(0.00743)**
$ITINV_{t-3}$	-0.00306 (0.00579)	-0.0162*** (0.00409)	-0.00511 (0.00510)	-0.0162** (0.00505)	-0.00672 (0.00442)	-0.0164*** (0.00366)
Controls						
Firm-Level			✓	✓	✓	✓
Industry Level					✓	✓

Dependent variables are as follows: TFPCHANGE (MPI) and TECHEFFCHANGE (technology change). Variables of interest are STAFFCOST (investment in staff) and its lags up to 3 periods, and ITINV (investment in IT equipment) and its lags up to 3 periods. (3) and (4) control for firm-level variables only, while (5) and (6) control for both firm and industry-level variables. Firm-level and industry-level controls are as per in table 3. Standard errors are shown in parentheses.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 8	Dependent Variables		
	(1)	(2)	(3)
	ACFPROD	ACFPROD	ACFPROD
$STAFFCOST_{t-1}$	**2.039****	**2.653***	**2.653***
	(0.748)	(1.210)	(1.229)
$STAFFCOST_{t-2}$	-0.328	-0.342	-0.342
	(0.174)	(0.332)	(0.232)
$STAFFCOST_{t-3}$	0.0443	0.0582	0.0582
	(0.139)	(0.198)	(0.169)
$ITINV_{t-1}$	0.0680	-0.352	-0.352
	(1.620)	(1.628)	(2.272)
$ITINV_{t-2}$	**3.187***	**2.149**	**2.149**
	(1.534)	**(1.946)**	**(1.360)**
$ITINV_{t-3}$	-0.244	-0.459	-0.459
	(1.149)	(1.196)	(1.004)
Controls			
Firm-level		✓	✓
Industry-level			✓

Dependent variables are as follows: ACFPROD (annual productivity change as per Ackerberg-Caves-Frazer). Variables of interest are STAFFCOST (investment in staff) and its lags up to 3 periods, and ITINV (investment in IT equipment) and its lags up to 3 periods. (3) and (4) control for firm-level variables only, while (5) and (6) control for both firm and industry-level variables. Firm-level and industry-level controls are as per in table 3. Standard errors are shown in parentheses.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

7. Discussion

7.1 Implications

Amidst the fast-changing competitive environment of today's insurance industry, any insurance company, small or large, has to strive in order to remain profitable, productive and relevant. From the preliminary analysis on productivity changes via the MPI, we see that in general, a large majority of insurers have observed an increase in productivity over the sample period from 2011 - 2017. As shown from the correlation coefficients between the MPI index and its constituents, it can be posited that the increase in productivity is largely driven by improvements to the current technology of the time. However, at this point, it remains to be seen if and how insurers have been able to capitalize on the improvements in technology to raise their own productivity.

From the regression analysis conducted on the MPI and its components, it can be implied that the productivity of insurers could be improved through investments in IT infrastructure and equipment, as well as investments in staff enhancement and incentives, before and after accounting for other firm-related variables that would affect it. This goes in line with

7.2 Limitations

While the relationship between IT and staff investments and insurer productivity can be statistically implied from the analysis done, there are still some limitations pertaining to the methodology used. Firstly, with respect to the variables of interest, there is a lack of breakdown into their constituents, which makes it difficult to isolate the portion of investment directly pertaining to digitisation in technology expenses, and staff enhancement in staff expenses. Details are as follows:

- Other costs that make up part of computer investment could simply refer to maintenance of existing computer equipment; no clear indication on what the increase in computer investments is attributed to.

Table 9	Dependent Variables								
	(1) CHGROE	(2) CHGROE	(3) CHGROE	(4) CHGVAIC	(5) CHGVAIC	(6) CHGVAIC	(7) CHGVAHC	(8) CHGVAHC	(9) CHGVAHC
$ITINV_{t-1}$	0.00217 (0.00479)	0.00163 (0.00609)	0.00103 (0.00697)	0.0169 (0.299)	-0.00893 (0.160)	-0.0489 (0.212)	0.00217 (0.00479)	0.00163 (0.00609)	0.00103 (0.00697)
$ITINV_{t-2}$	**0.00376** **(0.00202)**	**0.00574*** **(0.00253)**	**0.00624***** **(0.00127)**	**0.184***** **(0.0299)**	**0.128**** **(0.0496)**	**0.120***** **(0.0238)**	**0.171***** **(0.0303)**	**0.123*** **(0.0553)**	**0. 115***** **(0.0294)**
$ITINV_{t-3}$	-0.000479 (0.00231)	-0.000914 (0.00191)	-0.0000511 (0.00367)	-0.00348 (0.0400)	-0.115 (0.108)	-0.000479 (0.00231)	-0.000914 (0.00191)	-0.0000511 (0.00367)	-0.00348 (0.0400)
$STAFFCOST_{t}$	0.000676 (0.00477)	0.00395 (0.00622)	0.00346 (0.00624)	-0.219 (0.177)	-0.128 (0.107)	0.000676 (0.00477)	0.00395 (0.00622)	0.00346 (0.00624)	-0.219 (0.177)
$STAFFCOST_{t-1}$	**0.000724** **(0.00498)**	**-0.000994** **(0.00502)**	**-0.000142** **(0.00530)**	**0.409*** **(0.171)**	**0.357**** **(0.127)**	**0.449**** **(0.138)**	**0.390** **(0.220)**	**0.339*** **(0.138)**	**0.430*** **(0.186)**
$STAFFCOST_{t-2}$	-0.00178 (0.00158)	-0.00176 (0.00175)	-0.00157 (0.00256)	-0.196 (0.155)	-0.226 (0.144)	-0.216 (0.132)	-0.195 (0.148)	-0.223 (0.143)	-0.213 (0.169)
$STAFFCOST_{t-3}$	0.000332 (0.000828)	0.000699 (0.00102)	0.000429 (0.00136)	-0.0413 (0.0337)	-0.00196 (0.0403)	-0.0227 (0.0351)	-0.0401 (0.0345)	-0.00251 (0.0397)	-0.0231 (0.0420)
SGP	0.0309 (0.0171)	-0.0229 (0.0294)	-0.0217 (0.0425)	0.150 (1.059)	-0.963 (1.260)	-0.654 (2.305)	0.127 (1.123)	-1.004 (1.332)	-0.693 (2.013)
Controls									
Firm-Level		✓	✓		✓	✓		✓	✓
Industry-Level			✓			✓			✓

Dependent variables are as follows: CHGROE (change in return on equity), CHGVAIC (change in value add per unit invested capital) and CHGVAHC (change in value-add per unit human capital). Equations (2), (5) and (8) control for firm-level variables, while (3), (6) and (9) control for both firm and industry-level variables. Variables of interest are STAFFCOST (investment in staff) and its lags up to 3 periods, and ITINV (investment in IT equipment) and its lags up to 3 periods. Firm-level and industry-level controls are as per in table 3. Standard errors are shown in parentheses.

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

- Technology-wise, computer investment as a proxy may not cover for certain types of insurance innovation such as
- Other costs that make up part of staff expenses could simply refer to salaries and bonuses paid out to staff. (Note: cost of hiring is stated as a separate item under the Cadenza documents).

As such, where possible, a breakdown of IT and staff investment components would provide the researcher with a better understanding of the types/categorisations of technology that insurers invest in, the amounts invested into each type (or at least as a proportion of total IT investment), as well as how each type of technology contributes to total factor productivity and its components. However, it is to be noted that financial regulations in Singapore do not require insurers to declare such information in Cadenza documents (Insurance Act (Chapter 142), 2018), thus making it difficult to collect such data.

Secondly, the use of the MPI as the measure of insurer productivity may be subjective. While section 4.1.1 relates the MPI to the Solow residual representing total factor productivity change, the definition of productivity as a tangible metric is not clear, since it does not necessarily translate to something that can be measured in terms of real output, unlike other measures of output such as value-add per worker. However, this issue has been mitigated to some extent by the robustness checks as shown in table 9, where more tangible performance metrics such as value add per unit invested capital and return on equity were used.

8. Conclusion

We have shown that there is some significant positive relation between IT investment and staff investment, and insurer productivity. From the results derived as per in section 5, Insurers have a tendency to reap productivity gains from IT investment 2 years after the investment was made, and reap productivity gains from staff investment/enhancement 1 year after the investment was made. Why does this merit further research?

As Industry 4.0 continues to gain traction and more companies in different sectors look to enhancing their operations through the adoption of new technologies, it is important to measure the impact of the usage of such technologies on companies' operating performance in an objective and quantifiable way, as it would give firms a visible perspective of the benefits to their operations. To better understand the impact of adopting specific types of technologies on insurer performance (e.g. integrated mobile applications, direct-to-consumer interfaces, big data analytics), more in-depth research must be done. This can be facilitated through collecting primary data from insurers through surveys and interviews conducted with company management.

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Appendix A: Applied Innovation Institute Singapore Insurance Innovation and Digital Benchmark Ranking, 2018

Company	Overall Ranking
NTUC Income	1
AXA	2
Aviva	3
AIA	4
Singapore Life	5
AIG	6
Direct Asia	7
FWD Singapore	8
CHUBB	9
Great Eastern	10
Budget Direct	11-25
China Taiping	11-25
China Life	11-25
Ecics Limited	11-25
EQ Insurance	11-25
Etiqa Insurance	11-25
HL Assurance	11-25
India International Insurance	11-25
Liberty Insurance	11-25
Manulife	11-25
MSIG	11-25
Prudential	11-25
QBE Insurance	11-25
Sompo Japan	11-25
Tokio Marine	11-25

Appendix B: Pearson Correlation Coefficients between TFP Change and Its Constituents

	(1)
	TFPCHANGE
TECHEFFCHANGE	0.616***
EFFICHANGE	0.613***
PUREEFFCHANGE	0.311***
SCALEEFFCHANGE	0.322***
N	209

t statistics in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Appendix C: Complete Regression Results for Equations (3), (4) and (5)

Equation (3)	Dependent Variables (no controls)				
	(1) TFPCHANGE	(2) TECHEFFCHANGE	(3) EFFICHANGE	(4) PUREEFFCHANGE	(5) SCALEEFFCHANGE
$STAFFCOST_{t-1}$	0.00156	0.00281*	0.000925	0.00242	-0.000485
	(0.00127)	(0.00122)	(0.00177)	(0.00216)	(0.00209)
$STAFFCOST_{t-2}$	-0.00228	-0.00331*	-0.00101	-0.00160	-0.0000652
	(0.00195)	(0.00165)	(0.00248)	(0.00301)	(0.00146)
$STAFFCOST_{t-3}$	-0.00212	-0.000712	-0.000692	-0.00168	0.000140
	(0.00161)	(0.00125)	(0.00144)	(0.00213)	(0.00143)
$ITINV_{t-1}$	-0.00617	-0.00155	-0.00789	-0.0187**	0.00464
	(0.00422)	(0.00461)	(0.00817)	(0.00711)	(0.00839)
$ITINV_{t-2}$	0.0260**	0.0253***	0.00560	0.00675	-0.000521
	(0.00862)	(0.00660)	(0.0109)	(0.00731)	(0.00847)
$ITINV_{t-3}$	-0.00306	-0.0162***	0.00631	0.0172***	-0.00371
	(0.00579)	(0.00409)	(0.00633)	(0.00466)	(0.00502)
_CONS	1.147***	1.154***	1.026***	1.088***	0.987***
	(0.0439)	(0.0179)	(0.0379)	(0.0314)	(0.0304)
/ SIGMA_U	3.16e-13	5.36e-21	2.74e-18	1.64e-18	0
	(0.0475)	(1.11e-18)	(6.43e-17)	(1.12e-18)	(4.86e-18)
SIGMA_E	0.481***	0.354***	0.434***	0.447***	0.314***

	(0.0364)	(0.0402)	(0.0827)	(0.0479)	(0.0507)
R^2					
AIC	302.5	175.3	261.7	265.2	124.4
BIC	339.0	208.5	295.0	298.2	157.3
F					
N	204	204	207	200	200

Dependent variables are as follows: TFPCHANGE (MPI), its components TECHEFFCHANGE (technology change), and EFFICHANGE (efficiency change), and the components of efficiency change, PUREEFFCHANGE (pure efficiency change) and SCALEEFFCHANGE (scale efficiency change). Variables of interest are STAFFCOST (investment in staff) and its lags up to 3 periods, and ITINV (investment in IT equipment) and its lags up to 3 periods. Firm-level and industry-level controls are as per in table 3. Standard errors are shown in parentheses.

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Equation (4)	Dependent Variables (regressed on firm-level controls only)				
	(1) TFPCHANGE	(2) TECHEFFCHANGE	(3) EFFICHANGE	(4) PUREEFFCHANGE	(5) SCALEEFFCHANGE
$STAFFCOST_{t-1}$	0.00368** (0.00110)	0.00272* (0.00132)	0.00118 (0.00205)	0.000195 (0.00239)	0.00198 (0.00154)
$STAFFCOST_{t-2}$	-0.00186 (0.00192)	-0.00302** (0.00116)	-0.000469 (0.00194)	-0.00120 (0.00373)	-0.000254 (0.00116)
$STAFFCOST_{t-3}$	-0.00167 (0.00150)	-0.000831 (0.00116)	-0.000309 (0.00128)	-0.00162 (0.00262)	0.000199 (0.000922)
$ITINV_{t-1}$	-0.00401 (0.00863)	-0.00125 (0.00718)	-0.00369 (0.00764)	-0.0167 (0.00888)	0.00651 (0.00852)
$ITINV_{t-2}$	0.0239*** (0.00648)	0.0251*** (0.00696)	0.00400 (0.0105)	0.00704 (0.00998)	-0.000612 (0.00639)
$ITINV_{t-3}$	-0.00511 (0.00510)	-0.0162** (0.00505)	0.00552 (0.00554)	0.0165** (0.00558)	-0.00605 (0.00415)
Firm-Level Controls					
SOLV	-0.00000531 (0.390)	-0.0000348 (0.0669)	0.00000255 (0.237)	-0.0000289 (0.0832)	-0.0000188 (0.0760)
LPREANNREV	0.120 (0.266)	0.0478 (0.0527)	-0.000258 (0.205)	-0.0776 (0.109)	-0.0461 (0.119)
LTOTASSET	-0.143 (0.285)	-0.0269 (0.0482)	-0.0346 (0.189)	0.0948 (0.0959)	-0.0206 (0.0954)

EXPREV	0.389 (0.395)	0.410^{*} (0.205)	-0.0587 (0.106)	-0.0638 (0.0726)	-0.0631 (0.126)
EAR	-0.0826 (1.407)	0.140 (0.270)	-0.173 (0.791)	0.109 (0.397)	-0.278 (0.362)
ROE	0.445 (0.274)	0.0944 (0.215)	0.275 (0.183)	0.120 (0.137)	0.0751 (0.166)
ILR	-0.000351 (0.00542)	-0.000215 (0.00122)	-0.000184 (0.00336)	-0.000295 (0.00352)	-0.0000229 (0.00203)
_CONS	1.261 (1.671)	0.322 (0.783)	1.740^{*} (0.857)	0.671 (0.458)	2.374^{**} (0.746)
/ SIGMA_U	0.0856 (0.0551)	2.27e-16 (0.0246)	1.37e-18 (7.79e-19)	$3.55e\text{-}18^{***}$ (8.12e-19)	6.34e-19 (2.69e-16)
SIGMA_E	0.431^{***} (0.0431)	0.307^{***} (0.0219)	0.347^{***} (0.0306)	0.388^{***} (0.0281)	0.315^{***} (0.0574)
R^2					
AIC	270.6	129.7	177.2	217.5	134.1
BIC	326.7	185.8	230.0	273.0	186.4
F					
N	200	200	201	194	194

Dependent variables are as follows: TFPCHANGE (MPI), its components TECHEFFCHANGE (technology change), and EFFICHANGE (efficiency change), and the components of efficiency change, PUREEFFCHANGE (pure efficiency change) and SCALEEFFCHANGE (scale efficiency change). Variables of interest are STAFFCOST (investment in staff) and its lags up to 3 periods, and ITINV (investment in IT equipment) and its lags up to 3 periods. Firm-level and industry-level controls are as per in table 3. Standard errors are shown in parentheses.

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Equation (5)	Dependent Variables (regressed on firm-level and industry-level controls)				
	(1)	(2)	(3)	(4)	(5)
	TFPCHANGE	TECHEFFCHANGE	EFFICHANGE	PUREEFFCHANGE	SCALEEFFCHANGE
$STAFFCOST_{t-1}$	0.00688**	0.00314*	0.00358*	0.0000229	0.00318
	(0.00223)	(0.00149)	(0.00174)	(0.00244)	(0.00213)
$STAFFCOST_{t-2}$	-0.00329	-0.00321*	-0.00127	-0.00151	-0.000338
	(0.00185)	(0.00147)	(0.00173)	(0.00389)	(0.00120)
$STAFFCOST_{t-3}$	-0.00218	-0.000895	-0.000858	-0.00135	-0.000269
	(0.00162)	(0.00111)	(0.00127)	(0.00203)	(0.000973)
$ITINV_{t-1}$	-0.00411	-0.00125	-0.00447	-0.0154	0.00527
	(0.00559)	(0.00641)	(0.0102)	(0.00865)	(0.00945)
$ITINV_{t-2}$	0.0281***	0.0256***	0.00615	0.00817	-0.000889
	(0.00589)	(0.00743)	(0.00827)	(0.00932)	(0.00699)

$ITINV_{t-3}$	-0.00672	-0.0164***	0.00512	0.0150**	-0.00533
	(0.00442)	(0.00366)	(0.00426)	(0.00521)	(0.00353)
Firm-Level Controls					
SOLV	5.47e-08	-0.0000341	0.00000907	-0.0000295	-0.00000959
	(0.291)	(0.117)	(0.263)	(0.134)	(0.0884)
LPREANNREV	0.163	0.0534	0.0338	-0.0742	-0.0209
	(0.220)	(0.0750)	(0.216)	(0.101)	(0.133)
LTOTASSET	-0.260	-0.0424	-0.112	0.0776	-0.0494
	(0.205)	(0.0741)	(0.188)	(0.0987)	(0.120)
EXPREV	0.454	0.418	-0.0125	-0.0617	-0.0420
	(0.287)	(0.254)	(0.154)	(0.140)	(0.195)
EAR	1.340	0.331	0.715	0.317	-0.0919

	(1.417)	(0.441)	(1.098)	(0.579)	(0.837)
ROE	0.246	0.0678	0.143	0.110	0.0460
	(0.312)	(0.125)	(0.170)	(0.262)	(0.167)
ILR	-0.0000783	-0.000178	-0.0000348	-0.000222	-0.0000186
	(0.00503)	(0.00121)	(0.00177)	(0.00341)	(0.00266)
Industry-Level Controls					
LIFE	-0.846***	-0.113	-0.552***	-0.0820	-0.156
	(0.214)	(0.101)	(0.128)	(0.132)	(0.353)
COMPOSITE	-0.0719	-0.00872	-0.0969	0.0791	-0.105
	(0.129)	(0.0663)	(0.0822)	(0.104)	(0.0925)
_CONS	2.829**	0.533	2.688***	0.926	2.507**
	(1.083)	(1.102)	(0.793)	(0.727)	(0.900)
/					

SIGMA_U	2.72e-16	1.29e-18	1.79e-18**	5.56e-19	1.84e-19
	(0.0576)	(0.0239)	(5.90e-19)	(7.49e-19)	(0.0210)
SIGMA_E	0.402***	0.307***	0.330***	0.387***	0.312***
	(0.0375)	(0.0245)	(0.0194)	(0.0368)	(0.0522)
R^2					
AIC	242.8	132.8	160.2	220.2	138.6
BIC	308.8	195.5	219.6	282.3	204.0
F					
N	200	200	201	194	194

Dependent variables are as follows: TFPCHANGE (MPI), its components TECHEFFCHANGE (technology change), and EFFICHANGE (efficiency change), and the components of efficiency change, PUREEFFCHANGE (pure efficiency change) and SCALEEFFCHANGE (scale efficiency change). Variables of interest are STAFFCOST (investment in staff) and its lags up to 3 periods, and ITINV (investment in IT equipment) and its lags up to 3 periods. Firm-level and industry-level controls are as per in table 3. Standard errors are shown in parentheses.

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Appendix D: Complete Regression Results for Robustness Check (different measures of firm performance)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	CHGROE	CHGROE	CHGROE	CHGVAIC	CHGVAIC	CHGVAIC	CHGVAHC	CHGVAHC	CHGVAHC
$ITINV_{t-1}$	0.00217	0.00163	0.00103	0.0169	-0.00893	-0.0489	0.00217	0.00163	0.00103
	(0.00479)	(0.00609)	(0.00697)	(0.299)	(0.160)	(0.212)	(0.00479)	(0.00609)	(0.00697)
$ITINV_{t-2}$	**0.00376**	**0.00574***	**0.00624*****	**0.184*****	**0.128****	**0.120*****	**0.171*****	**0.123***	**0. 115*****
	(0.00202)	**(0.00253)**	**(0.00127)**	**(0.0299)**	**(0.0496)**	**(0.0238)**	**(0.0303)**	**(0.0553)**	**(0.0294)**
$ITINV_{t-3}$	-0.000479	-0.000914	-0.0000511	-0.00348	-0.115	-0.000479	-0.000914	-0.0000511	-0.00348
	(0.00231)	(0.00191)	(0.00367)	(0.0400)	(0.108)	(0.00231)	(0.00191)	(0.00367)	(0.0400)
$STAFFCOST_{t}$	0.000676	0.00395	0.00346	-0.219	-0.128	0.000676	0.00395	0.00346	-0.219
	(0.00477)	(0.00622)	(0.00624)	(0.177)	(0.107)	(0.00477)	(0.00622)	(0.00624)	(0.177)
$STAFFCOST_{t-1}$	**0.000724**	**-0.000994**	**-0.000142**	**0.409***	**0.357****	**0.449****	**0.390**	**0.339***	**0.430***
	(0.00498)	**(0.00502)**	**(0.00530)**	**(0.171)**	**(0.127)**	**(0.138)**	**(0.220)**	**(0.138)**	**(0.186)**
$STAFFCOST_{t-2}$	-0.00178	-0.00176	-0.00157	-0.196	-0.226	-0.216	-0.195	-0.223	-0.213
	(0.00158)	(0.00175)	(0.00256)	(0.155)	(0.144)	(0.132)	(0.148)	(0.143)	(0.169)

$STAFFCOST_{t-3}$	0.000332	0.000699	0.000429	-0.0413	-0.00196	-0.0227	-0.0401	-0.00251	-0.0231
	(0.000828)	(0.00102)	(0.00136)	(0.0337)	(0.0403)	(0.0351)	(0.0345)	(0.0397)	(0.0420)
LPREANNREV		-0.00994	-0.00315		4.622	5.793		4.594	5.757
		(0.0582)	(0.0532)		(5.610)	(5.351)		(5.671)	(5.502)
LTOTASSET		-0.0547	-0.0528		-6.962	-7.677		-6.828	-7.540
		(0.0672)	(0.0561)		(5.753)	(5.488)		(5.676)	(5.688)
SOLV		0.0000370	0.0000409		12.89	13.92		12.60	13.63
		(0.0999)	(0.0844)		(12.95)	(13.61)		(13.38)	(12.92)
EXPREV		-0.555	-0.551		-25.66*	-25.56*		-24.97*	-24.87
		(0.316)	(0.357)		(12.71)	(12.24)		(12.48)	(13.19)
EAR		-0.390	-0.492		-60.54	-69.18		-58.90	-67.46
		(0.436)	(0.416)		(44.98)	(49.92)		(42.05)	(45.07)
ILR		0.000448	0.000403		0.00476	0.00204		0.00451	0.00181
		(0.000850)	(0.00105)		(0.0784)	(0.0115)		(0.0347)	(0.0449)

LIFE			0.0256			0.193			0.172
			(0.0874)			(4.186)			(3.393)
COMPOSITE			-0.0660			-5.545			-5.503
			(0.0728)			(4.204)			(4.388)
_CONS	-0.0418	1.873	1.726	-0.257	83.27	77.55	-0.209	80.30	74.69
	(0.0223)	(1.151)	(1.244)	(1.472)	(51.93)	(47.91)	(1.646)	(50.08)	(46.68)
R^2									
AIC	.	.	.	.	.	.	.	.	.
BIC	.	.	.	.	.	.	.	.	.
F									
N	206	201	201	199	199	199	201	200	200

Dependent variables are as follows: TFPCHANGE (MPI), its components TECHEFFCHANGE (technology change), and EFFICHANGE (efficiency change), and the components of efficiency change, PUREEFFCHANGE (pure efficiency change) and SCALEEFFCHANGE (scale efficiency change). Variables of interest are STAFFCOST (investment in staff) and its lags up to 3 periods, and ITINV (investment in IT equipment) and its lags up to 3 periods. Firm-level and industry-level controls are as per in table 3. Standard errors are shown in parentheses

* $p<0.05$, ** $p < 0.01$, *** $p < 0.001$

Appendix E: A Review of Ackerberg, Caves and Frazer (2015)

For the purpose of this section, we will first highlight some assumptions made by Olley-Pakes (1996) and Levinsohn and Petrin (2000) in the measurement of production function estimation and productivity, followed by the application of these assumptions and an exposition on the Ackerberg, Caves and Frazer (2015) framework. Such production function estimation methods are commonly used in industrial organisation literature (Pavcnik (2002), Sokoloff (2003), Sivadasan (2004), Fernandes (2003), Ozler and Yilmaz (2001), Criscuola and Martin (2003), Topalova (2003), Blalock and Gertler (2004), and Alvarez and Lopez (2005)), particularly in empirical research whereby the subjects are firms in the manufacturing sector. To the best of the author's knowledge, such techniques have not been applied to firms in the financial sector in the current literature.

Ackerberg, Caves and Frazer (2015)

Olley-Pakes (996) and Levinsohn-Petrin (2000) make some assumptions as follows:

(i) Strict monotonicity - for the former investment must be strictly monotonic in ω_{it} (at least when it is non-zero), while for the latter intermediate input demand must be strictly monotonic in ω_{it}. Monotonicity is required for the non-parametric inversion because otherwise, one cannot perfectly invert out ω_{it} and completely remove the endogeneity problem.

(ii) ω_{it} is the only unobservable entering the functions for investment (OP) or the intermediate input (LP). We refer to this as a "scalar unobservable" assumption. This rules out, e.g. measurement error or optimization error in these variables, or a model in which exogenous productivity is more than single dimensional. Again, the reason for this assumption is that if either of these was the case; one would not be able to perfectly invert out ω_{it}.

(iii) k_{it} is assumed to have been decided exactly at (OP) or exactly at/prior to (LP) time period t - 1. Any later than this would violate the moment condition, as k_{it} would likely no longer be orthogonal to the innovation term ξ_{it}. For OP, were

i_{it-1} (and thus k_{it}) to be decided any earlier than t - 1, then one could not use i_{it-1} to invert out ω_{it}, making first-stage estimation problematic.

(iv) l_{it} must have no dynamic implications. Otherwise, l_{it} would enter the investment demand function and prevent identification of the labor coefficient in the first stage. In LP, labor can have dynamic implications, but one would need to adjust the procedure suggested by LP by allowing l_{it-1} into the intermediate input demand function. Note that in principle, this still allows one to identify the coefficient on labor in the first stage.

(v) For LP it is important that l_{it} and m_{it} are assumed to be perfectly variable inputs. By this we mean that they are decided when ω_{it} is observed by the firm. If m_{it} were decided before learning ω_{it}, then m_{it} could not be used to invert out ω_{it} and control for it in the first stage. If l_{it} were chosen before learning ω_{it}, then l_{it} would also be chosen before m_{it}. In this case, a firm's choice of materials m_{it} would directly depend on l_{it} and l_{it} would enter the LP non-parametric function, preventing identification of the labor coefficient in the first stage.

This paper proposes a production estimation structure similar to that of Olley-Pakes (1996) and Levinsohn and Petrin (2000), but also attempts to account for collinearity issues that occur when is collinear with the non-parametric component of the equation that is being estimated. The key difference between this methodology and that of Olley-Pakes (1996) and Levinsohn-Petrin (2000) is that, in this approach, no coefficients will be estimated in the first stage of estimation. Instead, the input coefficients are all estimated in the second stage. However, it is important to note that the first stage is still needed to net out the untransmitted error term from the production function.

For the first stage, we consider the production function equation as shown below:

$$y_{it} = \beta_0 + \beta_1 l_{it} + \beta_2 k_{it} + \omega_{it} + \eta_{it} \tag{23}$$

Note that we allow for labour inputs to be chosen before material/investment input, or more specifically, after time *t-1* and before time *t*. We assume that ω_{it} follows a first-order Markov process between the period *t-1, t-b* (which we refer to as the time that l_{it} is chosen), and *t*. Given this timing assumption, we express the intermediate input/investment as a function of labour and capital inputs and productivity.

$$m_{it} = m_{it}(k_{it}, l_{it}, \omega_{it}) \tag{24}$$

We then invert ω_{it} and substitute it into the production function equation as follows:

$$y_{it} = \beta_1 l_{it} + \phi_{it}(k_{it}, l_{it}, m_{it}) + \eta_{it} \tag{25}$$

Since the labour term and the non-parametric term are clearly correlated, we cannot directly estimate β_1 like we do in Olley-Pakes (1996) and Levinsohn-Petrin (2000). However, we can estimate the following composite term, which represents output net of the untransmitted shock η_{it}:

$$\phi_{it}(k_{it}, l_{it}, m_{it}) = \beta_0 + \beta_2 k_{it} + \omega_{it}(k_{it}, l_{it}, m_{it}) \tag{26}$$

As such, this allows us to isolate and eliminate the portion of output determined by either shocks unanticipated at t or by measurement error. However, at this point, we still have not estimated the coefficients for labour and capital, which is done in the 2nd stage. This, in turn, requires 2 moment conditions. Note that since l_{it} is chosen after time t, at time t-b, l_{it} will be correlated with part of ξ_{it}. On the other hand, lagged labour, l_{it-1}, was chosen at time t – b - 1. Hence, it is in the information set l_{it-1} and will be uncorrelated with ξ_{it}. Thus, the following is implied:

$$\omega_{it} = E(\omega_{it}|\omega_{it-1}) + \xi_{it} \tag{27}$$

$$E\left(\xi_{it}\middle|\begin{matrix} k_{it} \\ l_{it-1} \end{matrix}\right) = 0 \tag{28}$$

$$E(\xi_{it} \cdot \begin{matrix} k_{it} \\ l_{it-1} \end{matrix}) = 0 \tag{29}$$

These are the 2 moment conditions required to estimate β_1 and β_2. We can recover the implied ξ_{it}'s for any value of the parameters $(\beta_1; \beta_2)$ as follows. First, given a candidate value of $(\beta_1; \beta_2)$, compute the implied $\omega_{it}(\beta_1; \beta_2)$'s for all t using the formula:

$$\omega_{it}(\beta_1; \beta_2) = \hat{\phi}_{it} - \beta_2 k_{it} - \beta_1 l_{it} \tag{30}$$

Secondly, non-parametrically regress $\omega_{it}(\beta_1; \beta_2)$ on $\omega_{it-1}(\beta_1; \beta_2)$ (and a constant term), deriving the residuals from this regression which are the implied $\xi_{it}(\beta_1; \beta_2)$'s. Given these implied $\xi_{it}(\beta_1; \beta_2)$'s, one can derive the following sample analogue to the moment condition above, and thus estimating $(\beta_1; \beta_2)$ by minimizing said sample analogue:

$$\sum_{t} \sum_{i} \xi_{it}(\beta_1;\ \beta_2) \cdot \frac{k_{it}}{l_{it-1}} \tag{31}$$

Productivity estimators are similarly derived as per Olley-Pakes (1996) and Levinsohn and Petrin (2000).

6.4.3.1 Variables

For this analysis, the dependent variable used is simply the productivity estimator derived from the Ackerberg-Caves-Frazer (2006) framework. Note that unlike in the case of the Malmquist index, we are unable to break down the productivity estimator into different components pertaining to efficiency and technology change. For the purpose of estimation, total asset value was used as the capital input in the production function equation, total labour cost was used as the labour input, and total investment was used as the investment proxy. Note that in the second case, we use total staff cost due to lack of data availability on number of staff, which is a more commonly used variable in most literature.