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JAPAN'S PRODUCTIVITY STAGNATION: USING DYNAMIC HSIEH–KLENOW DECOMPOSITION*

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Abstract

This study provides a new perspective on Japan's stagnant aggregate productivity by extending the Hsieh and Klenow (2009) framework to account for productivity growth, entry and exit, and product variety change. We measure the technical efficiency (TE) and allocative efficiency (AE) by the aggregate production possibility frontier and the distance from the frontier, respectively. We apply our approach to establishment- and firm-level datasets from Japan and find that the AE among survivors declined during the banking crisis period, while the TE declined during the global financial crisis period.

Keywords: Technical Efficiency, Allocative Efficiency, Japan

JEL classification: D24, O40, O47

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I. INTRODUCTION

The aggregate productivity in Japan has been stagnant since the 1990s. The average growth rate of the aggregate total factor productivity (TFP) over the 1995–2015 period was 0.2% (Japan Productivity Database 2018). Further, the TFP stagnation in Japan has been higher and has lasted longer than other developed economies, which have experienced a decline in TFP growth.[5]

Many researchers have pointed out that the slow or misdirected reallocation of resources in the 1990s is among the possible causes of the stagnant TFP in Japan (e.g., Kwon, Narita, and Narita 2015). Japanese banks, burdened with non-performing loan problems, continued to provide loans to otherwise insolvent firms ("zombies") in the 1990s. The presence of zombies depressed job construction and destruction, resulting in lower aggregate productivity (Caballero, Hoshi, and Kashyap 2008).

To measure the impact of reallocation on aggregate productivity, many preceding studies apply aggregate productivity decomposition approaches to Japanese plant- or firm-level data; these approaches were developed by Foster, Haltiwanger, and Krizan (FHK, 2001) and Petrin and Levinsohn (PL, 2012), among others. They decompose

[5] According to the EU KLEMS Growth and Productivity Accounts, the average TFP growth rates for Germany (from 1995 to 2017), the UK (from 1995 to 2017), and the US (from 1997 to 2017) were 1.0%, 0.7%, and 0.7%, respectively.

aggregate productivity into the productivity distribution shift among survivors (i.e., within effect), market share reallocation among survivors (i.e., reallocation effect), entry, and exit. These decomposition approaches are effective in quantifying the degree to which the actual reallocation of resources contributes to aggregate productivity growth.

Another method of quantifying the effect of slow or limited mobility of resources is to measure the foregone output caused by such immobility of resources. These two types of approaches are complementary and closely related, but not identical. Assuming that producers are constantly hit by productivity shocks; without any frictions, resources shift from producers hit by negative shocks to those hit by positive shocks. However, if resources do not move across producers at all, the reallocation effect is, by definition, zero; however, allocation is now inefficient in that more productive producers do not expand and less productive producers do not shrink. Moreover, this inefficiency increases as the productivity gap across producers increases, but the reallocation effect remains zero. Thus, this alternative approach is expected to shed new light on the causes of aggregate productivity growth, especially when resources are stuck at each producer owing to the presence of various frictions, such as zombies, firing costs, and barriers to entry. Evidence shows that these frictions are high in Japan.[6]

We pursue this alternative approach to identify the driving forces of stagnant aggregate productivity in Japan. We first expand on the method by Hsieh and Klenow (HK, 2009) to include a dynamic setting comprising productivity shocks, entries and exits, and product variety changes. We then apply our dynamic Hsieh–Klenow decomposition (DHKD) approach to establishment- and firm-level panel datasets from Japan (i.e., the Census of Manufacture (CM) and the Basic Survey of Japanese Business Structure and Activities (BSJBSA), respectively, which are conducted by the Ministry of Economy, Trade and Industry (METI)).[7] We found that the allocative efficiency (AE) among survivors declined during the banking crisis period (1996–2000) and the technical efficiency (TE) declined during the global financial crisis (GFC) period (2006–2010). Moreover, almost throughout the sample period, both entering and exiting establishments were more efficient than survivors; this indicates a positive entry effect and a negative exit effect, respectively. Meanwhile, the variety effect depends on the data sources. For

[6] Regarding firing costs, according to the indicators of the strictness of employment protection legislation (EPL) for regular workers, published in the OECD Economic Outlook (2013), employment protection is higher (stricter) in Japan than in the US and the UK, but lower than that in Germany and France. Regarding entry barriers, according to the indicators of starting a business published in World Bank's Doing Business 2013, Japan ranks 114th among 133 economies.

[7] For the data from 2011, we used the Economic Census for Business Activity 2012 conducted by the Ministry of Economy, Trade and Industry(METI) and the Ministry of Internal Affairs and Communications(MIC). However, we refer to these two datasets as CM for simplicity.

the CM, it tended to be negative except during the bubble period (1987-1990) while for the BSJBSA, it tended to be positive.

The HK and DHKD approaches are useful for investigating the sources of the aggregate productivity slowdown in Japan, which has limited resource mobility. However, they have limitations, such as assumptions on functional forms and parameter values, measurement errors, and the absence of investment decisions by multi-plant firms (Kehrig and Vincent 2019). To address these issues, first, we conduct a sensitivity check by varying the parameter values of demand elasticity. Second, we estimate the role of additive measurement errors following the work by Bils, Klenow, and Ruane (2020). Third, we estimate the role of the change in the share of multi-plant firms in our measurement of AE. Although we did not find evidence that these factors drive our main results, it should be noted that a possibility remains that they account, at least partially, for our results.

This study is related to the literature on the methodology of aggregate productivity decomposition. While the FHK decomposition is intuitive and most widely used in applied studies, it does not consider the decreasing marginal product of inputs.[8] By considering the decreasing marginal product of inputs, PL (2012), Petrin and Sivadasan

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[8] To the best of our knowledge, PL (2012) were the first to highlight the difference between the reallocation effect and the allocative efficiency (AE).

(2013), Osotimehin (2019), and Baqaee and Farhi (2020) extend the standard growth accounting to a framework comprising producer heterogeneity and allocative frictions. These studies measure the reallocation effect in terms of the difference between the value of the marginal product of input and its price (input gap).[9] The input gap is equivalent to the difference between the output elasticity and share of input, which is also the basis of the AE of DHKD. However, except for Osotimehin (2019), these studies aim to measure the contribution of input reallocation to aggregate productivity growth and, hence, use the input share given.[10] Meanwhile, Osotimehin (2019) and DHKD aim to measure the efficiency of allocation and, hence, use the distortions given. Thus, the reallocation effect of PL and Petrin and Sivadasan is different from the AE in either Osotimehin or DHKD. The difference between Osotimehin and DHKD is the reference point of TE; while Osotimehin measures TE using the previous period's *actual* allocation as the reference point, DHKD measures the efficiency using the previous period's *optimal* allocation.[11]

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[9] Petrin and Sivadasan (2013) showed that the input gap is exactly equal to the change in aggregate output that would occur if that plant changed this input's use by one unit. They further measured the plant-level input gap using the Chilian manufacturing data and showed that the increase in the input gaps over time are related to the increase in severance pay.

[10] Refer to Osotimehin (2019) for the different objectives between her decomposition and other existing ones.

[11] Osotimehin (2019) selected her reference point to capture the effect of the change in inputs that is required to hold AE constant after the change in firm-level productivity as technical efficiency. Conversely, we select the reference point of DHKD to measure the change in the optimal output.

Thus, Osotimehin's TE depends on the previous period's AE, while that of DHKD does not.[12]

By extending the Hsieh–Klenow framework to a dynamic setting with idiosyncratic productivity shocks, entry and exit, and product variety changes, this study contributes to preceding studies on aggregate productivity decomposition. Following the work by Hsieh and Klenow (2009), we measure the TE as the change in the aggregate production possibility frontier and the AE as the distance from the frontier. We believe that our decomposition is straightforward from a microeconomic perspective. Furthermore, we explicitly consider the roles of three extensive margins in aggregate productivity: efficiency of entrants relative to that of survivors (i.e., entry effect), efficiency of exiting producers relative to that of survivors (i.e., exit effect), and change in the variety of products (i.e., variety effect). Baqaee and Farhi (2020) have not explicitly considered these extensive margins, whereas Osotimehin (2019) considers only the entry and exit effects. The variety effect emerges if the aggregate output increases with the larger variety of intermediate inputs produced, rendering the total amount of inputs produced constant.[13]

II. ILLUSTRATION OF DYNAMIC HSIEH–KLENOW DECOMPOSITION

[12] We compare the differences among DHKD, PL, and Osotimehin (2019) in Section 2.

[13] Refer to Fattal-Jaef (2018) for the role of the variety effect in aggregate productivity.

This section illustrates our decomposition (i.e., DHKD) using a simple example and compares it with two closely related decomposition methods: PL and Osotimehin (2019).

Dynamic Hsieh–Klenow Decomposition (DHKD)

Figure 1 presents the DHKD in terms of TE and AE. For simplicity, suppose that two producers operate in period $s = t - 1$ and t, and no entry or exit occurs. Producer *i* (where *i* = *1* or *2*) produces output Y_{is} using input K_{is}. The production technology is represented by the production function $Y_{is} = A_{is}f(K_{is})$, where A_{is} is producer *i*'s total factor productivity (TFPQ) in period s, $f'(K_{is})>0$, and $f''(K_{is})<0$.[14] Without loss of generality, we assume that $A_{1t-1} > A_{2t-1}$. Further, suppose that the total amount of K_s is fixed. Then, the total output is maximized when the marginal product of the capital is the same across producers: $A_{1s}f'(K_{1s}{}^{*}) = A_{2s}f'(K_{2s}{}^{*})$. However, in period *t-1*, producer 1 underuses *K*, whereas producer 2 overuses *K* relative to the optimal allocation due to some frictions: $K_{1t-1} < K_{1t-1}{}^{*}$ and $K_{2t-1} > K_{2t-1}{}^{*}$. Consequently, the actual output is smaller than the optimal output by area *C*. In period *t*, producer 1's productivity increases from $A_{1,t-1}$ to $A_{1,t}$ $(A_{1,t-1} < A_{1,t})$, but the allocation does not change due to

[14] In this section, for exposition purposes, we assume decreasing returns to scale technology and use the dispersion in marginal product of capital across producers to measure the AE. In Section III, we assume constant returns to scale technology, assume a common demand elasticity (and hence markup) across producers within an industry, and use the dispersion in revenue productivity (TFPR) to measure the AE.

some frictions. Consequently, the output increases by area *A*. However, if input *K* was allocated optimally both in periods *t-1* and *t*, then the output would increase as the sum of both areas A and B. Specifically, our TE measure is this hypothetical increase in output due to productivity gain. Conversely, output loss due to misallocation of inputs increases by *B* (from *C* to *B*+*C*), which is exactly the negative of our AE measure.

'Place Figure 1 approximately here'

Petrin and Levinsohn 2012 (PL)

PL measures the reallocation effect in terms of the input gap (i.e., the difference between the value of the marginal product of input and its price) by using the input share given, rather than the distortions. Figure 1 shows that PL's reallocation effect is zero because reallocation of input does not occur.[15]

Osotimehin (2019)

Osotimehin (2019) measures TE as a combination of weighted averages of producer-level productivity changes, with the previous period's allocation as the reference point. We illustrate her decomposition in Panel B of Figure 1; this is the same as that of Panel A with area B divided into two parts: B_2, which has the same area as C,

[15] This example is similar to Osotimehin's (2019, pp. 182) discussion.

and B_1, which is the rest area of B. Her TE is $A + B_1$, whereas her AE is $-B_1$ because the reference point of her TE is $B_2 (= C)$.

III. FRAMEWORK OF DYNAMIC HSIEH–KLENOW DECOMPOSITION

In this study, we follow the work by Hsieh and Klenow (2009) to measure the value of the marginal product for each producer and each input and aggregate producer-level physical productivity (TFPQ) to sectoral and economy-wide productivity (for details, refer to the Hsieh–Klenow Framework in Appendices).

Sectoral Decomposition

We first decompose the sectoral TFP growth into the TE and AE of survivors and the three extensive margins. Let A_{st} denote the TFP of sector s in period t, η_s, the demand elasticity for firms in sector s that comes from the CES production function of the sectoral goods producer, and N_{st}, the number of producers in sector s in period t.[16] Hence, we define the average TFP for all producers in period *t* as

$$\bar{A}_{st} = (1/N_{st})^{\frac{1}{\eta_s - 1}} A_{st}. \quad (1)$$

Similarly, we define the average TFP for producers that survive from period *t* to *t+1* as

[16] We refer to the producer-level physical productivity as "TFPQ" and the sectoral and aggregate productivity as "TFP" rather than "TFPQ" following HK, although sectoral (aggregate) "TFP" denotes how much sectoral (aggregate) output can be produced given the sectoral (aggregate) capital and labor. See Section Hsieh-Klenow Framework in Appendices for the derivation of A_{st}.

$$\overline{A^{C_{st}}_{st}} = \left(1/N^{C_{st}}_{st}\right)^{\frac{1}{\eta_s-1}} A^{C_{st}}_{st}\,. \tag{2}$$

Here, C_{st} denotes the set of survivors, $N^{C_{st}}_{st}$ denotes their number, and $A^{C_{st}}_{st}$ denotes their aggregate productivity. Using Equations (1) and (2) and the identity $ln\left(\frac{A_{s,t+1}}{A_{st}}\right) = ln\left(\frac{A^{C_{st}}_{s,t+1}}{A^{C_{st}}_{st}}\right) + ln\left(\frac{A_{s,t+1}}{A^{C_t}_{s,t+1}}\right) - ln\left(\frac{A_{st}}{A^{C_{st}}_{st}}\right)$, we can decompose the sectoral TFP growth as follows:[17]

$$ln\left(\frac{A_{s,t+1}}{A_{st}}\right) = ln\left(\frac{\overline{A^{C_{st}}_{s,t+1}}}{\overline{A^{C_{st}}_{st}}}\right) + ln\left(\frac{\overline{A_{s,t+1}}}{\overline{A^{C_{st}}_{s,t+1}}}\right) - ln\left(\frac{\overline{A_{st}}}{\overline{A^{C_{st}}_{st}}}\right) + \frac{1}{\eta_s - 1} ln\left(\frac{N_{s,t+1}}{N_{st}}\right). \tag{3}$$

We further decompose the first term for survivors into changes in TE and AE. Let $\overline{H^{C_t}_{st}}$ denote the hypothetical average TFP achieved without any distortions on survivors.[18] Then, we define the ratio of the actual and hypothetical average productivity for survivors by $\overline{D^{C_{st}}_t} = \overline{A^{C_{st}}_t} / \overline{H^{C_{st}}_t}$. In particular, a higher $\overline{D^{C_t}_t}$ indicates better allocation among survivors. We obtain the following decomposition through this definition:

$$ln\left(\frac{A_{s,t+1}}{A_{st}}\right) = \underbrace{ln\left(\frac{\overline{H^{C_{st}}_{s,t+1}}}{\overline{H^{C_{st}}_{st}}}\right)}_{\substack{\text{Technical}\\ \text{efficiency}\\ \text{(TE)}}} + \underbrace{\ln\left(\frac{\overline{D^{C_{st}}_{t+1}}}{\overline{D^{C_{st}}_t}}\right)}_{\substack{\text{Allocative}\\ \text{efficiency}\\ \text{(AE)}}} + \underbrace{ln\left(\frac{\overline{A_{s,t+1}}}{\overline{A^{C_{st}}_{s,t+1}}}\right)}_{\substack{\text{Entry}\\ \text{effect}}} - \underbrace{ln\left(\frac{\overline{A_{st}}}{\overline{A^{C_{st}}_{st}}}\right)}_{\substack{\text{Exit}\\ \text{effect}}} + \underbrace{\frac{1}{\eta_s-1}\ln\left(\frac{N_{s,t+1}}{N_{st}}\right)}_{\substack{\text{Variety}\\ \text{effect}}}. \tag{4}$$

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[17] Melitz and Polanec (2015) and Hosono, Takizawa, Wieland and Yang (2016) use this identity to isolate the relative efficiency of entrants and exiters.

[18] See Section Hsieh-Klenow Framework in Appendix for the derivation of $\overline{H^{C_t}_{st}}$.

Here, the first and second terms represent the productivity improvement effect (TE) of survivors and the improvement in allocative efficiency (AE) among survivors, respectively. The sum of the third (entry effect) and fourth (exit effect) terms is referred to as the net entry effect.

We measure AE by using the distortions as given, following the work by Hsieh and Klenow (2009). In fact, these distortions reflect various factors that cause deviations from marginal revenue and marginal cost of inputs. They include taxes and regulations, as well as adjustment costs of inputs (Asker, Collard-Wexler, and De Loecker 2014), financial frictions (e.g., Midrigan and Xu 2014), and endogenous markups (Peters 2020). Thus, a more structural model is required to measure the AE that allows for endogenous distortions and consequently, become more model-dependent.

It is also worth noting that our entry and exit effects are different from FHK's counterparts because we do not use entrants' and exiters' shares as given, but FHK do. Therefore, our entry effect is high if the TE of entrants is high relative to that of survivors and/or if the AE among entrants is high relative to that of survivors. Similarly, our exit effect is high if the TE of exiters is low relative to that of survivors and/or if the AE among exiters is low relative to that of survivors. Thus, we can decompose the entry and exit effects into two components. Let $\overline{H_{st}}$ denote the hypothetical average TFP that would be achieved without any distortions on *all* producers in sector s, and $\overline{D_{st}} = \overline{A_{st}}/\overline{H_{st}}$. Then, the entry and exit effects can be further decomposed into the relative TE of entrants and exiters and their relative AE as follows:

$$\underbrace{ln\left(\frac{\overline{A_{s,t+1}}}{A^{C_{st}}_{s,t+1}}\right)}_{\text{Entry effect}} = \underbrace{log\left(\frac{\overline{H_{st+1}}}{H^{C}_{st+1}}\right)}_{\text{TE for entrants}} + \underbrace{log\left(\frac{\overline{D_{st+1}}}{D^{C}_{st+1}}\right)}_{\text{AE for entrants}} \tag{5}$$

$$\underbrace{-ln\left(\frac{\overline{A_{s,t}}}{A^{C_{st}}_{s,t}}\right)}_{\text{Exit effect}} = \underbrace{-log\left(\frac{\overline{H_{st}}}{H^{C}_{st}}\right)}_{\text{TE for exitors}} - \underbrace{log\left(\frac{\overline{D_{st}}}{D^{C}_{st}}\right)}_{\text{AE for exitors}}. \tag{6}$$

<u>Economy-wide Aggregation</u>

Based on the Cobb–Douglas production technology for aggregation, we aggregate the sector-level change in productivity to the change in aggregate productivity using the following specification:

$$ln\left(\frac{A_{t+1}}{A_t}\right) = \sum_s \theta_{st} ln\left(\frac{A_{st+1}}{A_{st}}\right). \tag{7}$$

Here, $\theta_{st} = P_{st}Y_{st}/P_tY_t$, where P_{st} and P_t denote the sectoral and aggregate price, respectively, and Y_{st} and Y_t denote the sectoral and aggregate outputs, respectively.[19]

IV. DATA

<u>Data Sources</u>

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[19] See Section <u>Hsieh-Klenow Framework</u> in Appendix for the derivation of Eq. (7).

We mainly use two data sources to conduct our analysis. For our main analysis, we use the establishment-level data in the CM published by the Ministry of Economy, Trade and Industry (METI). In years ending with 0, 3, 5, and 8, the CM covers all establishments that are located in Japan (excluding those owned by the government) and fall into the manufacturing sector.[20] In other years, the CM covered establishments with four or more employees. As we required data on fixed tangible assets to construct an establishment-level TFPQ, we use only those establishments for which such data are available. The CM reported fixed tangible assets for establishments with 10 employees or more for 1986–2000 and 2005, and for those with 30 employees or more for 2001–2004 and 2006–2013. For 2014, we use the Economic Census for Business Frame conducted by the Statistics Bureau of Japan, covering establishments with 10 employees or more. We restrict our sample to establishments with 30 employees or more to maintain consistency over time. The most significant benefit of the CM is its long horizon and its wide coverage of establishments in the manufacturing sector. However, the CM excluded establishments in non-manufacturing industries.

Another micro-level data source that we use is the BSJBSA published by the

[20] Although the data are at the establishment level and not the firm level, single establishment firms own most of the establishments. For example, in 2008, single-establishment firms owned 84.4% of the establishments (222,145 out of 263,061 establishments).

METI. This annual survey mainly aims to quantitatively gauge the activities of Japanese enterprises, including capital investment, exports, foreign direct investment, and investment in R&D. In particular, the survey covers enterprises in Japan with more than 50 employees and with paid-up capital of over 30 million yen. The sample covers firms in both manufacturing and non-manufacturing industries, and the sample period was from 1995 to 2015.

Variables

Data from the CM. We use the CM for the period 1986–2014.[21] The information that we use from the CM are an establishment's labor compensation (excluding non-wage compensation), value added, the number of workers and capital stock, and industry classification (i.e., at the four-digit level) of an establishment.[22]

Data from the BSJBSA. We use BSJBSA data for the period 1995–2015. The information that we use from the BSJBSA are a firm's output and input data (i.e., sales, cost of sales and selling, and general and administrative expenses, the number of workers, and tangible capital stock) and industry classification (i.e., at the three-digit level) of a firm.[23]

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[21] Although data for 2015 are available from the 2016 Economic Census for Business Activity, we could not connect them with the data for 2014 from the Census of Manufactures 2014.

[22] Refer to subsection Data from the CM in Appendices for details.

[23] Refer to subsection Data from the BSJBSA in Appendices for details.

We reclassify establishments from the Census into 52 manufacturing industries based on the Japan Industrial Productivity (JIP) Database 2015, published by the Research Institute of Economy, Trade and Industry (RIETI), to use the industry-level labor shares of the JIP Database. Moreover, we reclassify the firms from the BSJBSA into 39 manufacturing and 26 non-manufacturing industries based on the JIP Database 2015. We set the rental price of capital to R = 0.1 assuming that the interest rate is 4% and the depreciation rate is 6%. For the baseline specification, we set the elasticity of substitution between products, η_s, to 3 for all industries in accordance with Hsieh and Klenow (2009) and Osotimehin (2019).

We set α_s as one minus the industry-level labor share; in other words, we assume that, in each industry, rents from markups are divided pro rata into payments to labor and capital. Moreover, industry-level labor shares are obtained from the JIP Database. To obtain the industry-year specific TFP, we measure P_{st} as the sectoral deflator from the JIP Database, and then we compute Y_{st} as the simple sum of value added, divided by the sectoral deflator.[24] We suppose that each producer (establishment and firm for the CM and BSJBSA, respectively) produces a single product and do not consider multiple-product producers due to data limitations. We identify survivors as producers that appear

[24] The industry-year specific TFP refers to κ_s in Eq. (A7) in The Hsieh-Klenow Framework in Appendices.

in the dataset for two consecutive years.[25] To exclude outliers, we trim the 1% tails of TFPQ and revenue-based productivity (TFPR). For the analysis using the CM, the number of establishments per observation year varies from 34,608 to 57,626 during the investigated period. The number of total establishment–year observations in our dataset is 1,386,336. For the analysis using the BSJBSA, the number of firms per observation year varies from 21,512 to 28,662 during the investigated period. The total number of firm–year observations in our dataset is 585,208. One caveat is that we do not adjust for capital utilization or hours worked due to data limitations; hence, our TE may capture the variations in them.

V. EMPIRICAL RESULTS

Establishments in Manufacturing Industries

DHKD. We first present the results of DHKD from the establishment-level dataset from the CM over the period 1987–2014. Table 1 presents the descriptive statistics of the year-on-year change in aggregate TFP and its components for 28 years (1987–2014).[26] The average aggregate TFP growth rate was 1.3%. The TE for survivors is relatively large

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[25] If a firm changes the industry it belongs to and continues to operate, we define it as a survivor. This definition slightly varies from that under the subsection Sectoral Aggregation in Section III, where survivors are defined as producers that operate in the same sector. However, we changed our definition here to ensure that the sum of the decomposed components is equal to the economy-wide aggregate TFP.

[26] Figure A1 in Appendices shows year-on-year changes in aggregate TFP and its components for the baseline results.

(3.8%) but is partially offset by the AE for survivors (-0.7%), net entry effect (-1.1%), and variety effect (-0.8%). The net entry effect is the sum of the positive entry effect (7.2%) and the negative exit effect (-8.3%). The TE for survivors is more volatile than the aggregate TFP growth, while the AE for survivors and the variety effect are relatively stable. Further decomposition of entry effects into the TE and AE for entrants indicates that both are positive (2.8% for the TE and 4.3% for the AE). Conversely, the TE and AE for exiters are both negative (-4.2% for the TE and -4.0% for the AE).

'Place Table 1 approximately here'

Table 2 illustrates the averages of the year-on-year changes in aggregate TFP and its components for each of the 5-year sub-periods (except for the 4 years of the first sub-period of 1987–1990 and the last one of 2011–2014). We refer to the sub-period of 1987–1990 as the bubble period, that of 1996–2000 as the banking crisis period, and that of 2006–2010 as the GFC period.[27] This shows that the TE for survivors shifted from negative in the bubble period to positive in the first half of the 1990s, and then it subsequently accelerated until the GFC, when it shifted to negative again. However, the TE was then picked up in the early 2010s (2011–2014). Conversely, the AE for survivors

[27] When we present the results from the BSJBSA in the subsection Firms in the Manufacturing and Non-manufacturing Industries, we refer to the period of 1995–2000 as the banking crisis period, although it is slightly different from the definition here.

continued to decline from 0.5% in the bubble period to 0% in the banking crisis period, and it further declined to -2.8% in the first half of the 2000s. However, it fluctuated between positive and negative values thereafter. The entry effect and its components were positive for all the sub-periods; this indicates that entrants were more efficient than survivors in both TE and AE. Conversely, the exit effect and its components were negative for all the sub-periods; this indicates that exiting establishments were more efficient than survivors in both TE and AE. Noticeably, the absolute values of the relative TE for exiters tended to increase from the 1990s, while those of the relative AE tended to decrease. The variety effect shifted from positive in the bubble period to negative thereafter; this indicates that the number of establishments decreased after the 1990s.

The decline in AE for survivors and the negative exit effect during the banking crisis period seem to be consistent with the zombie lending view (e.g., Caballero, Hoshi, and Kashyap 2008). The negative TE for exiters for the entire period is not consistent with the natural selection mechanism through which the market eliminates inefficient firms. However, this is consistent with the view that Japanese firms relocated production units abroad (Fukao, Kim, and Kwon 2009).

Moreover, the following question remains: How can we interpret the negative TE for survivors during the GFC? This case seems to be consistent with the view that

Japanese firms were hit by the crisis due to the decline in export demands (Hosono, Takizawa, and Tsuru 2016); as such, a demand shock is likely to cause a decline in measured TE, which is caused by a decline in capital utilization rates and work hours. Another possibility is that the GFC caused credit crunch, and it thus deteriorated firms' productivity due to the constraints in the financing for an intermediate input. However, such a credit crunch hypothesis is not likely to account for the major part of the decline in TE for survivors during the GFC; this is because the banking system in Japan did not suffer from severe damage due to the GFC, and most banks kept their balance sheets healthy.[28]

The DHKD aggregate TFP growth can be different from that of the JIP Database because of the differences in the aggregation of output and in the data covered.[29] Therefore, we compare the 5-year average of the year-on-year change in DHKD aggregate TFP growths with that in the JIP Database (Column 12 of Table 2).[30] We found

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[28] According to the Tankan published by the Bank of Japan, the diffusion index (DI) for the lending attitude of financial institutions declined to negative value in 2009. However, this decline was relatively small and short lived when compared to that in 1998 and 1999. The average values of the DI for small firms were 0.0 for 2005–2010, while they were -2.6 for 1996–2000 and -1.8 for 2001–2005. Further, the average DIs for medium-sized firms were also larger for 2005–2010 (7.1) than for 1996–2000 (3.0) or 2001–2005 (3.2). For large firms, the average DIs had positive and relatively high values (12.0 for 2005–2010 vs. 10.7 for 1996–2000 and 13.7 for 2001–2005).

[29] The DHKD uses the CES function to aggregates plant-level TFPQ into sectoral TFP and the Cobb-Douglas function to aggregate the sectoral TFP to aggregate TFP. Refer to the Hsieh-Klenow Framework in Appendices.

[30] For the JIP data, we used the data for 1987–1994 from the JIP Database 2015 and the data for 1995–2014 from the JIP Database 2018.

that both the sample period average and cyclical pattern are similar, although DHKD aggregate TFP growth measure is more volatile than the JIP and, in particular, the former in the bubble period is substantially lower than the latter.

'Place Table 2 approximately here'

Table 3 presents the correlation matrix among the aggregate TFP growth and its components. The aggregate TFP growth is positively correlated with the TE for survivors (with a correlation coefficient of 0.759), while it is negatively correlated with the AE for survivors (-0.306); however, it is not significant. Moreover, the TE and AE for survivors were negatively correlated with each other (-0.695). This might be because the adjustment costs of inputs hinder the smooth movement of inputs across establishments when some establishments are hit by positive productivity shocks. The TE for survivors was also negatively correlated with the entry effect (-0.861), exit effect (-0.882), and variety effect (-0.222).

'Place Table 3 approximately here'

Table 4 presents the dynamic correlation of the growth rate of aggregate output with the aggregate TFP growth and its components.[31] It shows that the aggregate TFP growth is not significantly correlated with the lagged, contemporaneous, or leading

[31] Refer to (A13) in Appendices for the aggregate output.

aggregate output growth. The TE for survivors is positively correlated with one-year ahead of aggregate output growth, and a positive TE may be contemporaneously offset, at least partially, by a negative AE owing to adjustment costs. The negative contemporaneous correlation between the output growth and AE is consistent with this view. It is also consistent with the findings by Osotimehin (2019) that when using a dataset of French manufacturing and service firms, her measure of the within-sector AE is countercyclical.

'Place Table 4 approximately here'

Comparison Between FHK and Dynamic Olley–Pakes Decomposition (DOPD). We conducted the FHK decomposition and compared the results with those from DHKD as the FHK decomposition has been the most popular method in the literature. Moreover, we conducted the Dynamic Olley–Pakes Decomposition (DOPD) developed by Melitz and Polanec (2015) because it measures the entry effect in comparison with the current period's industry productivity as we do, while the FHK uses the previous period's industry productivity as the reference for the entry effect. The same establishment data that we used to conduct DHKD were utilized for the FHK decomposition and DOPD.[32] For FHK and DOPD, we used the logarithm of $TFPQ_{it}$ as a measure of plant-level productivity

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[32] See subsections titled FHK's decomposition and Dynamic Olley-Pakes Decomposition in Appendices for the FHK decomposition and DOPD, respectively.

and sales share as a measure of weight. Here, it is worth noting that FHK and DOPD are not directly comparable with DHKD owing to their methodological differences in measuring aggregate productivity growth.[33] Owing to this difference, the average rate of increase in aggregate TFP is higher for FHK and DOPD (2.0%) than that for DHKD (1.3%). The FHK and DOPD series are more volatile than DHKD (the standard deviations are 20.9% for the FHK and DOPD and 6.2% for DHKD).[34]

Figure 2 presents the comparison of the three decompositions for the 5-year sub-periods. Panel A shows that the within effects for survivors in terms of FHK and DOPD and TE for survivors in terms of DHKD exhibit similar trends. Meanwhile, Panel B shows that the reallocation effects of survivors in terms of FHK and DOPD and AE for survivors in terms of DHKD exhibit quite different trends. The FHK reallocation effect is positive and sizable and does not decline during the banking crisis period.[35] As is easily seen from the discussion in Section II, the positive correlation between the productivity growth rate and the share growth does not necessarily indicate an improvement in AE in terms of

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[33] FHK and DOPD use the weighted average of plant-level productivity to derive an aggregate productivity. For the aggregation in DHKD, see footnote 25.
[34] Figure A2 in Appendices shows the aggregate TFP growths for the FHK and DOPD.
[35] The FHK's reallocation effect comprises the between effect (the fixed productivity-weighted sum of the change in shares among surviving producers) and the covariance effect (the sum of the multiples of the changes in shares and productivity of producers). While the between effect is negative for all the sub-periods, the covariance effect is positive and outweighs the negative between effect for all the sub-periods. Refer to Figure A3 in Appendices for the decomposition of the reallocation effect of FHK.

DHKD. The DOPD’s reallocation effect for survivors is also quite different from that of the DHKD’s AE for survivors. In particular, the DOPD’s reallocation effect is positive and accelerates from the previous period in the banking crisis period.

Panel C of Figure 2 shows the entry effects of the three decompositions. The FHK and DOPD entry effects exhibit similar trends (although their reference periods vary) and are quite different from the entry effect in terms of DHKD. The entry effects of the FHK and DOPD are negative for the sub-periods until 2000 and positive thereafter, whereas the DHKD’s entry effects are consistently positive and sizable. Panel D shows the exit effects, exhibiting a similar trend among the three series, although the level of DOPD’s exit effects is consistently lower than that of the other two decompositions. The differences in the entry and exit effects between the DHKD, on the one hand, and the FHK and DOPD, on the other hand, can be because the entry and exit effects in terms of DHKD capture the relative AE for entrants and exiters, as well as their relative TE.

'Place Figure 2 approximately here'

<u>Firms in the Manufacturing and Non-manufacturing Industries</u>

In this subsection, we present the DHKD results from the firm-level dataset from the BSJBSA over the 1994–2015 period. Table 5 shows the averages of the decomposition of the year-on-year changes in aggregate TFP for the 5-year sub-periods (except for the 6-

year sub-period of 1995–2000). We found that the TE for survivors was positive and relatively high for all the sub-periods, except for the GFC period. Conversely, the AE for survivors was negative for the banking crisis period (1995–2000) and the first half of the 2000s. The entry effect was consistently positive, which is consistent with the CM results. However, while the AE for entrants was consistently positive, the TE for entrants was negative for the banking crisis period and the first half of the 2000s, possibly because the BSJBSA covered large firms relative to the establishments covered by the CM. The exit effect and its components were consistently negative except for the TE during the banking crisis period, which is consistent with the CM results. The net entry effect was negative except for the banking crisis period when the exit effect was negative but small. The variety effect was positive (except for the first half of the 2000s, when it was zero) due to an increase in the number of firms entering the non-manufacturing industries.[36]

'Place Table 5 approximately here'

VI. SENSITIVITY ANALYSIS

In this section, we examine the extent to which our baseline results from the CM depend on the set parameters and suffer from measurement errors, which may also reflect

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[36] We present the results from manufacturing and non-manufacturing firms, separately, that are contained in the BSJBSA in subsections Results from Manufacturing Firms in the BSJBSA and Results from Non-manufacturing Firms in the BSJBSA, respectively, in Appendices.

the specification error. We further discuss whether our results are driven by the multi-plant firms' optimal investment decisions (Kehrig and Vincent 2019).

Different Elasticities of Substitution Across Industries

In the baseline specification, we assumed the same elasticity of substitution of goods across industries ($\eta_s = 3$). To examine the sensitivity of our baseline results to this assumption, we alternatively set different η_s for Rauch's (1999) three goods categories: commodity, reference priced, and differentiated. The results are qualitatively similar to the baseline results from common η_s across sectors.[37]

Measurement Error

Both marginal product and input price potentially suffer from measurement errors due to any omitted variables (e.g., capital utilization/vintages and labor hours/skill levels), misspecification of the production function, and data reporting errors (Bils, Klenow, and Ruane 2020). We implicitly assumed that such measurement errors are constant over time. This assumption is evidently too strong, especially for procyclical capital utilization. Therefore, our TE may capture the variations in them, as mentioned in Section IV.

To identify the role of measurement errors in aggregate TFP, we followed the study by Bils, Klenow, and Ruane (2020) and focused on the additive measurement

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[37] Refer to subsection Different Elasticity of Substitution Across Sectors in Appendices.

errors.[38] We found that 10% of the observed variance in $\log(TFPR_{it})$ is accounted for by additive measurement errors. The estimated size of the measurement errors in our dataset is close to that of David and Venkateswaren (2019) for China (8%) and the United States (12%). If A_{it} and $TFPR_{it}$ are jointly lognormally distributed, sector-level TFP A_{st} decreases by $\frac{\eta_s}{2}Var(\log(TFPR_{it}))$ (Hsieh and Klenow 2009). Therefore, under the baseline specification of $\eta_s = 3$ for all sectors, measurement errors account for 15% of aggregate TFP. Although the measurement error does not seem to account for a major part of aggregate TFP, a possibility remains that fluctuations in measurement errors account, at least partially, for the fluctuations in aggregate TFP and its decomposition.[39]

Multi-plant Firms

Kehrig and Vincent (2019) theoretically show that when a multi-plant firm faces an external financial constraint and plant-level fixed investment costs, it should maintain a certain level of dispersion in marginal revenue products of capital across its plants.[40]

For DHKD, examining the extent to which the measured AE reflects *changes* in such an optimal ("good") dispersion, rather than its level, is important. The results from

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[38] We ran an egression that is similar to that of David and Venkateswaren (2019) and Bai, Jin, and Lu (2019). Refer to subsection Measurement Error in Appendices.

[39] Note also that other types of measurement errors, such as multiplicative ones, might exist.

[40] They further demonstrate that, in US manufacturing, one-quarter of the total variance of revenue products of capital reflects such a "good dispersion," while in emerging economies, almost all dispersion reflects misallocation (i.e., "bad dispersion").

the firm-level dataset of the BSJBSA suggest that the changes in the plant-level marginal revenue of inputs within a multi-plant firm are not likely to be the main driver of the results from the plant-level data of the CM.[41] However, we explicitly examined the role of multi-plant firms in the dispersion of TFPR across plants in the CM dataset.

Using the CM database, we found that, while the variance of TFPR across multi-plant firms is higher than that across single-plant firms by 25% on average (0.939 vs. 0.754), the share of multi-plant firms is significantly stable (i.e., its mean and standard deviation are 73.6% and 0.9%, respectively). Thus, the effect of the change in the share of multi-plant firms on the measured AE is minimal. Under the assumption of $\eta_s = 3$ for all industries, it is 0.08% at most for the 5-year average of the measured AE.[42]

VII. CONCLUSION

In this paper, we have provided a new perspective on stagnant aggregate productivity in Japan by extending the Hsieh and Klenow (2009) framework; in this extended framework, we account for the productivity growth, entry and exit, and change in product variety. We have applied this DHKD to an establishment-level dataset of manufacturing industries and a firm-level dataset of manufacturing and non-manufacturing industries in Japan. The results from these two datasets demonstrate that

[41] Refer to footnote 16 as well.
[42] Refer to subsection Multi-plant Firms in Appendices.

the AE among survivors declined during the banking crisis period of the latter half of the 1990s, while the TE declined in the GFC period of the latter half of the 2000s. Our results for AE are consistent with the zombie lending perspective and in contrast with the results of the FHK decomposition and the DOPD. Thus, our results suggest that AE matters for aggregate TFP in the medium to long-term.

While the strength of the Hsieh–Klenow framework and DHKD are their identification of AE, which is a deviation from the optimal level of output, they have the following limitations: assumptions on functional forms and parameter values, measurement errors, and absence of investment decisions by multi-plant firms. We have attempted to address these issues but have not found evidence that such confounders affect our main results. However, a possibility remains that these factors account, at least partially, for our results.

To identify the driving factors of each component of aggregate productivity growth, focusing on specific shocks, such as financial shocks, export shocks, and natural disasters, might be effective by exploiting variations in each component across industries and regions. Hence, our future work will focus on these aspects.

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TABLE 1

Descriptive statistics of aggregate TFP growth and its components: baseline result

Variables	Mean	Median	SD
TFP	1.3%	1.3%	6.2%
TE for survivors	3.8%	7.4%	22.7%
AE for survivors	-0.7%	-0.6%	5.6%
Entry effect	7.2%	4.2%	8.8%
TE for entrants	2.8%	1.4%	4.5%
AE for entrants	4.3%	3.2%	4.5%
Exit effect	-8.3%	-8.0%	7.1%
TE for exitors	-4.2%	-4.0%	5.3%
AE for exitors	-4.0%	-3.5%	2.6%
Variety effect	-0.8%	-0.6%	1.5%
(Net entry effect)	-1.1%	-3.7%	14.4%

Note. Descriptive statistics for the 28 sample years of 1987-2014.

TABLE 2

Sub-period averages of aggregate TFP growth and its components: baseline result

Period	(1) TFP	(2) TE for survivors	(3) AE for survivors	(4) Entry effect	(5) TE for entrants	(6) AE for entrants	(7) Exit effect	(8) TE for exitors	(9) AE for exitors	(10) Variety effect	(11) (Net entry effect)	(12) (TFP from JIP)
1987-1990	0.7%	-0.7%	0.5%	9.3%	3.4%	5.8%	-9.0%	-4.3%	-4.7%	0.6%	0.3%	3.3%
1991-1995	0.7%	0.6%	0.4%	5.1%	1.0%	4.1%	-5.0%	-0.7%	-4.3%	-0.5%	0.1%	0.6%
1996-2000	1.5%	2.2%	0.0%	6.7%	2.5%	4.2%	-6.4%	-2.3%	-4.1%	-1.0%	0.3%	1.5%
2001-2005	3.7%	12.0%	-2.8%	5.2%	1.7%	3.6%	-9.6%	-5.3%	-4.2%	-1.2%	-4.3%	1.7%
2006-2010	0.5%	-5.5%	4.0%	10.6%	5.5%	5.2%	-7.9%	-4.7%	-3.3%	-0.7%	2.7%	1.2%
2011-2014	0.4%	15.8%	-7.2%	6.4%	3.0%	3.4%	-12.8%	-9.2%	-3.6%	-1.9%	-6.4%	1.2%
1987-2014	1.3%	3.8%	-0.7%	7.2%	2.8%	4.3%	-8.3%	-4.2%	-4.0%	-0.8%	-1.1%	1.5%

Notes. Column (12) shows the TFP growth of manufacturing industries from the JIP database 2015 (for 1987-1994) and the JIP database 2018 (for 1995-2014).

TABLE 3

Correlation matrix of aggregate TFP growth and its components: baseline result

	TFP	TE for survivors	AE for surivors	Entry effect	TE for entrants	AE for entrants	Exit effect	TE for exitors	AE for exitors	Variety effect	(Net entry effect)
TFP	1.000										
TE for survivors	0.759 ***	1.000									
AE for surivors	-0.306	-0.695 ***	1.000								
Entry effect	-0.590 ***	-0.861 ***	0.409 **	1.000							
TE for entrants	-0.649 ***	-0.893 ***	0.486 ***	0.969 ***	1.000						
AE for entrants	-0.492 ***	-0.773 ***	0.306	0.968 ***	0.875 ***	1.000					
Exit effect	-0.592 ***	-0.882 ***	0.625 ***	0.637 ***	0.680 ***	0.554 ***	1.000				
TE for exitors	-0.580 ***	-0.842 ***	0.677 ***	0.550 ***	0.579 ***	0.486 ***	0.956 ***	1.000			
AE for exitors	-0.447 **	-0.710 ***	0.342 *	0.633 ***	0.690 ***	0.534 ***	0.804 ***	0.594 ***	1.000		
Variety effect	0.024	-0.222	0.166	0.220	0.163	0.264	0.118	0.093	0.134	1.000	
(Net entry effect)	-0.652 ***	-0.960 ***	0.559 ***	0.925 ***	0.926 ***	0.864 ***	0.883 ***	0.808 ***	0.783 ***	0.192	1.000

Note. ***, **, and * denote the significance levels of 1%, 5%, and 10%, respectively.

TABLE 4

Dynamic correlation with aggregate output growth and aggregate TFP and its components: baseline result

	output(t-1)	output(t)	output(t+1)
TFP	-0.126	-0.255	0.215
TE for survivors	-0.398 **	-0.009	0.328 *
AE for surivors	0.100	-0.338 *	-0.183
Entry effect	0.471 **	0.084	-0.373 *
TE for entrants	0.444 **	0.093	-0.328 *
AE for entrants	0.469 **	0.070	-0.396 **
Exit effect	0.450 **	-0.101	-0.296
TE for exitors	0.287	-0.053	-0.323
AE for exitors	0.651 ***	-0.169	-0.157
Variety effect	0.249	0.336 *	0.161
(Net entry effect)	0.512 ***	0.002 *	-0.374 *

Note. ***, **, and * denote the significance levels of 1%, 5%, and 10%, respectively.

TABLE 5

Decomposition of aggregate TFP growth of manufacturing and nonmanufacturing firms in BSJBSA

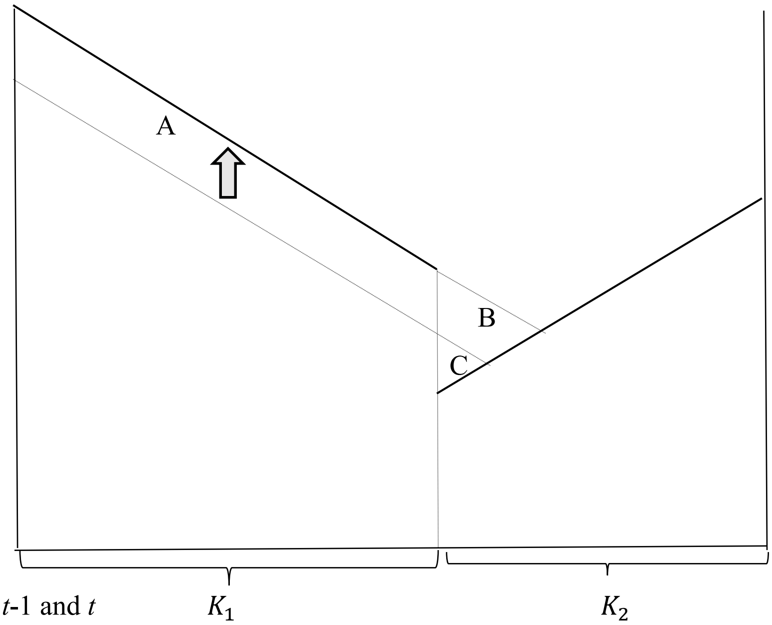
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
Period	TFP	TE for survivors	AE for survivors	Entry effect	TE for entrants	AE for entrants	Exit effect	TE for exitors	AE for exitors	Variety effect	(Net entry effect)
1995-2000	5.0%	6.0%	-3.0%	3.6%	-4.5%	8.1%	-2.3%	1.7%	-4.0%	0.8%	1.3%
2001-2005	6.9%	13.6%	-5.2%	4.4%	-0.3%	4.7%	-5.9%	-5.3%	-0.6%	0.0%	-1.5%
2006-2010	6.8%	4.1%	4.0%	7.9%	2.9%	5.0%	-9.5%	-6.4%	-3.2%	0.4%	-1.7%
2011-2015	2.6%	9.2%	0.5%	3.8%	0.6%	3.2%	-11.0%	-6.2%	-4.8%	0.1%	-7.2%
1995-2015	5.3%	8.1%	-1.1%	4.8%	-0.5%	5.4%	-7.0%	-3.8%	-3.2%	0.4%	-2.1%

Note. $\eta = 3$

FIGURE 1

Panel A. DHKD

Producer 1's marginal product: $A_{1s}f'(K_1)$ Producer 2's marginal product: $A_{2s}f'(K_2)$

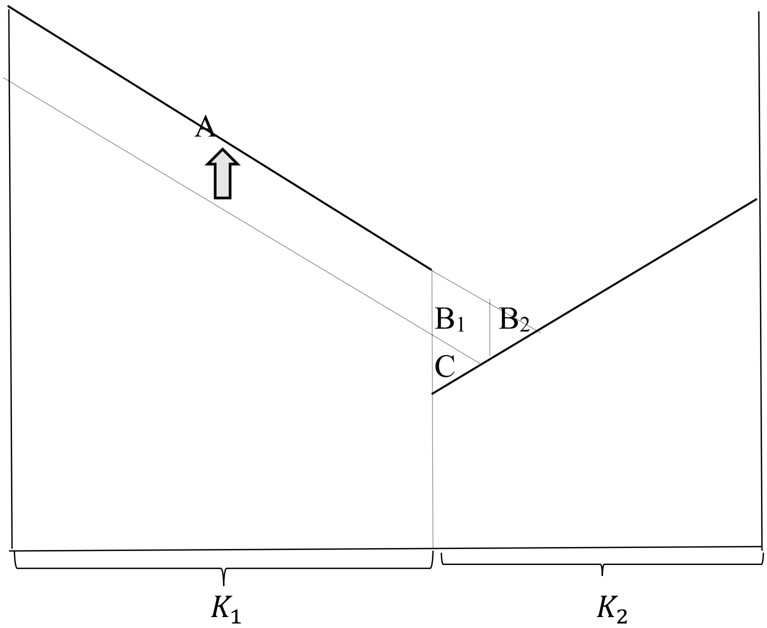


Allocation in *t*-1 and *t*

TE= A+B and AE=-B

Panel B. Osotimehin (2019)

Producer 1's marginal product: $A_{1s}f'(K_1)$ Producer 2's marginal product: $A_{2s}f'(K_2)$



TE= A+B_1, where B_1=B- B_2 and B_2=C, and AE=- B_1.

FIGURE 2
Comparison of the three decompositions (FHK, DOPD and DHKD) for the 5-year sub-periods