1. Why has long-run productivity growth tended to slow-down in advanced economies?

A common feature of advanced economies since the 1980s has been lower growth of productivity (here, real GDP per worker). Suggested reasons for this include: business cycle phenomena (investment, innovation and uncertainty); chronically weak demand; slower international trade growth; and education and other institutional deficiencies.

Using World Bank global productivity data, together with other data and information of your choice, and focusing on the 10 advanced market economies listed below:

a) Identify, evaluate and justify the main factors contributing to variations in growth of productivity (as defined in the World Bank study) for the set of 10 advanced market economies between 1980 and 2018 (or later).
b) Apply your analysis to the sub-periods 1980-2000 and 2000-2018. Examine for structural breaks. Report and explain your findings and compare and contrast them with the results of the full-period analysis.
c) Examine how the factors you have identified influence variations in productivity growth among the 10 economies and, if relevant, among 'convergence clubs' of economies exhibiting similar characteristics.
d) Comment on the relationships between productivity growth, capital deepening and total factor productivity (TFP). Is there evidence of a 'productivity J-curve'? (See Brynjolfsson et al. 2017)

* The 10 advanced market economies are: Australia, Canada, France, Germany, Italy, Japan, Netherlands, Spain, United Kingdom, United States.

(1994 Words & 8 Tables)

1. Introduction

Labour productivity is a key factor influencing economic growth. In fact, most cross-country differences in per capita income growth – the principal agent of poverty reduction – can be attributed to labour productivity growth variations. This is what makes the 50% reduction since the 1980s of labour productivity growth in advancing economies so worrying. (World Bank 2020)

This study uses econometric analysis to explore the factors contributing to variations in productivity growth. It also investigates themes of convergence and a productivity J-curve to address the slowdown of productivity growth seen in recent years.

Table 1: Literature Review		
Author (Year)	**Investigation focus**	**Summary of Findings**
	FACTORS INFLUENCING PRODUCTIVITY GROWTH	
World Bank, Dieppe et al. (2020)	Impacts of proximate sources, market development and the supporting environment on labour productivity	Proximate sources refer to innovation and capital (human and physical), market development refers to foreign direct investment and economic complexity, whilst supporting environments include institutions and economic stability. Through a Bayesian approach to panel data, these are found to be drivers of productivity growth with changing impact over time.
Kim and Loayza (2019)	The determinants of total factor productivity (TFP) growth	Using TFP - rather than labour productivity - to measure productivity growth, through a panel data approach the paper classifies innovation, education, market efficiency, infrastructure and institutions as the principal factors influencing productivity growth. By constructing an index for each factor, they find that market efficiency contributes the most and infrastructure the least among OECDs in the last decade.
Acemoglu and Dell (2010)	Productivity differences in the Americas between and within countries through a labour income focus	This study assesses the impact of technological capabilities, institutions and human capital on productivity differences within and between countries. Through collecting data on labour income, it finds that roughly half of between country/municipality differences are due to human capital. It also finds technology adoption is a determinant at the country level, whilst local institutions are a determinant within countries.
Griffith et al. (2004)	The impact of innovation on the growth of productivity in OECD countries	Through investigating data on 12 OECD countries from 1974-1990, this paper finds that research and development (R&D) and human capital have both an economically and statistically significant impact on productivity growth through stimulating innovation.
Barro (1996)	Variations in growth due to democracy	Results from regressions of panel data on roughly 100 countries from 1960-1990 expand upon the neoclassical growth model. He finds that once factors such as the rule of law, human capital and policy outcomes are controlled for, democracy has weakly negative impacts on growth, although it may have a positive impact in developing nations starting with few political rights.
	CONVERGENCE CLUBS	
Battisti and Parmeter (2013)	Similarities in the *levels* of productivity	When including variables of TFP, human capital and physical capital, 2-3 clusters of convergence clubs are found when considering productivity levels for 1950-2000. The World Bank (2020) builds on this methodology to find four clubs by 2018, but Club 1 (denoting a club at the frontier) still consists of only advancing economies.
Phillips and Sul (2009)	Similarities in the *trajectories* of productivity	When considering common productivity trajectories from 1970-2000, 5 convergence clubs are found, with only advancing economies in Club 1. The World Bank (2020) builds on this to find 16 emerging markets and developing economies (EMDEs) in Club 1 by 2018. By considering a sample of these EMDEs alongside the advanced economies, I further investigate factors influencing productivity growth among convergence clubs.
	PRODUCTIVITY J-CURVE	
Brynjolfsson et al. (2017)	The existence of a J-curve (within US markets)	Both studies find evidence that due to intangible investment and stock effects, there exists a J-curve in productivity growth (TFP) mismeasurement through delayed adoption. In response to an investment shock, it seems to underestimate productivity in the short run and overestimate it in the long run. 2017 focuses on the example of AI and machine learning whilst 2018 introduces R&D, software and hardware investments. Earlier works of David (1990) support this argument with an Industrial Revolution example while Cusolito and Maloney (2018) suggest a future increase in productivity as recent innovations feed through. In this spirit, I investigate the short and long run relationships between productivity growth, TFP and capital deepening.
Brynjolfsson et al. (2018)		

2. Theoretical Framework

2.1 Factors influencing productivity growth

This study focuses on advancing economies, where "growth was almost entirely driven by within-sector productivity growth" (World Bank 2020) rather than sectoral reallocation. Thus, I focus on a factor inputs approach.

An extension of the traditional Solow-Swan growth model to include the level of human capital defines labour productivity growth as…

$$\Delta LP_t = (1-\alpha)\Delta k_t + \Delta a_t + \alpha\Delta h_t$$

…where k_t is log of the capital-labour ratio, h_t is the log of the human capital level and a_t is the log of TFP calculated as a residual. Thus, growth is increasing in capital deepening and TFP.

My analysis extends this model to include proxies for these factor inputs, as well as supplementary factors linked with trade and the supporting environment, in order to analyse the determinants of productivity growth.

2.2 Convergence Clubs

Through methodology following Phillips and Sul (2009), countries form a club if deviations from a common attraction point fall over time, with sixteen EMDEs joining the advancing economies in club 1 since 2000.

I focus on seven[1] of these EMDEs, which are relevant due to a focus on **trajectories**, allowing for deeper analysis of factors leading to convergence at the frontier.

2.3 A productivity J-curve

Brynjolfsson focuses on TFP, estimates of which are prone to inaccuracy due to levels of factor input utilization and any misspecification of the growth model. In accordance with the focus of this study, I

[1] Bulgaria, China, Hungary, India, Poland, Romania, Turkey

investigate the short and long run impacts of an investment shock on labour productivity, to further analyse the relationship between productivity growth, capital deepening (Δk_t) and TFP growth rates.

Table 2: Variables and Data Summary

Variable	Definition	Justification	Mean	Standard Deviation	Minimum	Maximum
dlpe	Labour productivity growth rate (%)	This study focuses on variations in productivity growth **rates**, not levels, so I use dlpe throughout as the **dependent variable**	1.23	1.45	-5.78	7.38
FACTORS INFLUENCING PRODUCTIVITY GROWTH						
patents	Resident patent applications per 10,000 people	A proxy for technological change, which is a factor impacting growth rates stemming directly from the neoclassical growth model.	4.62	6.98	0.326	30.3
gfcf	Gross fixed capital formation (% of GDP)	A measure of physical capital accumulation, affecting productivity growth through its influence on capital per worker	22.4	3.37	15.4	34.2
educ	Index of adult years of schooling and expected years of child schooling	Influences the human capital input of the growth model; better educated workers should be more productive. (Im and Rosenblatt 2015)	0.787	0.0945	0.591	0.943
le	Life expectancy at birth	Influences the human capital input of the model; healthier workers should be more productive (Benhabib and Spiegel 2003)	78.6	2.64	72.7	84.2
fdi	Foreign direct investment (FDI) net inflows (% of GDP)	FDI inflows can encourage productivity growth through improved technology and as a source of capital.	2.91	7.30	-39.5	86.6
xmprcnt	Imports and Exports (% of GDP)	Evidence suggests that relatively open economies are more productive (De Loecker 2013)	52.8	27.7	16.0	159
eci	Economic complexity index (Hidalgo and Hausmann 2009)	This index portrays diversification and production capabilities, which can impact productivity growth (Diao et al 2019)	1.38	0.696	-0.846	2.62
law	Strength of and adherence to the law (index)	Rule of law can influence productivity (Bazzi and Clemens 2013) through securing rights and controlling corruption	5.37	0.653	3	6
stability	(-1)*Inflation rates (consumer prices)	Inflation is used as a proxy for uncertainty to consider the impacts of stability on productivity growth.	-3.23	3.26	-21.1	1.35
urban	Urban population (% of total population)	Urbanisation leads to agglomeration, which influences productivity through knowledge spill-over and skills matching.	77.7	5.85	64.7	91.6
CONVERGENCE CLUBS						
agri, mine, manu, util, cnstrct, trde, trnsprt, fin, oth	Through taking log differences of World Bank sectoral data, growth rates of labour productivity in agriculture, mining, manufacturing, utilities, construction, trade services, transport, finance and other services respectively. These are later used to explain developing nation convergence in Club 1.		N/A Also note that all other figures are reported for the dataset of only the 10 advancing economies.			
PRODUCTIVITY J-CURVE						
dtfp	TFP growth (%)	As measured in the World Bank productivity dataset, these are used to further investigate their relationships with productivity growth.	0.201	1.34	-6.25	4.92
capdeep	Capital deepening (% contribution)		0.685	0.612	-0.623	3.18

3. Data

This study features panel data on ten advanced economies from 1980-2018 (and seven EMDEs post-2000). Labour productivity growth rates – the dependent variable throughout this study – are provided by the World Bank cross-country database of productivity. This defines labour productivity as real GDP per worker, avoiding purchasing power parity (PPP) measurements as they face considerable error due to reliance on infrequent price surveys and extrapolation.

Regressors[2] were chosen considering theoretical impacts supported by literature and the quality of data available. The majority of data for regressors is from the World Bank WDI database, with the UNDP and OEC supplementing for indexes of education and economic complexity respectively. The ICRG dataset provides a law and order index.

There were occurrences of missing data for some variables that could not be gathered from any of the sources used. Values were manually imputed using adjacent data within context, such as using following years at the beginning of the dataset and recent years at the end. Data for R&D was considered as a further proxy of innovation – and may have provided further insight – but was disregarded due to excess missing data.

[2] Table 2 includes variable list with data summary and justifications

Table 3: Diagnostics Results			
Issue	Test	Results	Comments
FACTORS INFLUENCING PRODUCTIVITY GROWTH (ADVANCING ECONOMIES)			
Random effects suitability	Hausman	H_0: Random effects more suitable (due to efficiency) p = 0.0792	This rejects the use of random effects estimation at the 10% level but doesn't at the 5% level. Since the influence of unobserved effects follows theory of my model, I proceed without random effects for brevity.
First differences suitability	Levin-Lin-Chu unit root test for panel data on errors	H_0: Unit root in errors p = 0.0000	Errors with a random walk would suggest that first difference estimation is preferred to fixed effects. This test suggests no unit root, so I proceed with both methods of estimation and compare each.
Serial Correlation	Wooldridge (2002)	H_0: No first-order autocorrelation p = 0.0013	Tests strongly suggests that serial correlation and heteroscedasticity are issues, invalidating standard errors, so I proceed with (HAC) standard errors.
Heteroscedasticity	Breusch-Pagan	H_0: Constant variance p = 0.0000	
	White	H_0: Constant variance p = 0.0000	
Misspecification	Ramsey RESET	H_0: No function misspecification (higher-order variables not appropriate) p = 0.5830	This suggests that perhaps higher order variables are inappropriate in my model, so I proceed (cautiously) with it unchanged.
Multicollinearity	Pairwise correlation assessment	None of the dependent variables have correlations higher than 0.63, with only three cases of correlation above 0.5 (patents/eci, educ/urban, le/stability)	This could suggest that the cause of estimation issues is not multicollinearity.
Normal distribution of errors	Skewness and kurtosis test for panel data	H_0: idiosyncratic errors are normal p = 0.0228 H_0: unobserved effect is normal p = 0.0000	This strongly implies the assumption of normal errors is invalid. Thus, asymptotic approximations of fixed effects estimation are likely to be impacted as the model doesn't feature large N (countries) and small T (years).
PRODUCTIVITY J-CURVE			
Order of integration	Augmented Dickey Fuller Test (assuming a constant)	For all 10 countries, all variables are found to be I(0) apart from in seven cases of I(1) capdeep variables	An augmented dickey fuller test can be a trial-and-error approach which often requires more rigour (considering inclusion/exclusion of constants and trends), but we proceed with our ARDL process as results suggest conditions are met.
Significance of long run relationship	Cointegration Bounds Test (Pesaran et al. 2001)	H_0: No long run relationship To reject, must exceed upper bound for the case of no intercept and no trend (2 exogenous variables): F=3.83	Running this test post-estimation, I am able to reject the null for two countries – Japan and Germany – but cannot for seven countries. (Canada isn't tested as initial estimation suggests no long-run relationship)

4. Model Specification

3.1 Factors influencing productivity growth

Here, my model is specified as such:

$$y_{it} = \gamma_0 + \delta_2 d2_t + ... + \delta_{39} d39t + \beta_1 x_{it1} + ... + \beta_k x_{itk} + \alpha_i + u_{it}$$

y_{it} represents the dependent variable, labour productivity growth rates. For the thirty-nine time periods I implement thirty-eight dummies (to avoid the dummy variable trap), whilst k = 10 for our ten regressors. a_i represents the country-specific time-invariant factors influencing productivity growth, such as locational factors. u_{it} represents the idiosyncratic error.

Given the examples above, it is likely that the unobserved time-invariant factors are correlated with our regressors. Thus, a pooled OLS regression is rejected as it would violate the Gauss-Markov assumption of exogeneity. This also suggests a random effects regression is inappropriate, and a Hausman test rejects its use at all significance levels above 7.92%, so we proceed without random effects for brevity.

This leaves me with fixed effects (FE) and first differences (FD) as models to consider. Econometric theory states that FE is more efficient in the absence of serial correlation, but a Wooldridge test strongly rejects this assumption. If the error term follows a random walk, FD is a better choice as it will remove this correlation. However, a Levin-Lin-Chu test rejects the presence of a unit root in the idiosyncratic error with one lag. Since further diagnostics strongly suggest the presence of heteroscedasticity, I proceed with both FE and FD estimations with heteroscedasticity and autocorrelation consistent (HAC) errors.

FE estimation removes endogeneity caused by α_i through subtracting averages over time from the RHS and LHS of the equation, leading to unbiased estimates of β_k as long as regressors are not correlated with the idiosyncratic error. Under this assumption, FD will also lead to unbiased estimates, removing α_i by differencing between adjacent periods.

3.2 Productivity J-curve

To investigate the existence of a productivity J-curve, I apply the linear autoregressive distributed lag (ARDL) cointegration approach of Pesaran et al. (2001) to each advancing economy:

$$\Delta dlpe_t = \Sigma^n_{j=1}\alpha_j \Delta dlpe_{t-j} + \Sigma^n_{j=0}\beta_j \Delta dtfp_{t-j} + \Sigma^n_{j=0}\gamma_j \Delta capdeep_{t-j} + \theta_1 dlpe_{t-1} + \theta_2 dtfp_{t-1} + \theta_3 capdeep_{t-1} + \varepsilon_t$$

Here, labour productivity growth responds to an investment shock – an increase in contribution of capital deepening – over time. If γ_j are negative/insignificant (where j is the number of lags) then this explains a decline/stagnation of growth in the short run, while a positive and significant θ_3 represents a long run improvement in growth.

This estimation allows for variables to be integrated of order zero or one at the highest, with a cointegration bounds test required to confirm the long run relationship. My diagnostics results account for these conditions.

Table 4: Factors influencing productivity growth (advancing economies), dependent variable: dlpe

	1980-2018		1980-1999		2000-2018		2008-2018	
	FE	**FD**	**FE**	**FD**	**FE**	**FD**	**FE**	**FD**
patents	-0.0000319	0.00583*	-0.00120*	0.00548*	0.00572	0.00679	-0.000872	0.00689
	(0.00197)	(0.00263)	(0.000391)	(0.00266)	(0.00441)	(0.00673)	(0.0112)	(0.0129)
gfcf	-0.0626	-0.139	-0.243	-0.0613	-0.0614	-0.235	0.0594	-0.321
	(0.0872)	(0.0871)	(0.138)	(0.115)	(0.0563)	(0.137)	(0.107)	(0.197)
educ	-0.0107	-0.0159	-0.00540	0.00636	-0.00960	-0.0368	-0.0284	-0.0536
	(0.00558)	(0.0147)	(0.0123)	(0.0187)	(0.0137)	(0.0223)	(0.0180)	(0.0353)
le	-0.223	0.0187	-0.447	-0.453	0.0485	0.338	0.325	0.126
	(0.163)	(0.347)	(0.280)	(0.483)	(0.210)	(0.518)	(0.592)	(0.903)
fdi	0.0168*	0.00861	0.0178	-0.0631	0.0136*	0.00801	0.0126*	0.00465
	(0.00681)	(0.00772)	(0.130)	(0.156)	(0.00477)	(0.00896)	(0.00413)	(0.0136)
xmprcnt	0.0336	0.156***	0.0185	0.0680	0.0461*	0.215***	0.0750	0.291***
	(0.0168)	(0.0371)	(0.0268)	(0.0353)	(0.0187)	(0.0522)	(0.0546)	(0.0725)
eci	0.530	-1.101	1.432*	0.454	-0.0173	-1.317	-0.655	-1.332
	(0.604)	(0.740)	(0.475)	(1.620)	(0.844)	(0.873)	(0.579)	(1.016)
law	0.111	0.380	-0.531	0.305	0.624***	0.413	-2.127**	1.476
	(0.175)	(0.284)	(0.292)	(0.455)	(0.123)	(0.306)	(0.562)	(2.382)
stability	0.102	0.284***	0.131	0.328***	0.119	0.288**	0.0615	0.341*
	(0.0984)	(0.0604)	(0.103)	(0.0731)	(0.122)	(0.107)	(0.132)	(0.139)
urban	-0.0246	-0.370	0.0631	-0.208	-0.160***	-0.471	0.0430	-0.542
	(0.0347)	(0.275)	(0.0901)	(0.361)	(0.0239)	(0.345)	(0.468)	(1.010)
N	390	380	200	190	190	190	110	110

HAC standard errors in parentheses, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$
N represents number of observations, FE represents fixed effects, FD represents first differences

5. Results

World Bank (2020) notes the ‘corrosive effects’ on productivity growth that financial crises can have, so I include regressions for 2008-2018 for further analysis. Initially, results seem erratic, but this can be explained by precise interpretation and evaluation.

4.1 Interpretation

<u>Factor Inputs</u>

The impact of patents lacks both economic and statistical (at the 5% level) significance for 1980-2018. Both FE and FD report significant coefficients at the 10% level for 1980-1999, but with opposite signs and little magnitude. Meanwhile, for the 2000-2018 and post-crisis regressions the lack of significance remains. Investment and education report negative coefficients of relatively greater magnitude throughout, but these lack statistical significance. FE and FD report life expectancy coefficients of opposite signs for 1980-2018, which may be explained by its negative impact reported for 1980-1999 and positive impact for both regressions after 2000. However, statistical significance is absent here also.

<u>Trade</u>

For 1980-2018, both FDI and economy openness (proxied by xmprcnt) have positive impacts on productivity growth, reported with statistical significance by FE and FD respectively. The statistical significance (and economic significance in the case of xmprcnt) is much greater for post-2000 regressions in comparison to a lack of significance for 1980-1999. This suggests that trade and inflows of foreign investment played a larger role in contributing to growth rates in the new millennium. Meanwhile FE and FD estimates of the impact of economic complexity have opposite signs for 1980-2018, which can perhaps be implied by negative impacts reported post-2000 but a positive impact (statistically significant in FE) for 1980-1999. Aside from this, ‘eci’ coefficients lack statistical significance.

<u>Supporting Environment</u>

The rule of law lacks significance for 1980-1999, as well as the overall 1980-2018 regression. This might be explained by reports of opposite magnitude that are of high economic and statistical (1% level) significance for the 2000-2018 and post-crisis regressions respectively. Results may suggest an initial positive impact of the rule of law post-2000, followed by an opposite impact due to stress caused by the financial crises. Stability has a positive impact on productivity growth throughout, with a unique cause of similar-magnitude coefficients between the overall regression, 1980-1999 and 2000-2018. However, only FD reports statistical significance, which falls over time to the 10% level in the post-crisis regression. Meanwhile, urbanisation reports largely negative coefficients throughout, with statistical significance only present for the 2000-2018 regression.

4.2 Discussion

Convergence

The membership of advancing economies in the convergence club at the frontier of productivity levels (Battisti and Parmeter 2013) can explain unexpected negative coefficients as convergence theory postulates the lower growth rates of such economies. Since I investigate variations in **growth**, a negative coefficient doesn't imply that the regressor worsens productivity *levels*, but just that any increase it might cause is insufficient to improve growth rates. A regression with productivity levels as the dependent variable was considered (but omitted as I focus on productivity growth), with a high frequency of economically and statistically significant coefficients, being positive in many cases.

FE vs FD

Clear heterogeneity between estimations complicates interpretation, whilst diagnostics make it difficult to choose one as superior. A 39-year time period (large T) also makes FE estimation more sensitive to violating its asymptotic assumptions. The nature of results reflects the limitations of the model, calling for a more sophisticated approach. Regardless, investigating growth determinants poses severe challenges[3], leading to evidence of specification searching to achieve statistical significance in the literature (Bruns and Ioannidis 2020). Thus, the lack of significance in my model is not surprising and doesn't discredit the existence of these determinants.

[3] Table 8 includes discussion of study's drawbacks

Table 5: Structural break examination	
Is there evidence of a structural break in 1999?	
Australia	No (p-value = 0.9575)
Canada	No (p-value = 0.5514)
France	**Yes (p-value = 0.0578)**
Germany	No (p-value = 0.2325)
Italy	No (p-value = 0.6332)
Japan	No (p-value = 0.1052)
Netherlands	No (p-value = 0.2848)
Spain	**Yes (p-value = 0.0284)**
United Kingdom	No (p-value = 0.2630)
United States	No (p-value = 0.5701)
Here I have tested the null hypothesis of homogeneity of coefficients in the periods 1980-1999 and 2000-2018 within each country cross-section. "Yes" indicates H_0 is rejected and "No" indicates that H_0 is not rejected, with p-values shown regarding the respective Chow test at the 10% significance level.	

4.3 Structural Breaks

Interpretation shows changes in panel regression coefficients between time periods, but this lacks precision and ignores country specifics. After deeper analysis of each country, a Chow test for the homogeneity of coefficients for the periods 1980-1999 and 2000-2018 rejects this assumption (indicating a structural break) for only France and Spain. However, note that the large number of regressors makes it difficult to reject the null, whilst test assumptions of normal errors and constant variance are likely invalid.

Table 6: Factors influencing productivity growth (EMDEs), dependent variable: dlpe							
	2000-2018		2008-2018			SECTOR CORRELATIONS	
	FE	**FD**	**FE**	**FD**			dlpe
patents	-0.537	1.329	-0.649	0.183		dlpe	1.0000
	(0.314)	(1.087)	(0.371)	(1.046)			
						agri	0.3075
gfcf	0.225	0.385	0.273	0.478			
	(0.109)	(0.244)	(0.288)	(0.305)		mine	0.1263
educ	-22.31	3.660	-7.639	26.33		manu	0.4247
	(26.95)	(37.51)	(20.14)	(35.93)			
						util	0.1915
le	0.253	-1.395	0.206	-1.102			
	(0.579)	(1.318)	(0.870)	(1.726)		cnstrct	0.4447
fdi	-0.00583	-0.0104	-0.00291	0.000929		trde	0.3891
	(0.0129)	(0.0286)	(0.00828)	(0.0290)			
						trnsprt	0.4864
xmprcnt	-0.00610	0.109	0.0714	0.183*			
	(0.0223)	(0.0635)	(0.0405)	(0.0890)		fin	0.3201
eci	-4.783	-1.885	1.088	-1.711		oth	0.3828
	(2.758)	(2.962)	(2.723)	(2.372)			
law	0.561	-0.439	-0.952	-0.609			
	(0.940)	(1.425)	(0.726)	(1.976)			
stability	-0.0235	0.120	0.115	0.163			
	(0.0374)	(0.133)	(0.192)	(0.160)			
urban	0.222	-0.456	0.224	-0.334			
	(0.269)	(0.690)	(0.337)	(1.139)			
N	133	126	77	77			
HAC standard errors in parentheses, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$						By taking log differences using sector productivity data from post-2000, correlations of sector specific growth rates with overall growth rates are calculated	

4.4 Convergence Club 1 (EMDEs)

The relevance of my study of the seven EMDEs stems from their common convergence with advancing economies in productivity **trajectory**. This allows for greater analysis of convergence at the frontier.

Only the positive impact of economy openness (FD) post-crisis shows statistical significance. However, we have ignored sector reallocation, which caused 40% of growth in EMDEs. The correlations of productivity growth within sectors and overall growth rates show that factor reallocation from low productivity sectors such as agriculture towards service sectors and manufacturing has contributed to growth among EMDEs of the top convergence club.

Table 7: ARDL results to test for evidence of a J-curve, dependent variable: dlpe

	capdeep: Short run	capdeep: Long run		Estimation results
Australia	-0.015 (0.711), j=1	0.859 (0.000)		B
Canada	1.035 (0.000), j=0	0.366 (0.888)		C
France	-0.110 (0.106), j=1	0.914 (0.023)		B
Germany	-0.007 (0.849), j=1	1.501 (0.003)		A
Italy	-0.002 (0.944), j=2	1.245 (0.000)		B
Japan	-0.008 (0.744), j=2	1.093 (0.000)		A
Netherlands	0.004 (0.805), j=1	1.172 (0.000)		B
Spain	-0.010 (0.224), j=1	1.151 (0.000)		B
United Kingdom	0.007 (0.800), j=1	1.418 (0.000)		B
United States	0.024 (0.317), j=1	0.024 (0.000)		B

Values of the coefficient are reported, with the corresponding p-value in brackets. This p-value represents that from a test of H_0 that the coefficient equals zero. For the short run coefficients, j represents the j^{th} lag, where (in most cases) the lowest value of j is reported providing evidence for a J-curve.

Estimation results:

- "A" shows that the country's coefficients provide evidence for a J-curve and its results from the ARDL bounds test suggest a long run relationship.
- "B" shows that the country's coefficients provide evidence for a J-curve, but its results from the ARDL bounds test do not suggest a long run relationship.
- "C" shows that the country's coefficient for the long run lacks statistical significance, so there isn't evidence of a J-curve.

4.5 Productivity J-curve

By applying the ARDL approach[4] to countries individually, evidence is found of a J-curve for all countries bar Canada. Subsequently, the bounds test rejects a long run relationship for all countries bar Germany and Japan. Thus, there is some evidence of a J-curve implying that we may see a future improvement in growth rates among advancing economies.

[4] Table 8 includes evaluation of analysis

Table 8: Drawbacks and Limitations	
Issue	Comments & Solutions
DATA LIMITATIONS	
Missing data	Missing data was manually imputed considering adjacent observations, which can cause issues of bias. This was likely an issue with estimation 'educ' coefficients, as UNDP data only started from 1990. Multiple imputation through regression analysis was considered, but this often led to unrealistic results (negative values) and relies on data missing at random. A more thorough multiple imputation process combined with greater use of individual nations' data sources would have been ideal.
Nature of variables	My dataset features labour productivity measured by real GDP per worker employed, rather than considering labour hours. This leads to a measurement error, that causes **attenuation bias** if correlated with regressors. This is likely, as the level of development (indicated by regressors) may influence hours per worker. Due to the nature of advanced economies as similarly developed countries, many indexes have little variation in the dataset, leading to increased variance of estimates. This is especially an issue with 'law' (Table 2), as it is a discrete index from 1 to 6 increasing at levels of 0.5. Whilst providing useful insight into the rule of law, this leads to insignificant estimations. A thorough search for more suitable variables combined with further research for more reliable measurements of labour productivity would improve this study.
Weak Proxies	A possible cause of economically and statistically insignificant estimations is the use of weak proxies. For example, whilst patents and capital formation seem like theoretically useful proxies for innovation and capital-labour substitution, correlations between these proxies and their factor inputs are only 0.126 and 0.395 respectively. Capital formation does not control for increases in labour input whilst patents only represent a portion of innovation. Meanwhile, 'stability' coefficients may be unreliable as the described transformation of inflation rates rewards deflation as stable. Inflation may also be a weak proxy for economic stability as the policy ineffectiveness proposition states that only **unexpected** changes in inflation impact the output gap (Sargent and Wallace 1975). A more exhaustive search for proxies with high quality data would have better represented growth determinants.
METHODOLOGY DRAWBACKS	
Interaction terms and squared variables	Many of the regressors may have increasing effects on productivity growth with diminishing marginal returns, requiring squared variables. This argument likely applies to education, health and possible innovation (Gordon 2012). Interaction terms may have also been appropriate for the impact of stability on investment (Sirimaneetham and Temple 2009) and education on innovation (Chen and Dahlman 2004). The omission on above likely contributed to biased coefficient estimates; their inclusion was considered but led to issues of multicollinearity calling for a more complex model.
Endogeneity	Whilst perhaps implicitly present in observations of investment and stability, the lack of an explicit independent variable for demand causes endogeneity through omitted variable bias. Consumer confidence data from the ICRG dataset were considered but rejected due to missing observations and potential bias. Furthermore, my model assumes instantaneous impacts of regressors. The use of lagged variables or a Bayesian model to account for initial conditions (as seen in World Bank 2020) may have been more appropriate. The use of higher-order belief dynamics to model demand (Angeletos et al. 2018) would improve my model. Endogeneity through simultaneity remains an issue regardless, as many regressors are determined in equilibrium alongside productivity growth in reality, so interpretations must be made cautiously.
Signal-to-Noise ratio	Aside from the use of HAC errors and the consideration of growth **rates** rather than levels, this is a key factor. Statistical significance is increasing in this ratio due to lower estimator variance, as the signal represents explained variation and the noise represents unexplained variation. However, the signal is reduced due to little variation in observations among developed economies (see variable measurements). Further, the omission of an explicit variable representing demand may have increased noise if variation here is large among the advancing economies. Thus, the low signal-to-noise ratio gives reason for the low significance seen, calling for improved model specification.
Structural Breaks Tests	My Chow test analysis of individual countries has limitations, only allowing me to test for known structural breaks. It also assumes homoscedasticity, which is likely invalid. A much more rigorous approach would involve the sup-MZ test (Ahmed et al. 2017), which allows for detection of heterogeneity of coefficients at an unknown point, allowing for heteroscedasticity.
ARDL approach	The ARDL approach is an effective method of estimating short and long run impacts of capital deepening, but a thorough examination requires greater rigour than included in this study. Firstly, my augmented Dickey Fuller test only provide a trial-and-error approach of assessing integration of variables, requiring further consideration of constant and trend inclusion/exclusion in tests. Secondly, my ARDL model reflects a case of no intercept or trend, but many other cases exist (Pesaran et al. 2001) involving the consideration of cases of the restriction of intercept and trend, which requires further assessment. Finally, employing a non-linear ARDL approach (Shin et al. 2014) would have provided a more accurate portrayal of the short and long run impacts of an investment, through allowing for separate effects of positive and negative shocks.

6. Conclusion

Investigating the factors causing productivity growth variation is a far from simple task. This study finds that trade factors such as economy openness and FDI beside macroeconomic stability are the clearest contributors to growth variations. These findings must be considered with caution in light of the limitations discussed, and do not necessarily disparage the role of other contributors. Meanwhile, convergence provides insight into the productivity slow-down we have witnessed in advanced economies, whilst some evidence of a productivity J-curve provides indefinite hope for a future revival.

Based on my findings, I make tentative policy propositions to promote productivity growth:

- Encouragement of firm exposure to foreign direct investment and trade for inflow of innovation and efficient practices
- Enforcement of property rights and public-private partnerships to extend technology throughout markets (Cirera and Maloney 2017)
- Prioritising a stable macroeconomy to create a growth-friendly environment

Naturally, these must also be contemplated vigilantly.

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