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CHAPTER 2

The Lag Structure of Investment and Productivity Growth

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2.1 Introduction

"Growth is up", as the European Commission acknowledges (European Commission, 2017). Countries invest in their productivity. The European member countries have seemed to gradually overcome the burden of the financial crisis. However, the link between the type of investment and TFP growth is unclear. To shed light on this relationship, we investigate the following topics in this chapter:

- The time lag characterising the impact of investment (tangible, intangible, and ICT) on TFP.

- The total contribution of each type of investment to TFP in the long term.

Assuming a non-linear Poisson-lag structure model, we calculate lag structures for three types of investment and identify the following time-lag structures: tangible assets, approximately 8 to 9 years; intangible assets, approximately 12 years; and ICT, approximately 14 years. The investment lag for investments in tangibles appears robust for all the models we performed. For investments in intangibles and ICT, significant results can be detected only for the most innovative countries. France, mid-ranked in terms of innovativeness, according to the European Scoreboard (ESB), delivers no further evidence for shorter lag structures. There is no indication either for a higher impact of investment on TFP or for shorter investment lag structures. The results suggest that France invests excessively in intangibles. This finding challenges France's high public support of investments in intangibles.

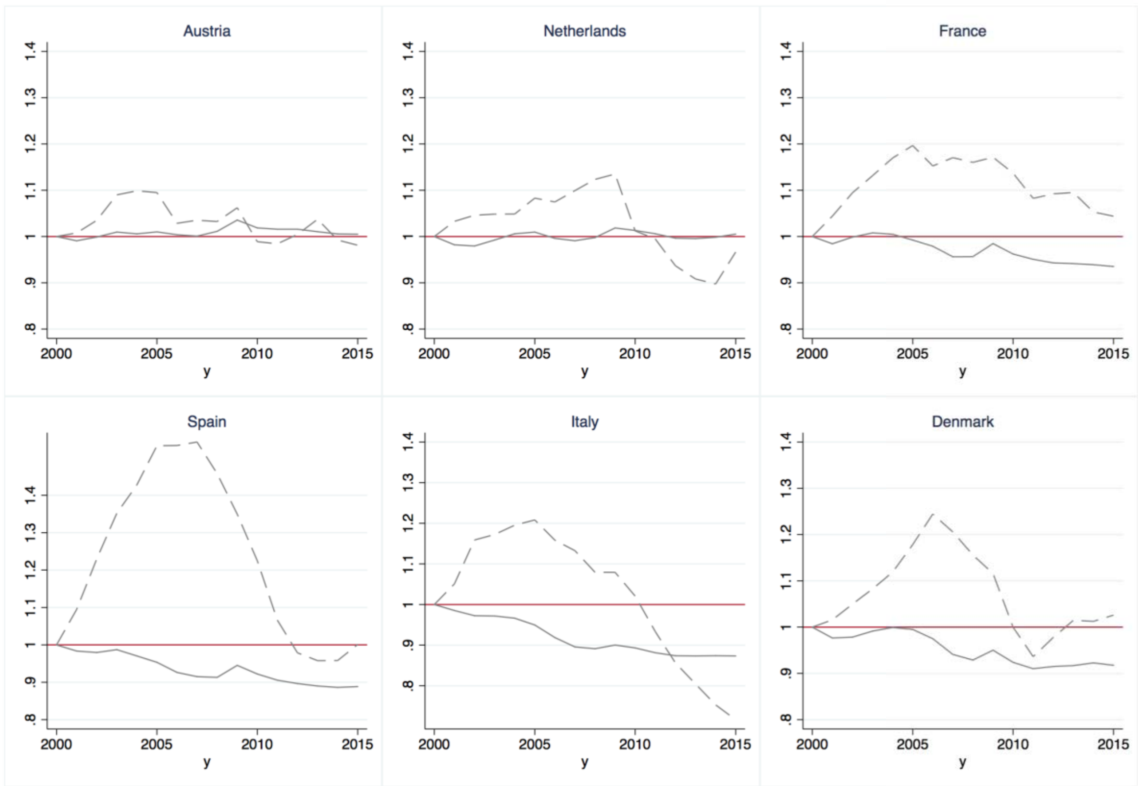
2.2 Investment and Productivity Growth

To date, Germany takes the lead in productivity growth. For this reason, we use it as a benchmark. Figure 2.1 illustrates the performance of various countries with respect to their productivity and investment growth relative to Germany as the benchmark.

In all six panels of Figure 2.1, the solid line represents countries' total factor productivity (TFP in the following, with 2000=100) relative to Germany's TFP (2000=100); the dashed line indicates countries' total investment (2000=100) relative to Germany's total investment (2000=100). Whereas Austria and the Netherlands closely follow Germany's TFP pattern, France, compared to Germany, has been facing a fall in relative TFP growth since the mid-2000s. This is puzzling when examining the relative investment index (dashed line) between France and Germany. France persistently made relatively higher investment efforts than Germany. Austria and the Netherlands, shown in the middle panel of the upper row in Figure 2.1, follow a pattern of TFP growth similar to that of Germany. Their relative increase in investment has also been slightly higher than that of Germany. The Netherlands reduced its investment sharply after the financial crisis while catching up in recent years. France, yet the third-largest economy in the EU, seems to have difficulties translating its investments into productivity gains, although its relative investment efforts were up to

20% higher than Germany's.[11] The three remaining countries, as depicted in this figure, show a similar evolution. The gradient of investment growth relative to Germany is higher for Spain, Italy, and Denmark; their productivity growth gradient, however, is lower. In Italy, investments apparently started to plummet after the financial crisis.

Figure 2.1: Countries' relative TFP (solid line) and relative total investment (dashed line)[12]



Source: EU KLEMS project

Not all countries invest in the same way, and not all manage to translate their investments in the same way into productivity (Castellani et al., 2016; Bacchiocchi and Montobbio, 2010). One possible explanation is the so-called *structural composition*. With regard to the composition of France's economy, as pointed out in Section 2.1, the manufacturing sector represents approximately 11% of GDP compared to that of Germany, with a share of 22.6%. As the manufacturing sector is more R&D intensive than the service sector, it is a matter of consequence that Germany should be investing more in R&D than France. A more challenging explanation, which we try to detect here, is the possible lack of capacity to translate investment into productivity (Ortega-Argilés et al. 2014).

The objective of this section is to investigate the differences in investment effects among European countries. With the econometric specification that we use, possible

[11] The term relative investment efforts takes the "fixed effects" of countries into account. This means that, for example, starting from a lower level of total investment in absolute terms, France increased its investment more intensively than Germany. Nevertheless, Germany, in absolute terms, spends more in investment than France.

[12] The solid line is the ratio between the TFP of the respective country and the German TFP. The TFP measure stems from the EU KLEMS data. It is an index (2000=100); thus, the ratio starts with 1 in 2000.

lag structures can be identified to reveal how much time it takes for investment to achieve its full effect. The duration between the time of investment and the resulting impact on productivity is unclear.[13] Some investments, such as investments in infrastructure to speed up transportation time, may have an immediate effect on productivity. The effect of other investment decisions will be less immediate and may not come to the fore in productivity statistics for years; the investment in R&D is one example.

To address this research question, we must ensure that the following requirements are met: (a) the data to be used must contain information on different types of investments, (b) the time span of the data must be sufficiently large to allow for a delayed effectiveness of investments as well as for a decay – in case the investment becomes obsolete over the course of time, and (c) the econometric specification must allow us to capture these mechanisms.

The database from the EU KLEMS project meets these requirements and is presented in *sub-section B*. The empirical procedure, i.e., the distributed lag model, that we use to document the translational dynamics of investment into productivity (*sub-section C*), will allow us to model the cumulative effect of investment on productivity growth. The results are documented in *sub-section D*, in which we distinguish between the investment lag observed in investments in total assets and the different lags when decomposing investment into investments in tangible, ICT, and intangible assets.

As the results show, an investment lag can be identified, not only for total investment but also for sub-types of investment, that is, tangible, intangible, and ICT investments. The expected time of tangible investment's maximum effect is approximately 7 years. With respect to intangible and ICT investments, we could identify plausible investment lags only for the group of highly innovative countries. For these, the average time of maximum investment effectiveness is approximately 12 years for intangible investments and 14 years for ICT investment. Conversely, we could not find empirical evidence for decomposed investment types in the group of less innovative countries. Including France in the group of high-performing countries, an increase in the average investment lag, though not significant, could be detected. The results give some indication in favour of the hypothesis that France is possibly less successful in translating investment into productivity than the more innovative countries in Europe.

2.3 EU KLEMS Data

The data that we use stem from the Groningen project EU KLEMS (van Ark and Jäger, 2017). It offers the possibility of distinguishing ten different types of investments on the country level. It covers 12 countries of the European Union: Austria, Belgium, the Czech Republic, Denmark, Finland, France, Germany, Italy, Netherlands, Spain, Sweden, and the United Kingdom. The types of investment classes they offer are computing equipment, communications equipment, computer software and databases, transport equipment, other machinery and equipment, total non-residential investment, residential structures, cultivated assets, research and development, and other assets. We converted all variables into euros using OECD conversion rates.

To end up with the highest number of observations possible, we used the most fine-grained industry classification that the EU KLEMS data provide. The following

[13] Since France seems to invest significantly in ICT, we decided to specifically emphasise this type of investment. Therefore, we built three categories: tangible, intangible, and ICT.

industries were selected: food products, beverages and tobacco (10-12); textiles, wearing apparel, leather and related products (13-15); wood and paper products; printing and reproduction of recorded media (16-18); coke and refined petroleum products (19); chemicals and chemical products (20-21); rubber and plastics products, and other non-metallic mineral products (22-23); basic metals and fabricated metal products, except machinery and equipment (24-25); electrical and optical equipment (26-27); machinery and equipment n.e.c. (28); transport equipment (29-30); other manufacturing; repair and installation of machinery and equipment (31-33); wholesale and retail trade and repair of motor vehicles and motorcycles (45); wholesale trade, except for motor vehicles and motorcycles (46); retail trade, except for motor vehicles and motorcycles (47); transport and storage (49-52); postal and courier activities (53); publishing, audio-visual and broadcasting activities (58-60); telecommunications (61); IT and other information services (62-63); and professional, scientific, technical, administrative and support service activities (70-79).

The variables we employ in our production function estimation approach, presented in the next sub-section, concern the variables from the EU KLEMS project reported in

Table 2.1

Variable	Description	EU KLEMS Label
Y	Gross output, volume (2010 prices)	GO_QI
M	Intermediate inputs, volume (2010 prices)	II_QI
L	Total hours worked by persons engaged	H_EMP
I^{tot}	All assets*	Iq_GFCF
I^{ICT}	Computing equipment*	Iq_IT
	Communications equipment*	Iq_CT
I^{IN_TAN}	Computer software and databases*	Iq_Soft_DB
	Research and development*	Iq_RD
	Other IPP assets*	Iq_OIPP
I^{TAN}	$I^{tot} - I^{IN\_TAN}$	
$I^{TAN\_WO\_ICT}$	$I^{tot} - I^{IN\_TAN} - I^{ICT}$	
VA	Gross value added, volume (2010 prices)	VA_QI

** Real gross fixed capital formation volume (2010 prices)*

Table 2.1: Description of variables taken from the EU KLEMS database.

Variable	Description	EU KLEMS Label
Y	Gross output, volume (2010 prices)	GO_QI
M	Intermediate inputs, volume (2010 prices)	II_QI
L	Total hours worked by persons engaged	H_EMP
I^{tot}	All assets*	Iq_GFCF
I^{ICT}	Computing equipment*	Iq_IT
	Communications equipment*	Iq_CT
I^{IN_TAN}	Computer software and databases*	Iq_Soft_DB
	Research and development*	Iq_RD
	Other IPP assets*	Iq_OIPP
I^{TAN}	$I^{tot} - I^{IN\_TAN}$	
$I^{TAN\_WO\_ICT}$	$I^{tot} - I^{IN\_TAN} - I^{ICT}$	
VA	Gross value added, volume (2010 prices)	VA_QI

** Real gross fixed capital formation volume (2010 prices)*

In Table 2.2, we present summary statistics. When the most fine-grained disaggregation possible was chosen, more than 11 thousand observations could be retrieved.

Table 2.2: Summary statistics

Variable	Obs.	Mean	Std. Dev.	Min.	Max.
ln(Y)	11,659	10.279	2.049	2.822	17.099
ln(L)	11,698	12.246	2.509	1.579	19.446
ln(M)	11,472	9.656	1.984	2.512	16.319
ln(I^{tot})	11,679	7.397	2.764	0.000	14.948
ln(I^{TAN})	11,469	7.099	2.743	0.000	14.721
ln(I^{INTAN})	11,469	5.562	2.824	0.000	13.567
ln(I^{ICT})	11,469	4.221	2.409	0.000	12.108
ln($I^{TAN\_WO\_ICT}$)	11,469	6.982	2.771	0.000	14.666
ln(VA)	11,730	9.482	2.124	-0.132	16.488

To provide an overview of the total investment of countries, the investment intensity of countries is reported in Table 2.3. The investment share in value added is calculated using the industry aggregation type of EU-KLEMS labelled "MARKT".[14] On average, 22% of value added (VA) accounts for total investment (I^{tot}), ICT investment (I^{ICT}) of approximately 1%, investment in tangible assets (I^{TAN}) of 17%, and investment in intangible assets (I^{IN_TAN}) of 5%. France's total investment share of 20% ranges in the middle, as does investment in ICT with a share of 1%. The investment of France in intangible and tangible assets amounts to 7% and 13%, respectively.

Table 2.3: Investment share in percent of value added (EU KLEMS type of aggregation: "MARKT").

In %VA	I^{tot}	I^{ICT}	I^{IN_TAN}	I^{TAN}	$I^{TAN\_WO\_ICT}$
Austria	23	2	5	19	17
Czech Republic	31	2	4	27	25
Germany	19	1	4	14	13
Denmark	22	1	6	16	15
Spain	23	1	3	20	18
Finland	20	1	7	13	12
France	20	1	7	13	12
Italy	21	1	3	17	16
Luxembourg	17	1	2	16	15
Netherlands	18	1	5	13	12
Sweden	26	2	10	16	14
Slovakia	26	2	2	24	23
United Kingdom	17	1	5	12	12
Mean	22	1	5	17	16

[14] This means the exclusion of the following sectors: real estate activities (L); public administration and defence; compulsory social security (O); education (P); health and social work (Q); activities of households as employers; undifferentiated goods- and services-producing activities of households for own use (T); and activities of extraterritorial organizations and bodies (U).

Because the objective of this exercise is to detect differences not only in investment lags among types of investment but also between countries, we intended to perform regressions on each country. However, single-country regressions did not render any significant results, possibly due to the low number of observations. Therefore, we used groups of countries to produce plausible results. The criterion for grouping countries is the country ranking by the European Innovation Scoreboard (EIS).[15] As investment is key to a country's innovativeness, and we thought it would be straightforward to group countries according to their innovativeness. The most innovative countries (*HIGH_SB*) according to the European Innovation Scoreboard are Austria, Denmark, Finland, Germany, the Netherlands, Sweden, and the United Kingdom. The group of low-performing countries (*LOW_SB*) in our sample consists of the Czech Republic, Spain, Italy, Luxembourg, and Slovakia. These two groups bracket France as a mid-performing country in terms of innovativeness.

2.4 Econometric Specification

With respect to the econometric specification, we follow a production function estimation approach. The traditional Cobb-Douglas production function reads as follows:

$$Y = AK^{\beta_K}L^{\beta_L}M^{\beta_M}$$

Since capital stock (K) is a compound measure of past investment, the time dimension may be lost in the aggregation process. Therefore, we adapt the production function to the following form:

$$Y = A(\prod_{\tau=1}^{\tau=T} e^{\omega_{t-\tau}} I_{t-\tau})^{\beta_K} L^{\beta_L} M^{\beta_M} \qquad (1)$$

Instead of capital (K) as a stock variable, we use investment attached to a distributed lag structure. This ensures that we capture the time dimension of productivity effects from investment. Letter A in equation 1 denotes total factor productivity; Y, total output; L, labour; and M, material. The parameters to be estimated, which are associated with labour, material and investment, are labelled β_L, β_M, and β_K, respectively. Parameter ω indicates the weights of the time-dependent investment type, lagged by τ years. The optimal number of lags T must be determined in the regression procedure later.

The advantage of a distributed-lag-structure model is that it circumvents the autoregression problem faced in aggregated time series by imposing a specific lag structure. The drawback is that which parametric structure appears plausible for the effectiveness of investment must be decided beforehand. The literature on distributed-lag-structure models provides many conceivable specifications: Koyck (1954) proposes a structure with geometrically successively decreasing lags, Solow (1960) generalises Koyck's idea with a Pascal distribution, Almon (1965) implements a polynomial structure, and Gambardella (1995) and others use a Poisson structure. Each of the lag structures makes strong assumptions about the dynamic process, which can lead to quite implausible results. A polynomial lag of more than two degrees often leads to negative coefficients. Although it might be conceivable that investment might have negative effects on productivity at times, on an aggregate level, it seems rather implausible. Using a Poisson lag structure, negative effects are excluded by definition. In other words, a Poisson lag structure imposes the assumption that investments always have a positive effect on productivity. As we perform our analysis

[15] see http://ec.europa.eu/growth/industry/innovation/facts-figures/scoreboards_en

on an aggregate level, comparing productivity effects of investment across countries, we decided to make this strong assumption and use a Poisson lag structure.

To implement this approach, we take the log of equation 1. Lowercase letters indicate logged values. Therefore, the extended production function distributed lag structure, including an error term ε, reads as follows:

$$Y = a + \beta_L l + \beta_M m + \sum_{j=1}^{J} \beta_K^j \sum_{\tau=1}^{L} \omega_\tau \, i_\tau^j + \varepsilon \qquad (2)$$

To impose a Poisson lag structure, we substitute ω_τ for $e^{-\lambda}\lambda^\tau/\tau!$ and obtain equation 3 with the typical Poisson weights:

$$Y = a + \beta_L l + \beta_M m + \sum_{j=1}^{J} \beta_K^j \sum_{\tau=1}^{L} \frac{e^{-\lambda}\lambda^\tau}{\tau!} \, i_\tau^j + \varepsilon \qquad (3)$$

The different types of investment are denoted i^j. The weights $e^{-\lambda}\lambda^\tau/\tau!$ for the specific investment type j can be interpreted as the total resulting variation in output given one unit change in i^j. As the weights follow a Poisson distribution, a unit change may affect output immediately and decay over time, or it may initially increase and then decline after a given time.

For implementation purposes, the following steps are taken:

1. Subtract country-industry fixed effects, and add the overall mean of the logged variables.
2. Instrument labour (L), as it is an endogenous variable (1st-step regression).
3. Determine the optimal lag structure. (2nd-step regression).
4. Retrieve the mean time lag (λ) and the impact coefficient (β_K).
5. Compare the λs according to the selected classification of the investment and country groups.

This procedure was applied in all subsequent models. Note that lowercase letters indicate logged and demeaned variables. To instrument labour, we use a two-stage least-square approach: we regress the log of labour *(l)* on the log of material input *(m)*, the log of capital stock *(k)*, a full set of year dummies, and the contemporaneous and the first two lags of the differenced values of labour (*l)*. We use the predicted values from the OLS regression as an instrument for labour in the successive estimation. Since the Poisson lag structure is non-linear, non-linear estimation techniques must be applied.[16] To determine the optimal lag length, we use the Akaike information criterion (AIC).

2.5 Results

2.5.1 The Lag Structure of Investment on Gross Output

[16] We use STATA 15 to perform all regressions. We start with two lags and use the estimates as initial values for the regression model with three lags, etc.

For a general picture of the investment lag structure across countries, we start with countries' total investment. The second-step non-linear regression model reads as follows:

$$Y = a + \beta_L * l + \beta_M * m + \beta_K^{tot} \sum_{\tau=1}^{T} \frac{e^{-\lambda}\lambda^{\tau}}{\tau!} i_{\tau}^{tot} + D + \varepsilon \qquad (4)$$

The constant is labelled *a*. We include the log of labour (*l*) with its associated parameter β_L as well as the log of material (m) with parameter β_M. As pointed out above, instead of capital stock, we use investment, i.e., the log of total investment (i^{tot}) with a Poisson lag structure. The lag-specific weights, denoted $e^{-\lambda}\lambda^{\tau}/\tau!$, depend on parameter λ, which reflects the mean number of years to pass until the maximum impact of investment takes effect. The optimal number of lags to use in the respective 2[nd] step regression is represented by *T*, whereas *D* stands for a full set of year dummies. The dependent variable *Y* stands for gross output.

Although not all of the regression runs are of interest, we report the regression results for a selected number of lags (see Table 2.4) to show the consistency of our regressions. When the regressions based on the AIC information criterion are compared, the lowest AIC value serves as the selection criterion for choosing the optimal lag length. The optimal number of lags to choose, in this case, appears to be 10 lags, as the model with 10 lags shows the lowest AIC value. The estimate of β_L suggests that approximately 37% of the output can be explained by labour, 53% by material, and approximately 9% by investment. The parameter of interest, i.e., λ, indicates approximately seven or eight years until an additional euro of investment unfolds its maximum impact on total output.

The estimates of the remaining regressions show that the estimates of β_L and β_M are quite stable despite using different time lags for investment. Parameter β_K^{tot}, which stands for the impact of investment on output, remains stable up to eleven lags (model 8). When the number of lags is increased beyond 11 years, the estimates skyrocket and become insignificant. Therefore, the AIC of the respective models tell us to reject lags longer than 10 years.

In Table 2.5, we repeat the same exercise with investments in tangible assets i^{TAN}. Recall that this variable does not contain investment in computer software, databases, research and development or investment in other IPP assets. The specification of the regression equation is as follows:

$$Y = cons + \beta_L * l + \beta_M * m + \beta_K^{TAN} \sum_{\tau=1}^{T} \frac{e^{-\lambda}\lambda^{TAN^{\tau}}}{\tau!} i_{\tau}^{TAN} + D + \varepsilon \qquad (5)$$

The selection of regression models with different lags, shown in this table, delivers a very similar picture. A lag of ten to eleven years provides the best estimation results. Compared to Table 2.4, the estimates of λ^{TAN} are slightly lower, reporting less than seven years. Note that when higher lags are used in this setting, the estimates of all coefficients remain stable. This finding suggests that the turbulence observed in the coefficient estimates with higher lag orders in Table 2.4 must be related to the investments in intangible assets.

Table 2.4: Lag structure of total investment and its impact on total output

Dependent Variable: ln(y)												
VARIABLES	2 lags	5 lags	6 lags	7 lags	8 lags	9 lags	10 lags	11 lags	12 lags	13 lags	14 lags	15 lags
β_L	0.305***	0.297***	0.299***	0.308***	0.328***	0.359***	0.373***	0.373***	0.377***	0.405***	0.421***	0.410***
	(0.028)	(0.028)	(0.027)	(0.027)	(0.027)	(0.026)	(0.025)	(0.025)	(0.026)	(0.028)	(0.028)	(0.028)
β_M	0.570***	0.561***	0.559***	0.554***	0.545***	0.533***	0.528***	0.528***	0.537***	0.539***	0.541***	0.550***
	(0.015)	(0.015)	(0.015)	(0.015)	(0.015)	(0.015)	(0.015)	(0.015)	(0.015)	(0.015)	(0.016)	(0.017)
β_K^{tot}	0.069***	0.074***	0.074***	0.076***	0.078***	0.086***	0.091***	0.091***	0.114***	1.717	2.906	4283972.7
	(0.012)	(0.009)	(0.008)	(0.008)	(0.008)	(0.009)	(0.009)	(0.009)	(0.027)	(4.135)	(10.985)	(0.000)
λ^{tot}	1.600**	2.858***	3.077***	3.650***	4.771***	6.724***	7.765***	7.765***	10.355***	18.505***	19.945***	41.533***
	(0.680)	(0.368)	(0.345)	(0.362)	(0.422)	(0.539)	(0.571)	(0.571)	(1.092)	(4.918)	(7.243)	(0.318)
a	0.744***	0.744***	0.721***	0.647***	0.490**	0.242	0.111	0.111	0.092	-0.104	-0.238	-0.120
	(0.199)	(0.196)	(0.195)	(0.194)	(0.192)	(0.189)	(0.188)	(0.188)	(0.201)	(0.219)	(0.223)	(0.217)
Observations	2,832	2,832	2,832	2,832	2,832	2,832	2,832	2,832	2,587	2,342	2,097	1,852
R^2	0.814	0.816	0.817	0.817	0.817	0.818	0.819	0.819	0.805	0.803	0.810	0.813
Min. year	2001	2001	2001	2001	2001	2001	2001	2001	2002	2003	2004	2005
AIC	-7978,68	-8010,84	-8014,97	-8020,21	-8025,65	-8035,1	-8045,88	-8045,88	-7618,9	-7212,15	-6737,69	-6286,26
RMSE	0.0588	0.0585	0.0585	0.0584	0.0583	0.0582	0.0581	0.0581	0.0552	0.0515	0.0481	0.0439
Adj. R^2	0.813	0.815	0.815	0.816	0.816	0.817	0.817	0.817	0.804	0.802	0.809	0.812
Numb. iterations	3	10	11	20	44	31	22	5	32	361	19	265

Standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

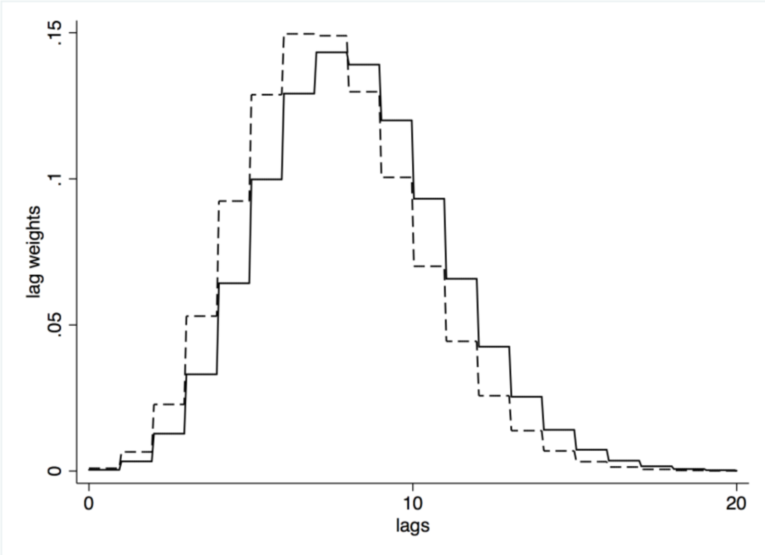
Table 2.5 Lag structure of investment in tangible assets (TAN) and the impact on output (y)

Dependent Variable: ln(y)												
VARIABLES	2 lags	5 lags	6 lags	7 lags	8 lags	9 lags	10 lags	11 lags	12 lags	13 lags	14 lags	15 lags
β_L	0.249***	0.237***	0.235***	0.237***	0.238***	0.238***	0.239***	0.239***	0.234***	0.247***	0.287***	0.319***
	(0.027)	(0.027)	(0.027)	(0.027)	(0.027)	(0.026)	(0.026)	(0.026)	(0.028)	(0.031)	(0.032)	(0.033)
β_M	0.611***	0.611***	0.613***	0.613***	0.612***	0.611***	0.611***	0.611***	0.614***	0.609***	0.594***	0.584***
	(0.015)	(0.015)	(0.015)	(0.015)	(0.015)	(0.015)	(0.015)	(0.015)	(0.015)	(0.016)	(0.018)	(0.019)
β_K^{TAN}	0.027***	0.041***	0.048***	0.064***	0.053***	0.048***	0.045***	0.045***	0.045***	0.046***	0.048***	0.052***
	(0.008)	(0.009)	(0.011)	(0.017)	(0.008)	(0.005)	(0.005)	(0.005)	(0.006)	(0.006)	(0.007)	(0.009)
λ^{TAN}	1.085	4.447***	5.555***	7.316***	7.054***	6.875***	6.970***	6.970***	6.989***	7.069***	7.449***	8.254***
	(0.849)	(0.868)	(0.920)	(1.054)	(0.798)	(0.643)	(0.569)	(0.569)	(0.612)	(0.647)	(0.756)	(0.944)
a	1.215***	1.262***	1.252***	1.204***	1.186***	1.179***	1.165***	1.165***	1.215***	1.112***	0.787***	0.533**
	(0.203)	(0.200)	(0.198)	(0.195)	(0.195)	(0.194)	(0.193)	(0.193)	(0.208)	(0.231)	(0.240)	(0.240)
Observations	2,732	2,732	2,732	2,732	2,732	2,732	2,732	2,732	2,487	2,242	1,997	1,752
R^2	0.817	0.818	0.819	0.820	0.821	0.821	0.822	0.822	0.812	0.810	0.810	0.814
Min. year	2001	2001	2001	2001	2001	2001	2001	2001	2002	2003	2004	2005
AIC	-7982,96	-8003,2	-8013,3	-8031,42	-8041,69	-8048,08	-8054,2	-8054,2	-7556,59	-7104,53	-6514,97	-5972,75
RMSE	0.0558	0.0556	0.0555	0.0553	0.0552	0.0552	0.0551	0.0551	0.0526	0.0493	0.0470	0.0436
Adj. R^2	0.816	0.817	0.818	0.819	0.820	0.820	0.821	0.821	0.811	0.809	0.809	0.812
Numb. iterations	6	15	12	13	8	7	8	2	7	6	7	8

Standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

Figure 2.2 illustrates the results of a 10-year lag structure found in Tables 2.4 and 2.5. The solid line describes the lag structure of total investment. The dashed line depicts tangible assets, subtracting intangible investments, investment in computer software, databases, research and development, and investment in other IPP assets from total investment. Compared to investment in total assets, the dynamics of the effectiveness of tangible investments are slightly lower.

Figure 2.2: Poisson lag structure with $\boldsymbol{\lambda}^{tot} = \mathbf{7.77}$ (solid line) and $\boldsymbol{\lambda}^{TAN} = \mathbf{6.97}$ (dashed line)



2.5.2 The Lag Structure of Types of Investment on Gross Output

The decomposition of investment allows us to shed some light on the time lags of specific investments and their effect on output. To carve out certain types of investment, we decided to use the following classification: investment in tangible assets without tangible investment in ICT ($I^{TAN\_WO\_ICT}$), investment in intangible assets (I^{IN_TAN}), and investment in ICT (I^{ICT}). In principle, the estimation procedure is the same as above. After instrumenting labour in the first step, the second-stage non-linear regression equation is as follows:

$$Y = cons + \beta_L * l + \beta_M * m + \sum_{z=1}^{3} \beta_K^i \sum_{\tau=1}^{T} \frac{e^{-\lambda} \lambda^{i^{\tau}}}{\tau!} i_\tau^z + D + \varepsilon \qquad (6)$$

for $z = \{TAN\_WO\_ICT, IN\_TAN, \mathrm{ICT}\}$. The results are gathered in Table 2.6, which summarises three groups of regressions. Each group contains the second-stage regression with two different lag lengths. Models 1 and 2, for example, are based on the same regression equation but with different time lags. Regression 1 assumes a lag of 10 years and regression 2 a lag length of 15 years.[17] According to the AIC, model 2 is the preferred model. The average time until the main effect of ICT investment unfolds is almost 17 years. The choice of the lag length also holds for models 4 to 6; the preferred lag length is 15 years. In model 4, λ^{ICT} is approximately 17 years. When including all three types of investment in a single regression, as in model 6, λ^{ICT} and λ^{IN_TAN} increase even more, λ^{ICT} to approximately 20 years and λ^{IN_TAN} to approximately 22 years, in contrast to $\lambda^{TAN\_WO\_ICT}$, which remains stable at approximately 7 years. The problem, however, is that the impacts of the investment in intangible assets $\beta_K^{IN\_TAN}$ and of ICT investment β_K^{ICT} are insignificant. Hence, a direct impact on output growth cannot be

[17] We performed several regressions with different lag lengths and chose the lag lengths with the lowest AIC.

corroborated. Only parameters $\beta_K^{TAN\_WO\_ICT}$ and $\lambda^{TAN\_WO\_ICT}$ remain robust, with approximately 0.05 and 7, respectively.

Table 2.6: Investment decomposition: tangibles, intangibles, and ICT.

	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	10 lags	15 lags	10 lags	15 lags	10 lags	15 lags
β_L	0.324***	0.338***	0.303***	0.332***	0.294***	0.345***
	(0.031)	(0.031)	(0.033)	(0.033)	(0.032)	(0.031)
β_M	0.597***	0.576***	0.592***	0.564***	0.611***	0.566***
	(0.018)	(0.019)	(0.019)	(0.019)	(0.018)	(0.018)
$\beta_K^{TAN\_WO\_ICT}$	0.050***	0.050***	0.033***	0.040***	0.035***	0.042***
	(0.010)	(0.007)	(0.007)	(0.006)	(0.006)	(0.005)
$\lambda^{TAN\_WO\_ICT}$	8.642***	7.714***	7.104***	6.920***	7.145***	7.089***
	(1.052)	(0.459)	(0.961)	(0.551)	(0.880)	(0.493)
$\beta_K^{IN\_TAN}$	$539.1*10^3$	0.090*			$2.3*10^6$	0.174
	$(2.2*10^6)$	(0.054)			(0.000)	(0.767)
λ^{IN_TAN}	39.207	16.88***			41.355***	21.880*
	(55.643)	(2.773)			(0.475)	(12.207)
β_K^{ICT}			0.104	0.101**	191.805	0.287
			(0.097)	(0.043)	(2,290.826)	(0.221)
λ^{ICT}			13.18***	17.09***	27.941	20.36 ***
			(2.837)	(1.895)	(18.306)	(2.417)
a	0.273	0.136	0.627***	0.493**	0.495**	0.192
	(0.233)	(0.231)	(0.243)	(0.239)	(0.231)	(0.225)
Observations	1,741	1,741	1,752	1,752	1,741	1,741
R^2	0.837	0.841	0.815	0.820	0.838	0.848
Min. year	2005	2005	2005	2005	2005	2005
AIC	-6163,91	-6202,5	-5980,56	-6026,86	-6169,67	-6280,4
RMSE	0.0408	0.0403	0.0434	0.0429	0.0407	0.0394
Adj. R^2	0.836	0.839	0.813	0.818	0.836	0.846
Numb. iterations	3321	40	26	46	1237	76

Standard errors in parentheses: *** p<0.01, ** p<0.05, * p<0.1

Next, we will investigate whether there is a difference in investment effects between the most innovative and the least innovative countries. A specific focus will be placed on France. As regressions for individual countries do not converge in most cases because of insufficient information, we decided to perform all regressions with and without France to test whether France makes a difference. With respect to the ranking of countries, the European Innovation Scoreboard is employed to obtain country rankings according to their innovative performance. As pointed out above, the high-performing countries contained in the EU KLEMS dataset are Austria, Denmark, Finland, Germany, Sweden, the Netherlands, the United Kingdom(, and France) (*HIGH_SB*), and the lower-performing group (*LOW_SB*) is the Czech Republic, Spain, Italy, Luxembourg, Slovakia(, and France).

Table 2.7: Investment lags of highly innovative countries.

	(7)	(7fr)	(8)	(8fr)	(9)	(9fr)
VARIABLES	without FR	with FR	without FR	with FR	without FR	with FR
β_L	0.370*** (0.032)	0.340*** (0.031)	0.354*** (0.045)	0.340*** (0.041)	0.386*** (0.043)	0.347*** (0.039)
β_M	*0.487**** (0.020)	*0.528**** (0.019)	*0.498**** (0.029)	*0.531**** (0.026)	*0.482**** (0.028)	*0.527**** (0.024)
β_K^{tot}	0.155*** (0.020)	0.169*** (0.033)				
λ^{tot}	8.989*** (0.713)	10.074*** (0.925)				
β_K^{TAN}			0.104*** (0.009)	0.094*** (0.008)	0.106*** (0.009)	0.097*** (0.009)
λ^{TAN}			8.644*** (0.469)	8.655*** (0.485)	8.545*** (0.455)	8.561*** (0.475)
$\beta_K^{IN\_TAN}$					0.048*** (0.012)	0.044*** (0.014)
λ^{IN_TAN}					11.713*** (2.256)	12.741*** (2.799)
β_K^{ICT}			0.128*** (0.013)	0.124*** (0.014)	0.113*** (0.015)	0.112*** (0.017)
λ^{ICT}			13.839*** (0.672)	14.278*** (0.754)	14.311*** (0.888)	14.895*** (1.037)
a	0.361 (0.234)	0.395* (0.224)	0.350 (0.299)	0.270 (0.288)	-0.114 (0.302)	-0.033 (0.285)
Observations	1,609	1,849	949	1,114	949	1,114
R^2	0.784	0.798	0.797	0.812	0.803	0.815
Min. year	2000	2000	2005	2005	2005	2005
AIC	-4804.58	-5615.04	-3375.04	-4043.08	-3396.4	-4055.23
RMSE	0.0539	0.0526	0.0401	0.0388	0.0396	0.0385
Adj. R^2	0.781	0.796	0.794	0.810	0.799	0.812
Numb. iterations	9	10	13	15	17	16

Table 2.7 reports the results when performing the above regressions on the sub-sample of the best-performing group of countries (HIGH_SB). Model 7 uses regression equation (4) and thus takes into account the investment in total assets of HIGH_SB countries when calculating the underlying lag structure. The optimal number of lags in this model is 10 years. The corresponding results indicate $\lambda^{tot} = 8.99$. Hence, the maximum effect of an additional euro, invested in HIGH_SB countries, can be expected after approximately 9 years. Adding France to this group renders column 7fr. As a result, λ^{tot} slightly increases to 10.1 years. In other words, the average investment effects slow down by one year. Unfortunately, there is no statistical evidence that this change is significant. A further decomposition of tangible investments into tangible investments without ICT ($I^{TAN\_WO\_ICT}$) and investment in ICT (I^{ICT}) discloses a significant gap in the time lapse of effectiveness between the two investment types.

Table 2.8: Explicit and accumulated lag weights (specification model (9))

lag	weight TAN	weight INTAN	weight ICT	weight TAN	weight INTAN	weight ICT
	a)	explicit weights		b)	accumulated weights	
1	0.00	0.00	0.00	0.00	0.00	0.00
2	0.00	0.00	0.00	0.00	0.00	0.00
3	0.01	0.00	0.00	0.01	0.00	0.00
4	0.02	0.00	0.00	0.03	0.00	0.00
5	0.04	0.01	0.00	0.07	0.01	0.00
6	0.07	0.02	0.00	0.15	0.02	0.00
7	0.11	0.03	0.01	0.25	0.05	0.01
8	0.13	0.05	0.01	0.38	0.10	0.03
9	0.14	0.07	0.03	0.52	0.17	0.05
10	0.13	0.09	0.04	0.65	0.27	0.10
11	0.11	0.11	0.06	0.76	0.38	0.16
12	0.09	0.12	0.08	0.84	0.49	0.23
13	0.06	0.11	0.09	0.91	0.61	0.33
14	0.04	0.10	0.10	0.95	0.71	0.43
15	0.02	0.09	0.11	0.97	0.80	0.54
16	0.01	0.07	0.10	0.99	0.86	0.64
17	0.01	0.05	0.09	0.99	0.91	0.73
18	0.00	0.03	0.08	1.00	0.95	0.80
19	0.00	0.02	0.06	1.00	0.97	0.86
20	0.00	0.01	0.05	1.00	0.98	0.91
21	0.00	0.01	0.03	1.00	0.99	0.94
22	0.00	0.00	0.02	1.00	1.00	0.96
23	0.00	0.00	0.01	1.00	1.00	0.98
24	0.00	0.00	0.01	1.00	1.00	0.99
25	0.00	0.00	0.01	1.00	1.00	0.99
26	0.00	0.00	0.00	1.00	1.00	1.00

Model 8, not counting France among the group of high performers, shows that the expected time span until the maximum effectiveness of tangible investments is approximately 9 years, in contrast to investments in ICT, which take approximately five years longer.[18] Adding France to this group of countries increases λ^{ICT} again – though not to a significant extent. Model 9 disaggregates investment types into three categories ($I^{TAN\_WO\_ICT}, I^{IN\_TAN}, \text{and } I^{ICT}$). With all three types of investments included (model 10), investment in tangible assets has its largest effect after approximately 12 years, and ICT investments take approximately 14 years. When France is added, the time spans for intangibles as well as ICT investment slightly increase – but also not to a significant extent. The difference between Table 2.6 and Table 2.7 is that we leave out the less innovative countries. The exclusion renders the coefficients $\beta_K^{IN\_TAN}$ and β_K^{ICT} significant; hence, the group of high-performing countries provides evidence that investments in all three types of assets translate into productivity growth. Conducting the same exercise for the low-performing group of countries delivers neither plausible nor significant results. For this reason, we did not report those estimations.

For high performers, the evidence supports the intuition that investments increase productivity. The magnitude of the coefficients also indicates that there are different degrees of effectiveness. When France is counted among the group of highly innovative countries (model 9fr), $\beta_K^{TAN\_WO\_ICT}$ is approximately 0.1, $\beta_K^{IN\_TAN}$ is 0.04, and β_K^{ICT} is 0.11.

[18] In models 7 and 7fr, we use 10 lags, and in models 8, 8fr, 9, and 9fr, we use a lag of 15 years to estimate the lag structure of investment types. The lag length was decided based on the the AIC.

Suppose that investment increases by 10%; output will eventually increase by 1%, 0.4%, and 1.1% due to investment in tangibles, intangibles, and ICT, respectively. To illustrate the dynamics, Table 2.8 reports the corresponding lag-specific weights. The column "weight TAN" reflects the lag weights for tangible investment. We observe the highest lag weights for the lag of nine years with weight = 0.14; for intangibles, it is 12 years (weight INTAN = 0.12), and for ICT, it is 15 years (weight ICT =0.11). Accumulating each column of the explicit weights leads to the last three columns of that table. For tangible investments, 52% of the total effect is reached after 9 years, and after 18 years, the growth effect fades out; i.e., the accumulated weight reaches 1. For intangibles, 50% of the total effect is reached after 12 years with a fade-out of 22 years, and for ICT, the half-time is less than 15 years with a fade-out of 26 years. Whereas these weights indicate only the shares in the total effect of investment that sums up to one, they do not describe the actual growth effect. For this, the weights must be multiplied by their respective β-coefficients. The latter scale the timely effect of investment. Figure 2.3 illustrates the relationship between weights and impact parameters β.

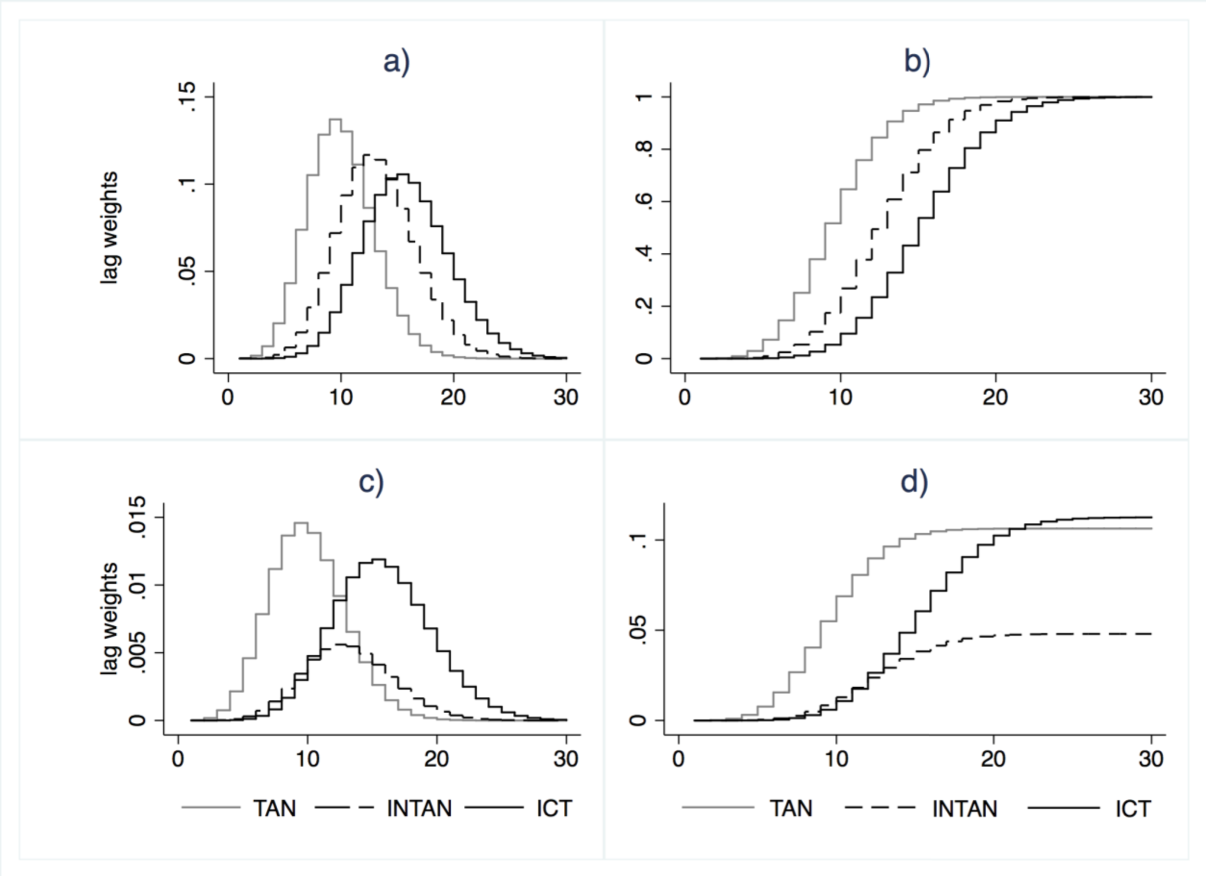
Panel a) illustrates the explicit weights, as reported in Table 2.8 (columns a). Panel b) depicts the last three columns, which are the accumulated counterparts (columns b). Multiplying the β-coefficients by their explicit weights rescales the weight distribution. The outcome is the actual effect of investment on output. This reduces the weights to 10% for tangible investments (grey line in panel a), to 4% for intangibles and to 11% for ICT. Panel c) illustrates the evolution of the actual impact of investment on productivity.

As the four panels point out, investments in tangibles have the most immediate effect on productivity growth, followed by investments in intangible assets and ICT investments. As far as the accumulated long-term effect of investment is concerned (panel d), the results suggest that the long-term effect of ICT investments is highest compared to investments in tangibles and intangibles. The effect of ICT investments is twice as high as that of investments in intangible assets. It is even slightly higher than the long-term effect of investments in tangibles.

These results support the findings of Thum-Thysen et al. (2017) and the work by Corrado et al. (2012, 2013). Thum-Thysen et al. (2017) underline the role of investments in intangible assets. As we use a Poisson lag structure estimation technique instead of a heterogeneous dynamic panel regression model (pooled mean group (PMG) estimation),[19] we obtain time lags for each type of investment. The discrepancy between their and our findings is that the effect of investments in intangibles is not three times as much as the effect of investment in tangibles. This is due to distinguishing three types of assets with ICT as a third category.

[19] The pooled mean group (PMG) estimation, which they use, is an error correction model that yields an average time span of investment effects on productivity growth. The Poisson lag structure allows us to distinguish different time spans between different kinds of investment in a single model.

Figure 2.3: Lag weights (a), accumulated lag weights (b), effective lag weights (c), and accumulated effective lag weights (d)



2.5.3. Scenarios

The results show that the type of investment is decisive in boosting output. The investment in tangible assets takes the largest share in total investment, whereas the impact on output is largest for ICT investments ($\beta_K^{ICT} = 11\%$), according to our model (9fr). Among the three types of investment, the investments in intangibles have the lowest impact, with $\beta_K^{INTAN} = 4\%$. Hence, the effect of one euro invested in ICT in total is almost three times as high as in the case of intangibles.

Given the robustness of the results, the investment strategy followed by France can be put into perspective. For one euro value added, France (Germany) invests 0.8% (*1.0%*) in ICT, 12.9% (*5.4%*) in intangibles and 10% (*14.0%*) in tangibles. To understand the extent to which this investment strategy matters in terms of output, we develop several scenarios. Using Germany as a benchmark, we calculate counterfactuals for France: What effect would a different investment strategy have on French output? The scenarios that we consider are summarised in Table 2.9.

Table 2.9: Scenarios for France using different investment strategies

		France	Germany
Level of Investment	France	Scenario S0	Scenario S2
	Germany	Scenario S1	Scenario S3

The scenarios include the following counterfactual items:

S0: Keep actual investment situation in France (base scenario)

S1: Adjust the French total investment per value added ratio to the German ratio

S2: Keep the French investment structure and impose the German investment level

S3: Adjust both the structure and the level of France's investment to the German structure and level of investment

The base scenario (S0) is calculated according to equation (7):

$$S0 = \beta_K^{TAN} \sum_{\tau=1}^{T} \frac{e^{-\lambda} \lambda^{TAN^\tau}}{\tau!} i_\tau^{TAN} + \beta_K^{INTAN} \sum_{\tau=1}^{T} \frac{e^{-\lambda} \lambda^{INTAN^\tau}}{\tau!} i_\tau^{INTAN} + \beta_K^{ICT} \sum_{\tau=1}^{T} \frac{e^{-\lambda} \lambda^{ICT^\tau}}{\tau!} i_\tau^{ICT} \quad (7)$$

For scenario S1, we rescale the investment variables $i_\tau^{TAN}, i_\tau^{INTAN}, and\ i_\tau^{ICT}$ so that the sum of all three types of investment reaches the relative investment level per value added of Germany while keeping the share of investment types (investment structure) constant. In scenario S2, the amount of the total investment of France remains unchanged, but the structure is adjusted to the German case. Scenario 3 combines the two manipulations with a rescaling and a restructuring of French investments to match the German case.

Having calculated all four scenarios, we compare scenarios S1, S2, and S3 with the base scenario, S0, by calculating the relative change in output yielded by each scenario. Table 2.10 collects the results. Comparing scenario S0 with itself generates trivia, as it renders a change of 0%, whereas changing only the structure of French investments to the German structure (S1) produces a change of 3.5%. Hence, output would increase by 3.5%. Adjusting the level of investments to Germany's investment level is tantamount to reducing French investments in all three types by the same proportion (S2). In this scenario, the French output would decrease by 2.9%. Combining both in scenario S3, that is, reducing France's investment level and adjusting its structure to that of Germany, would still induce an increase in output of 0.6%.

Table 2.10: Scenarios for France using different investment strategies

		France	Germany
Level of investment	France	0.0%	-2.9%
	Germany	3.5%	0.6%

Despite the fact that our estimations are based on aggregate data, which possibly do not capture all the relevant information about countries' output determinants, these results reveal that France does not necessarily have a general investment problem per se. It invests more per euro of value added than Germany does. Solely reducing investments would make the output situation worse, but changing the composition of investment could create a positive effect on output. According to the estimations, France could even reduce its investments without hurting output, provided that it restructured its composition of investments.

Furthermore, France invests more than twice as much as Germany, measured in value added, in intangible assets. Considering the relatively low impact (β_K^{INTAN}=4.4%) of intangibles on output, it seems that France invests excessively in intangibles. A euro invested in ICT or tangibles would have a much higher impact. Differences in the investment structure might be due to the differences in countries' sectoral composition. Nonetheless, it is doubtful whether the incentive to invest in intangibles in France can be explained solely by market forces. Figure 2.12 in chapter 0 substantiates this conjecture even further. In contrast to Germany, France supports private R&D with substantial tax incentives, yet its innovative output is lower than that of Germany (Grebel, 2017).

It must be emphasised that this study requires further research based on less aggregated data to provide a full understanding of the mechanism behind investment behaviour. What we may conclude from this study, however, is that France should reconsider its public R&D support.

2.6 Summary, Discussion, and Caveats

This chapter investigated the lag structure of investment. We applied a 2-stage non-linear least square estimation technique to estimate the lag structure of different types of investment in selected European countries. To cope with endogeneity, we instrumented labour in a first-stage regression. We used its predictions as instruments, which were inserted in the 2nd-stage non-linear regression model. The basic regression equation resembles a standard Cobb-Douglas production function estimation procedure. Instead of using capital as the typical stock of capital, we substituted capital for an investment lag structure. In doing so, we capture the dynamic effects of investment on output growth.

The data in this study stem from the EU KLEMS project. As these data are generated in a consistent way across a selection of European countries, they are predestined for this type of analysis. Furthermore, the EU KLEMS data offer a detailed classification of investment types, which we make use of in our study.

The results show that different lag structures for different types of investment can be identified. Tangible investment, intangible investment and ICT investment require different time spans to take effect. On average, tangible investments can be expected to unfold their maximum effect on output after approximately 8 to 9 years. With respect to investments in intangibles and ICT, the lag structure is equivocal when all countries are taken into account. Decomposing the sample into two sub-samples of more and less innovative countries also delivers significant results for the investment lag structures of intangibles and ICT. Accordingly, the time span of the effect of investment in intangibles is approximately 12 years, and that for ICT is approximately 14 years. The analysis of the low-performing country group does not provide significant results either for the lag structure of investment in intangibles or for investments in ICT. The estimate that seems robust across all regressions is the estimated time lag of investments for tangibles. As far as Solow's paradox is concerned, at least for more innovative countries, a significant though delayed impact of ICT investment on output can be detected.

Among the countries in the dataset, France is mid-ranked in terms of innovativeness. Since the early 2000s, France has made considerable efforts to increase its investments, and it systematically invests more per value added than Germany. The downside of this development is that France has difficulty translating investments into productivity. Compared to Germany, which increased its TFP by 5% within the time period considered, France has not managed to increase its TFP.

France is outstanding in its relative share of investment in intangibles. It invests more than twice as much in intangibles as Germany, notwithstanding the fact that this investment does not pay off: Setting aside the fact that the effectiveness of France's investment is lower than that of Germany's, the return on investment in intangibles is much lower than that for investments in tangibles and ICT, according to our study. Together with the generous tax incentives that France grants firms, our results clearly challenge this policy. France needs to reconsider its public R&D support.

In future research, there are several caveats to be considered. For estimating lag structures, longer time series data should be employed. Instead of using aggregate data, which blur the underlying mechanisms, we suggest performing this exercise with firm-level data. Firm-level data are available for most European countries. The challenge in this regard is to cope with the confidentiality restrictions of countries when trying to perform comparative studies. Finally, policy interventions should be taken into account as well. They tend to distort the link between private R&D investments and productivity growth. It would be interesting to determine whether France, when reducing its support for R&D investments, could eventually benefit from a higher efficiency of R&D investments.

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