What Level of Education Matters Most for Growth? Evidence from Portugal

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Abstract:

We decompose an annual average years of schooling series for Portugal into different schooling levels series. By estimating a number of vector autoregressions, we provide measures of aggregate and disaggregate economic growth impacts of different education levels. Increasing education at all levels except tertiary have a significant effect on growth. Investment in education does not significantly crowd out physical investment and average years of schooling semi-elasticities have comparable magnitude across primary and secondary levels.

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1. Introduction

Economic theory suggests that education, or human capital, is positively related to growth[1]. One strand of the literature emphasises human capital as an additional production factor, along labour and physical capital. In a seminal paper, Mankiw, Romer and Weil (1992) augmented the Solow model with human capital and showed that the econometric fit of a cross-section growth regression is much better when this factor is considered, human capital investment (schooling) implying a future increased human capital stock (education attainment) and therefore a higher income level. Other economic growth models directly relate human capital and new technology conception or adoption. This is namely the case of a number of endogenous growth models, including Romer (1990). In a relevant manner for catching up countries, Nelson and Phelps (1966) had already suggested in a seminal paper that those economies would decrease their distance towards the technological leader at a rate that depends on human capital levels.

In this paper we provide evidence that human capital formation was an important growth factor for the Portuguese economy from 1960 to 2001. Increasing average years of schooling had both direct and indirect, through physical investment, effects on GDP per worker. Estimated education semi-elasticities of output per worker have a comparable magnitude across primary and three different secondary levels. In most instances crowding in prevailed – more education stimulated physical investment, with reinforcing growth effects. However, we did not find evidence linking tertiary education to the Portuguese growth experience. Our results were made possible by resorting to vector autoregression (VAR) analysis, a time series technique rarely found in the education and growth empirical literature.

The fact that different schooling levels may have different effects on growth has been addressed in a small set of recent papers, providing heterogeneity evidence. Petrakis and Stamatakis (2002) provide evidence that primary and secondary education matter more for growth in less developed countries as opposed to more developed economies, where higher education becomes more important. Papageorgiou (2003) finds that primary education is more important in final goods production, whereas post-primary education is essentially related to technology adoption and innovation. In the same vein, Vandenbussche, Aghion and Meghir (2004) present an endogenous growth model where the growth effect of skilled labour is stronger when a country gets closer to the technological frontier. In a sample of 19 developed countries between 1960 and 2000, they find that it is skilled human capital, and not total human capital, that matter for growth. Self and Grabowski (2004), a rare country-specific time series study, investigated whether education had a causal impact on growth in India. Their analysis was done in terms of Granger causality, finding that primary education has a strong impact on growth, evidence for a similar effect in what concerns secondary education being more limited.

Empirical research on the education impact on growth has progressed basically by means of cross-sectional regressions where the growth rate is the dependent or explained variable and an education related variable is one of the explanatory variables. This literature has not provided a consensual quantified range for the influence of education on growth. What is more, some researchers presented results where the correlation between education and growth is statistically insignificant[2].

Data on education is seldom available in annual periodicity. This is probably one of the reasons cross-country regressions have been the main empirical tool in this research field. However, they are subject to a number of limitations. Some critics of growth regressions note that correlation evidence is seldom proof of causation. Bils and Klenow (2000) provide evidence that most correlation results between education and growth could in fact derive from a reverse causation effect – more growth would cause more education, and not the contrary. Temple (1999) pointed out that "the correlation between increased human capital and growth may sometimes be hidden in the cross-country data by a number of unrepresentative observations." (page 131). In their survey on education and growth, Krueger and Lindhal (2001) emphasise that "the positive effect of the initial level of education on growth seems to be a phenomenon that is confined to low-productivity countries" (page 1130). In more

[1] For recent literature surveys on the influence of human capital formation on growth, see Krueger and Lindahl (2001), Sianesi and Van Reenen (2002) and De la Fuente and Ciccone (2002).
[2] This is the case of Benhabib and Spiegel (1994) and Pritchett (2001).

general terms, we note that too much parameter heterogeneity lead to inconsistent estimates[3]. For example, school quality not being constant across countries is another important source of parameter heterogeneity[4]. Moreover, heterogeneity is likely to be reinforced if different schooling levels have unequal effects on growth.

The above-mentioned limitations of cross-country regressions call for different research methods on the nexus between education and growth. Cross-country heterogeneity implies that there is much more room for country-specific studies, wherever data restrictions do not apply. This is the case of Portugal, as annual time series for average years of schooling are available, as described in section 2. Moreover, these data allow for disaggregation along schooling levels.

Section 3 describes in more detail how VARs are used to evaluate the impact of education on growth. This methodology allows for the problem of reverse causality – that education may well be caused by output, and not the contrary. More generally, VAR analysis allows for dynamic effects between all variables considered.

Main results are presented in section 4. Based on estimated VARs, it is possible to perform Granger causality tests, to compute impulse response functions and to derive the implied long run elasticities and semi-elasticities. Obtained values for Portugal are compared to other available estimates. The main conclusions of our analysis are summarised in section 5.

2. Data

Raw data used in this paper is reproduced in the appendix. Here, we describe its definitions, sources and some main characteristics.

Gross Domestic Product, physical investment and employment

GDP, investment and employment data series were taken from the AMECO database, updated in May 2004. GDP is the gross domestic product measured at 1995 prices,

[3] See Pesaran and Smith (1995) for an econometric reference.
[4] Barro and Lee (2001), Barro (2001) and Hanushek and Kimko (2000) provide evidence in favor of the importance of education quality in explaining different growth performances.

investment is gross fixed capital formation at 1995 prices for the total economy and employment is civilian domestic employment.

GDP and investment per worker growth rates from 1961 to 2001 are plotted in figure 1. As in most economies, investment is more volatile than GDP. Both variables grew faster before 1974. Economic growth slowed down in the mid-seventies and was reinforced in the mid-eighties, when Portugal became a member of the European Community.

Human Capital

Human capital is proxied by average years of schooling. Series are taken from Pereira (2004)[5]. The author builds annual series for the population between 15 and 64 years old for the period 1960-2001. The Portuguese population is divided in ten levels. Three of them include illiterate individuals, people that learned to read and write on their own and those that attended but did not conclude primary education. The other seven concern complete levels of schooling, as specified in Table 1.

Table 1 –Complete levels of schooling

Level	Definition	Assigned number of years of schooling
1	Concluded primary school (basic 1st cycle)	4
2	Concluded basic 2nd cycle	6
3	Concluded basic 3nd cycle	9
4	Concluded upper secondary (11th year)	11
5	Concluded upper secondary (12th year)	12 (was introduced in 1977-78)
6	Concluded lower higher education (*ensino médio*)	14
7	Concluded higher education	16 (17, if concluded after 1982)

We point out that the author anchored his series on census data. Figures between census were computed using data on school enrolment, migration, mortality and

[5] Pereira (2004) is available from the authors on request.

retirement rates, avoiding interpolations or estimations. Also, variations on the course length during the period were taking into account by transferring courses from one level to another, and by using different aggregation formulas.

Considering completed levels of schooling only, the average years of schooling for the Portuguese population is the series H, specified below:

$$H_t = \begin{cases} \dfrac{4L_{4,t} + 6L_{6,t} + 9L_{9,t} + 11L_{11,t} + 14L_{14,t} + 16L_{16,t}}{L_t}, & \text{if } t < 1978, \\ \dfrac{4L_{4,t} + 6L_{6,t} + 9L_{9,t} + 11L_{11,t} + 12L_{12,t} + 14L_{14,t} + 16L_{16,t}}{L_t}, & \text{if } 1978 \le t < 1983, \\ \dfrac{4L_{4,t} + 6L_{6,t} + 9L_{9,t} + 11L_{11,t} + 12L_{12,t} + 14L_{14,t} + HE_t}{L_t}, & \text{if t} \ge 1983. \end{cases} \quad (1)$$

with $HE_t = 16.L_{16,t} + PE_{17,t} + \sum_{j=1983}^{t-1} \left(PE_{17,j} . \prod_{i=j}^{t-1} \left(1 - \delta_i\right) \right).$

The variable $L_{s,t}$ refers to the number of persons with schooling years s in year t. L_t is the total number of individuals between 15 and 64 years old. The variable $PE_{17,t}$ represents the flux of higher education completion and δ_t is a mortality rate. There are definition breaks in 1978 and 1983 because from 1978 onwards secondary education includes one more year of study. Consequently, higher education conclusion also implied one more year from 1983 onwards. To take this into account, HE_t is a weighted stock of higher education years, considering people that got their degree before 1983 and those who did it afterwards, attaining 16 and 17 years of schooling, respectively.

In the present study we use not only the series H but also series for different levels of schooling, namely H_4, H_6, H_9, H_{11} and H_{sup}, which are defined as follows:

$$H_{4t} = \frac{4L_{4,t}}{L_t}, \; H_{6t} = \frac{6L_{6,t}}{L_t}, \; H_{9t} = \frac{9L_{9,t}}{L_t}, \; H_{11t} = \frac{11L_{11,t}}{L_t}, \; H_{sup_t} = \begin{cases} \dfrac{16L_{16,t}}{L_t}, \text{for t} < 1983, \\ \dfrac{HE_t}{L_t}, \text{for t} \ge 1983. \end{cases} \quad (2)$$

These series concern, respectively, to the stock of schooling years derived from basic first cycle, basic second cycle, basic third cycle, secondary and tertiary levels. We did not use the 12th year of the secondary level because it was introduced in 1977 only, nor the lower higher education level, which almost disappeared in Portugal from 1987 onwards.

Next we briefly analyse the different profiles of these series. The smooth growing profile of average years of schooling (figure 2) shows an improvement of the Portuguese educational attainment over the period, albeit still displaying low values compared to European standards. In 1960 about two thirds of the population had at most a primary school degree, with few people having completed secondary school and even fewer having a university degree[6]. H_4 and in some sense H_6 show an inverted U pattern (see figures 3 and 4) This reflects the fact that Portuguese population has achieved increasingly higher levels of education. Therefore, after a certain point in time, the stock of people with at most 4 years of schooling, for example, starts decreasing because of older people retirements. On the other hand, the H_{sup} series (higher education, figure 7) started at a very low level and shows an increase over the entire period, particularly at the end of the sample (the 1990s).

3. Methodology

The VAR Approach

To measure the impact of education on Portuguese economic growth, we estimate VARs with three variables each. Our vector X_t includes y, i, and h_k, the logs of GDP per worker, of investment per worker and of a human capital variable, respectively. Each educational level is analysed *de per se*, as including several ones in the same VAR would dramatically decrease the degrees of freedom.

Some authors have followed a comparable modelling strategy when estimating the impact of physical capital on growth. Namely, the VAR approach has been adopted by researchers interested in measuring the growth conseuquences of public capital

[6] Hartog, Pereira and Vieira (2001) note that in 1956 compulsory education changed from three to four years but for boys only. For girls this change only occurred in 1960. By 1960 compulsory education was increased to six years of schooling. It was to increase to nine years in the mid 1980s only.

formation[7]. Some researchers have considered a cointegrated VAR, or a VAR with an error-correction mechanism, when series are cointegrated. Our approach is close to the one developed by Pereira (2000) and Pereira and Andraz (2002). These authors estimate different VAR systems considering different types of public capital. In results presented in section 4, we consider different categories of human capital instead.

In methodological terms, our approach is more complete than Self and Grabowski (2004). Our disaggregation of educational variables is more detailed, and, as we consider a full system, we are not only able to test for Granger causality, but also to measure the full impact of education on growth, direct, and through feedback effects. Namely, we allow for human capital investment to have an effect on physical investment and therefore on growth.

We test and measure the impact of education on growth in three different but complementary ways. These are Granger causality tests, the analysis of the impulse response functions and the computation of long-run semi-elasticities. We explain each of these procedures in turn, but before that, we clarify some important econometric issues related to cointegration among, and stationarity of, considered variables.

Cointegration and stationarity

Consider the following levels VAR, with X_t defined as previously:

$$X_t = c + \sum_{j=1}^{p} \Gamma_j X_{t-j} + \varepsilon_j \ , \qquad (3)$$

If the variables in X_t are I(1), the VAR in equation (3) is not a stationary one. If there is no cointegration, statistical inference is not possible using the usual tests and p-values, as statistics will not have standard tabulated distributions. In this case, it is appropriate to first difference the series and to estimate a first differences VAR of the form:

[7] Examples are Crowder and Himarios (1997), Lau and Sin (1997) and Pereira (2000) for the US, Evareart (2003) for Belgium, and Ligthart (2000), Pereira and Andraz (2002) and Pina and St. Aubyn (2004) for Portugal.

$$\Delta X_t = c + \sum_{j=1}^{p} \Gamma_j \Delta X_{t-j} + \varepsilon_j \ . \tag{4}$$

When there is cointegration, there is at least one linear combination of X_t , also called a cointegrating vector, that produces a stationary variable. In this case, the VAR in equation (3) can be rewritten as:

$$\Delta X_t = c + \sum_{j=1}^{p} \Gamma_i \Delta X_{t-j} + \Pi X_{t-1} + \varepsilon_t \ . \tag{5}$$

In equation (5), Π is a rank r matrix that can be decomposed as:

$$\Pi = \alpha\beta' , \tag{6}$$

where α is a 3 x r loading matrix and β is a 3 x r matrix of cointegrating vectors, r being the number of cointegrating vectors.

We tested for the number of cointegrating vectors in (3) following Johansen (1988) procedure. If there were none, analysis proceeded taking a first differences VAR. When there was one or more, the cointegrating vectors were estimated and a cointegrated VAR like the one in (5) was considered.

Granger causality tests

In our first differences, no cointegration VAR formulation, consider the equation for GDP per worker:

$$\Delta y_t = c_y + \sum_{j=1}^{p} \beta_{y,j} \Delta y_{t-j} + \sum_{j=1}^{p} \beta_{i,j} \Delta i_{t-j} + \sum_{j=1}^{p} \beta_{h_k,j} \Delta h_{k,t-j} + \varepsilon_{y,t} \tag{7}$$

In a causality test as first proposed by Granger (1969), we consider the null hypothesis that coefficients of lagged values of the education variable Δh_k are not statistically significant in equation (7). The test that $\beta_{h_k,1} = \beta_{h_k,2} = ... = \beta_{h_k,p} = 0$ is a standard chisquare test. As the dependent variable is the GDP per worker growth rate, we are here testing if there is a *direct* impact of education on growth. Education may also have an indirect impact on growth as it impinges on investment.

Impulse response functions

It is standard practice in VAR analysis to identify structural shocks as orthogonal innovations to each variable. In order to do this, some restrictions have to be imposed. We follow here the well-known Cholesky decomposition, which is akin to "ordering" the VAR variables. In our variables ordering, we assume that the education variable takes the third and last place. This implies that innovations to education do not influence GDP or investment in the same period they occur. On the other hand, innovations in GDP or investment immediately affect the education variable. These seem sensible restrictions for two reasons. Firstly, the economic advantages of education only take place after students are employed. Secondly, shocks to GDP or investment will almost surely affect labour market conditions and therefore decisions to remain in or to leave school.

Impulse response functions trace deviations of a variable from a baseline following a shock to another variable. In our case, we are especially interested in responses of economic growth to education innovations. As economic growth depends also on investment changes and lagged past growth, a full interpretation of all dynamic effects is only possible if the response of investment to education is also taken into account. In any case, we only consider responses to education. As these functions do not depend on the ordering of GDP and investment in the VAR, there was no need for additional restrictions.

Long-run semi-elasticities

Previous studies on the impact of education on growth, including some for Portugal, have provided estimates of elasticities or semi-elasticities. In this framework, a semi-elasticity tells us the percentage increase in GDP per worker due to a unit increase in average years of schooling. In our study, we compute these semi-elasticities to assess whether it paid more, say, to increase the number of primary school conclusions or secondary school ones, in terms of economic growth.

Semi-elasticities are computed from the economic growth impulse response functions. Let ε be the education elasticity of GDP per worker:

$$\varepsilon = (\text{percentage increase in } y) \,/\, (\text{percentage increase in } h_k). \qquad (8)$$

In a VAR defined in log changes, we estimate ε as the ratio of the cumulated change in y over the cumulated change in h_k. Furthermore, denote by η the education semi-elasticity of GDP per worker. We compute $\eta = \varepsilon/h_k$, considering the sample average value for the education variable.

Note that these semi-elasticities take into account the full effects of an increase in education. For example, when education increases induce more physical investment, the positive effects of a higher capital stock on output are included when computing the output response to an impulse in human capital. In this case, this dynamic feedbacks semi-elasticity is higher than a *ceteris paribus* one. The latter would imply that all factors but human capital that have an influence on growth would rermain constant[8].

4. Empirical results[9]

Stationarity tests

Augmented Dickey Fuller (ADF) test results for all variables considered in this study are presented in Table 2. When the ADF statistic is smaller than the critical value, the null non-stationarity hypothesis is rejected. In every case, the number of lags included in the regression was chosen starting from a relatively high value, nine lags, and sequentially reducing it to 0[10]. The final number of lags was chosen according to the minimum observed value for the Akaike Information Criterion (AIC) statistic[11].

[8] Pina and St. Aubyn (2004) introduce this distinction and compute both *ceteris paribus* and dynamic feeedbacks rates of return for public capital in Portugal.

[9] Econometric results presented in this section were obtained using GiveWin and PcGive 10. See Doornik and Hendry (2000, 2001) for a complete description of this software.

[10] The chosen maximum number of lags results from the formula proposed by Shwert (1989): $p_{max} = \left[12\left(\frac{T}{100}\right)^{\frac{1}{4}} \right]$, where T is the number of observations.

[11] This whole procedure is suggested by Hayashi (2000).

Table 2 – Unit root tests

Variable	Lags included	CT=Const.+trend C=Constant	ADF statistic	Critical level 5%	Critical level 1%	Presence of unit root?	Cointe-gration with y and i?
Series in levels							
y	2	CT	-2.322	-3.528	-4.209	Yes	
i	1	CT	-3.158	-3.525	-4.202	Yes	
h	1	CT	0.03378	-3.525	-4.202	Yes	**No**
h_4	7	C	-1.023	-2.95	-3.635	Yes	Yes
h_6	2	C	-1.747	-2.938	-3.607	Yes	**No**
h_6	1	CT	-6.248**	-3.52	-4.20	**No**	
h_9	1	CT	-0.7182	-3.52	-4.20	Yes	**No**
h_{11}	0	CT	-0.282	-3.522	-4.196	Yes	**No**
h_{sup}	2	CT	-4.212**	-3.528	-4.209	**No**	
Series in first differences							
Dy	1	C	-3.99**	-2.938	-3.607	**No**	
Di	1	C	-4.765**	-2.938	-3.607	**No**	
Dh	0	C	-2.079	-2.936	-3.602	Yes	
Dh_4	1	C	-0.2997	-2.938	-3.607	Yes	
Dh_6	0	C	-3.534*	-2.936	-3.602	**No**	
DH_9	0	C	-3.004*	-2.936	-3.602	**No**	
DH_{11}	1	C	-2.284	-2.938	-3.607	Yes	
DH_{sup}	7	C	-3.471*	-2.953	-3.642	**No**	

* Rejection at the 5 percent level.
** Rejection at the 1 percent level.

The upper part of the table contains results for the series in levels. A trend was included in all cases except for h_4, which displays no trend (see figure 3). For h_6, both "trend" and "no trend" cases were considered. No stationarity was never rejected, except in two instances – for h_{sup} and for h_6 when a trend was included.

The lower part of the table includes results for first-differenced series. These are annual growth rates, and so there is no reason to include a time trend. It was not possible to reject the no stationary null hypothesis in three cases only – for *h*, h_4 and h_{11}. In conceptual terms, it is difficult to believe that changes in average years of schooling have random walk properties, so the no rejection probably results from the fact that our sample is small – it is well known that stationarity tests are not very powerful in small samples. Therefore, we opted to consider all differenced series as stationary.

Evidence from table 2 and the considerations above lead us to consider all series as I(1), non-stationary variables, with the exception of h_{sup}, which can be described as trend-stationary.

Cointegration

If one of the considered educational variables is also I(1), then there is the possibility that these three variables are cointegrated. We have tested for cointegration between i, y and each of the non-stationary human capital variables (all but h_{sup}), following the Johansen (1988) procedure. Results from five VARs used to determine the number of cointegrating vectors are summarised in table 3[12]. With the trace test, the number of cointegrating vectors exceeds 0 under the alternative hypothesis. When applying the maximum eigenvalue test, the alternative is that the number of cointegrating vectors equals 1. In both cases tests include a small sample correction suggested by Reimers (1992). In every case, we present the probability value corresponding to the null hypothesis that there are no cointegration vectors. Results only allow to reject the no cointegration hypothesis in one case – with h_4, the primary schooling variable. Therefore, we have proceeded to consider first differences VARs in all cases except with h_4, where a cointegrated VAR with one cointegrating vector was estimated[13].

Table 3 – Cointegration Tests

Variable	VAR specification	Trace test (p-value)	Max test (p-value)
h	3 lags, trend.	0.203	0.425
h_4	4 lags, trend.	0.054	0.018
h_6	7 lags, trend.	0.313	0.528
h_9	4 lags, trend.	0.145	0.448
h_{11}	7 lags, no trend.	0.666	0.847

VAR specification was chosen according to information criteria and residuals normality and no autocorrelation.
Trace test: null hypothesis of no cointegration against alternative of one cointegrating vector.
Max test: null hypothesis of no cointegration against alternative of one or more cointegrating vectors.

[12] Doornik and Hendry (2000), vol. II, includes a complete presentation of these tests.
[13] There was no statistical evidence in favour of more than one cointegrating vector.

The VAR order and inclusion of a trend were decided following a model reduction strategy. Starting from seven lags and trend inclusion, we sequentially reduced the number of lags and did not include a trend when this was acceptable both from a residuals analysis criterion (autocorrelation, normality) and from three information criteria (Schwarz, Hanann-Quin and Akaike)[14].

First differences VAR estimation results and Granger causality tests

Table 4 summarises first differences VAR estimation and Granger causality tests results. Again, the VAR order was decided considering results of residuals normality and no autocorrelation tests and the three above mentioned information criteria.

Table 4 – Differences VAR Estimation Results

Human Capital Variable	VAR Order	Granger Test in GDP equation (p-value)	Dummies
h	2	0.0703	none
h_6	3	0.0000	1983
h_9	2	0.0560	none
h_{11}	3	0.0040	none
h_{sup}	1	0.1099	1974

VAR order was chosen according to information criteria and residuals normality and no autocorrelation.
Granger test: joint significance of human capital coeeficients in GDP equation.
Dummy variables are impulse dummies. 1983 was a recession year. 1974 was the democratic revolution year in Portugal.

The p-value Granger test presented in the table corresponds to the previously mentioned F-statistic. Note that we are testing a direct effect of the human capital variable on GDP growth. The null hypothesis that there is no causal link is rejected at a 92.97 % (=100% - 7.03%) confidence level for h (all levels considered). Evidence of a causal link is stronger when different levels are considered separately, with the exception of h_{sup}. Confidence levels vary between 94.4% (h_9) and 99.92 % (h_6). The confidence level for a direct causal effect from tertiary education to growth equals 89.01 percent. More importantly, this effect was actually estimated as a negative one. This combination of a somewhat counterintuitive result with limited statistic significance leads us not to consider h_{sup} in further computations.

[14] See Doornik and Hendry (2000), vol. II, for a presentation of these tests.

Impulse response functions

Figures 8 to 17 display the response functions of GDP and investment per worker growth to a standard error impulse to each of the human capital variables. The first three columns of table 5 present the corresponding accumulated changes. Two patterns are to be distinguished:

i) The crowding in case. In the long run, an impulse to the human capital variable increases both investment and GDP. This is the case of h, h_6 and h_9. In figures 8, 10 and 11 (GDP) and 13, 15 and 16 (investment), periods when response functions are above the baseline more than compensate for periods below it. In net terms, human capital formation induces physical capital investment, which reinforces economic growth. The accumulated effect on growth and physical investment derived from an impulse on human capital is greater than zero in those cases, as can be read from table 5.

Table 5 - Long run effects of independent impulses in human capital variables

	GDP per worker change (1)	Physical investment change (2)	Human capital change (3)	Long run elasticity (4)=(1)/(3)	Human capital sample average (5)	Human capital semi-elasticity in 2001 (6) = (4)/(5)
h	0.036	0.035	0.024	1.510	4.163	0.363
h_4	0.057	-0.013	0.082	0.695	1.504	0.462
h_6	0.018	0.010	0.111	0.166	0.712	0.233
h_9	0.050	0.061	0.110	0.456	0.697	0.654
h_{11}	0.020	-0.024	0.094	0.208	0.391	0.532

Columns (1), (2) and (3) correspond to accumulated responses to an orthogonal impulse in a human capital variable.

ii) The crowding out case. With h_4 and h_{11}, there is also a positive long run effect on GDP per worker (see table 5 and figures 9 and 11). However, human capital investment crowds out physical investment (see table 5 again and figures 14 and 17). In the long run, crowding out is never sufficiently strong to offset the GDP benefits of human capital formation.

Long-run semi-elasticities

A long run education semi-elasticity of income per worker give us the percentage increase in GDP per worker resulting from a unit increase in average years of schooling. Average years of schooling may increase either because there are more people with primary education only, or, say, because the number of individuals that concluded upper secondary school augmented. These two different reasons are not distinguishable if one takes the *H* measure, as done by most researchers. However, with our disaggregation, it becomes possible to compare them.

Table 5 summarises our findings in what concerns elasticities and semi-elasticities. Recall that columns (1), (2) and (3) contain cumulated changes, i.e. the sum of responses to the human capital variable impulse plotted in previously presented figures. As the variables are in logs, these are percentage changes. The long run education elasticities of GDP per worker are simply the ratio of columns (1) and (3) and are presented in column (4). Elasticities, however, are not a good measure for comparison, as a one-percentage point increase differs across human capital variables in absolute terms. Semi-elasticities are more directly comparable, because they measure the effect of absolute changes in human capital variables, which are measured in the same units (years). Semi-elasticities are time varying, as they are the ratio of elasticities and human capital values. It seems therefore natural to compute them using average values, as done in column (6).

From Table 5 we retain the following findings:

i) The long run elasticity (or semi-elasticity) when aggregate average years of schooling (*h)* are considered is substantially higher than the *ceteris paribus* ones usually found in previous studies on the Portuguese economy[15]. This comes as no surprise, as we are considering a dynamic feedbacks elasticity. Increasing average years of schooling in one year leads to a long-run 36.3 percent change in GDP per worker. More average years of schooling have a direct positive effect on production. They also stimulate growth indirectly, as they lead to higher physical investment.

ii) When there is a significant education to growth direct link, estimated semi-elasticities are always positive, even when there is some evidence of physical

[15] Estimated GDP level elasticity with respect to average years of schooling is close to 0.42 according to Teixeira and Fortuna (2004) and Pina and St. Aubyn (2004). Pina and St. Aubyn (2002) estimates are similar – between 0.36 and 0.48.

investment crowding out, as when h_4 or h_{11} are considered[16]. Semi-elasticities do not display a tendency to become higher or lower as the educational level increases.

iii) We provide evidence that both primary and secondary education had a significant positive impact on recent Portuguese economic growth. On the other hand, we could not conclude the same for tertiary education. These results are broadly in accordance to the cross-sectional ones provided by Petrakis and Stamatakis (2002) and by Papageorgiou (2003) – in the sample period, Portugal fits the picture of a developing country starting with very low educational levels, where primary and secondary education increases were most important to increased productivity in final goods and foreign technology adoption. As tertiary education only assumed some numeric importance in Portugal recently, it comes as no surprise that its probable positive effects do not show in our estimations.

5. Conclusions

In this paper we have investigated the impact of different schooling levels on Portuguese economic growth. The use of time series tools like VARs, Granger causality tests and impulse response functions was made possible by annual data availability.

Portuguese GDP per worker increased more than fourfold between 1960 and 2001. Our results provide evidence that increased schooling of the working age population was an important growth-driving factor. Independent impulses in average years of schooling led to direct and indirect increases in GDP per worker, with a corresponding dynamic feedbacks semi-elasticity close to 36 percent.

Average years of schooling increased at different schooling levels during the sample period. Decomposition into these different levels allowed us to estimate differentiated effects on growth. Taking exception of tertiary education, there is no evidence of

[16] Pina and St. Aubyn (2004) found that an aggregate increase in average years of schooling had a modest effect on GDP, as it strongly crowded out private (but not public) physical investment. Here, we do not make the distinction between private and public investment.

striking growth impact differences among considered primary and secondary levels. Namely, estimated semi-elasticities do not vary monotonously with schooling level.

We allowed for both direct and indirect impact of education on growth. The indirect impact of education occurs by means of a physical investment variable. There is no reason to expect *a priori* the indirect impact to be positive or negative. A crowding out scenario would imply less physical capital investment when positive independent impulses in human capital investment occur. We provide evidence that crowding *in* prevails – investment in education usually stimulated physical investment. This indirect effect reinforced human capital direct growth enhancing properties and is partly responsible for the high semi-elasticities estimates we provide.

Tertiary education increased markedly in Portugal in recent years only. Therefore, it is not surprising that there is no statistical link between the related human capital variable and economic growth. Together with the strong evidence of lower educational levels growth linkages, and adding to fact that the Portuguese economy could but be classified as far from the technological frontier in the 1960-2001 period, these results are in accordance with Vandenbussche, Aghion and Meghir (2004) view of the relationship between human capital composition and distance to the frontier. These authors provide a model and some empirical evidence where tertiary education, or skilled labour, have a stronger effect on growth when a country becomes closer to the technological frontier. On the other hand, less skilled human capital formation is more important when the closing of the technological gap is still beginning.

Our chosen methodology proved to be effective in detecting important patterns in a specific country economic growth process. We showed how it is possible to use a time series approach to test the link between education and growth, including the estimation of dynamic feedbacks elasticities and semi-elasticities. It would be an interesting idea for further research to adopt a similar approach to other countries in order to collect evidence that would shed some more light on the issue of differentiated human capital level effects on growth.

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Appendix – Time series used in this paper

Year	Employment	GDP	H	H_4	H_6	H_9	H_{11}	H_{sup}	Investment
1960	3743.599	18.194	1.744	1.291	0.141	0.089	0.047	0.123	4.258
1961	3726.690	19.142	1.808	1.300	0.182	0.098	0.051	0.123	4.543
1962	3716.545	20.406	1.875	1.310	0.224	0.108	0.055	0.123	4.621
1963	3705.273	21.605	1.951	1.326	0.268	0.119	0.060	0.123	5.327
1964	3695.127	23.175	2.032	1.344	0.314	0.130	0.065	0.122	5.539
1965	3683.855	24.928	2.121	1.367	0.359	0.141	0.073	0.123	6.111
1966	3661.310	25.889	2.218	1.396	0.407	0.152	0.082	0.124	7.205
1967	3638.765	27.980	2.318	1.427	0.453	0.165	0.089	0.127	7.578
1968	3616.220	30.547	2.422	1.460	0.498	0.179	0.099	0.128	6.871
1969	3593.675	31.576	2.528	1.493	0.541	0.194	0.113	0.129	7.431
1970	3789.816	33.973	2.658	1.540	0.584	0.213	0.129	0.133	8.279
1971	3778.544	36.209	2.735	1.572	0.573	0.237	0.138	0.144	9.122
1972	3754.872	39.121	2.831	1.611	0.564	0.264	0.149	0.155	10.399
1973	3723.309	43.513	2.938	1.637	0.576	0.292	0.165	0.167	11.474
1974	3694.000	44.000	3.078	1.656	0.568	0.357	0.192	0.188	10.768
1975	3724.000	42.100	3.202	1.660	0.587	0.405	0.212	0.203	9.625
1976	3789.000	44.998	3.325	1.665	0.601	0.442	0.233	0.230	9.747
1977	3784.000	47.482	3.455	1.654	0.649	0.472	0.263	0.256	10.864
1978	3772.000	48.819	3.624	1.656	0.657	0.546	0.268	0.290	11.540
1979	3854.000	51.572	3.787	1.660	0.679	0.589	0.297	0.317	11.385
1980	3940.000	53.939	3.965	1.674	0.708	0.624	0.321	0.342	12.356
1981	3918.000	54.812	4.157	1.707	0.731	0.662	0.356	0.371	13.036
1982	3928.000	55.982	4.258	1.698	0.753	0.665	0.424	0.394	13.331
1983	4128.000	55.885	4.381	1.692	0.772	0.688	0.452	0.421	12.380
1984	4075.000	54.834	4.500	1.683	0.796	0.708	0.476	0.449	10.227
1985	4057.000	56.374	4.630	1.665	0.827	0.745	0.495	0.479	9.865
1986	4059.700	58.708	4.771	1.645	0.868	0.780	0.515	0.504	10.937
1987	4148.200	62.455	4.909	1.622	0.910	0.833	0.520	0.533	12.905
1988	4252.400	67.132	5.047	1.601	0.958	0.862	0.536	0.563	14.820
1989	4346.700	71.456	5.200	1.578	0.993	0.923	0.540	0.590	15.362
1990	4438.500	74.279	5.359	1.557	1.022	0.979	0.553	0.618	16.530
1991	4562.700	77.523	5.520	1.530	1.049	1.035	0.556	0.654	17.080
1992	4468.400	78.368	5.679	1.494	1.045	1.108	0.595	0.696	17.853
1993	4389.000	76.767	5.894	1.471	1.038	1.208	0.636	0.752	16.863
1994	4381.600	77.507	6.109	1.444	1.024	1.286	0.705	0.830	17.323
1995	4358.400	80.827	6.317	1.413	0.997	1.385	0.729	0.913	18.457
1996	4388.400	83.692	6.512	1.373	0.986	1.460	0.770	1.001	19.506
1997	4477.300	87.006	6.685	1.329	1.007	1.517	0.803	1.094	22.217
1998	4597.599	90.992	6.854	1.297	1.006	1.568	0.847	1.196	24.763
1999	4683.735	94.450	7.004	1.262	1.004	1.614	0.897	1.298	26.345
2000	4784.265	97.641	7.156	1.224	0.993	1.683	0.932	1.404	27.341
2001	4848.412	99.307	7.285	1.191	0.981	1.728	0.982	1.510	27.356

Employment – Civilian domestic employment, 1000 persons. Source: AMECO, Annual macro-economic database of the European Commission's Directorate General for Economic and Financial Affairs (DG ECFIN), May 2004.
GDP – Gross domestic product at 1995 market prices, 10^9 euros. Source: AMECO, May 2004.
H, H_4, H_9, H_{11} and H_{sup} – Human capital. See main text for definitions. Source: Pereira (2004).
Investment – Gross fixed capital formation at 1995 prices for the total economy. 10^9 euros. Source: AMECO, May 2004.

Figure 1 – GDP and investment per worker growth rates

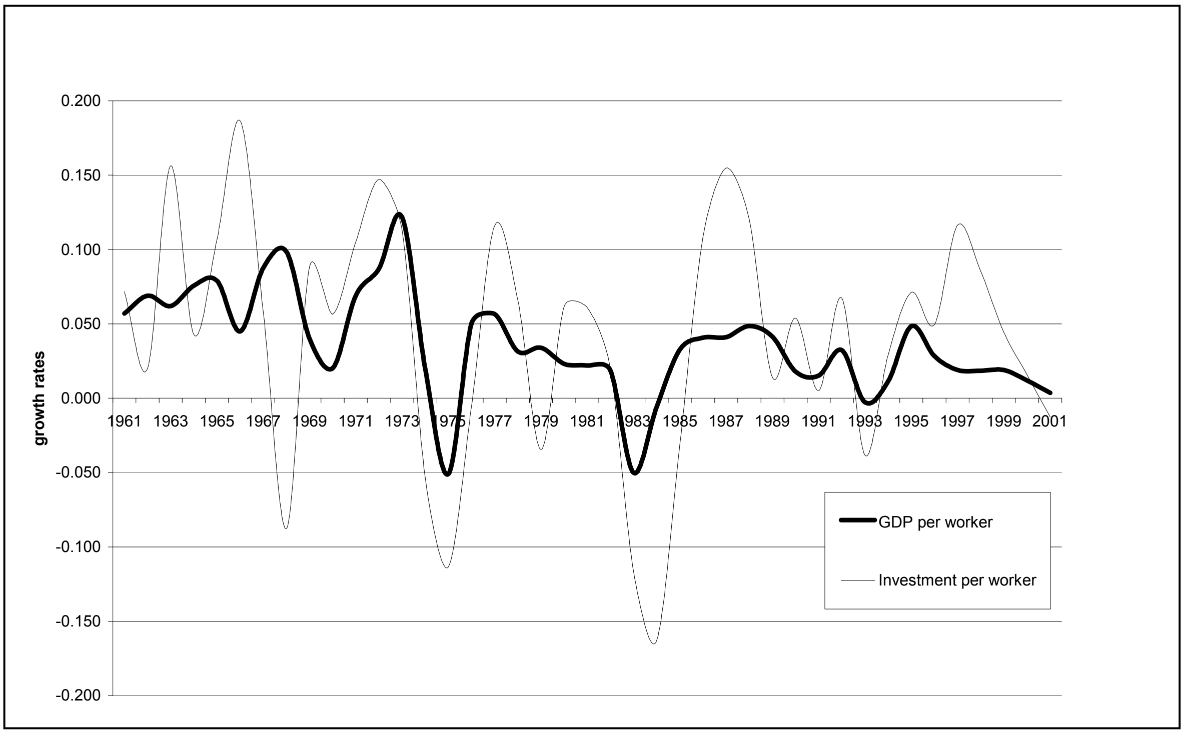

Figure 2 – Series *H*

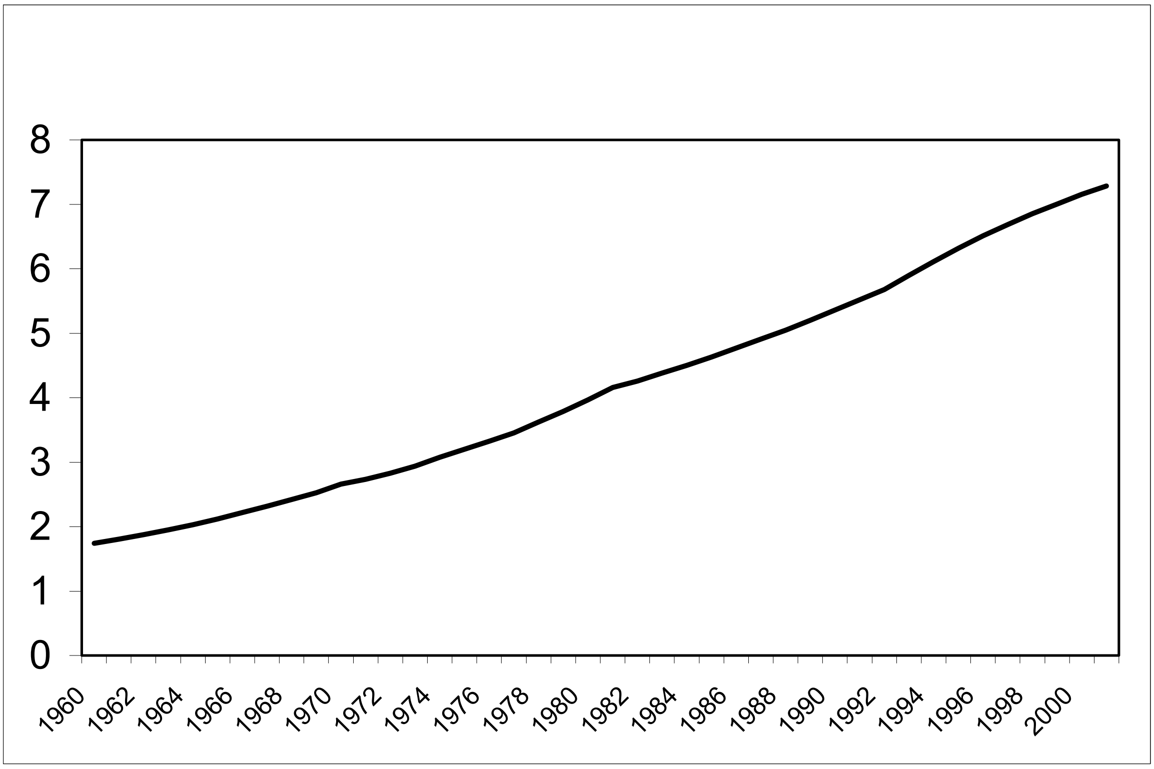

Figure 3 – Series H_4

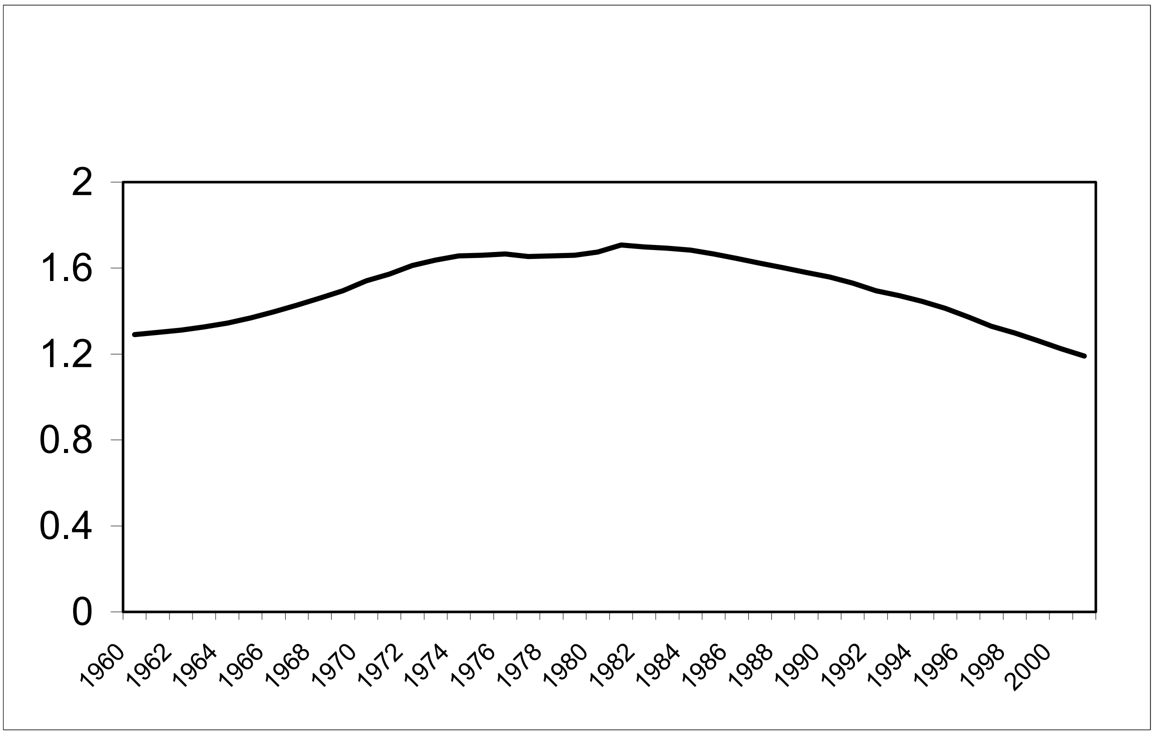

Figure 4 – Series H_6

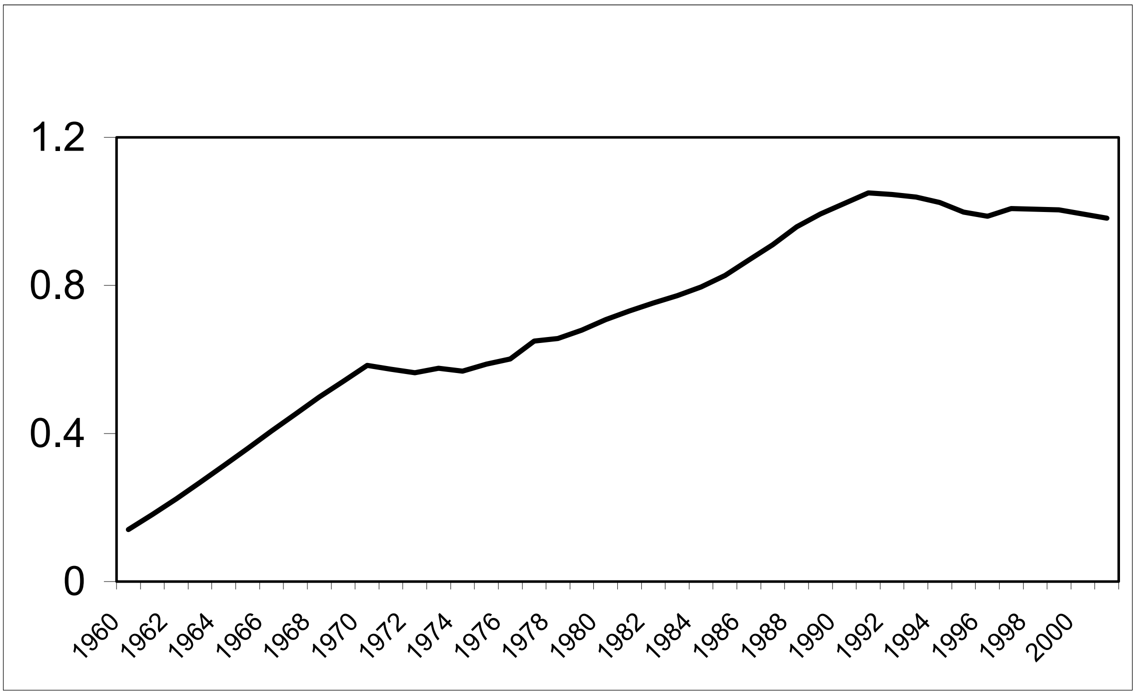

Figure 5 – Series H_9

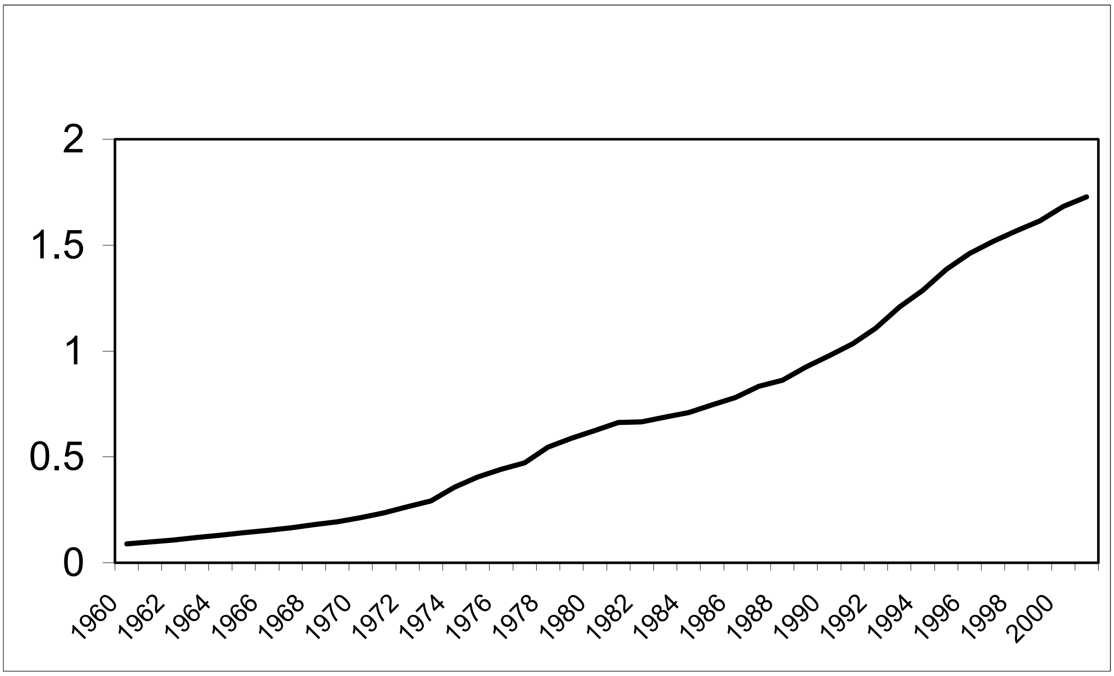

Figure 6 – Series H_{11}

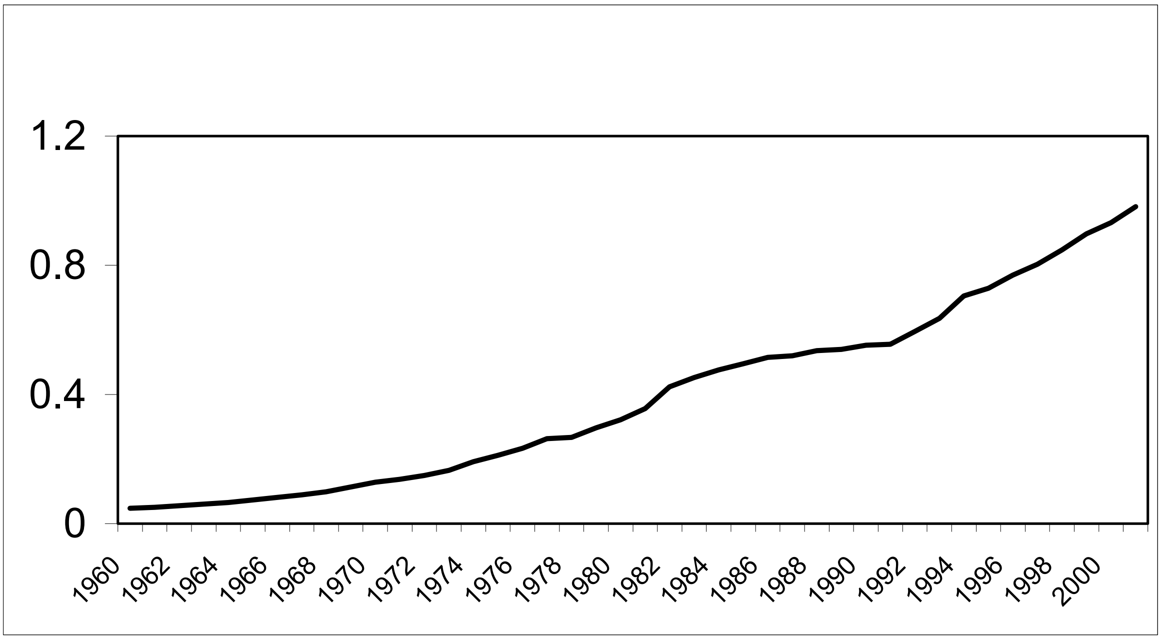

Figure 7 – Series H_{sup}

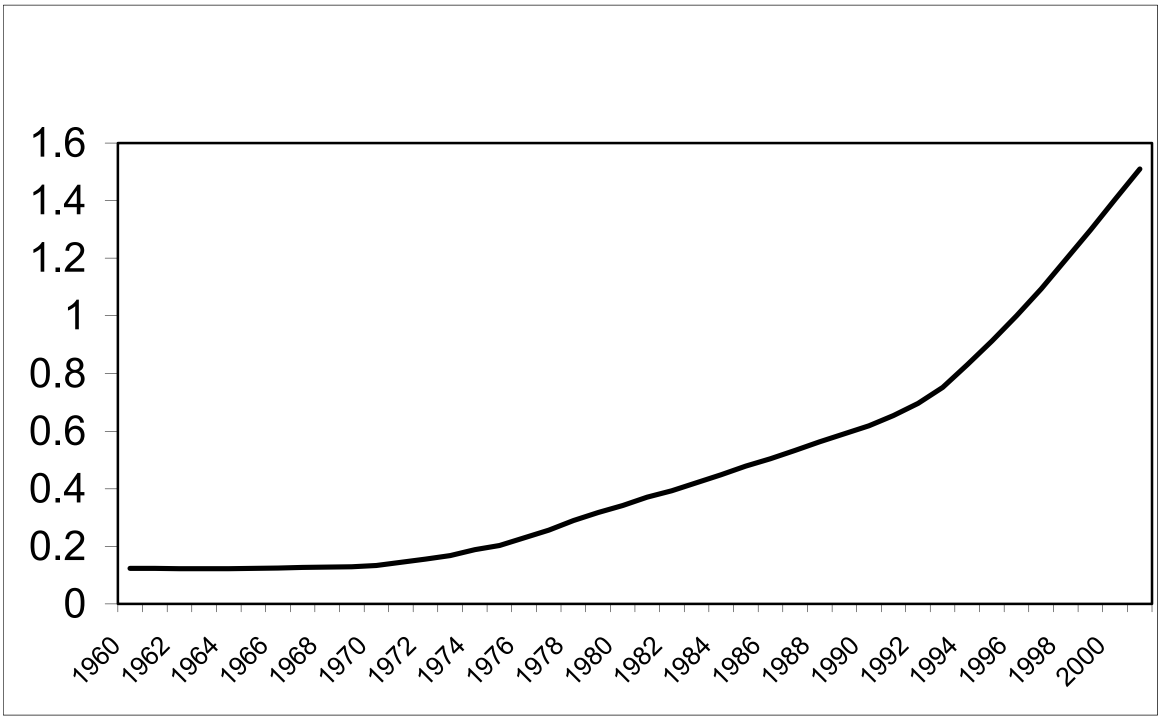

Figure 8 – *Dy* response to *Dh*

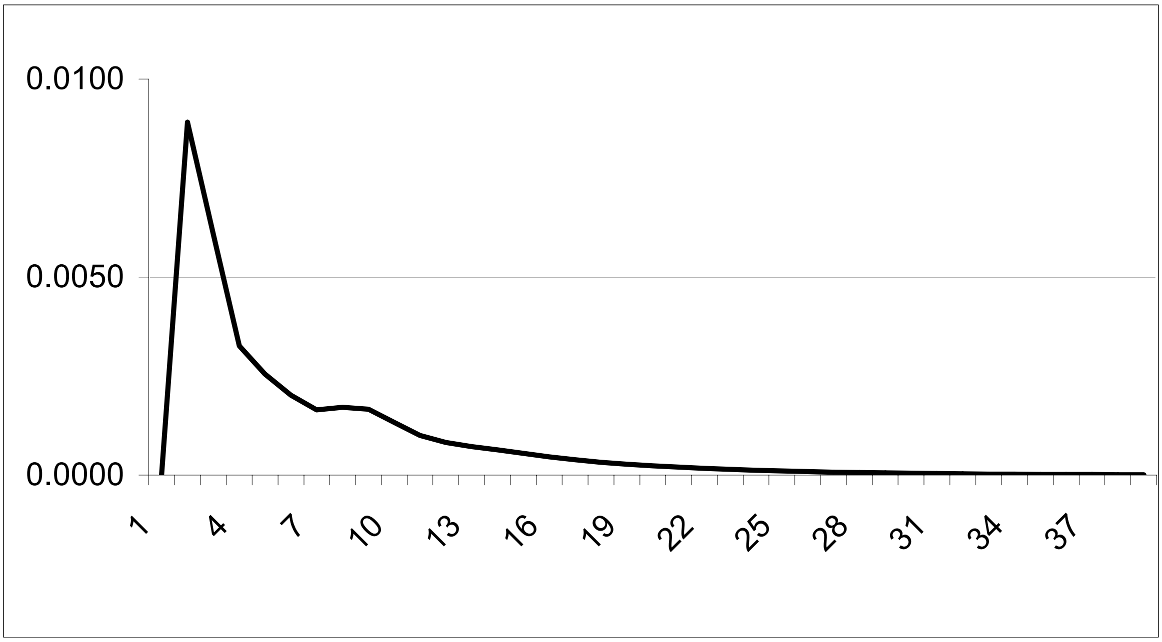

Figure 9 – *Dy* response to *Dh*$_4$

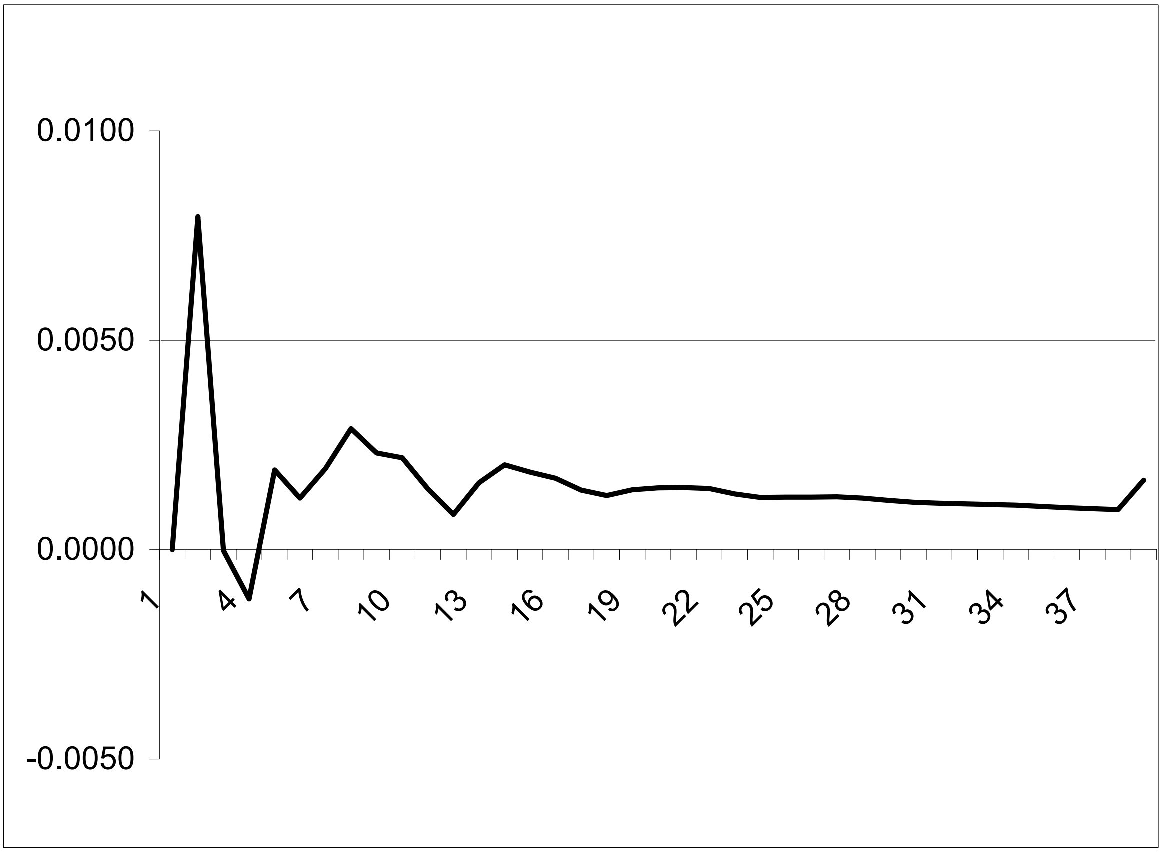

Figure 10 – *Dy* response to *Dh₆*

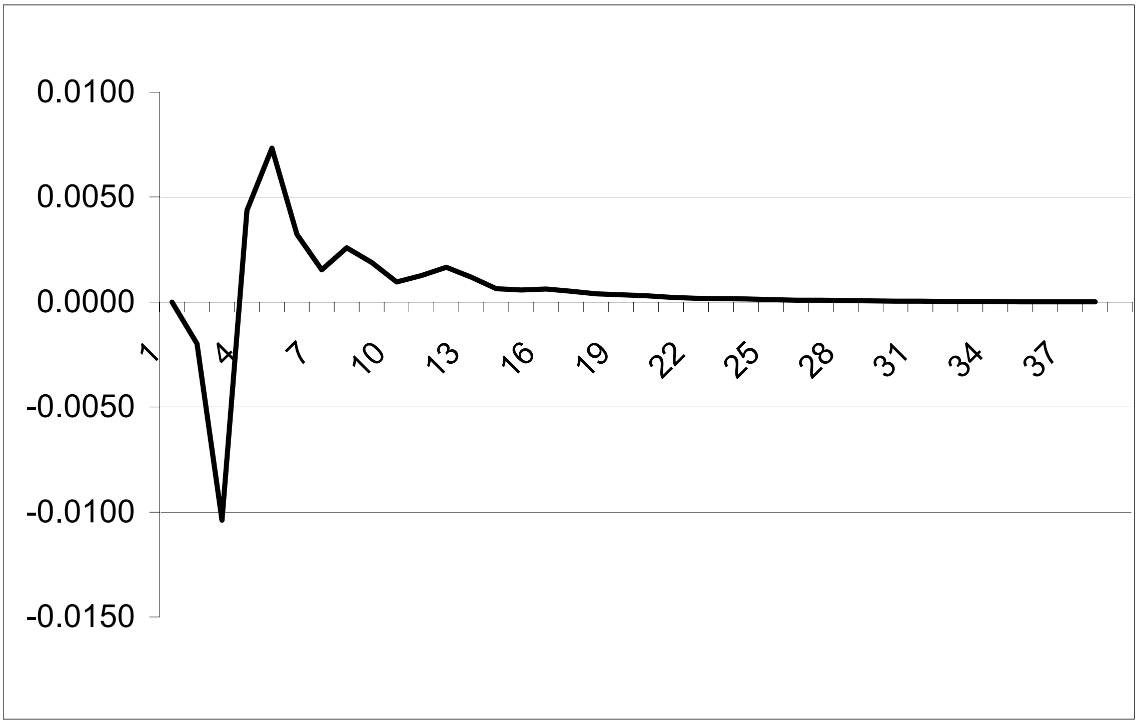

Figure 11 – *Dy* response to *Dh₉*

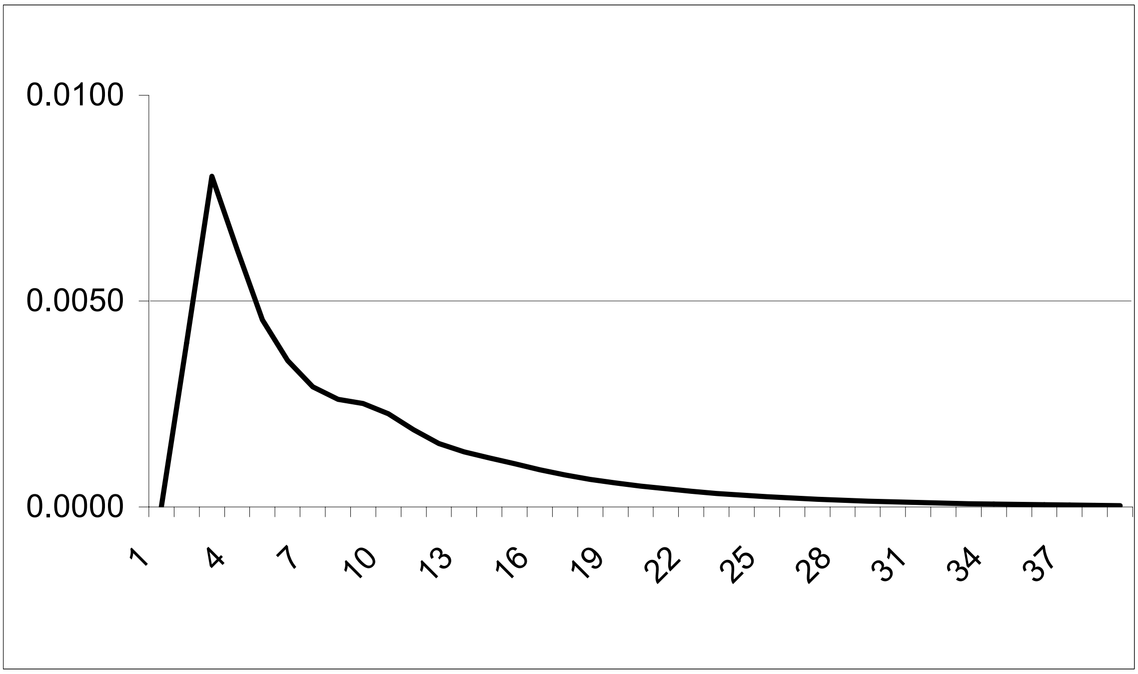

Figure 12 – *Dy* response to Dh_{11}

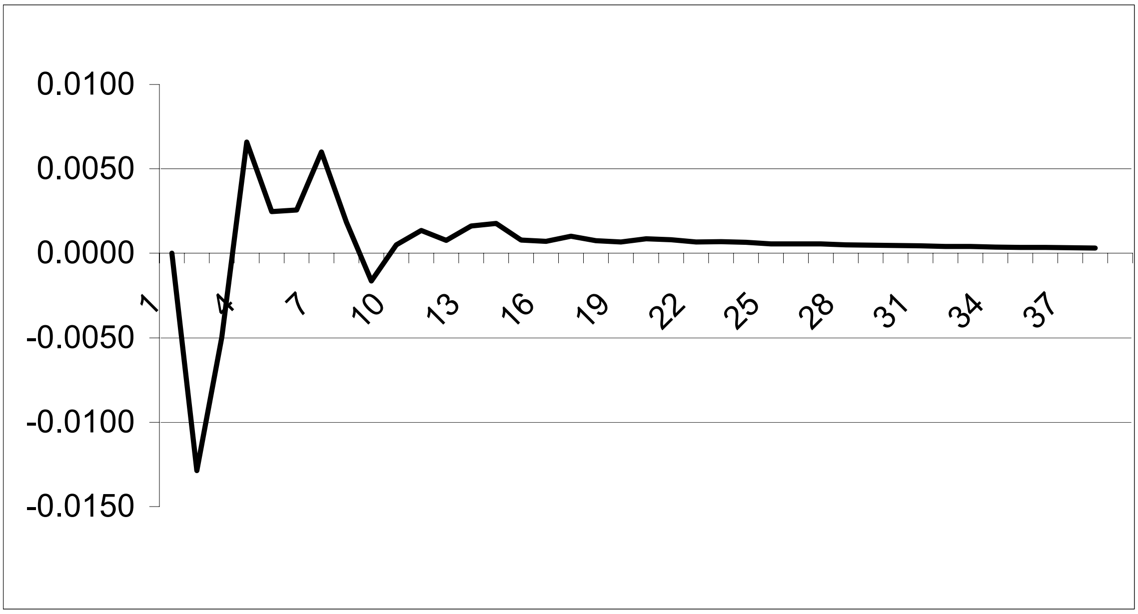

Figure 13 – *Di* response to *Dh*

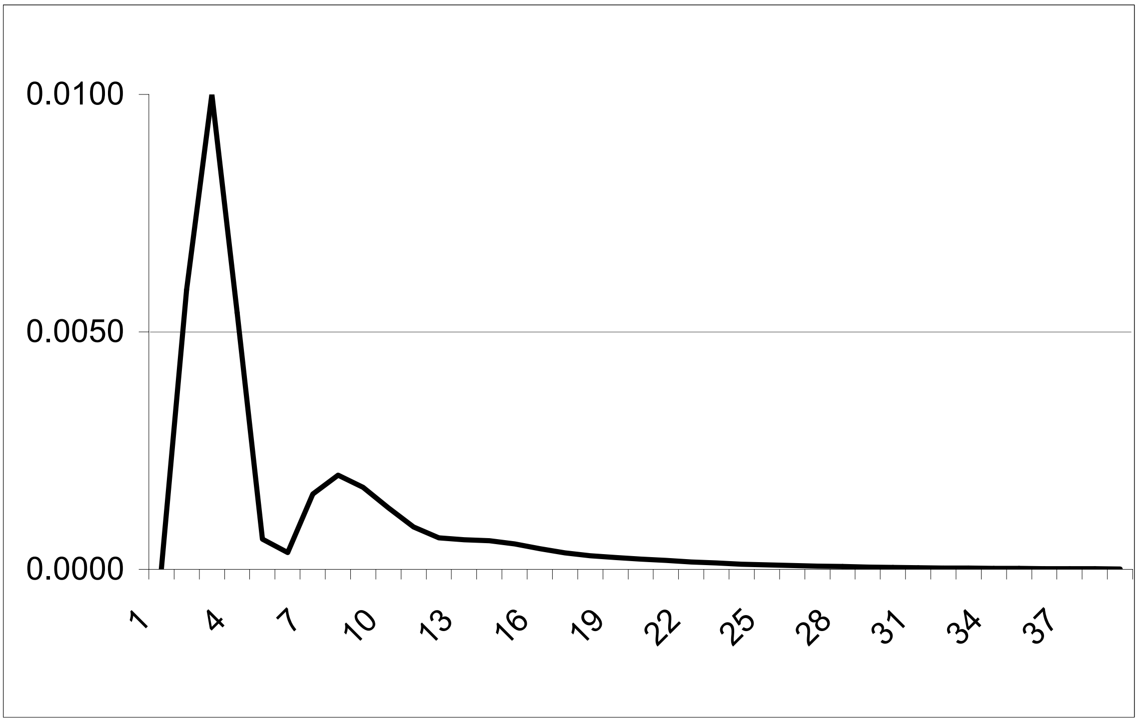

Figure 14 – *Di* response to *Dh$_4$*

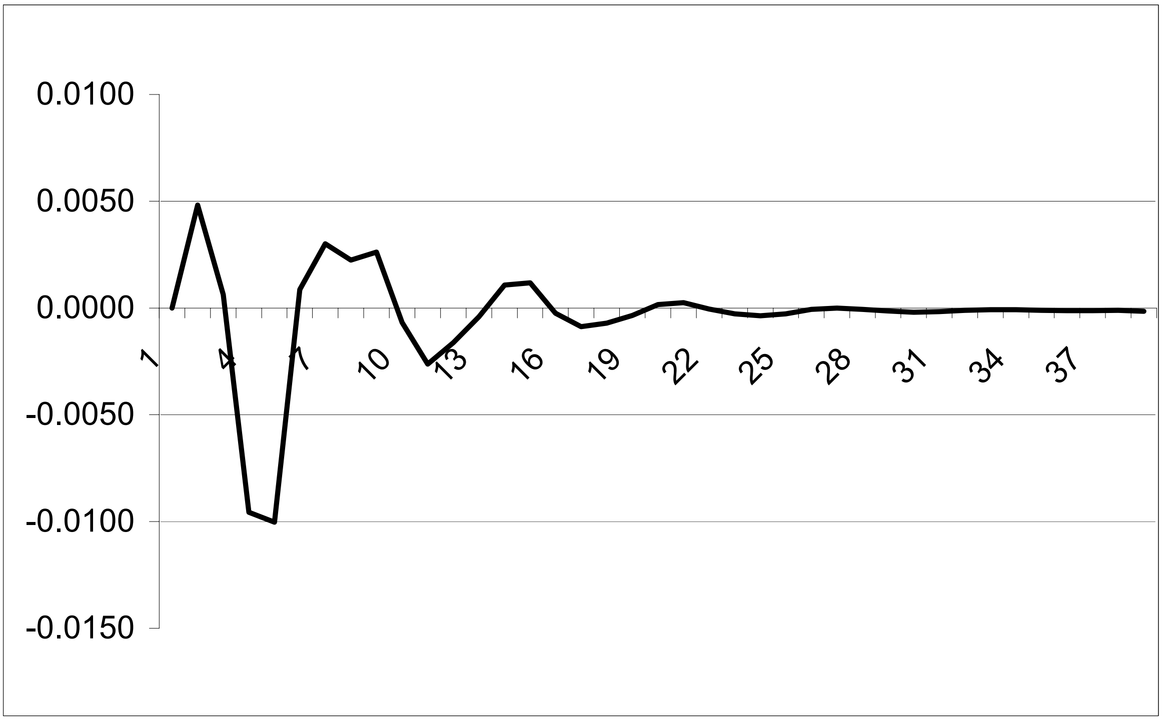

Figure 15 – *Di* response to *Dh$_6$*

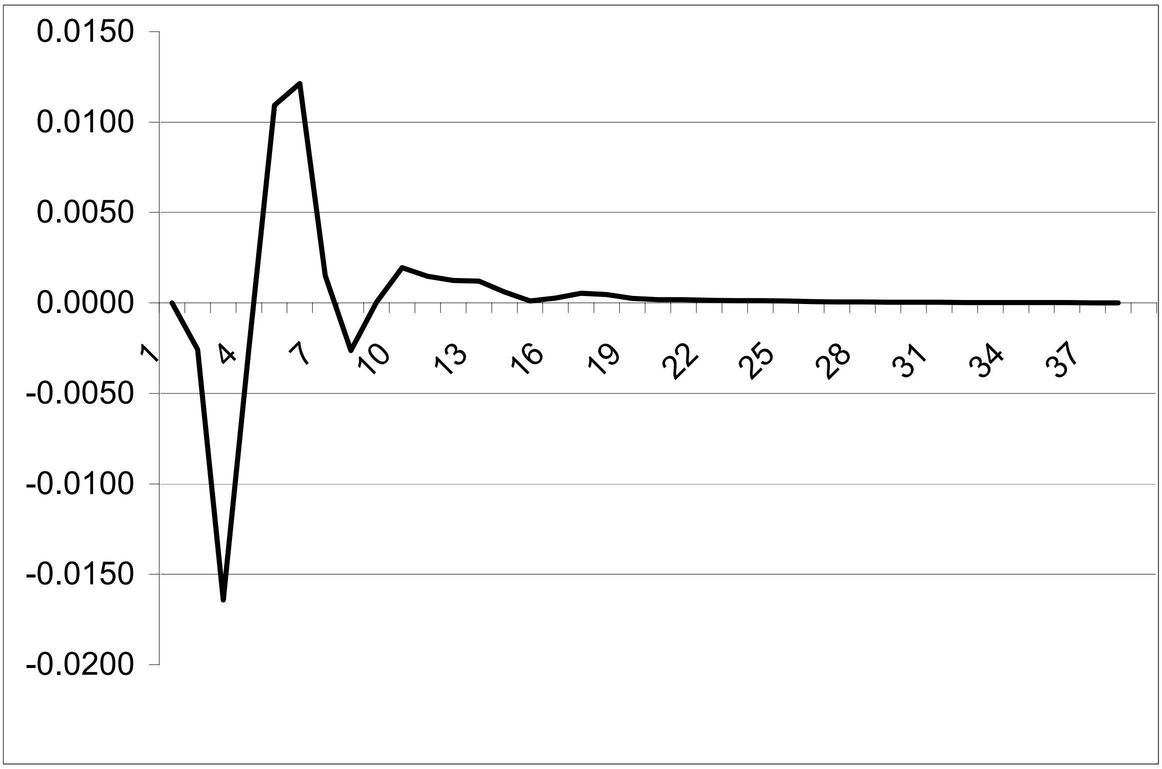

Figure 16 – *Di* response to *Dh*$_9$

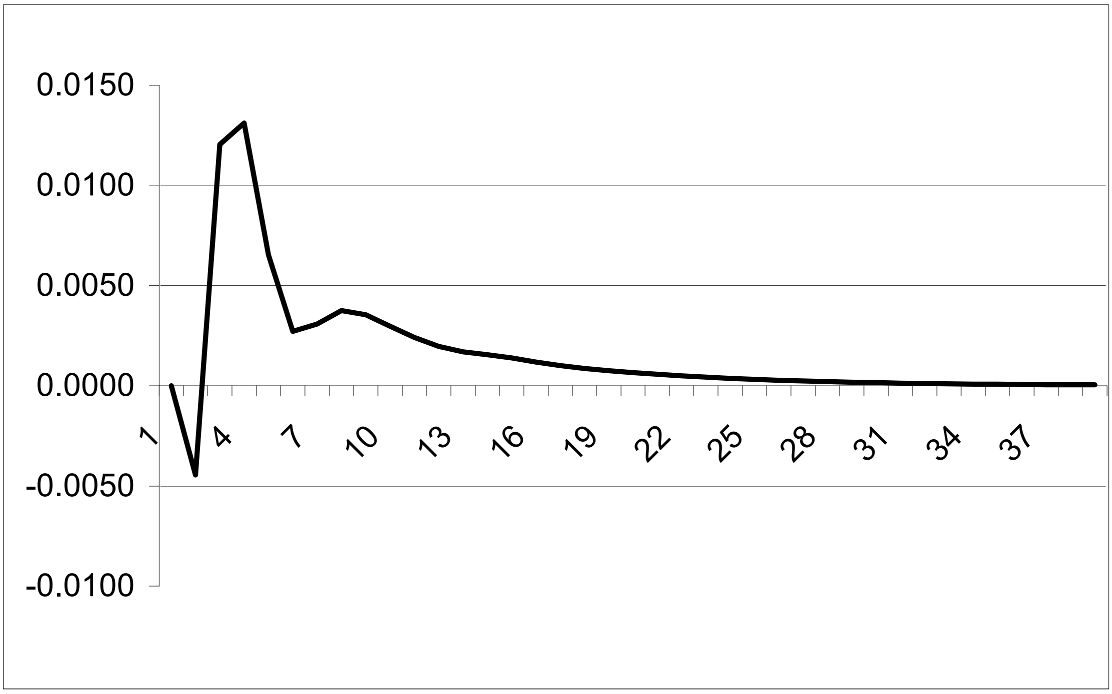

Figure 17 – *Di* response to *Dh*$_{11}$