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DISCUSSION PAPER SERIES

IZA DP No. 15237

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ABSTRACT

Characterizing the Schooling Cycle*

This paper develops a novel and tractable empirical approach to estimate the cycle in schooling participation decisions, which we denominate the schooling cycle. The estimation procedure is based on unobserved components time series models that decompose higher education enrollment rates into a slow-moving stochastic trend and a stationary cyclical factor. By doing so, we obtain a full characterization of the cyclical dynamics of schooling participation and analyze its relationship with the business cycle in a time-varying fashion. Using data for 16–24-year-olds attending full-time post-secondary education in the United Kingdom from 1995Q1 to 2019Q4, we find evidence of a very persistent schooling cycle largely, but not exclusively, explained by the business cycle. Additionally, we find that the direction of the response of schooling participation to the business cycle, say, pro-, counter- or a-cyclical, is largely time-dependent, as is the degree of synchrony between both cycles. We note, however, that results are heterogeneous across gender.

JEL Classification: E3, I2, J2, C32

Keywords: human capital, business cycle, state space, kalman smoother

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1 Introduction

Countercyclicality in higher education enrollments in OECD countries is a well-established finding in the economics of education literature (see Sakellaris and Spilimbergo, 2000; Dellas and Sakellaris, 2003; Johnson, 2013; Reiling and Strom, 2015; Boffy-Ramirez, 2017; Alessandrini, 2018). While these findings are robust, they could potentially tell an incomplete story. Generally, countercyclicality is based on the estimation of static average effects of standard regressions that do not account for time variation. These estimates do not allow for changes in schooling cyclicality over time but rather average them out, limiting our understanding of the cyclicality of schooling participation to a unique static coefficient. This limitation is due to the lack of a direct estimate of the cycle present in schooling participation decisions, or what we denominate the schooling cycle. Dellas and Sakellaris (2003) highlight that the precise impact of the business cycle on aggregate human capital—accrued primarily through schooling—depends on the measure of the cyclical component in schooling participation decisions.[1] Nevertheless, such a measure has never been estimated, at least not in a structural way. As such, the cyclicality of schooling has never been fully characterized, nor has its relationship with the business cycle been analyzed in a time-varying fashion. Determining the cyclicality in schooling decisions constitutes an important issue for business-cycle research and it is so for at least three reasons. Schooling decisions might act as a propagation/feedback mechanism on the business cycle itself, playing an important role in the long-run aggregate costs of the business cycle and its long-run effects on inequality.

In this paper, we develop a novel and tractable empirical approach that relies on the Kalman smoother to estimate the cycle in schooling participation decisions. This cycle is first analyzed in isolation to provide an in-depth analysis of the cyclical properties of schooling. Then, we conduct a joint analysis with an estimate of the business cycle. This work therefore complements the existing literature by extending the analysis to the case when the relationship between schooling and the business cycle is allowed to be time-varying. In this way, we explore the whole spectrum of co-movement between schooling decisions and the business cycle, providing further insights on the direction, timing and size of the effect. Our framework allows us to address pending questions such as: what are the cyclical properties of schooling? Is the response of schooling participation to the business cycle different over time? Is there a schooling

[1] We view human capital as a set of skills that increase through formal schooling. The reason is twofold: first, schooling constitutes the most easily observable component of all human capital investments and second, although there is more to human capital than schooling, the same forces that affect schooling are also likely to affect non-schooling investments. Therefore, we can infer from the patterns of schooling investments what might be happening to overall human capital accumulation (Acemoglu and Autor, 2011).

cycle that is not completely determined by the business cycle?

We make three contributions to the existing literature. The first is methodological. In contrast to the vast majority of previous empirical work (see Bedard and Herman, 2008; Méndez and Sepúlveda, 2012; Johnson, 2013; Alessandrini, 2018) that infers cyclical fluctuations in schooling participation by estimating average effects of labor market indicators on schooling, we obtain a direct measure of the cycle. We do this by modeling all components in our schooling series—trend, cycle, and slope—without discarding any unwanted information present in the series as it is the case with filtering techniques, which have been shown to be problematic (Hamilton, 2018). To this end, we estimate unobserved component (UC) time series models with the Kalman smoother to decompose enrollments in higher education into a slow moving stochastic trend and a stationary cyclical factor. Enrollment corresponds to 16–24-year-olds attending full-time higher education in the United Kingdom (U.K.) from 1995Q1 to 2019Q4. We also conduct our estimations using enrollment by gender to explore potential demographic heterogeneity in cyclicality. We note that existing literature has largely abstracted from estimating the trend and the cycle separately in schooling participation series. This can lead to confusion regarding the role played by structural long-run and transitory short-run effects and the possible interaction between the two.[2] Next, using the same methodology, we obtain an estimate of the business cycle extracting the cycle in real GDP data for the U.K. Our second contribution is a joint analysis of both the schooling and the business cycles focusing on the time-varying properties of their relationship. Our third contribution is understanding the role played by the channels through which the business cycle affects schooling participation: the *ability-to-pay*—channel, or funding for further education; and the *opportunity-cost* channel, or foregone earnings due to time spent in education channels. These channels vary greatly over the business cycle and, thus, are subject to their own cycles. We estimate these cycles and explore their ability to explain enrollment cyclicality and fluctuations over time. Lastly, we conduct an unconditional variance decomposition on enrollment to measure the share of variation explained by the business cycle.

Firstly, our findings show the presence of a persistent and significant cycle in our enrollment series for our estimation period of 1995Q1 to 2019Q4. When analyzing this cycle jointly with the estimated business cycle, we find evidence that the response to the business cycle is largely time-varying. We observe that counter-cyclicality takes place only during two periods in our sample, with the longest one taking

[2] Previous works have at best estimated a trend component from an assumed equilibrium condition using cointegration or used filtering techniques such as the Hodrick and Prescott (1981,1997) filter (McVicar and Rice, 2001)

place during the Great Financial Crisis (GFC). This is in line with the results of existing literature that estimates static average effects for advanced economies (see Johnson, 2013; Reiling and Strom, 2015; Boffy-Ramirez, 2017; Alessandrini, 2018). A counter-cyclical pattern suggests that, on average, individuals are substituting away from low job opportunities during economic downturns with longer stays in education. For the remaining periods, we find pro-cyclical (enrollments increase when economic activity is high) and a-cyclical (enrollments are unresponsive to economic fluctuations) responses. Pro-cyclicality is observed at the start of our sample from mid-1995 until end of 1997 and in two other occasions, from mid-2001 until late 2002 and from late 2015 until mid-2018. The no-response/a-cyclical scenario occurs between early 2002 and mid-2005, from 2012 to 2015 and at the end of our sample from late 2018 until late 2019. Cross-correlation analysis and least-squares estimates allowing for breakpoints support this visual finding and show that the business cycle leads ahead of the schooling cycle by seven quarters. By looking at enrollment by gender, we find some significant heterogeneity in schooling participation cyclicality. Lastly, our variance decomposition exercise shows that the business cycle is able to explain up to 44% of the total variation in enrollments, while 20% of the variation can be attributed to enrollments' own cyclical variation.[3] Interpreted through the lens of our model, this suggests that schooling participation possesses a cycle of its own which is independent of the business cycle.

Regarding what drives the cyclicality of enrollments over time, we find that the relative size and direction of the movements in the *ability-to-pay* and *opportunity-cost* channels are able to successfully track observed movements in enrollments. Additionally, the relative fluctuations in the channels, *ability-to-pay* versus *opportunity-cost*, for different time periods are able to predict the direction taken by the observed cyclicality in enrollments in the same fashion as found for our baseline estimations.

Our work relates closely to two studies that explore the cyclicality of human capital investment decisions. Dellas and Sakellaris (2003) and Méndez and Sepúlveda (2012) explore the cyclical behavior of skill acquisition activities—enrollments in schooling and training—in the U.S. They both present evidence that cyclical fluctuations in aggregate economic activity cause significant swings in enrollments in a strong counter-cyclical fashion. However, in both works, the authors do not estimate the cycle present in the demand for schooling, but rather extract deterministic trends. In contrast to our paper, their estimated cyclical fluctuations do not rely on a model and are not analyzed jointly with the cycle present in the

[3] The remaining share is distributed among other controls in our regression. We have admitted them for the sake of clarity, as they do not add to the discussion.

economy.

More generally, our work also relates to studies concerning schooling participation in the U.K. Whitfield and Wilson (1991) examine the socio-economic factors determining the rates of staying on at school for 16-year-olds from 1956 to 1986. They find that the set of determinants for staying-on rates vary across different time periods. Thus, they point to the need for time-varying analysis of schooling decisions over time. McVicar and Rice (2001) use cointegration analysis and find that short-run dynamics in schooling seem to be related to fluctuations in labor demand and youth unemployment. Taken together, these works offer support for the importance of macroeconomic conditions for schooling participation and highlight the time-varying properties of this relationship and the importance of short- and long-run dynamics.

The outline of the paper is as follows. Section 2 gives a full description of the data and specifics of the education system in the U.K. Section 3 presents the empirical specification and the estimation method. The results are presented in Section 4. In Section 5 we discuss a robustness analysis and offer our conclusions in Section 6.

2 Data

In this paper we use quarterly data on post-secondary enrollment rates in the U.K. obtained from Thomson Reuters Datastream sourced from the Labour Force Survey, published by the Office for National Statistics (ONS). Enrollment rates are calculated by dividing the number of individuals in a particular age group enrolled in either further or higher education in each period by the same age group population. Our baseline sample consists of all individuals between the ages of 16 to 24 enrolled in full-time education. An individual is considered enrolled if they attend a full-time college or university program on a regular basis. Full-time students are defined as those who commit to undertake more than 75% of total course credit in a given year. We use data from 1995Q1 to 2019Q4, which gives a total of $T = 100$ observations.

The education system in each of the five countries in the U.K. consist of five stages: early years, primary, secondary, further education (FE) and higher education (HE). The law states that full-time education is compulsory for all children between the ages of 5 (4 in Northern Ireland) and 16. In England, compulsory education or training has been extended to 18 for those born after September 1st,

1997. This means that those reaching 16 years of age in 2013 will have a different compulsory school leaving age. However, individuals can choose to either stay in full-time education by starting college, an apprenticeship, or traineeship, or spend 20 hours or more per week working or volunteering while in part-time education or training.[4] FE is non-compulsory, and covers non-advanced education which can be taken at further (including tertiary) education colleges and HE institutions. The fifth stage, HE, is study beyond A levels or Business and Technology Council diplomas (BETCs) (and their equivalent) which, for most full-time students, takes place in universities, colleges and other HE institutions. Further education in the United Kingdom and Ireland, similar to continuing education in the United States, refers to education that is distinct from the higher education offered in universities. It may be at any level above compulsory secondary education, from basic skills training to higher vocational qualifications. A distinction is usually made between FE and HE, an education at a higher level than secondary school, usually provided in distinct institutions such as universities. FE in the United Kingdom is usually a means to attain an intermediate or follow up qualification necessary to attend university, or begin a specific career path, e.g., Quantity Surveyor, Town Planner or Veterinary Surgeon, for anyone over 16, primarily available at Colleges of Further Education, work-based learning, or adult and community learning institutions.

We also obtain enrollment data for different demographic groups: by gender, i.e., male/female, and for two different age groups, i.e., 16–17/18–24. The former is used to explore potential gender differences regarding schooling choices when faced with fluctuations in the same business cycle. The latter will be used in the robustness analysis for our baseline results. Given some potential overlapping of 16 years old still in compulsory education, we check whether the results for the 16-17-year-old sub-sample differ considerably from those for the 18-24-year-old one. This way we are able to rule out any bias present in our results driven exclusively by individuals who may still be part of the compulsory education scheme. To estimate the business cycle, we use real quarterly GDP provided by Thomson Reuters Datastream sourced from the ONS. Finally, to control for supply side effects in enrollments, we use data on annual government spending on education provided by the ONS also obtained from Thomson Reuters Datastream shown in Figure A-1. All our series are seasonally adjusted, and when not, we conduct our own seasonal

[4] Apprenticeships combine practical training in a job with study. An apprentice will: 1. be an employee earning a wage and receiving holiday pay, 2. work alongside experienced staff, 3. gain job-specific skills, and 4. be given at least 20% of normal working hours as time for training related to role-related study. Apprenticeships take 1 to 5 years to complete, depending on their level. A traineeship is a course with work experience that prepares trainees for work or an apprenticeship. It can last from 6 weeks up to 1 year, though most traineeships last for less than 6 months. Source: https://www.gov.uk/know-when-you-can-leave-school

adjustment to rule out any systematic seasonal effects in our estimations. Furthermore, since the series for government spending in education is only available at annual frequency over our estimation period, we obtain quarterly series via linear interpolation.

3 Empirical implementation

3.1 Univariate UC time series models

We estimate univariate UC time series models independently for both the enrollment rates and GDP data. We assume that each series can be expressed as a combination of a non-stationary trend and a stationary cyclical component that moves around the trend symmetrically. Our dependent variable y_t in period t is assumed to be given by the following latent factor model:

$$y_t = \tau_t + c_t + \beta X_t^S + \varepsilon_t \qquad \varepsilon_t \sim iid\mathcal{N}(0, \sigma_\varepsilon^2), \qquad t = 1, ..., T, \tag{1}$$

where y_t is the main series of interest to be decomposed (i.e., enrollment rates/real GDP), τ_t is the stochastic trend component, and c_t is the stochastic cycle, X_t^S is an exogenous variable to account for supply side effects on schooling, with the corresponding coefficient β only included in the enrollments equation. The error term ε_t accounts for measurement error and it is assumed to be a Gaussian white noise process with mean 0 and variance σ_ε^2. We note that our final regression also includes a dummy variable D to account for permanent level jumps observed in both enrollments and GDP series after the Great Financial Crisis (GFC). This is meant to capture one-time-off persistent effects of the GFC in the U.K. economy. It takes value 0 from 1995Q1 to 2007Q4 and 1 thereafter.

The trend factor τ_t is assumed to follow a random walk process with a stochastic slope factor g_t. Likewise, g_t is assumed to follow a random walk process, such that

$$\tau_t = \tau_{t-1} + g_{t-1} + \nu_t \qquad \nu_t \sim iid\mathcal{N}(0, \sigma_\nu^2) \tag{2}$$

$$g_t = g_{t-1} + \omega_t \qquad \omega_t \sim iid\mathcal{N}(0, \sigma_\omega^2), \tag{3}$$

where the error terms ν_t and ω_t are Gaussian white noise processes. In turn, the cycle is modeled as a stationary AR(2) process, such that

$$c_t = \phi_1 c_{t-1} + \phi_2 c_{t-2} + e_t \qquad e_t \sim iid\mathcal{N}(0, \sigma_e^2), \tag{4}$$

where ϕ_1 and ϕ_2 are AR parameters for which $-1 < \phi_1 + \phi_2 < 1$.

3.2 Bivariate UC time series model

Next, to allow for the identification of additional parameters, we model enrollments and GDP jointly in a bivariate UC time series model so that $y_t = [G_t \ E_t]'$, where G_t is real GDP and E_t is the enrollment rate. For the model specification we follow Clark (1989) and extend the univariate representation given in the previous section. We allow the enrollment cycle to be determined both by its own cycle and by the business cycle. This gives the following bivariate model:

$$G_t = \tau_t + c_t + \varepsilon_t \qquad \varepsilon_t \sim iid\mathcal{N}(0, \sigma_\varepsilon^2) \tag{5}$$

$$\tau_t = \tau_{t-1} + g_{t-1} + \nu_t \qquad \nu_t \sim iid\mathcal{N}(0, \sigma_\nu^2) \tag{6}$$

$$g_t = g_{t-1} + \omega_t \qquad \omega_t \sim iid\mathcal{N}(0, \sigma_\omega^2) \tag{7}$$

$$c_t = \phi_1 c_{t-1} + \phi_2 c_{t-2} + e_t \qquad e_t \sim iid\mathcal{N}(0, \sigma_e^2) \tag{8}$$

$$E_t = L_t + z_t + \beta X_t^S \tag{9}$$

$$L_t = L_{t-1} + l_{t-1} + \xi_t \qquad \xi_t \sim iid\mathcal{N}(0, \sigma_\xi^2) \tag{10}$$

$$l_t = l_{t-1} + \zeta_t \qquad \zeta_t \sim iid\mathcal{N}(0, \sigma_\zeta^2) \tag{11}$$

$$z_t = \alpha_0 z_{t-1} + \alpha_1 c_{t-1} + \alpha_2 c_{t-2} + \tilde{e}_t \qquad \tilde{e}_t \sim iid\mathcal{N}(0, \sigma_{\tilde{e}}^2), \tag{12}$$

where L_t is the trend component of enrollments, l_t is the stochastic slope component of the trend and z_t is the stationary cyclical component for enrollments. X_t^S corresponds to the education supply exogenous variable, which is equivalent to the one used in the univariate specification in the previous Sub-section 3.1. The bivariate specification also includes the GFC dummy, D, as described in the univariate specification.

3.3 Estimation method

To obtain estimates for the unobserved trend and cycle components τ_t, c_t, L_t, and z_t; the slope components g_t and l_t; and the parameters in both models β, ϕ_1, ϕ_2, α_0, α_1, α_2, σ_ε, σ_ν, σ_ω, σ_e, σ_ξ, σ_ζ and $\sigma_{\tilde{e}}$ (where

t=1, ..., T) we first put the models described by eqs.(1)-(4) and eqs.(5)-(12) in state space form. In particular, we estimate a Gaussian linear state space system. See Appendix B for full descriptions of the state space representations of both models. The parameters in the system are estimated via maximum likelihood. The estimates of the unobserved states are obtained with the Kalman smoother, which in contrast with the filter, provides optimal states with respect to all the available data in our sample. We refer to chapters 2 and 3 of Kim and Nelson (1999) for details on Kalman filtering techniques and maximum likelihood estimation of model coefficients.

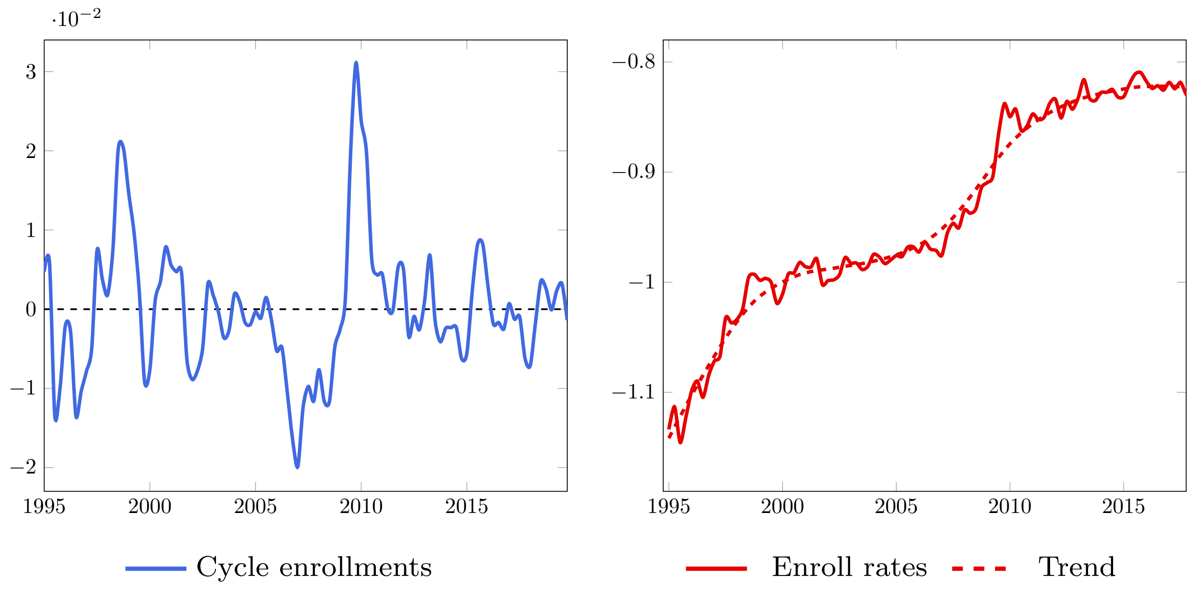
4 Results

This section presents the empirical results of both univariate and bivariate models estimated using data on enrollments and real GDP for the U.K. from 1995Q1 to 2019Q4. We discuss the implications of these results on our understanding of the schooling cycle and in relation with the business cycle. Results correspond to the empirical frameworks described in Section 3. We also discuss potential explanations for what is behind our findings, particularly whether there is a role for the two channels, *ability-to-pay* for FE and *opportunity-cost* of spending time in education, through which the business cycle affects schooling decisions over time. We construct factors that capture each of the channels and analyse how they relate to cyclicality of schooling and enrollment series.

4.1 Univariate cyclical evidence

Our first result provides evidence of a persistent and significant cycle in schooling participation. This is shown in Figure 1 together with the estimated stochastic trend. These two components, trend and cycle, are obtained by estimating the univariate model given by eqs.(1)-(4) using enrollment rates, while controlling for supply side effects. The persistence of the cycle in enrollments is confirmed by the sum of the estimated AR coefficients, $\phi_1 + \phi_2$, for the transitory component, which equals 0.82. Furthermore, to assess the relevance of the cycle component in our model, we conduct a likelihood ratio test that compares our trend-cycle decomposition model with an alternative restricted model in which there is no cyclical component. This restricted model is obtained from our model by setting the AR(2) coefficients ϕ_1 and ϕ_2 equal to zero. The test result strongly rejects the null hypothesis of no cycles supporting the presence of a stationary cyclical component in the enrollment rates. Finally, statistical tests are conducted to determine the adequacy of the specification and the dependency structure of the series. A Ljung-Box test for autocorrelation at 4 and 12 lags is conducted on the estimated one-step-ahead standardized prediction errors of each equation. These are reported in Table A-2, which shows that the null hypothesis of no autocorrelation is never rejected at the 5% level of significance. This supports our modeling choices, particularly for the stationary cyclical component as an AR(2) process. Furthermore, we test for heteroskedasticity conducting the same Ljung-Box test on the squared prediction errors. The null is never rejected so that there is no evidence of heteroskedasticity. The estimated variances σ_i^2 for $i = \nu, e, \omega$ for the system are in general of small magnitude and in most cases significant. Therefore, we conclude that our chosen model specification is appropriate to capture the dynamics present in the data.

Figure 1: Cycle and trend of enrollment rates for 16–24-year-olds

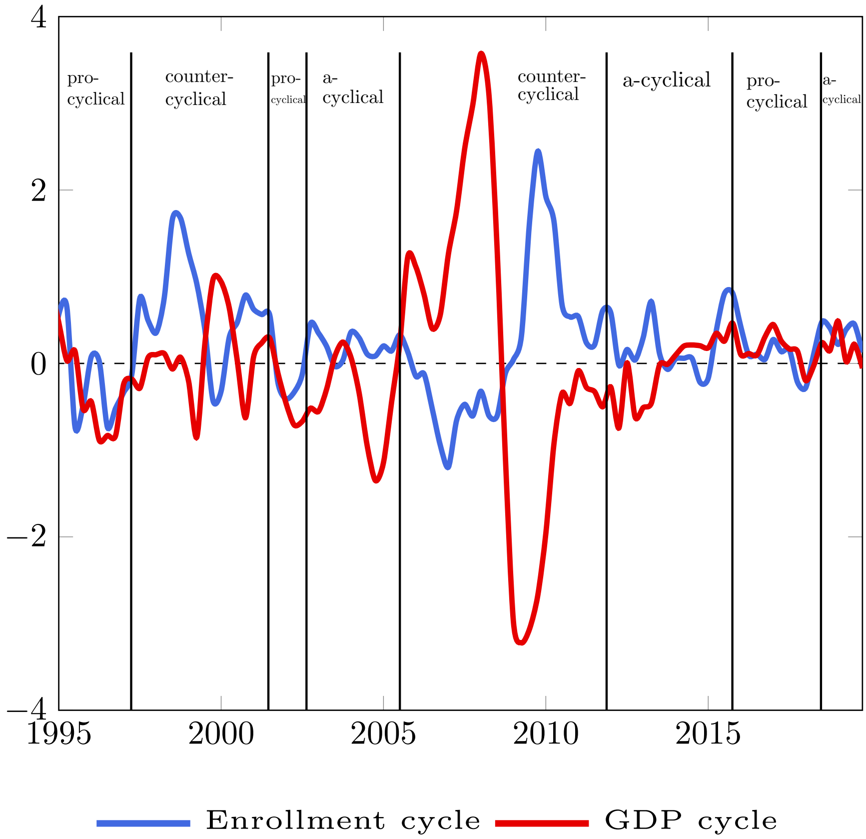


Next, we compare the schooling cycle with the estimated business cycle obtained from real GDP data. We simply plot the two series together as shown in Figure 2. We first note that our business cycle estimate does a good job of capturing changes in aggregate economic conditions in the U.K. over our sample period. This can be seen in Figure A-4, were we show that the business cycle is able to accurately track all recessionary periods in the U.K., as identified by the OECD Composite Leading Indicator represented by grey shaded areas in the chart.[5] We take this as support for the adequacy of our cyclical economic measure.

[5]The OECD CLI is a composite indicator of activity whose components are time series, which exhibit leading relationship with the reference GDP series at turning points. Country CLIs are compiled by combining de-trended smoothed and normalized components. The component series for each country are selected based on various criteria such as economic significance, cyclical behavior, data quality, timeliness, and availability.

From visual inspection of Figure 2, it stands out that the direction and size of the relationship between the cycles cannot be summarized in one average measure, since they are largely time-dependent. That is to say, the response of schooling participation to the business cycle can be counter-, pro- or a-cyclical depending on the time period under consideration. This time-dependency is also reflected in the fact that schooling responses are largely dependent on the size of the macroeconomic shock. This becomes evident during the GFC where the synchrony between both series seem to have largely increased.[6]

Figure 2: Schooling cycle for 16–24 year-olds and the business cycle



On closer inspection, we observe that counter-cyclicality in schooling participation takes place during two time periods: a 3.5-year period from mid-1997 to end of 2001 and a 6 year period from the start of 2006 to the end of 2011, which includes the GFC. For the rest of the sample, we find that schooling participation presents either a pro-cyclical pattern or simply a null response to changes in macroeconomic conditions, i.e., an a-cyclical pattern. Pro-cyclicality is observed at the start of our sample from mid-1995 to the end of 1997 and in two other periods from mid- 2001 to late 2002 and from late 2015 to mid-2018. Finally, the no-response/a-cyclical scenario occurs between early 2002 and mid 2005, from 2012 to 2015

[6]Synchrony can be broadly defined as the temporal coordination of relational behaviors into patterned configurations.

and at the end of our sample from late 2018 to late 2019.

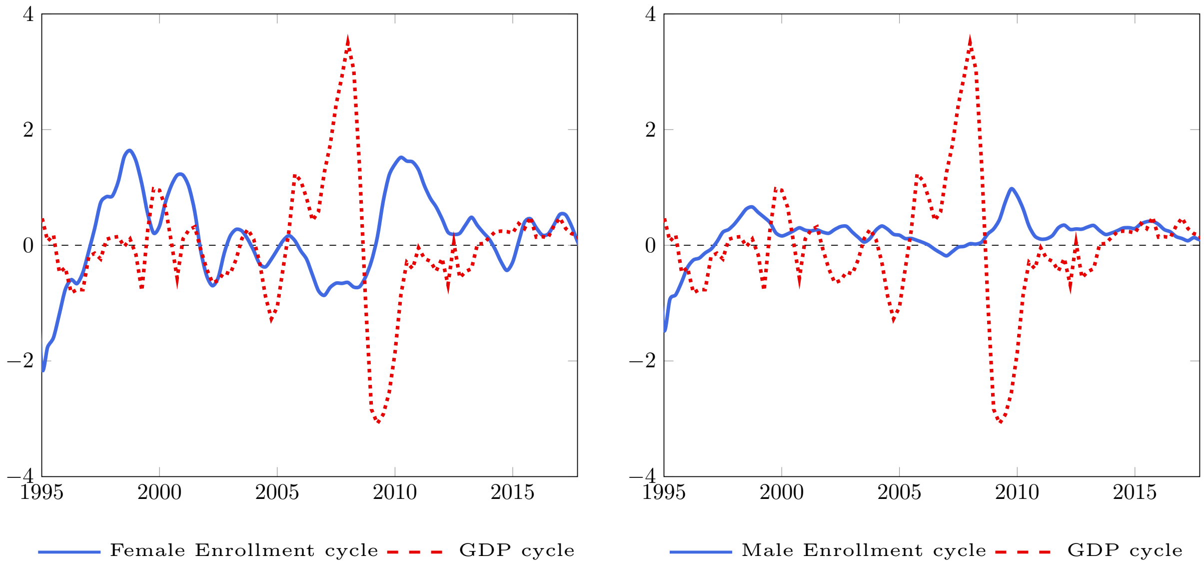
From the visual inspection we also note two regularities in the relationship between the series. First, time variation is also present in the degree of synchrony between the series—the speed of adjustment of schooling participation decisions to the business cycle—as shown in Figure 2. Second, we observe that the business cycle seems to lead the cyclical movements in enrollments. This is expected since people make their schooling decisions after observing the evolution of economic conditions. To examine these features more formally, say the synchrony between the cycles, and to support the visual results described above, we compute a range of cross-correlations and estimate a least squares regression allowing for breakpoints in the coefficients. We start with a Pearson-r correlation, the simplest measure of global synchrony. This coefficient is equal to -0.45, which supports existing literature's static average result of counter-cyclicality. Next, we compute this correlation for different time periods using a rolling window approach. The resulting series of Pearson-r correlations over time are shown in panel (a) of Figure A-5. The series clearly presents supporting evidence for time-variation in the correlations between both cycles. The chart shows that for the counter-cyclical periods shown in Figure 2, the correlations are close to -1 while for pro- and a-cyclical periods correlations are either above 0.5, or small enough to be non-informative. Next, we explore the degree by which the cycles move up or down together. For this, we compute the Instantaneous Phase Synchrony (IPS), which measures the period-to-period synchrony between the cycles, assessing if and when the two cycles move together or are out of tune. Panel (b) of Figure A-5 shows that the IPS is lowest for those periods when the cycles move counter-cyclically, while the highest point in the series, when cycles are most in tune, takes place at the beginning of the sample—identified in Figure 2 as pro-cyclical. Lastly, the IPS is inconclusive by the end of the sample, which supports our result of a-cyclicality. Finally, we explore directionality between the cycles, i.e., which cycle leads and which one follows, wherein the leader initiates a response that is repeated by the follower. To this end, we compute time-lagged cross-correlations (TLCC). In panel (c) of Figure A-5, we see that the business cycle leads the education cycle, and seems to do so for seven quarters on average.

We also estimate a breakpoint least squares regression of the cycles with the enrollment cycle as the left-hand side variable. The results of the regression are shown in Table A-3. We find that the results offer some support to our visual findings in Figure 2. The estimated coefficients are overall significant and present four breakpoints. The first coefficient reported corresponds to the 1995Q1-1998Q4 period, which fairly coincides with the first pro-cyclical period found in Figure 2. The next coefficient covers the 1999Q1-2009Q3 period and presents a negative sign. This time period does include pro-, a- and counter-cyclical findings with the latter being the The negative coefficients for the period between 1999Q1 to 2015Q1 coincide with the period of counter-cyclicality, while the largest variations in the series occur during the counter-cyclical phase. This larger variation could be influencing the resulting average coefficient for this particular period. Next, we find a stronger negative coefficient for the period from 2009Q4 to 2015Q1. This result captures the largest counter-cyclical period during the Great Financial Crisis (GFC), while the a-cyclicality found from 2012 to 2015 does not strong enough to affect the estimate. Lastly, we find a positive coefficient for the period from 2015Q2 until the end of the sample. This average coefficient seems to be picking up on the pro-cyclicality found for a fraction of this particular period.

4.2 Gender heterogeneity

In this section, we present the results of the schooling cycle and we analyze it in relation to the business cycle for males and females. Previous studies have found some systematic differences in the response of schooling participation to aggregate economic conditions across genders. Therefore, in Figure 3, we show the estimated schooling cycle by gender. We first note that the females' cycle presents higher volatility and is larger than the corresponding cycle for males. These features become evident during the GFC, when females reacted in a very timely and synchronized fashion to the economic downturn, while males present a much more muted effect. Additionally, females seem to present much more volatility over the whole sample period, which is in line with existing literature on the female elasticity of labor supply (Blundell et al., 2016). Furthermore, evidence has been found that males are more sensitive to structural factors such as increases in education fees (Bradley and Migali, 2019). This is an important result since increased schooling participation impacts female labor force participation, which has been the leading force behind aggregate participation rates for the last two decades. Increased female schooling participation during economic downturns increases participants' chances of successfully rejoining the labor market during recovery.

Figure 3: Enrollment cycle c_t by gender and the business cycle



4.3 Evidence from joint estimation of real GDP and enrollment rates

In this section we present and discuss the bivariate model given by eqs.(5)-(12), which allows us to jointly estimate the enrollment and GDP cycles. This specification extends the results obtained with the univariate model in three respects. First, the independently estimated univariate models depend on the assumption that trend and cycle are orthogonal to each other. While not fully abandoning this assumption, the bivariate setup allows for the disturbances of the cycle and the trend in enrollments (i.e., the shocks to the trend and the cycle) to be correlated while the system remains identified. Intuitively, this implies that a surge in demand for further schooling could generate a cyclical upturn as well as improving longer-run attachment to further education. Second, it permits for the business cycle to enter directly into the dynamic equation of the enrollments cycle, as in eq.(12). This way, the cycle in enrollments is influenced by both the business cycle and its own cyclical variation. In this setting, we can explore the relative contribution of these two components to explain temporary fluctuations in enrollments.

The maximum likelihood results are presented in Table A-2 and Figure A-3 presents the estimated cycles for enrollments and GDP. The values of the coefficients α_1 and α_2 that capture the effect of the first and second lag of the business cycle in the enrollment cycle dynamic equation are -0.344 and -0.060, respectively. The negative signs imply that on average an economic upturn will decrease the demand for further schooling, that is, it points to counter-cyclicality. Unsurprising, this confirms the standard result in the literature of average counter-cyclical effects. What is more novel, though, is that the first lag presents a much larger impact on the cyclicality of education than the second. This suggests that the speed of adjustment to changing economic conditions is rather contemporaneous. This is in line with our findings in Figure 2, where co-movement between the series appears to be well synchronized in most periods. Second, the covariance of cycle and trend of enrollments, $\sigma_{\tilde{e}_t,\xi_t}$, is equal to 0.010 and significant. This means that as far as the stationary component of enrollment is driven by its own innovations (the GDP cycle is also included in the equation), these innovations are not independent of the trend innovations in enrollments. Evidently, cycle-driven educational patterns do not cancel out when averaged over time, meaning they may represent more than pure timing and spill over to more structural impacts over time.

Using the bivariate setting, we are able to estimate the relative importance of the business cycle in the enrollments cycle determination. We do this by computing the unconditional variance decomposition of the enrollment rates equation given by eq.(9). This provides a simple statistic from the expression for the change in enrollments as follows:

$$\Delta E_t = \xi_t + \zeta_t + \alpha_0 \Delta z_{t-1} + \alpha_1 \Delta c_{t-1} + \alpha_2 \Delta c_{t-2} + \beta \Delta X_t^S + \Delta \tilde{e}_t,$$

which implies that the variance of the changes in enrollments, ΔE_t, can be expressed as

$$\sigma_{\Delta E}^2 = \sigma_\xi^2 + \sigma_\zeta^2 + \alpha_0^2 \theta_0 + \alpha_1^2 \rho_0 + \alpha_2^2 \rho_0 + \beta^2 V(\Delta X_t^S) + \sigma_{\tilde{e}}^2,$$

where θ_0 and ρ_0 are the unconditional variances of the first difference of the cycle process of enrollment and output, respectively.[7] We then construct the corresponding rates to calculate the fraction of $\sigma_{\Delta E}^2$ due to the business cycle, $\frac{\alpha_1^2 \rho_0 + \alpha_2^2 \rho_0}{\sigma_{\Delta E}^2}$, and to the enrollments own cycle, $\frac{\alpha_0^2 \theta_0 +}{\sigma_{\Delta E}^2}$. The higher this ratio, the higher the importance of the corresponding cycle to explain the movements in schooling participation. Interestingly, we find that around 20% of total variance is explained by schooling's own cycle, while 44% is explained by the business cycle. This shows a particularly large influence by the business cycle, but likely not as large as expected. At the same time, it shows a very persistent effect of schooling's own cyclical fluctuations over time. We should note, however, that this is an average measure that could be subjected to fluctuations over time.

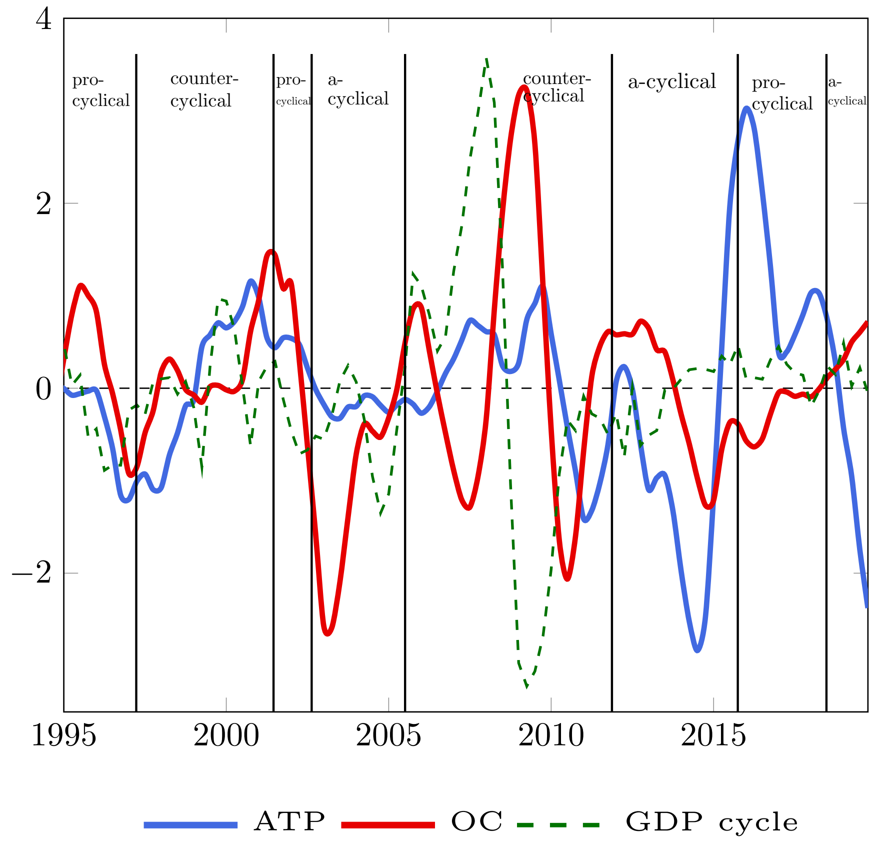
[7]By taking the first differences we drop the dummy variable in eq.(9).

4.4 What drives cyclicality over time?

Theory shows that the business cycle affects schooling participation through at least two channels that vary considerably along the business cycle. These channels are the *ability-to-pay* for schooling and the *opportunity-cost* of spending more time studying rather than at work. In this Section, we explore the importance of these channels to explain the time-variation in enrollment cyclicality found in Figure 2. To this end, we construct factors representing each channel by way of estimating two separate dynamic factor models using different groups of variables relevant to each channel. This way, we obtain an *ability-to-pay* factor and an *opportunity-cost* factor. These are shown in Figure A-2. Details of the dynamic factor model estimated to construct the factors are presented in detail in Appendix C. Lastly, in order to focus on the cyclical fluctuations that constitute the focus of our analysis, we extract the trend component to both factors using our univariate model described in eqs.(1)-(4). To construct the *ability-to-pay* factor, we use seven series relevant to the funding capacity of individuals: household net wealth, consumer credit lending, part-time jobs, disposable income, tuition fees, student loans and grants. For the *opportunity-cost* factor, we use instead five variables: real interest rate, real wage, unemployment rate for 25-69-year-olds, inflation rate, and expected long-term interest rates. A full description of each variable and their sources is presented in Table A-3.

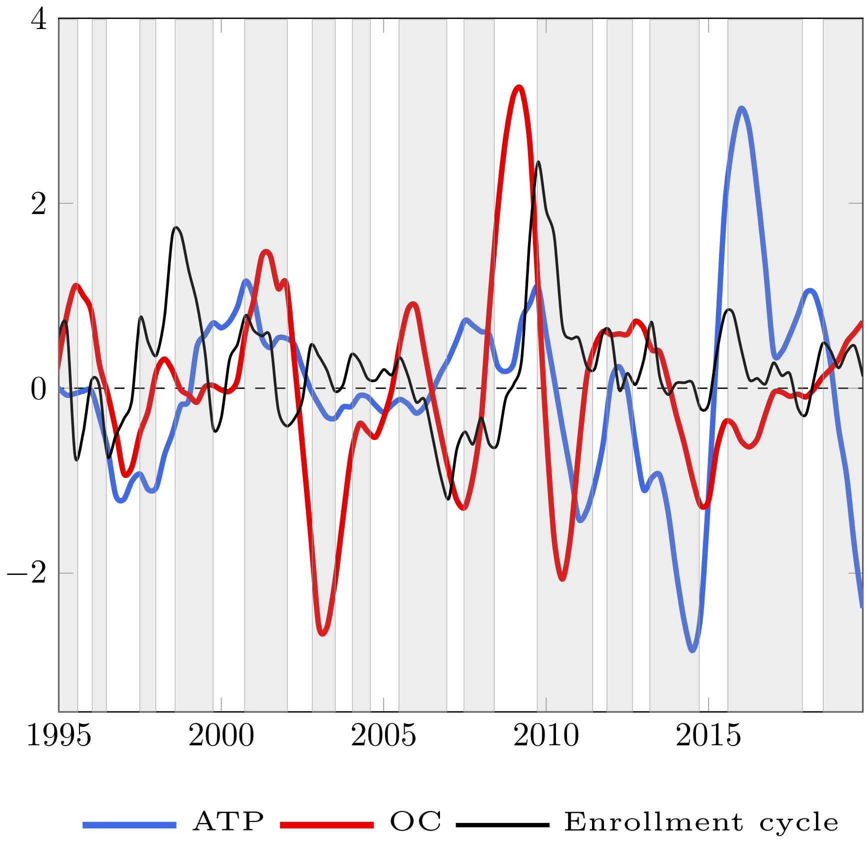
We first plot the estimated de-trended factors together with the business cycle in Figure 4. We find two different patterns in the relationship between the factors and the business cycle that shed some light on the forces behind the cyclicality found in Figure 2. For the pro-cyclical periods—1995Q1-1997Q4, 2001Q3-2002Q4 and 2015Q4-2018Q4—we find that overall both factors move in line with the business cycle. This yields several implications. A pro-cyclical *opportunity-cost* channel implies that for upward (downward) movements in the business cycle, the *opportunity-cost* is also increasing (decreasing) pointing to less (more) schooling. At the same time, a pro-cyclical *ability-to-pay* channel implies increasing (decreasing) ability to pay for extra schooling when the business cycle moves up (down) this points to more (less) schooling. These opposing forces yield a pro-cyclical schooling participation coming from the more negative *ability-to-pay* channel that seems to cancel out *opportunity-cost* considerations. On the other hand, for counter-cyclical periods, while the *opportunity-cost* factor still moves in line with the business cycle, the *ability-to-pay* factor moves in the opposite direction. The pro-cyclical *opportunity-cost* bears the same implications as before, while a counter-cyclical *ability-to-pay* implies that for an upward (downwards) movements in the business cycle the ability to pay contracts (augment) implying less (more) schooling. Here, both channels point to the direction of schooling participation cyclicality. Therefore, the ability to pay supports opportunity cost considerations in yielding a counter-cyclical pattern in schooling participation. Finally, in the a-cyclical periods, the patterns are, unsurprisingly, somewhat undefined.

Figure 4: Business cycle channels



Next, in Figure 5 we plot the factors together with the enrollment cycle. We find that each channel's response to fluctuations in economic conditions and the relative difference of the responses will ultimately determine the observed outcome in enrollments. When factors move together we can observe one of two situations: both channels could increase in which case higher *opportunity-cost* and *ability-to-pay* point to less and more schooling, respectively; second, both channels could decrease for which case lower *opportunity-cost* and *ability-to-pay* channels yield more and less schooling, respectively. Given that factors push in opposite directions regarding schooling outcome, the size of the distance between them can prove decisive. Alternatively, factors could move in opposite directions: we could have *opportunity-cost* increasing (decreasing) and *ability-to-pay* decreasing (increasing), pointing to less (more) schooling. Taken together, these four different scenarios are able to track the developments in enrollment over time quite closely. In Figure 5 and Table 1 we present a period-by-period analysis of the movements in the factors and how they are able to match the observed enrollment outcome. Table 1 shows that in 25 out of 31 identified sub periods, the implications for the schooling outcome given by the movements in the factors did match reality.

Figure 5: Business cycle channels and enrollments



Notes: Shaded areas correspond to episodes in which enrollments are decreasing. Correspondingly, white rows mark those periods with upward movements in enrollments.

Table 1: Business cycle channels' tracking of the enrollment cycle

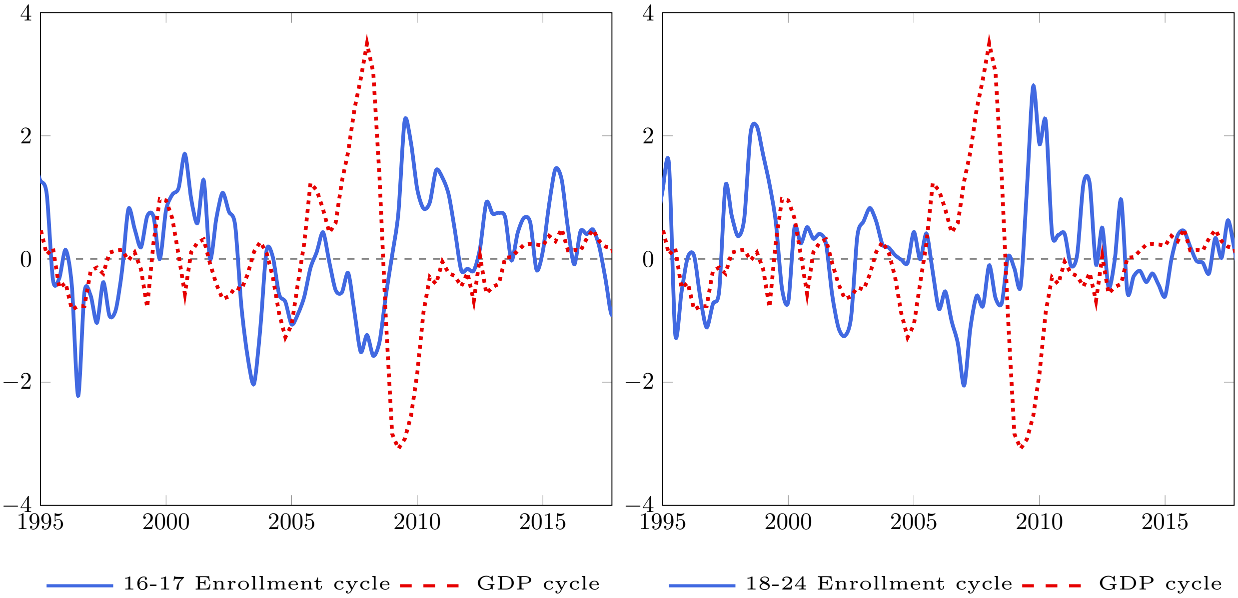
Period	Cyclicality	Channels	Schooling outcome
95Q1-95Q3	Pro-cyclical	↑ OC/ATP ↓	less
95Q3-96Q1	Pro-cyclical	↓ OC/ATP ↑	more
96Q1-97Q1	Pro-cyclical	↓ OC/ATP ↓ & larger ATP	less
97Q1-97Q3	Pro-cyclical	↑ OC/ATP ↑ & larger > negative ATP	more
97Q3-98Q1	Pro/Counter-cyclical	↑ OC/ATP ↓	less
98Q1-99Q1	Counter-cyclical	↓ OC/ATP ↑	more
99Q1-99Q4	Counter-cyclical	↓ OC/ATP ↑	**more**
99Q4-00Q2	Counter-cyclical	↑ OC/ATP ↑ & ATP larger	more
00Q2-00Q4	Counter-cyclical	↑ OC/ATP ↑ & ATP larger	more
00Q4-02Q1	Counter/Pro-cyclical	↑ OC/ATP ↓	less
02Q1-02Q4	Pro/A-cyclical	↓ OC/ATP ↓ & ATP higher	**less**
02Q4-03Q3	Pro/A-cyclical	↓ OC/ATP ↓ & ATP higher	less
03Q3-04Q1	A/Counter-cyclical	↑ OC/ATP ↑ & ATP higher	more
04Q1-04Q4	A-cyclical	↓ OC/ATP ↓ & ATP higher	less
04Q4-05Q3	A/Counter-cyclical	↑ OC/ATP ↑ & OC higher	less
05Q3-06Q1	Counter-cyclical	↓ OC/ATP ↑	more
06Q1-07Q1	Counter-cyclical	↓ OC/ATP ↑	**more**
07Q1-07Q4	Counter-cyclical	↓ OC/ATP ↑	more
07Q4-08Q3	Counter-cyclical	↑ OC/ATP ↓	less
08Q3-09Q4	Counter-cyclical	↓ OC/ATP ↑	more
09Q4-11Q3	Counter-cyclical	↓ OC/ATP ↓ & ATP higher	less
11Q3-12Q1	Counter-cyclical	↑ OC/ATP ↑ & ATP higher	more
12Q1-12Q4	Counter/A-cyclical	↑ OC/ATP ↓	less
12Q4-13Q2	A-cyclical	↓ OC/ATP ↑	more
13Q2-14Q4	A-cyclical	↓ OC/ATP ↓ & ATP more negative	less
14Q4-15Q4	A-cyclical	↑ OC/ATP ↑ & ATP higher	more
15Q4-16Q4	Pro-cyclical	↑ OC/ATP ↓	less
16Q4-17Q3	Pro-cyclical	↓ OC/ATP ↑	**more**
17Q3-18Q1	Pro-cyclical	↓ OC/ATP ↑	**more**
18Q1-18Q3	Pro-cyclical	↑ OC/ATP ↓	**less**
18Q3-19Q4	Pro/A-cyclical	↑ OC/ATP ↓	less

Notes: Shaded rows correspond to those episodes in which enrollments are decreasing. Correspondingly, white rows mark those periods with upward movements in enrollments. White rows with bold fonts represent episodes in which the predicted movement in schooling by the business cycle channels do not coincide with what is observed in the enrollments cycle in Figure 5.

5 Robustness analysis with different age sub-groups

In this section, we investigate whether our results remain the same if we were to restrict our sample to be composed of only 18-24-year-old individuals. By stripping our enrollment data of the 16-17-year-old group we explore whether the 16-24-year-old sample could be mistakenly capturing the effects of 16-year-old individuals still possibly subject to compulsory education. To this end, we replicate our baseline estimations to obtain the schooling cycle for both age sub-groups. Figure 6 presents the resulting schooling cycles for each age group together with the estimated business cycle.

Figure 6: Enrollment cycles c_t for age sub-groups and the business cycle



The estimated schooling cycles for each age group are very similar. From careful visual inspection, only a small size difference could be found between the cycles, with the 16-17-year-old cycle being somewhat smaller. Therefore, (18–24)-year-old group's cycle presents larger peaks, showing that they react to the business cycle somewhat more intensively than that of the (16–17)year-old group. We may speculate that this potentially implies that post-college education, i.e., the pursuit of a bachelor degree, could be more correlated and synchronized with the economic cycle than upper-secondary education. On the other hand, teenagers' employment dynamics in the U.K. could influence this results with a larger attachment of teenagers to continuing education which has been increasing over time. In the U.K., unemployment for teenagers since the structurally much higher than for young adults since the '90s and has not experienced the same recovery after the '90s recession as other groups. Taken together, this makes outside opportunities less tempting for teenagers to leave school. On the other hand, higher attachment to education has translated into decreasing labor force participation rates among teenagers fostered by growing parental emphasis on the rewards of education. Some support for this is found in the downward trend in the share of being not in education, employment, or training (NEET) among teenagers, while young adults present no such trend (Petrongolo and Van Reenen, 2011).

Overall, despite potential explanations for the size difference encountered between teenagers' and young adults' cycles, this could be expected to have only a negligible impact on our baseline results for the 16-24-year-old sample.

6 Conclusions

Human capital models state that schooling participation is a particular type of investment that can be addressed in a general framework of time and resource allocation decisions taken by utility-maximizing individuals (Becker, 1964; Ben-Porath, 1967). Individuals decide whether to work or to study and how much time to allocate to one or the other. This decision has been shown to be largely influenced by the state of the macro economy, i.e., the business cycle. Existing literature's well-rooted consensus is that we should expect a countercyclical behavior in higher education enrollments for developed economies (see Sakellaris and Spilimbergo, 2000; Dellas and Sakellaris, 2003; Johnson, 2013; Reiling and Strom, 2015; Boffy-Ramirez, 2017; Alessandrini, 2018). This consensus is based on the estimation of static average effects of standard regressions that do not account for time-variation. This could pose an important limitation to our understanding of the cyclicality of schooling participation, since it restricts the analysis to a unique static coefficient. This limitation is due, in fact, to the lack of a direct estimate of the cycle present in schooling participation decisions, which we denominate the schooling cycle. Such a measure has never been estimated, at least not in a structural way. As such, the cyclicality of schooling has never been fully characterized, nor has its relationship with the business cycle been analyzed in a time-varying fashion.

This paper therefore develops a novel empirical approach that relies on the Kalman smoother to estimate the cycle in schooling participation decisions. This cycle is first analyzed in isolation to provide an in-depth analysis of the cyclical properties of schooling. Then, we conduct a joint analysis with the estimated business cycle. In this way, we explore the whole spectrum of co-movement between schooling decisions and the business cycle, providing further insights on the direction, timing, and size of the effect. To this end, we estimate univariate and bivariate unobserved components time series models for higher education enrollment rates for the U.K. over the period from 1995Q1 to 2019Q4. Our estimations identify the presence of a persistent stationary cycle in enrollments. Upon comparison with the business cycle, we find that the cyclicality of schooling participation is indeed time-dependent with the direction, timing and size of the response varying across different time periods. In particular, we find counter-cyclicality for some periods, while for others we find pro-cyclical and even a-cyclical behavior. Furthermore, our results suggest that the synchrony (defined as the temporal coordination of relational behaviors) between the schooling and business cycles is subject to changes over time. When looking at enrollment by gender, we find substantial differences between the male and female cycles, with the latter being largely more responsive to the business cycle. We also find evidence that the business cycle is able to explain 44% of the total variation in enrollments, while 20% can be attributed to schooling's own cyclical variations. Finally, we explore the role played by the two business cycle channels affecting schooling participation cyclicality: *ability-to-pay* and *opportunity-cost*. We find that closer inspection of the relative size and direction of the movements in the factors for different time periods yield implications that support our main findings time-varying cyclicality in enrollment.

We note that our findings have implications relevant to policy. Pissarides (2010) postulates that regular education can be an effective counter-cyclical policy tool. During recessions, policies that facilitate regular education can prevent skills depreciation among the working population due to long spells of unemployment. For instance, hysteresis might occur after a recession because workers lose human capital whilst unemployed and unskilled workers are costly to retrain (Acharya et al., 2021). Timely policy interventions using regular education as a counter-cyclical tool (when agents fail to internalize the benefits of pursuing extra education during a recession) can help prevent persistent or permanent unemployment in the aftermath of a crisis. To achieve this, a time-varying measure of schooling responses to the business cycle is needed. This allows timely assessment of the direction, size, and timing, of schooling participation responses to determine when an intervention might be deemed necessary. Relying on average static effects that assume automatic counter-cyclical responses of individuals for all recessions could prove misleading.

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Appendix A. Supplementary Tables and Figures

Table A-2: Maximum-likelihood results of estimation of models given by eqs.(1)-(4) and eqs.(5)-(12)

	Univariate model$^{(a)}$						Bivariate model$^{(a)}$	
	Enrol 16–24	Enrol 16–24 Fem	Enrol 16–24 Male	Enrol 16–17	Enrol 18–24	GDP	Enrol 16–24	GDP
ϕ_1	0.841	1.333	1.285	0.847	0.742	1.374		1.386
	(0.063)	(0.151)	(0.643)	(0.068)	(0.358)	(0.005)		(0.098)
ϕ_2	-0.019	-0.436	-0.412	-0.007	0.019	-0.454		-0.481
	(0.005)	(0.086)	(0.926)	(0.009)	(0.005)	(0.006)		(0.166)
β	-0.012	0.002	-0.023	0.003	-0.024		-0.017	
	(0.011)	(0.013)	(0.012)	(0.010)	(0.016)		(0.040)	
σ_ε	4E-05	9E-05	7E-06	2E-05	3E-06	1E-09		7E-06
	(2E-05)	(2E-05)	(9E-05)	(2E-05)	(4E-05)	(1E-06)		(1E-05)
σ_ν	5E-09	4E-09	7E-09	5E-09	8E-06	3E-06		1E-03
	(9E-08)	(9E-08)	(7E-06)	(1E-06)	(6E-05)	(3E-06)		(3E-03)
σ_ω	1E-06	7E-07	3E-09	5E-07	2E-06	2E-06		0.011
	(1E-06)	(1E-06)	(1E-06)	(1E-06)	(3E-06)	(2E-06)		(0.003)
σ_e	7E-05	3E-05	7E-06	8E-05	3E-04	1E-05		0.040
	(4E-05)	(2E-05)	(3E-05)	(3E-05)	(2E-04)	(4E-06)		(0.004)
α_0							0.397	
							(0.104)	
α_1							-0.344	
							(0.313)	
α_2							-0.060	
							(0.093)	
σ_ξ							0.002	
							(0.005)	
σ_ζ							0.025	
							(0.011)	
$\sigma_{\tilde{e}}$							0.032	
							(0.004)	
$\sigma_{\tilde{e}_t,\xi_t}$							0.010	
							(3E-04)	
	Test for Autocorrelation$^{(b),(c)}$							
lag 4	1.59	3.25	1.22	3.60	0.33	8.86	10.36	25.94
	[0.620]	[0.484]	[0.126]	[0.537]	[0.012]	[0.935]	[0.965]	[0.999]
lag 12	12.85	17.63	7.15	17.72	12.49	18.35	19.47	26.27
	[0.189]	[0.872]	[0.153]	[0.876]	[0.594]	[0.895]	[0.922]	[0.990]
	Test for Heteroskedasticity$^{(b),(d)}$							
lag 4	12.38	5.21	3.89	4.54	16.26	18.71	22.62	4.48
	[0.985]	[0.734]	[0.578]	[0.662]	[0.997]	[0.999]	[0.999]	[0.655]
lag 12	17.32	14.00	11.40	11.06	23.77	22.79	35.88	4.49
	[0.862]	[0.699]	[0.505]	[0.476]	[0.978]	[0.970]	[0.999]	[0.027]

Notes: The models include: trend, slope, cycle and exogenous controls as shown in eqs.(1)-(12). (a) Standard errors in parentheses. (b) p-values in square brackets. (c) Box-Ljung statistic with H_0: no autocorrelation in the one-step-ahead prediction errors. (d) Test for equal variances H_0: homoscedasticity in the one-step-ahead prediction errors.

Table A-3: Breakpoints regression for 16–24 years old enrollments cycle.

Dependent var:	$\mathbf{cycle_t^{enrol}}$	Coefficients
$cycle_t^{econ}$	1995Q1-1998Q4	1.636
		(0.263)
$cycle_t^{econ}$	1999Q1-2009Q3	-0.467
		(0.116)
$cycle_t^{econ}$	2009Q4-2015Q1	-1.702
		(0.202)
$cycle_t^{econ}$	2015Q2-2019Q4	0.787
		(0.552)

Notes: Least squares estimates with breakpoints of regression $\mathbf{cycle_t^{enrol}} = \beta \mathbf{cycle_t^{econ}} + \varepsilon_\mathbf{t}$. Bai-Perron tests sequentially determined breaks and HAC standard errors. Quarterly data over the period from 1995Q1 to 2019Q4. Standard errors are reported in brackets.

Table A-3: Description of *opportunity-cost* and *ability-to-pay* channels components

Variable	Description	Primary Source(s)
	Opportunity-cost	
Real IR	Quarterly real interest rate given by personal sector real rate. Seasonally adjusted and expressed in percentage points.	Oxford Economics
Real wage	Quarterly change of total real earnings per-employee for the whole U.K. economy minus inflation. Seasonally adjusted.	Oxford Economics
UN rate 25-69	Quarterly unemployment rate for the population between 25 and 69 years old. Seasonally adjusted and expressed in percentage points.	U.K. Office for National Statistics
Inflation	Quarterly growth rates of consumer price index, all items, not seasonally adjusted.	IMF
Exp(LT IR)	Expected long-term real interest rate constructed as the difference between the nominal yield on new home mortgages and the expected inflation rate calculated as the average of the inflation rates in the last 12 quarters, not seasonally adjusted.	IMF, Oxford Economics
	Ability-to-pay	
Wealth	Quarterly household sector net wealth. Seasonally adjusted and expressed in percentage points.	Oxford Economics
Credit	Quarterly changes in net lending in consumer credit. Seasonally adjusted.	Bank of England
Part-time jobs	Quarterly data on the number of part-time workers who are students or at school. Seasonally adjusted.	Labour Force Survey - U.K. Office for National Statistics
Disposable income	Quarterly data on households, real disposable income. Constant prices, seasonally adjusted.	U.K. Office for National Statistics
Tuition fees	Annual data on tuition fees for higher education institutions. Expressed in British pounds per year at 2006 prices.	Dearden et al. (2014)
Maintenance loans	Annual data on student loans repayable as a percentage of earnings when the graduate is in employment and earning over a certain threshold. Expressed in British pounds per year at 2006 prices.	Dearden et al. (2014)
Maintenance grants	Annual data on student grants that are a non-repayable form of support for higher education. Expressed in British pounds per year at 2006 prices.	Dearden et al. (2014)

Figure A-1: Government spending in education in the U.K. as a % of GDP

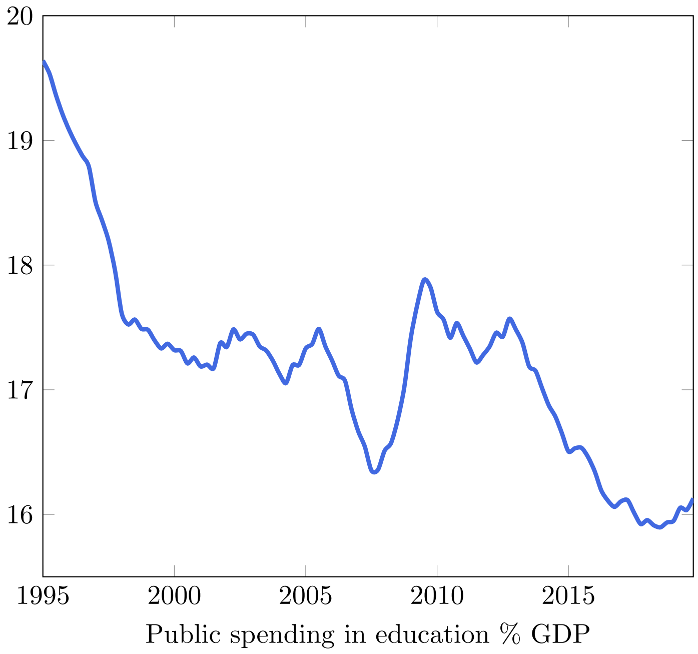
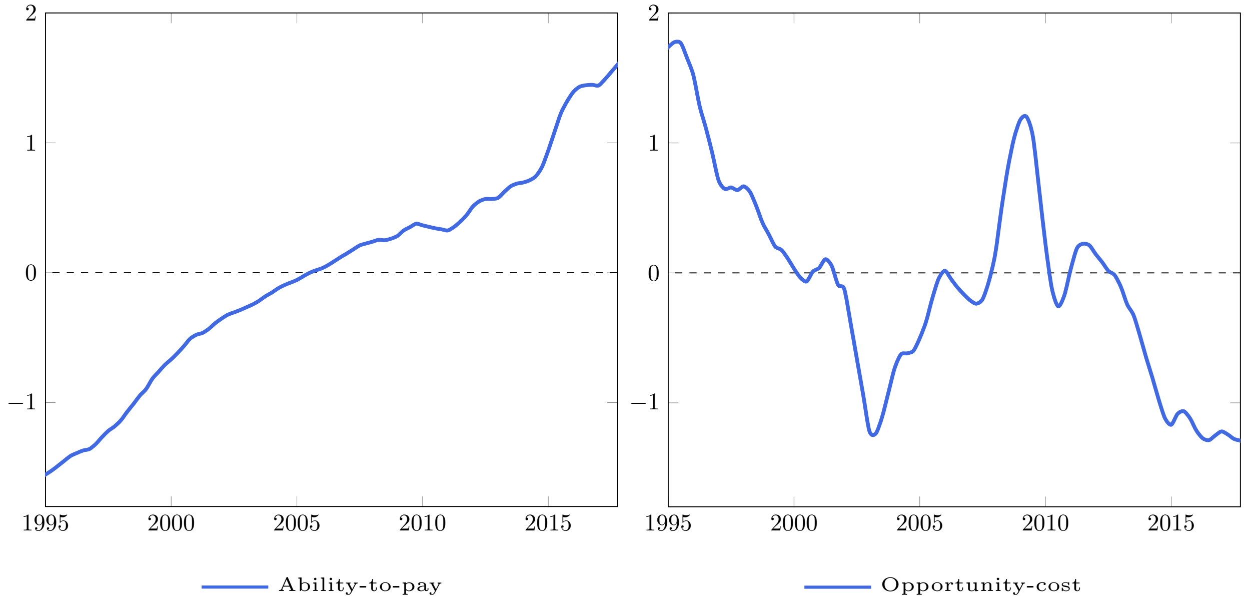
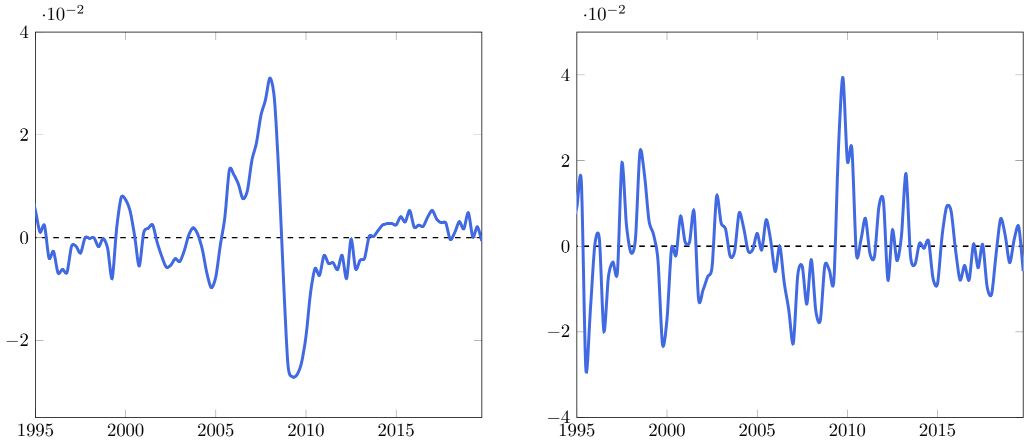


Figure A-2: *Ability-to-pay* and *opportunity-cost* factors



Notes: Lines correspond to the common factor in the dynamic factor model estimated with each group of variables described in Table A.3. They represent the business cycle channels affecting schooling participation decisions over the business cycle.

Figure A-3: Bivariate model cycles

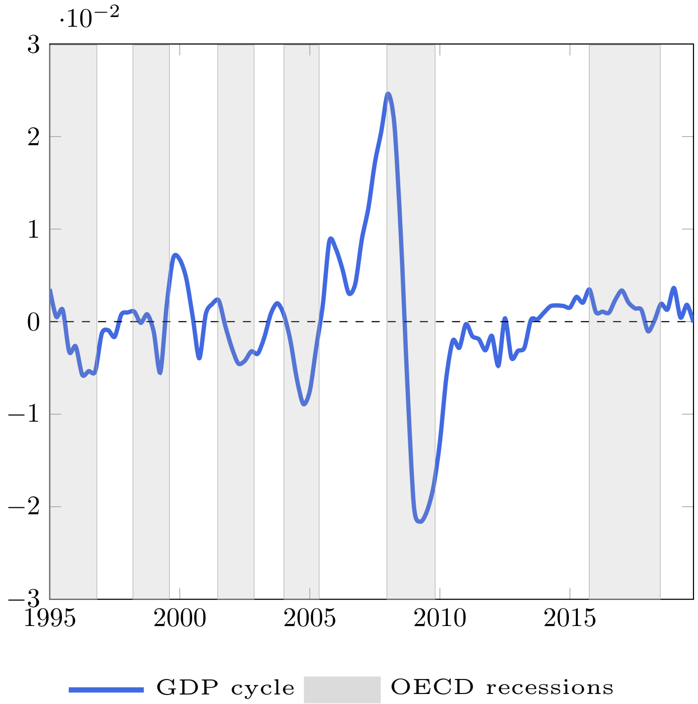


(a) Real GDP cycle

(b) Enrollment cycle

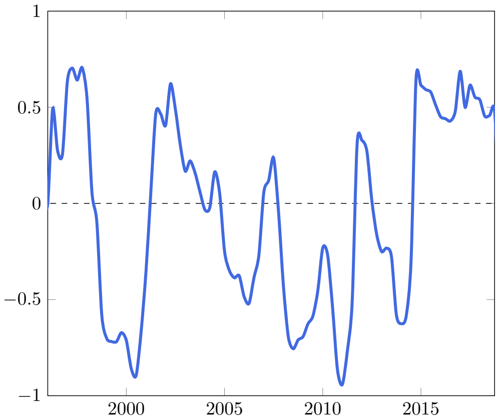
Notes: The cycles correspond to the stationary components (a) c_t and (b) z_t—estimated using the bivariate model given by eqs.(5)-(12).

Figure A-4: OECD recessions and estimated GDP cycle

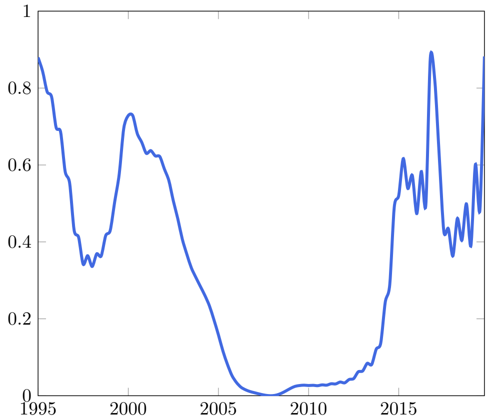


Notes: The OECD recessions are calculated with the Composite Leading Indicator (CLI) system. The OECD CLI system is based on the "growth cycle" approach, where business cycles and turning points are measured and identified in the deviation-from-trend series. GDP is used as the reference series for identification of turning points in the growth cycle. The components of the CLI are time series, which exhibit leading relationship with the reference series, GDP.

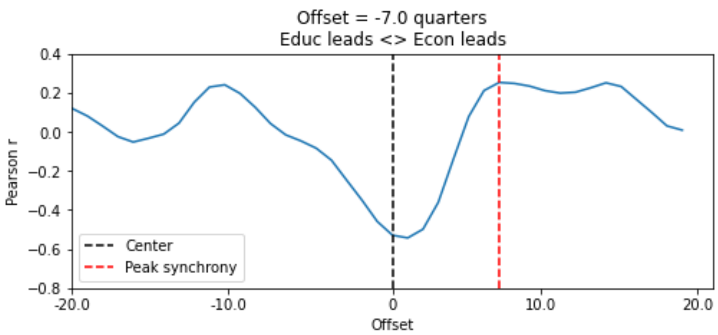
Figure A-5: Cross-correlations



(a) Rolling window Pearson-r



(b) Instantaneous Phase Synchrony



(c) Time-lagged cross correlations

Notes: (a) Window size is equal to 10 quarters. (b) IPS measures the phase similarities between the series at each time point. The phase refers to the angle of each series when it is resonating between 0 360 degrees or -π to π degrees. When the series line up in phase their angular difference is zero. The angles are calculated through the Hilbert transform. Phase coherence is quantified by subtracting the angular difference from 1. (c) TLCC is measured by incrementally shifting one series and repeatedly calculating the correlation between two series. If the peak correlation is not the the center (Offset=0), this indicates that one series leads the other. If peak happens at the left of the center, the education cycle leads, while if at the right, the business cycle is leading the education one. The peak happens 7 quarters to the right of the center.

Appendix B. State-space representation of the univariate and bivariate models

The state space system with state vector Ω_t is given by

$$Y_t = Z_t \Omega_t + \varepsilon_t \tag{B.1}$$

$$\Omega_t = T_t \Omega_{t-1} + \eta_t \tag{B.2}$$

with,

$$\begin{aligned} \varepsilon_{t|t-1} &\sim N(0, H) \\ \eta_{t|t-1} &\sim N(0, Q_t). \end{aligned}$$

The distribution of initial state vector $\Omega_1 \sim \mathcal{N}(a_1, P_1)$ is assumed to have a diffuse prior density initialized with $a_1 = 0$ and $P_1 \to \infty$.

For the univariate case, we have

$$Y_t = y_t$$

$$\Omega_t = [\tau_t \; c_t \; c_{t-1} \; g_t]'$$

$$\varepsilon_t = \varepsilon_t$$

$$\eta_t = [\nu_t \; e_t \; \omega_t]'$$

$$Z_t = [1\;1\;0\;0] \qquad H = \sigma_\varepsilon^2 \qquad T = \begin{bmatrix} 1 & 0 & 0 & 1 \\ 0 & \phi_1 & \phi_2 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix} \qquad Q_t = \begin{bmatrix} \sigma_\nu^2 & 0 & 0 & 0 \\ 0 & \sigma_e^2 & 0 & 0 \\ 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & \sigma_\omega^2 \end{bmatrix}$$

$$pars = \begin{bmatrix} \sigma_\varepsilon^2 & \sigma_\nu^2 & \sigma_\omega^2 & \sigma_e^2 & \phi_1 & \phi_2 & \beta & \delta \end{bmatrix}$$

For the bivariate case, we have

$$Y_t = [y_{1t}\ y_{2t}]'$$

$$\Omega_t = [\tau_t\ c_t\ c_{t-1}\ z_t\ L_t\ l_t\ g_t]'$$

$$\varepsilon_t = [\varepsilon_t\ 0]'$$

$$\eta_t = [\nu_t\ e_t\ 0\ \tilde{e}_t\ \xi_t\ \zeta_t\ \omega_t]'$$

$$Z = \begin{bmatrix} 1 & 1 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 1 & 1 & 0 & 0 \end{bmatrix} \qquad H = \begin{bmatrix} \sigma_\varepsilon^2 & 0 \\ 0 & 0 \end{bmatrix}$$

$$T = \begin{bmatrix} 1 & 0 & 0 & 0 & 0 & 0 & 1 \\ 0 & \phi_1 & \phi_2 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 & 0 & 0 \\ 0 & \alpha 1 & \alpha 2 & \alpha 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 1 & 1 & 0 \\ 0 & 0 & 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 1 \end{bmatrix} \qquad Q_t = \begin{bmatrix} \sigma_\nu^2 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & \sigma_e^2 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & \sigma_{\tilde{e}}^2 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & \sigma_\xi^2 & \sigma_{\tilde{e}_t,\xi_t} & 0 \\ 0 & 0 & 0 & 0 & 0 & \sigma_\zeta^2 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & \sigma_\omega^2 \end{bmatrix}$$

$$pars = \begin{bmatrix} \sigma_\varepsilon^2 & \sigma_\nu^2 & \sigma_\omega^2 & \sigma_e^2 & \phi_1 & \phi_2 & \sigma_\xi^2 & \sigma_\zeta^2 & \sigma_{\tilde{e}}^2 & \alpha_0 & \alpha_1 & \alpha_2 & \sigma_{\tilde{e}_t,\xi_t} & \beta & \delta_E & \delta_G \end{bmatrix}$$

Appendix C. Dynamic factor model to estimate the ***ability-to-pay*** and ***opportunity-cost*** factors

We estimate a dynamic factor model for each group of observable variables x_{it} (i = 1, 2,...,N) representing the *ability-to-pay* and *opportunity-cost* channels. The list of variables included in each group is described in full in Table A-3. The model is given by:

$$X_t = \lambda(L)F_t + \epsilon_t, \qquad (t = 1, 2, ..., T), \tag{C.1}$$

$$F_t = \nu(L)F_{t-1} + \eta_t, \tag{C.2}$$

where X_t is the vector with the N series so that X_t and ϵ_t—the idiosyncratic component—are Nx1. The F_t is the q common dynamic factor driven by a small number of factors that are common to all variables in each group so that F_t and η_t are qx1, L is the lag operator and the lag polynomial matrices $\lambda(L)$ and $\nu(L)$ are Nxq and qxq, respectively. The i^{th} lag polynomial $\lambda_i(L)$ is the dynamic factor loading for the i^{th} series, x_{it} so that $\lambda_i(L)F_t$ is the common component of the i^{th} series. All processes in eqs.(C.1)-(C.2) are assumed to be stationary. The idiosyncratic disturbances are assumed to be uncorrelated with the factor innovations at all leads and lags, that is, $E(e_t\eta'_{t-k}) = 0$ for all k. The idiosyncratic disturbances are also assumed to be mutually uncorrelated at all leads and lags, that is, $E(e_{it}e_{js}) = 0$ for all S if $i \neq j$. The only observable part in eq.(C.1) is the vector of variables included in x_{it}. The right-hand side is unobservable.

Estimation of dynamic factor models concern foremost the common component and thus, the idiosyncratic component is treated as residual. The common component given by eqs.(C.1)-(C.2) is consistently estimated in the frequency domain by spectral analysis. More specifically, the methods used concern consistent estimation by numerical quasi-maximum likelihood estimation based on the iterative Kalman filter application. We treat the number of common factors as known and we set them to be equal to one. The number of lags in the loading matrices are set at one, such that $L = 1$. For the specifics of the estimation method of the model, we refer to, among others, Bai and Ng (2008), Stock and Watson (2011), and Martin and Spånberg. (2017).