Intertemporal consistency and performance in project realization outcomes

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Abstract

In this thesis, I present a conceptual framework for studying project realization outcomes, grounded in the economic concepts of intertemporal consistency and performance. The framework distinguishes three behavioral margins of project pursuit: whether individuals translate project intentions into action, whether they sustain project-consistent behavior over time, and how well they execute project-consistent actions. I apply the framework in two empirical settings: entrepreneurship and education. For entrepreneurship, I use multi-wave Global Entrepreneurship Monitor (GEM) data merged with country-level institutional and macroeconomic indicators to estimate a multilevel model of early-stage entrepreneurial activity. For education, I use the Open University Learning Analytics Dataset (OULAD) to study course completion and withdrawal over time. Across both settings, the proxies for intertemporal consistency and performance are positively associated with project realization; in the education hazard model, they are also associated with lower withdrawal risk. Evidence that the consistency and performance dimensions reinforce each other is strongest in the course-completion model and more mixed in the entrepreneurship and withdrawal analyses. The evidence is descriptive, but it indicates that the framework is empirically implementable and informative across two distinct project settings.

Keywords: projects, entrepreneurship, intertemporal choice, education, performance, project realization outcomes.

Abstrakt

V této diplomová práce představuji koncepční rámec pro studium míry realizace projektů vycházející z ekonomických konceptů intertemporální konzistence a výkonu. Rámec rozlišuje mezi třemi ukazateli chování při realizaci projektů: zda jednotlivci převádějí záměry do činů, zda si v průběhu času udržují chování konzistentní s projektem a jak dobře provádějí akce konzistentní s projektem. Tento rámec uplatňuji ve dvou empirických konceptech: v oblasti podnikání a v oblasti vzdělávání. Pokud jde o oblast podnikání, využívám data z více vln průzkumu Global Entrepreneurship Monitor (GEM) v kombinaci s institucionálními a makroekonomickými ukazateli na úrovni jednotlivých zemí k odhadu víceúrovňového modelu rané fáze podnikatelské aktivity. Pro oblast vzdělávání využívám datový soubor Open University Learning Analytics Dataset (OULAD), abych zjistil, do jaké míry studenti v průběhu času studium dokončují, nebo jej předčasně opouštějí. Výsledky v obou případech poskytují popisné důkazy o tom, že je uskutečnění projektu svázáno s dlouhodobým úsilím při jeho realizaci a výkonem. V kontextu podnikání vykazují ukazatele intertemporální konzistence a výkonu pozitivní souvislost s ranou fází podnikatelské aktivity. V oblasti vzdělávání vykazují oba ukazatele a jejich interakce pozitivní souvislost s úspěšným absolvováním vzdělávání, zatímco analýza předčasného ukončení vzdělávání ukazuje, že oba tyto ukazatele snižují riziko předčasného ukončení vzdělávání. Získané poznatky mají popisný charakter, naznačují ale, že je tento rámec ve dvou odlišných projektových kontextech empiricky aplikovatelný a přínosný.

Klíčová slova: projekty, podnikání, intertemporální volba, vzdělávání, výkon, míra realizace projektů

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Contents

Introduction

In this thesis, I present a simple framework for estimating project realization outcomes. A project realization outcome is when a project pursued by an agent is realized. For example, when an agent becomes an entrepreneur, or when a student graduates. The framework I propose is applied in two econometric settings: entrepreneurship and education. I focus on these two settings as an initial test of the framework, but the model I present is generalizable to any project that is individually or collectively pursued. The framework I present matters for two reasons. First, project realization is a meaningful component of aggregate economic outcomes; identifying and testing previously underexplored sources of variation can therefore complement the growing economics literature that leverages behavioral data to study projects in entrepreneurship, schooling, and related contexts (Hanushek et al,. 2021;Sunde et al,. 2021;Einav and Levin, 2014). Second, behavior is often under-measured. In the absence of rich behavioral data, I show how to proxy key theoretical concepts directly from available data, in a way that can complement existing empirical work on entrepreneurship, schooling and other project realization outcomes.

The aim of this thesis is to introduce the framework conceptually, and to test it on the two specified econometric settings. Hence, my empirical strategy is fully descriptive, focused on how well the framework explains variation in project realization outcomes. I interpret the correlational results documented as an initial diagnostic test of the framework, rather as evidence of causal relationships.

The approach builds on the economic concepts of intertemporal consistency and performance, and I have coined it *project pursuit* (PP). The first captures whether individuals translate forward-looking intentions into project-consistent actions and sustain those actions over time. This connects to models of procrastination, present bias, and dynamic inconsistency, where agents may intend to pursue a forward-looking activity but delay action when an alternative is more immediately attractive (Strotz, 1955–56; Akerlof, 1991; O’Donoghue and Rabin, 1999, 2001; Gul and Pesendorfer, 2001; Lipman, 2011). The second concept, performance, captures the quality or effectiveness with which project-consistent actions are executed. This connects to economic models in which outcomes depend not only on whether an action is taken, but also on how well it is performed (Laffont and Martimort, 2001, Section 4.6, pp. 163–166).

There are numerous settings in which the PP approach yields a meaningful economic interpretation. Consider an agent aiming to become an entrepreneur who must allocate time between conducting market research and spending time with family. In the PP framework, market research represents an intertemporally consistent, forward-looking action, whereas time with family is an immediately rewarding alternative - an instance of procrastination in the sense of O'Donoghue (1999). Moreover, even conditional on choosing market research, the activity can be pursued with more or less effort, generating variation in performance (Laffont and Martimort, 2001, Section 4.6, pp. 163–166). The PP framework hence captures both (i) an agent's consistency in pursuing a project and (ii) the quality with which the activities are done. A parallel intuition applies in education. A PhD student must repeatedly devote time and effort to research and coursework over many months or years. Relative to peers, this student may be more or less consistent in sustaining effort over time and may also produce research of higher or lower quality. Both dimensions map naturally into the PP framework and help explain heterogeneity in realization outcomes.

Although the framework is designed to be general, its applicability in any given context is constrained by data availability. The key requirement is the availability of proxies for intertemporal consistency and performance. These proxies can be derived directly from observed variables or constructed from the data - for example as ratios, differences, or interactions of two or more measures. In the empirical applications below, I illustrate how to operationalize the PP approach in the two specified project pursuit settings.

The first application studies entrepreneurial project realization using data from the Global Entrepreneurship Monitor (GEM), merged with country-level institutional and macroeconomic indicators from the World Bank. The outcome is total early-stage entrepreneurial activity, measured at the individual level. Because GEM is a repeated cross-section and does not observe the same individuals over time, the entrepreneurship application focuses on how individuals translate the intention to become entrepreneurs into action. Hence, I construct a country-year proxy for intention-to-action conversion: the share of entrepreneurial intenders who report taking concrete steps toward starting a business. I interpret this measure as an empirical manifestation of intertemporal consistency, following theories of procrastination in which agents choose between delaying the start of a costly activity and taking immediate action (Akerlof, 1991; O'Donoghue and Rabin, 1999). Performance is proxied, more imperfectly, by perceived entrepreneurial skills. The model then tests whether these two dimensions are associated with early-stage entrepreneurial activity and whether their interaction is consistent with the complementarity prediction of the Project Pursuit framework.

As an additional specificity check, I adapt the cross-country entrepreneurship and investment framework of Djankov et al. (2010). This exercise compares whether the Project Pursuit proxy is associated with entrepreneurship-specific outcomes, especially business entry rates, rather than with broader economic outcomes such as investment, foreign direct investment, or business density. The purpose of this test is not to establish causality, but to examine whether the proposed proxy is more closely related to entrepreneurial entry than to general country-level economic dynamism.

The second application studies educational project realization using the Open University Learning Analytics Dataset (OULAD). This dataset links student demographics, registration and unregistration dates, assessment outcomes, and detailed Virtual Learning Environment activity. Unlike GEM, OULAD allows project pursuit to be observed over time. I construct measures of student consistency from repeated engagement with the online learning environment and measures of performance from assessment outcomes. I then estimate two models. The first is a mixed-effects logistic model of course success. The second is a discrete-time hazard model of course withdrawal. Together, these specifications test whether consistency and performance are associated with successful completion and whether they reduce the risk of abandoning the educational project.

The expected contribution of the thesis is twofold. The main contribution is conceptual: I propose Project Pursuit as a reduced-form framework for organizing behavioral variation in project realization outcomes. The second contribution is empirical: I show how the framework can be operationalized in two distinct settings using available data.

The thesis is organized as follows. Section 1 reviews related literature on behavior and project realization, with emphasis on intertemporal consistency, performance, entrepreneurship, and education. Section 2 introduces the Project Pursuit framework. Section 3 presents the empirical applications in entrepreneurship and education. Section 4 discusses the framework's advantages, limitations, and directions for future research. Section 5 presents conclusions of the thesis.

1 Literature review

This thesis relates to a broad literature that links behavior to project realization outcomes across domains such as entrepreneurship, schooling, and at the methodological level - at a more aggregate level - capital accumulation and economic development. In entrepreneurship, a central theme is that heterogeneity in *risk* and *time* preferences predicts entry into self-employment and entrepreneurial activity (Ekelund et al,. 2005). In education, related work shows that time preferences and time-inconsistent decision-making are associated with educational choices, study effort, and performance outcomes (Kemptner et al,. 2018). In macro and development contexts, patience (time preference) is frequently studied as a correlate of long-run development and the accumulation of physical and human capital.

The term *project pursuit (PP)* is not established in the literature. Instead, closely related constructs - patience/time preferences, risk attitudes, and cultural traits such as individualism - are typically studied as individual determinants of realized outcomes. A key gap, relative to the approach developed here, is that many studies introduce behavior using a single main measure and relate it to realization outcomes, rather than presenting a framework in which two distinct behavioral components interact. In contrast, my PP approach combines intertemporal consistency and performance into a unified, interpretable structure that can be mapped to both entrepreneurship, schooling and other project realization outcomes. Finally, much of the empirical evidence in this area is correlational, with a smaller subset of papers using designs aimed at stronger causal interpretation (de Blasio et al,. 2018).

The PP framework is grounded in two economic concepts. The first is intertemporal consistency: in dynamic choice problems, agents may display time-inconsistent plans, generating intention-action gaps and procrastination when costs are immediate and benefits delayed (Strotz, 1955; O'Donoghue and Rabin, 1999, 2001). A related formalization models "present bias" through quasi-hyperbolic discounting, which yields a behavioral wedge between short-run temptations and long-run objectives (Laibson, 1997), and temptation-based preferences provide an alternative representation of self-control problems. The second concept is performance: even conditional on choosing to pursue a project, realized outcomes depend on how intensely and effectively tasks are executed, a central theme in incentive and moral-hazard models (Holmström, 1979) and in multitask settings where effort allocation shapes measured performance (Holmström and Milgrom, 1991; Laffont and Martimort, 2001, Section 4.6, pp.

163–166). Empirically, these ideas motivate interpreting observed behaviors as reduced-form proxies for (i) consistency in sustaining forward-looking actions over time and (ii) the quality/intensity of execution conditional on pursuit, rather than estimating a fully structural model.

With these concepts in place, in the next lines I review empirical studies that relate behavioral proxies - often measured with a single index or survey item - to realized outcomes in entrepreneurship and schooling, and I highlight where a two-component perspective presumably adds structure.

Among the papers I review, Sunde et al. (2022, *ReStud*) is closest to offering an explicit *conceptual lens* for why a behavioral trait should map into realization outcomes. Using the Global Preference Survey (GPS), they document robust positive correlations between national patience and per-capita income, as well as with physical-capital accumulation, human-capital accumulation, and productivity - and show that these relationships also appear within countries (regions) and within regions (individuals). They then interpret these patterns through a multi-period (OLG) model in which patience affects savings and education decisions, providing structure for reading the correlations as consistent with an accumulation mechanism rather than a purely reduced-form association.

A second study presenting a framework is Hanushek et al,. (2022, *Economic Journal*), who connect national preference heterogeneity to educational outcomes by embedding patience into an education-production-function perspective. Empirically, they show that patience is positively associated with international student achievement, and - importantly for "two-dimensional" behavioral measurement - that the association becomes substantially clearer once patience and risk-taking are entered jointly, reflecting their interrelatedness. While their second preference component is *risk-taking*, the paper is directly informative for my thesis because it demonstrates how combining distinct behavioral dimensions can materially change the interpretation of behavior linked to realization outcomes.

A practical limitation in both studies concerns measurement of patience. In the GPS, the patience index is a weighted combination of (1) a self-assessed "willingness to wait" on an 11-point Likert scale and (2) an incentivized intertemporal choice between a smaller-sooner and larger-later payoff, with the qualitative self-assessment receiving about 71% weight and the choice item about 29% weight. This construction is attractive for cross-country comparability, but it implies that the measure's precision partly depends on respondents' ability to map an internal trait onto an ordinal scale - an issue that is useful to keep in mind when interpreting cross-country correlations.

In entrepreneurship, much of the evidence links *behavioral* proxies - often measured as survey-based beliefs and perceptions - to entrepreneurial entry and early-stage activity. Boudreaux, Nikolaev, and Klein (2019, *Journal of Business Venturing*) combine GEM individual data with the Economic Freedom of the World index for 45 countries (2002–2012) and estimate a multi-level model with country fixed effects. Their key behavioral measures entrepreneurial self-efficacy (perceived skills to start a business), opportunity alertness (perceived opportunities), and fear of failure - map naturally into the two channels emphasized in this thesis: self-efficacy and alertness are closest to the *execution* side (performance), while fear of failure captures an *avoidance* margin that can disrupt sustained pursuit even when opportunities exist. Empirically, self-efficacy and alertness strongly predict opportunity-motivated entrepreneurship, while fear of failure is deterrent. Importantly, these relationships are institution-dependent: higher economic freedom amplifies the positive predictive power of self-efficacy and alertness and attenuates the negative association of fear of failure.

Dutta and Sobel (2021, *European Journal of Political Economy*) corroborate the institutional moderation channel using GEM-based fear-of-failure measures and country-level policy/institution indicators. They argue - and document - that fear of failure depresses entrepreneurship less in environments with higher economic freedom, because broader opportunity sets lower the cost of failure by making it easier to pivot to subsequent opportunities; methodologically, they report estimates using System GMM and IV approaches. Related to the PP approach, these papers show (1) how behavioral proxies predict realization-relevant outcomes (entry or realization) and (2) how institutions reshape the behavioral outcome link, but they generally treat the behavioral inputs as separate predictors rather than as an interacting framework aimed specifically at project realization.

A complementary entrepreneurship strand focuses on biased beliefs, especially overconfidence, as a driver of project initiation and success. Koellinger, Minniti, and Schade (2007) use cross-country GEM data to show that subjective beliefs - most notably confidence in one's entrepreneurial skills - are strongly associated with new business creation, consistent with the idea that inflated success beliefs raise perceived returns and therefore increase entry under uncertainty. Evidence on this wedge appears in both field and lab contexts. Using a survey of French entrepreneurs, Landier (2003) documents systematically optimistic growth expectations relative to realized growth, illustrating how biased beliefs can distort project continuation and financing choices even after entry. In laboratory markets, Camerer and Lovallo (1999) show that overconfidence can cause excess entry into competitive environments, providing clean evidence that biased self-assessments translate into entry decisions that are privately chosen but ex post inefficient on average. A broader synthesis is offered by Kraft et al. (2022), who meta-analyze the entrepreneurship literature and distinguish types of overconfidence (overestimation, overplacement, overprecision) across phases of the entrepreneurial process. They conclude that overconfidence is generally associated with *more* entrepreneurial action-opportunity recognition, venture creation, and innovation - yet is linked to lower venture performance on average, highlighting the same trade-off: beliefs that encourage pursuit can also reduce realized success.

Relatedly, Andersen, Di Girolamo, Harrison, and Lau (2014) run field experiments in Denmark that elicit both risk preferences and individual discount rates for small-business entrepreneurs and a comparison sample from the general population. They find no meaningful difference in risk aversion under expected utility, but entrepreneurs display more optimistic probability weighting for favorable outcomes (i.e., they overweight the best outcome more than non-entrepreneurs). Further, related to PP, they also find lower discount rates among entrepreneurs - entrepreneurs are willing to wait longer for certain future rewards than the general population - while the estimated discounting is exponential (no evidence of quasi-hyperbolic "present-bias" in their specification). A complementary line focuses less on discount rates per se and more on self-control as a mechanism behind sustained project pursuit. Van Gelderen, Kautonen, and Fink (2015, *JBV*) study the entrepreneurial intention - action gap using longitudinal survey data (N = 161). They show that self-control strengthens the link between intentions and subsequent start-up actions: individuals with higher self-control are significantly more likely to translate intentions into action, in part because self-control suppresses action-related doubt, fear, and aversion that otherwise foster hesitation and procrastination. Taken together, these papers relate to the PP emphasis on consistency: entrepreneurs appear, on average, more future-oriented in incentivized time trade-offs, and - conditional on having entrepreneurial intentions - differences in volitional capacity/self-control help predict whether intentions become realized start-up behavior.

Moving beyond correlational evidence, Assmann and Ehrl (2018; published as Assmann & Ehrl 2021 in *Journal of Economic Behavior & Organization*) study the effect of national individualism on opportunity-driven entrepreneurship using cross-country data from the Global Entrepreneurship Index (GEI). They combine a fractional-probit framework with an instrumental-variables strategy that uses highly exogenous, historically rooted instruments based on genetic/biological distance measures (blood-distance and pathogen-prevalence proxies) to address reverse causality concerns. Their core result is that more individualistic countries exhibit higher opportunity-startup activity, and the association is robust to institutional controls (and related confounders such as education, religion, unemployment, and income). They also provide an interpretation through transmission channels: individualism is linked to more optimistic opportunity perception and higher innovation potential, which together explain a substantial share of the total relationship. In PP terms, this is useful because it highlights how culture can plausibly shift the propensity to pursue (via perceived opportunities/initiative).

Closely related, Motoki et al. (2022, *Journal of the Knowledge Economy*) exploit quasi-exogenous variation in colonial cultural heritage by using Portuguese vs. Spanish language as a proxy for inherited cultural context in GEM data (2011–2015) covering Iberian countries and their former colonies. They show that individuals in Portuguese-heritage contexts are more likely to perceive entrepreneurial opportunities, even though they also display higher risk intolerance on average. Importantly, they document that human capital both strengthens opportunity perception and reduces risk intolerance more strongly in Portuguese-heritage settings - suggesting that education/knowledge can mitigate behavioral barriers to entrepreneurial action.

Beyond entrepreneurship, the schooling literature repeatedly emphasizes present-biased behavior-procrastination and difficulty delaying gratification-as a barrier to educational project realization (e.g., completing assignments, sustaining study effort, and accumulating credits). A broad review in behavioral economics of education highlights that education investments involve salient up-front costs (studying, homework) with delayed and uncertain benefits, creating strong temptations to postpone effort. A particular study of present bias is provided by Franz (2019, AEA), who measures each student's delay as the gap between the day a student *plans* to start a homework assignment and the day they *actually* start. Regression results show that larger delays are negatively associated with (1) homework scores, and (2) grades in principles of micro- and macroeconomics, and (3) cumulative GPA. Importantly, the study also reports that students do not update their priors about their own behavior-they keep procrastinating despite evidence from their own past delays - consistent with persistent intention - action gaps.

A body of work in psychology and economics shows that effort-related traits rival cognitive ability in explaining educational outcomes. Self-discipline in adolescence has been found to predict GPA and even college attendance more robustly than IQ in some samples (e.g. Duckworth & Seligman, 2005). The related construct of grit (perseverance and passion for long-term goals) also has measurable impacts. Duckworth et al. (2007) introduced the grit scale and demonstrated that grit accounted for about 4% of the variance in success outcomes. Notably, grit was linked to higher educational attainment (years of education completed) in large adult samples, and to higher GPAs among high-performing students, even when controlling for IQ and Big Five conscientiousness. For example, grittier individuals were more likely to graduate from college or complete advanced degrees. While 4% of variance is modest, the results underscore that persistence and long-term passion contribute to academic success above and beyond raw talent. Other studies on adolescents' self-control similarly find that those with greater impulse control have better grades and are less likely to drop out.

A complementary body of work in psychology (and increasingly economics) argues that effort-related traits are central to educational project realization, often rivaling cognitive ability in explaining performance and attainment. In a longitudinal study of adolescents, Duckworth & Seligman (2005) show that self-discipline predicts a wide range of school outcomes - final grades, school attendance, and related behavior - and that it explains substantially more variance than IQ in their sample. In PP terms, self-discipline relates to intertemporal consistency because it captures resisting short-run temptations and sustaining planned study effort over time.

Overall, the empirical literature I reviewed typically links project realization outcomes to one primary behavioral measure at a time - for example patience, risk attitudes, self-efficacy, grit, or procrastination - while only a minor subset provides an explicit framework. I argue that this is a gap in the literature because project realization depends not only on whether agents remain intertemporally consistent with their initial plans (resisting postponement and sustaining engagement over time), but also on the performance they apply when executing each task along the way. In this thesis, my expected contribution is to make that structure explicit by separating these two margins - consistency and performance - and showing how their combination can help account for variation in realization outcomes across entrepreneurship, schooling, and other multi-period projects.

2 Project pursuit (PP)

This section presents the conceptual framework used in the empirical analysis. I refer to this framework as *Project Pursuit*. The purpose of the framework is to organize behavioral variation in project realization outcomes. A project realization outcome occurs when an individual, or group of individuals, successfully transforms an intended project into a realized outcome. Examples include becoming an entrepreneur, completing a course, graduating from a degree program, completing a research project, or bringing a business idea to market.

The framework is intentionally reduced-form. It does not estimate a fully structural model of preferences, effort, or production. Instead, it provides a conceptual frame for studying why some intended projects are realized while others are not.

The framework distinguishes three margins: project initiation, project continuation, and performance in execution. These distinctions are grounded in economic theory and motivate the empirical strategy developed in Section 3.

First, the framework separates individuals who intend to achieve a project from those who initiate it. This distinction is based on models of procrastination and present-biased choice. In such models, agents may plan to undertake a forward-looking action yet postpone it. As a result, intentions may fail to translate into action, even when the project remains desirable from a longer-run perspective (Strotz, 1955–56; Akerlof, 1991; Laibson, 1997; O'Donoghue and Rabin, 1999, 2001). In this thesis, I interpret initiation as an observable empirical manifestation of intertemporal consistency at the initiation margin. For example, in the entrepreneurship application, individuals who intend to become entrepreneurs and take concrete steps toward that goal are treated as having translated intention into action. An individual who intends to pursue a project and takes at least one project-consistent action is behaving consistently with that stated forward-looking intention, while an individual who intends but does not act may reflect an intention-action gap of the kind emphasized in the procrastination literature.

This distinction is also relevant at the level of groups, such as schools, cities, regions, or countries, depending on the empirical context. For example, in entrepreneurship, two cities may exhibit identical shares of entrepreneurial intenders, yet differ in the fraction who initiate action. I refer to the share of intenders who take at least one project-consistent action as *Initiation*.

Without separating intention from initiation, differences in realization outcomes may confound motivation with the behavioral translation of motivation into action.

This interpretation should be treated carefully. Failure to initiate does not necessarily imply present bias or lack of self-control. Individuals may fail to act because of credit constraints, lack of information, institutional barriers, health shocks, family constraints, or changes in expected returns. For this reason, initiation is best understood as a reduced-form behavioral margin: it measures whether intentions are translated into action, not the exact psychological mechanism behind that translation.

Second, among those who initiate a project, individuals differ in the extent to which they sustain project-consistent behavior over time. Project pursuit is inherently dynamic: degree programs, entrepreneurial ventures, and similar projects require repeated forward-looking actions. Let $b_t \in (0,1]$denote the share, or normalized intensity, of actions in period $t$that are consistent with the pursued project. Following the self-control and present-bias literature (Strotz, 1955–56; O'Donoghue and Rabin, 1999, 2001; Gul and Pesendorfer, 2001), I interpret $b_t$as a reduced-form measure of intertemporal consistency toward the project. More present-biased agents choose a smaller share of project-consistent actions; more forward-looking agents choose a larger share. Consistency in project pursuit is thus captured by the evolution of $b_t$over time.

Third, even conditional on acting consistently, individuals may differ in the quality with which actions are executed. Let $q_t \in (0,1]$ denote performance in execution, based on the contract-theory literature on effort and performance (Laffont and Martimort, 2001). Two individuals may both undertake market research, study for an exam, or complete a course activity, yet differ in the quality and effectiveness of execution.

The environment common to individuals in a given group is summarized by a vector x, such as startup costs, taxation, access to finance, networks, or institutional conditions. These characteristics may shift project realization probabilities but are conceptually distinct from individual pursuit behavior.

To capture effective pursuit, define the index

$$m_t = b_t^{\kappa} q_t^{\eta}, \qquad \kappa, \eta > 0,$$

which is increasing in both intertemporal consistency $b_t$and performance q_t, and exhibits complementarity between the two dimensions. This complementarity is intuitive. A student who studies frequently but performs poorly on assessments may still fail to complete the course. A student who is capable but rarely engages may also fail. Similarly, an entrepreneur with strong skills but little action may not start a business, while an entrepreneur who takes many steps but executes them poorly may not realize the project successfully. Project realization is most likely when consistency and performance are jointly present.

I assume that the probability of project realization depends on effective pursuit and the environment according to

$$p_t = f(m_t, x),$$

where $f(\cdot)$is strictly increasing in m_t and x is the environment (regulations, firm costs, etc).

In the empirical sections that follow, I operationalize these concepts in two settings. In entrepreneurship, the data mainly allow analysis of the initiation margin, because the same individuals are not followed over time. In education, the data allow a richer analysis of continuation because student engagement is observed repeatedly over the course. Across both settings, the framework is used as a descriptive tool for organizing variation in project realization outcomes.

3 Estimation approach

3.1 Model 1 – Entrepreneurship, multilevel logistic regression

This model evaluates whether the Project Pursuit (PP) approach helps explain entrepreneurial project realization, measured as early-stage entrepreneurial activity. As presented in the previous section, the PP framework suggests that realization depends on three conceptually distinct margins: whether individuals translate intentions into project-consistent action, whether they sustain such actions over time, and how effectively project-consistent actions are executed. The entrepreneurship application is designed to test the framework under an important data constraint. Because GEM is a repeated cross-section, individuals are observed only once, which prevents direct measurement of within-person continuation over time. As a result, the entrepreneurship model focuses on the PP-relevant margins that are identifiable in GEM: initiation, measured through intention-to-action conversion, and performance, measured through perceived entrepreneurial skills. The model also tests whether these two dimensions interact in a way consistent with PP complementarity.

3.1.1 Data

I assemble a repeated individual-level cross-national dataset by merging five waves of the Global Entrepreneurship Monitor, covering 2011 and 2014–2017, with country-level institutional and macroeconomic indicators for 78 countries. Missing GEM years are omitted because the relevant variables could not be harmonized consistently across the full period. The combined dataset is suitable for this application for three reasons. First, it links individual-level entrepreneurial characteristics with country-level institutional and macroeconomic conditions, allowing the model to account for both individual heterogeneity and contextual differences across countries and years. Second, GEM provides a binary indicator of early-stage entrepreneurial activity and variables that can be used to proxy the PP dimensions of initiation and performance. Third, the multi-wave structure makes it possible to exploit variation across survey years, reducing the risk that the results are driven by one particular GEM wave.

The outcome of interest is the binary variable TEA_bin, which indicates whether a respondent is involved in total early-stage entrepreneurial activity. This includes individuals engaged in nascent entrepreneurship or new business ownership and is interpreted here as a measure of entrepreneurial project realization.

The first key PP variable is the country-year proxy Initiation, which captures entrepreneurial initiation or intention-to-action conversion. It is constructed as the share of entrepreneurial intenders in a country-year who report having taken concrete steps toward starting a business. The numerator is based on the GEM variable suacts, which identifies individuals who have taken steps toward an entrepreneurial project, while the denominator is based on FUTSUPNO, which identifies individuals who intend to start a business within the relevant future horizon. Importantly, the numerator excludes respondents already classified as realized early-stage entrepreneurs in the TEA outcome. Therefore, Initiation is intended to capture pre-realization entrepreneurial initiation rather than realized entrepreneurial status itself. Conceptually, I interpret this intention-to-action conversion measure as an aggregate manifestation of intertemporal consistency: in country-years where more intenders take concrete steps, entrepreneurial intentions are more often translated into action rather than postponed or left unrealized.

The second PP variable is perceived entrepreneurial skill, measured by suskillL_bin. This is a weaker proxy for performance because it does not observe actual execution quality directly. Instead, it captures whether respondents believe they have the knowledge, skills, and experience required to start a business. I interpret it as a proxy for perceived capability or expected execution quality. The measure is therefore conceptually related to the PP performance dimension, but it should be interpreted cautiously because it reflects self-assessed ability rather than realized entrepreneurial performance.

I include a set of standardized country-level institutional and regulatory variables, including enforcement costs, credit coverage, tax burdens, and macroeconomic controls, including lagged GDP growth and employment rates, and individual-level demographic controls when available.

A key prediction of the PP framework is complementarity between project pursuit dimensions: increases in consistency/initiation should be more productive when actions are executed with higher quality, and vice versa. In this setting, complementarity implies that the association between the initiation environment (Initiation) and entrepreneurial realization (TEA) should be stronger for individuals with higher execution quality (Performance). Empirically, I implement this by including a cross-level interaction between Initiation and Performance. A positive interaction term indicates that high-skill individuals benefit more from a given initiation-conducive environment, consistent with PP's prediction that "acting" and "executing well" reinforce each other in producing realized outcomes.

I merged the GEM survey waves and the WB dataset, and the resulting dataset was used for analysis, containing one record per individual respondent. I transformed the binary survey to 0 and 1 indicators and constructed a country-year identifier for clustering. Continuous covariates, including lagged GDP growth (*gdplag1y*) and employment (*emplag1*), as well as regulatory measures, were mean-centered and scaled by their sample standard deviations for comparison of effect sizes.

Table 1 presents the summary statistics of the variables used in the model

Table 1. Summary statistics, entrepreneurship model.

Table 1. Entrepreneurship model – summary statistics

Variable	N	Mean	Median	SD	Min	Max
TEA (1/0)	783,407	0.117	0.000	0.321	0.000	1.000
Performance (1/0)	783,407	0.499	0.000	0.500	0.000	1.000
Initiation	783,028	0.251	0.250	0.099	0.020	0.519
GDP p.c., lag	783,028	2.792	2.524	2.676	-5.694	24.61
Employment	783,028	56.011	57.561	8.949	32.988	87.37

Table 1. Entrepreneurship model – summary statistics						
Variable	**N**	**Mean**	**Median**	**SD**	**Min**	**Max**
Enforcement: cost	783,028	26.886	23.600	12.325	9.700	81.70
Enforcement: time	783,028	643.966	515.000	297.497	150.000	1,715
Credit coverage	783,028	49.385	50.800	38.796	0.000	100.0
Start-up cost	783,028	8.977	4.700	12.920	0.000	118.8
Start-up time	783,028	18.252	13.000	16.797	1.500	85.98
Paying taxes	783,028	42.589	40.700	17.308	11.300	137.6
Min. paid-in capital	783,028	11.026	0.000	25.761	0.000	308.5

Note: Years = 2011, 2014, 2015, 2016, 2017. N = non-missing. Countries restricted to those used in the model.
The table reports descriptive statistics for the estimation sample. Years included are 2011, 2014, 2015, 2016, and 2017. The consistency proxy, labelled Initiation, is measured at the country-year level as the share of entrepreneurial intenders who report taking action toward entrepreneurship. Country-level continuous variables are shown in their original units for descriptive purposes but are standardized in the regression models. Countries are restricted to those included in the final estimation sample.

Table 1. Summary statistics of the variables used in the model. Own elaboration (2025).

The *starting a business* indicator measures regulatory procedures, time, cost, and any paid in minimum capital required to formally incorporate a limited liability company. It tracks the number of distinct steps an entrepreneur must take, the calendar days needed to complete them, the fees as a percentage of income per capita, and any minimum capital deposit. A higher score denotes fewer procedures, shorter duration, lower cost, and no or low capital requirements.

The *getting credit* indicator assesses the strength of a country's legal rights for borrowers and lenders, coverage, accessibility, and quality of credit information systems. Higher score is given to countries having easier access to credit.

The *paying taxes* indicator combines the number of tax payments a standard firm makes in a year, the total hours spent on tax compliance, and the total tax and mandatory contribution rate (as a share of profit). Economies where businesses face fewer filings, quicker processing, and lower overall tax burdens receive higher scores.

The *enforcing contracts* variables quantify the time, costs as percentage of claim, and procedural complexity to resolve a commercial dispute through the court system. Faster, cheaper, and more transparent judicial systems earn higher scores.

The *lagged GDP growth variable* measures one-year-lagged GDP per capita growth. A higher value indicates stronger recent economic growth, which can create business opportunities and market demand. This variable was lagged by one year to account for the plausible time gap between the macroeconomic event and the decision to become an entrepreneur.

The *employment rate* variable reflects the share of the labor force currently employed..

The key variable for my hypothesis, *Initiation* is an index that captures the share of adults who have acted upon their entrepreneurial intention, reflecting the translation of entrepreneurial intention into action. I constructed this variable by the quotient of two GEM variables: the numerator variable is suacts, which captures whether the respondent has acted on their entrepreneurial intention. The denominator variable captures the intention to become an entrepreneur. Hence, averaged at the country level, it represents the share of people who have acted towards their entrepreneurial goals.

The dependent variable *total early-stage entrepreneurial activity* (TEA) equals 1 if an individual is in the process of starting a business or has started one within the past 3.5 years. The overall mean TEA rate in our sample is about 11.7%, capturing the share of the adult population engaged in early-stage entrepreneurial activity across countries and years.

Performance is a dichotomous behavioral variable equal to 1 if the respondent scores above the country–year median on measures of perceived skills, knowledge, and confidence to start a business.

Because the Initiation proxy is measured at the country-year level and is central to the hypothesis, I examine its variation over time before presenting the regression results. This descriptive step is important because the models rely on both cross-country and within-country variation in the consistency proxy. Figure 1 therefore plots period-to-period changes in the consistency measure across the survey waves available.

Figure 1. Change in Initiation variable, by decile of average Initiation.

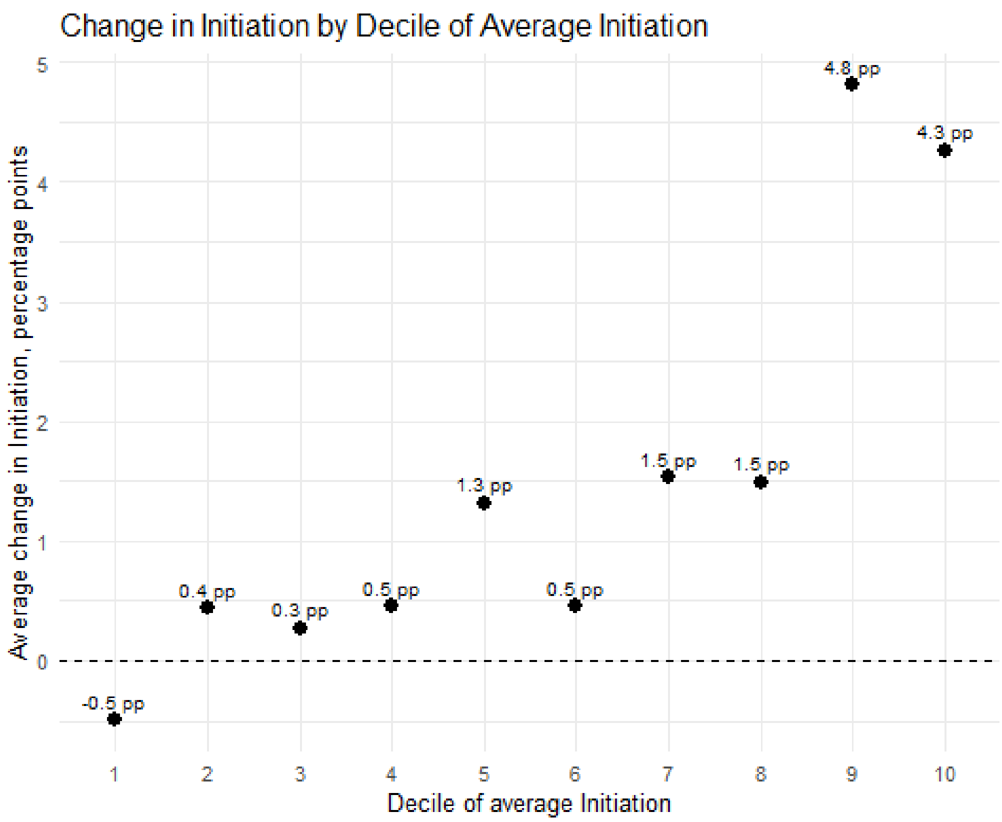

Figure 1. Decile of average initiation. Own elaboration using GEM data (2026). Notes: Initiation is measured at the country-year level as the weighted share of non-TEA entrepreneurial intenders who report having taken concrete steps toward starting a business. For each country, average Initiation is computed over the GEM waves 2011 and 2014–2017. Countries are ranked by this average and divided into deciles. The vertical axis reports the mean within-country change in Initiation, measured in percentage points, from the first to the last observed GEM wave in the period.

Figure 1 shows that the consistency proxy varies both across countries and within countries over the observed survey waves. The within-country variation is modest on average: among countries observed more than once, the median within-country standard deviation is around 0.35 standardized units, equivalent to roughly 3–4 percentage points in the original Initiation ratio. However, variation is uneven across countries, with some countries showing much larger period-to-period changes and others remaining comparatively stable. This suggests that the consistency proxy is relatively modest, while also indicating that much of its variation remains cross-sectional.

3.1.2 Methods

I estimate a multilevel logistic regression model with a logit link, where the dependent variable equals one if individual i, in country j, and year t, is involved in total early-stage entrepreneurial activity. The model is designed to assess whether perceived entrepreneurial skill – proxying performance - and the country-year consistency proxy – at the initiation margin – and their interaction, are associated with entrepreneurial activity. The regression is specified as follows:

$$logit\left[\Pr\left(TEA_{ij} = 1\right)\right]$$
$$= \left(\beta_0 + u_{0j}\right) + \beta_1 Initiation_{jt} + \beta_2 Peformance_{ijt}$$
$$+ \beta_3\left(Initiation_{jt} * Peformance_{ijt}\right) + \sum_{k=2}^{K} \beta_k X_{k,ijt}$$

where $Initiation_{jt}$ is the standardized country-year intertemporal consistency proxy (at the initiation margin), $Performance_{ijt}$is the individual-level perceived entrepreneurial skill indicator, and X_{jt} contains the macroeconomic and institutional controls. Year fixed effects, γ_t, are included to account for common shocks across survey waves.

The model includes a country-level random intercept, u_{0j}, which allows baseline entrepreneurial activity to differ across countries. It also includes a country-level random slope, u_{1j}, which allows the association between Initiation and entrepreneurial activity to vary across national contexts. This is important because the same Initiation margin may have different entrepreneurial outcomes implications in different institutional and economic environments. In addition, I include a country-year random intercept, v_{jt}, to account for unobserved shocks shared by all individuals in the same country-year.

The parameter is β_3, the interaction between Performance and Initiation. A positive coefficient would indicate that the association between the country-year consistency environment and individual entrepreneurial activity is stronger among Performance = 1 e.g., those who self-described as having entrepreneurial skill. This provides an empirical test of the project-pursuit prediction that consistency and performance reinforce each other in producing realized entrepreneurial outcomes.

The models are estimated using weighted logistic mixed-effects regression. Survey weights are included as model weights in the multilevel specifications. Because mixed-effects models do not fully reproduce complex survey-design inference, I also estimate a survey-weighted robustness model with country-year clustering. Additional robustness checks include a random-intercept-only model, a Mundlak correlated random-effects specification, and a model using the one-year lag of the consistency proxy.

3.1.3 Results

The results of the model are displayed in Table 2.

Table 2. PP approach applied in entrepreneurship project pursuit.

Table 2. Entrepreneurship project pursuit — Logit with random slope on Initiation; Year FE						
Term	**Coef.**	**2.5% CI**	**97.5% CI**	**SE**	**z**	**p**
Constant	-3.430***	-3.550	-3.310	0.061	-55.880	0.000
Performance	1.764***	1.744	1.785	0.010	168.189	0.000
Initiation	0.253***	0.177	0.328	0.038	6.565	0.000
GDP per capita, lagged (z)	0.021	-0.006	0.048	0.014	1.511	0.131
Employment rate (z)	0.119**	0.037	0.201	0.042	2.853	0.004
Contract enforcement cost (z)	0.167***	0.074	0.260	0.047	3.525	0.000
Contract enforcement time (z)	-0.042	-0.122	0.038	0.041	-1.023	0.306
Credit registry coverage (z)	-0.033	-0.101	0.035	0.035	-0.946	0.344
Start-up cost, men (z)	0.008	-0.050	0.067	0.030	0.284	0.776
Start-up time, men (z)	0.084*	0.010	0.157	0.038	2.217	0.027
Tax payment burden (z)	0.101**	0.028	0.174	0.037	2.708	0.007
Minimum capital requirement	-0.001	-0.002	0.000	0.001	-1.656	0.098
Performance × Initiation	0.031**	0.009	0.053	0.011	2.769	0.006

Note: Model includes a country-level random intercept, a country-level random slope for the consistency proxy, and a country-year random intercept.
Observations: 783,028 Countries: 78 Country-years: 263
Log Likelihood: -231,090.349 AIC: 462,222.698 BIC: 462,465.688
Marginal R^2: 0.218 Conditional R^2: 0.265
RE SD — country intercept: 0.414 country consistency slope: 0.209 country-year intercept: 0.149
RE correlation — country intercept and consistency slope: -0.424
Year fixed effects are included in the model but omitted from the table.
The dependent variable equals one if the respondent is involved in total early-stage entrepreneurial activity.
Consistency is measured as a country-year proxy for entrepreneurial action and standardized.
*** p<0.001, ** p<0.01, * p<0.05

Table 2. Results of the multilevel logistic regression model. Own elaboration (2026). Model includes a country random intercept, a country-level random slope for Initiation, and a country-year random intercept. Year fixed effects are included but omitted from the table. The dependent variable equals one if the respondent is involved in total early-stage

entrepreneurial activity. Initiation is measured as a standardized country-year proxy for intention-to-action conversion among entrepreneurial intenders. Perceived entrepreneurial skills is a binary self-assessment of whether the respondent has the knowledge, skills, and experience required to start a business.

Table 2 reports the mixed-effects logistic regression results for early-stage entrepreneurial activity. The dependent variable equals one if the respondent is involved in total early-stage entrepreneurial activity (TEA). The model includes year fixed effects, a country random intercept, a country-level random slope for Initiation, and a country-year random intercept.

The strongest individual-level predictor is perceived entrepreneurial skills. The coefficient is positive and highly significant $(\hat{\beta} = 1.76, p < 0.001)$. Since Initiation is standardized, this coefficient represents the association between perceived skills and TEA when Initiation is at its sample mean. The corresponding odds ratio is approximately $e^{1.76} = 5.84$, meaning that respondents who report having the skills, knowledge, and experience required to start a business have substantially higher odds of being involved in early-stage entrepreneurship than those who do not.

The Initiation proxy is also positive and highly significant $(\hat{\beta} = 0.25, p < 0.001)$. A one standard deviation increase in Initiation is associated with an odds ratio of approximately $e^{0.253} = 1.29$among respondents who do not report perceived entrepreneurial skills. Substantively, this suggests that country-years in which a larger share of entrepreneurial intenders translate intentions into concrete action also have higher rates of realized early-stage entrepreneurial activity.

The interaction between perceived skills and Initiation is positive and statistically significant $(\hat{\beta} = 0.031, p = 0.006)$. This supports the PP complementarity prediction in the entrepreneurship setting. For respondents without perceived entrepreneurial skills, the estimated Initiation slope is 0.253. For respondents with perceived entrepreneurial skills, the slope is $0.253 + 0.031 = 0.284$, corresponding to an odds ratio of approximately $e^{0.284} = 1.33$. Thus, Initiation is positively associated with TEA for both groups, but the association is somewhat stronger among respondents who also report having the skills required to start a business.

The macroeconomic and institutional controls should be interpreted cautiously, since they are country-level covariates and are not the main focus of the model. GDP per capita is not statistically significant. Employment is positive and significant $\left(\hat{\beta} = 0.119, p = 0.004\right)$, suggesting that higher-employment environments are associated with higher odds of TEA, conditional on the other covariates. Several regulatory variables also show significant associations. Contract-enforcement cost, start-up time, and tax-payment burden are positive, while minimum capital requirements are negative and marginally significant. These signs should not be given a causal interpretation; they may reflect broader institutional or economic differences across countries rather than direct effects of regulation on entrepreneurship. Contract-enforcement time, credit registry coverage, and start-up cost are not statistically significant.

The random-effects estimates indicate meaningful cross-country and country-year heterogeneity. The country random-intercept standard deviation is 0.414, showing that baseline TEA rates vary across countries even after accounting for observed covariates. The random-slope standard deviation for Initiation is 0.209, indicating that the strength of the Initiation–TEA association differs across countries. The country-year random-intercept standard deviation is 0.149, capturing additional variation specific to particular country-year contexts. The negative intercept–slope correlation $(\gamma-0.424)$suggests that countries with higher baseline TEA tend to have weaker marginal associations between Initiation and TEA, although this pattern should be interpreted descriptively.

Overall, Table 2 supports the entrepreneurship version of the PP framework. Perceived entrepreneurial skills and the country-year Initiation proxy are both positively associated with early-stage entrepreneurial activity, and their interaction is positive and statistically significant. The results are descriptive rather than causal, but they are consistent with the claim that entrepreneurial project realization is more likely when intention-to-action conversion and perceived execution capability are jointly present.

To assess whether the main findings depend on specific modeling choices, I estimate a set of robustness checks reported in Table 3. Each specification addresses a different concern.

First, I compare the preferred random-slope model with a simpler random-intercept model. The random-intercept model allows countries to differ in their baseline level of entrepreneurial activity, but it assumes that the association between the consistency proxy and TEA is identical across countries. The preferred model relaxes this assumption by allowing the consistency slope to vary across countries.

Second, I estimate a Mundlak correlated random-effects specification. This addresses the concern that unobserved country characteristics may be correlated with the country-level predictors. By adding country means of the time-varying covariates, the Mundlak model helps distinguish within-country associations from persistent between-country differences.

Third, I estimate a survey-weighted model with country-year clustering. The multilevel models include sampling weights as model weights, but mixed-effects estimators do not fully reproduce complex survey-design inference. The survey-weighted specification therefore checks whether the main findings are robust to design-based standard errors.

Finally, I estimate a model using a strict one-year lag of the consistency proxy. This addresses the timing concern that the GEM entrepreneurship measures do not have a perfectly sharp time dimension. In this specification, 2011 and 2014 are excluded because no previous calendar-year consistency measure is available.

Table 3 reports only the three theoretically central coefficients: performance, the consistency proxy Initiation, and their interaction. All models include the same control variables and year fixed effects.

Table 3. Robustness checks for the logistic model of entrepreneurial activity.

Table 3. Robustness checks for the logistic model of entrepreneurial activity

Term	(1) Main	(2) RI only	(3) Mundlak	(4) Survey	(5) Lagged
Performance	1.764***	1.768***	1.766***	1.802***	1.798***
	(0.010)	(0.010)	(0.010)	(0.050)	(0.014)
Initiation	0.253***	0.243***	0.260***	0.239**	0.188***
	(0.038)	(0.013)	(0.041)	(0.076)	(0.057)
Performance × Initiation	0.031**	0.031**	0.033**	0.068	-0.031*
	(0.011)	(0.011)	(0.011)	(0.065)	(0.015)
Controls	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes
Weights used	Yes	Yes	Yes	Yes	Yes
Country random intercept	Yes	Yes	Yes	No	Yes

Table 3. Robustness checks for the logistic model of entrepreneurial activity					
Term	**(1) Main**	**(2) RI only**	**(3) Mundlak**	**(4) Survey**	**(5) Lagged**
Country random slope	Yes	No	Yes	No	Yes
Country-year random intercept	Yes	No	No	No	Yes
Mundlak country means	No	No	Yes	No	No
Survey design	No	No	No	Yes	No
Initiation timing	Current	Current	Current	Current	t−1
Observations	783,028	783,028	783,028	783,028	435,457
Countries	78	78	78	78	57
Country-years	263	263	263	263	137

Note: The dependent variable equals one if the respondent is involved in total early-stage entrepreneurial activity.
Reported coefficients are log-odds. Standard errors are shown in parentheses.
All models include the same control variables and year fixed effects.
Model 1 is the preferred specification with a country random intercept, a country random slope for the consistency proxy, and a country-year random intercept.
Model 3 adds Mundlak country means to test robustness to correlated random effects.
Model 4 uses a survey-weighted design with country-year clustering.
Model 5 uses the strict one-year lag of the consistency proxy; 2011 and 2014 are excluded because no previous calendar-year observation is available.
*** p<0.001, ** p<0.01, * p<0.05

Table 3. Results of the robustness checks. Own elaboration (2026).

The robustness checks show that the two main associations are stable. Performance remains positive and statistically significant across all specifications, with coefficients ranging from 1.764 to 1.802. The consistency proxy Initiation also remains positive and statistically significant in every model. This includes the survey-weighted specification and the lagged model, where the coefficient is smaller than in all other models but remains positive $(\hat{\beta} = 0.188, p < 0.001)$. This suggests that the positive association between aggregate entrepreneurial action and individual TEA is not dependent on one specific model structure.

The interaction between skill and consistency is less stable. It is positive and statistically significant in the contemporaneous multilevel models, including the preferred model, the random-intercept model, and the Mundlak specification. However, it is not statistically significant in the survey-weighted model and becomes negative in the lagged specification. In the lagged model, the overall consistency association remains positive for both groups: the consistency slope is 0.188 for individuals without perceived skill and 0.157 for individuals with perceived skill. Therefore, the lagged result does not contradict the positive association between consistency and TEA, but it does weaken the evidence that performance consistently amplifies this association.

Overall, Table 3 supports a cautious interpretation. The evidence is strongest for the positive associations of Performance and Initiation with early-stage entrepreneurial activity. The evidence for complementarity between skill and consistency is present in the contemporaneous multilevel specifications, but it is sensitive to survey-design inference and timing assumptions. Therefore, the interaction result should be interpreted as suggestive rather than definitive.

Lastl, I ran tests to evaluate the fit and calibration of my mixed-effects logistic model, beginning with a binned residual plot of the Pearson residuals against deciles of predicted probability. In that plot, the average residuals remain tightly clustered around zero across the full range of fitted values, indicating no systematic over- or under-prediction at any level.

To assess discriminative performance, I computed the area under the ROC curve, obtaining an AUC of 0.77. This suggests that, in roughly 77 % of randomly chosen pairs of one realized and one unrealized project, the model assigns a higher probability to the realized case. This value lies in between what's called „acceptable" and ‚good". I also calculated the Brier score (0.0925), which quantifies the mean squared error between observed 0/1 outcomes and their predicted probabilities; being well below the non-informative benchmark of 0.25, this suggests that the models predicted probabilities are accurate.

Since the Initiation construct I presented in this model has not been elaborated elsewehre, I test how well this construct explains entrepreneurial outcomes in an alternative econometric setting. This test will be useful in assessing whether the Initiation construct is specific to entrepreneurship or it rather reflects a broader category.

3.1.4 Test of model 1 - Djankov et al. (2010) replication and behavioral extension

To assess the relevance and specificity of the key entrepreneurship PP proxy, Initiation, I build on the empirical setting of Djankov et al. (2010), who study the relationship between corporate taxation, investment, and entrepreneurship across countries. Their framework is useful for the present thesis because it includes both broad economic outcomes – investment, business density and FDI - and entrepreneurship-specific outcomes - business entry. This makes it possible to ask whether Initiation is associated specifically with entrepreneurial entry, rather than merely capturing general economic dynamism.

I use four outcomes following the logic of Djankov et al. The first two outcomes capture broad capital-allocation activity. Gross fixed capital formation as a percentage of GDP measures investment in fixed assets, including structures, machinery, equipment, and infrastructure. FDI net inflows as a percentage of GDP measure foreign investment flows into domestic enterprises relative to the size of the economy. The other two outcomes are more directly related to entrepreneurship. Business density measures the stock of registered limited-liability companies per 100 working-age people, while business entry rate measures newly registered limited-liability companies as a percentage of the existing stock of registered limited-liability companies. The entry-rate outcome is the most conceptually relevant for the PP framework because it captures the flow of new formal entrepreneurial projects, rather than broad investment activity or the stock of already existing firms.

The original Djankov-style replication, including statutory corporate tax rates, one-year effective tax rates, five-year effective tax rates, and tax-payment controls, is reported in the appendix. The specification I present in this section closely follows the original empirical design, but it has an important limitation for the present thesis: the Djankov outcomes refer to the early 2000s, whereas the Initiation proxy is constructed from GEM waves in 2011 and 2014–2017. This timing mismatch makes the original replication-extension useful as a historical external-validity exercise, but less ideal as the main specificity test.

For this reason, the main text reports a simplified matched-period version of the Djankov-style test. I reconstruct the four outcomes for the GEM years 2011 and 2014–2017 and average them at the country level, following Djankov et al.'s use of period averages. I then regress each country-level outcome on the period-average Initiation proxy:

$$Y_j = \alpha + \delta Initiation_j + \varepsilon_j.$$

This matched-period specification deliberately excludes the Djankov tax variables. The goal is not to re-estimate the effect of corporate taxation, nor to reproduce the full tax model. Rather, the goal is to test whether Initiation is selectively associated with entrepreneurial entry when measured over the same period as the GEM proxy. Excluding the tax variables also avoids mixing updated annual entrepreneurship outcomes with historical tax simulations that are not straightforward to reconstruct for 2011–2017.

Table 4. Specificity test using Djankov et al., (2010).

Table 4. Djankov-style specificity test using matched-period country averages

Term	(1) Investment	(2) FDI	(3) Business density	(4) Entry rate
Initiation	0.328	0.192	0.693	1.304*
	(0.516)	(0.971)	(0.678)	(0.648)
Outcome type	Gross fixed capital formation	FDI net inflows	Firm stock density	New firm entry
Period average	2011, 2014–2017	2011, 2014–2017	2011, 2014–2017	2011, 2014–2017

Table 4. Djankov-style specificity test using matched-period country averages				
Term	**(1) Investment**	**(2) FDI**	**(3) Business density**	**(4) Entry rate**
Estimator	OLS	OLS	OLS	OLS
SE type	Heteroskedasticity-robust	Heteroskedasticity-robust	Heteroskedasticity-robust	Heteroskedasticity-robust
N	80	84	70	70
R^2	0.004	0.000	0.013	0.057

Note: The table reports cross-sectional OLS regressions using country-level period averages for 2011 and 2014–2017.
Investment is gross fixed capital formation as a percentage of GDP. FDI is net inflows as a percentage of GDP.
Business density is the stock of registered limited-liability companies per 100 working-age people.
Entry rate is newly registered limited-liability companies as a percentage of the stock of registered limited-liability companies.
The Initiation proxy is averaged over the same period and standardized.
Heteroskedasticity-robust standard errors in parentheses. *** p<0.001, ** p<0.01, * p<0.05, . p<0.10

Table 4. Results of Djankov et al., (2010) replication. Own elaboration (2026).

The results support the specificity interpretation. Initiation is not significantly associated with investment, FDI, or business density. However, it is positively and statistically significantly associated with the business entry rate $\left(\hat{\delta} = 1.30, p = 0.048\right)$. This pattern is important: Initiation predicts the flow of new firm registrations, but not broader investment activity, foreign capital inflows, or the stock of existing firms. The Initiation coefficient is also comparable larger in the business entry rate than in the other three specifications. The result is therefore consistent with the interpretation that Initiation captures entrepreneurial initiation or intention-to-action conversion, rather than general country-level economic dynamism.

Because the analysis is cross-sectional and based on a relatively small country sample, it should not be interpreted with caution. Instead, it serves as a specificity and external-validity check. The evidence suggests that the PP proxy is most closely related to the outcome it should theoretically predict: new entrepreneurial entry. The appendix shows that a more literal Djankov-style specification with tax variables produces a similar qualitative pattern, but the matched-period version is preferred in the main text because it aligns the timing of the Initiation proxy and the outcome variables.

Taken together, this replication-extension exercise is informative in two ways First, it shows that the PP proxy remains predictive in an alternative entrepreneurship outcome based on formal business entry (World Bank business entry rates) rather than early-stage activity measured by GEM (TEA), which includes both formal and informal enterprises. Second, because the same empirical design is applied to investment, FDI, and business density, the fact that Initiation is robustly associated with entry but not with the other three outcomes is consistent with the proxy capturing a mechanism more specific to entrepreneurial project realization than to broad business or investment activity.

3.1.5 Summary of the Entrepreneurship project pursuit model.

Model 1 was introduced to test whether the Project Pursuit (PP) framework helps explain *entrepreneurial project realization*, operationalized as early-stage entrepreneurial activity (TEA) in GEM. Because GEM is a repeated cross-section, the model focuses on the PP margins that are identifiable: initiation/consistency and - to a degree - performance, plus their complementarity.

Using five GEM waves (2011, 2014–2017) merged with country-level institutional and macro indicators for 78 countries (783k individuals), I estimated a two-level logistic mixed model with a country random intercept and a random slope for the country-year Initiation measure (initiation margin of PP). Individual performance is proxied by Peforrmance (self-assessed start-up skills).

Before interpreting the regression results, it is important to note the variation in the Initiation proxy. Initiation varies both across countries and within countries over time, but the within-country variation is modest on average. Among countries observed more than once, the median within-country standard deviation is around 0.35 standardized units, equivalent to roughly 3–4 percentage points in the original Initiation ratio. This means that the model does exploit time variation across GEM waves, but much of the variation in Initiation remains cross-sectional. The results should therefore be interpreted as descriptive evidence combining cross-country and within-country variation, rather than as evidence based primarily on within-country changes.

Results support the PP predictions. Performance is the strongest predictor: skilled individuals have around 6× higher odds of TEA. Intiation is also positive and significant (30% higher odds per SD). Importantly, the Initiation × performance interaction is positive and significant, indicating complementarity: the association between initiation environment and TEA is stronger for high-performance individuals. The model also shows substantial cross-country heterogeneity (meaningful random intercept and random slope variation; negative intercept–slope correlation), consistent with countries differing in how effectively entrepreneurial actions translate into realized entry. Fit diagnostics are acceptable (AUC ~0.77; low Brier score; marginal/conditional pseudo-$R^2 \approx 0.22/0.28$).

The robustness checks support a cautious interpretation. The two main associations are stable: perceived entrepreneurial skills remain positive and statistically significant across all specifications, and Initiation remains positive and statistically significant in the random-intercept, Mundlak, survey-weighted, and lagged models. The evidence for complementarity is weaker. The Initiation × Performance interaction is positive and significant in the contemporaneous multilevel specifications, including the preferred model, the random-intercept model, and the Mundlak specification. However, it is not statistically significant in the survey-weighted model and becomes negative in the lagged specification. Therefore, the evidence is strongest for the positive independent associations of Initiation and perceived skills with TEA, while the complementarity result should be interpreted as suggestive rather than definitive.

As an external validity/specificity check, I extended Djankov et al. (2010) cross-country tax regressions by adding the key PP proxy Initiation. Initiation is not robustly related to investment, FDI, or business density, but is positive and significant for business entry rates. This pattern is consistent with Initiation capturing a mechanism more specific to entrepreneurial entry/project realization than to broader investment activity or the stock of firms.

The Initiation measure itself has advantages and limitations. An advantage is that the PP proxy was constructed by a quotient: its numerator is based on a direct, objective survey question - did the respondent actually take steps toward their stated entrepreneurial intention? - while its denominator is a straightforward binary indicator of intention. As a result, the measure is not based on subjective preference scales but on concrete, discrete behavior. On the other hand, it informs whether someone began acting on their intention, not how they progressed through subsequent stages of the entrepreneurial process, making the continuation margin unidentifiable in this model.

3.2 Model 2 – Educational project pursuit

This model evaluates whether the Project Pursuit (PP) approach helps explain differences in educational project realization, measured as *course pass/complete*. In the PP framework, realization depends on (1) whether individuals translate intention into project-consistent action (initiation), (2) whether they sustain such actions over time (continuation margin of intertemporal consistency), and (3) how well project-consistent actions are executed (performance). The educational application is designed to test PP in a complementary empirical environment to entrepreneurship: because OULAD provides repeated, high-frequency behavioral logs within each course, students can be observed throughout the project, which makes it possible to measure continuation directly and to construct a proxy for performance from graded assessments. At the same time, initiation is not an empirical margin in this setting - by construction, all individuals in the sample have already initiated the project by enrolling in a course. As a result, Model 2 focuses on two PP-relevant margins that are identifiable in OULAD: continuation and performance, and, importantly, whether these two dimensions interact in a way consistent with PP complementarity.

The continuation margin of intertemporal consistency is labelled as "Intertemporal Consistency", or abbreviated "IC".

The performance margin is labelled as "Performance"

3.2.1 Data

I use the Open University Learning Analytics Dataset (OULAD), an anonymised dataset from the UK Open University that links student demographics, registration histories, assessment results, and detailed logs of interaction with the university's Virtual Learning Environment (VLE), which is the enviroment where students learning activity is tracked. The released version covers 22 course offerings (in a given semester), which represent a particular course such as Biology, Mathematics, etc. There is data for 32,593 students, and contains over 10 million daily click records, making it well suited to imeplement the project pursuit approach in assessing educational project realization rates.

OULAD is organised into several linked tables: studentInfo (demographics and final result), studentRegistration (registration and unregistration dates), studentVle (daily click counts by resource), assessments (assessment metadata), and studentAssessment (assessment scores), among others. I joined these tables through common identifiers for student and courses.

The courses included in the analysis have assessment data available and correspond to undergraduate classes. I construct a student-course panel, where each record represents a student's participation in a specific course in a specific term. For example, participation of student Rene in Microeconomics in Fall 2023.

This dataset allows me to run two models. In the first model, I assess the relationship between Intertemporal Consistency and Performance, and the likelihood of project realization, defined by course pass. Using the course results (final_result) from student information (studentInfo), I code a binary indicator:

- $Y = 1$if the student's final result is Pass or Distinction
- $Y = 0$if the result is Fail or Withdrawn

For the second model, I exploit the time dimension of OULAD and model the weekly hazard of course withdrawal. Using the data on course unregistration (date_unregistration) in the student registry (studentRegistration), measured in days since the start of the course offering, I derive the week in which a student formally unregisters. Students who never unregister are treated as right-censored at their last observed week of VLE activity.

I derive and create proxies for both intertemporal consistency b_t and performance q_t. In this case, neither of these two proxies is binary. Both proxies – Intertemporal consistency and Performance – are constructed from continuous measures as explained in the following lines.

For *intertemporal consistency* b_t I use the Virtual Learning Environment (VLE) logs in studentVle to construct a weekly measure of project-consistent activity; for each student, I count the number of distinct days on which the student generated at least one VLE click, and divide by 7:

$$b_{it} = \frac{\text{no. of days with} \geq 1 \text{ click in week } t}{7} \in [0,1].$$

The resulting ratio captures the share of days in which the student chooses any project-related action, such as accessing to course materials, watching lectures, etc. Hence, this ratio proxies the share of consistency b_t: highly present-biased should exhibit low b_t, while forward-looking students sustain higher $b_t$over time. The essence of this proxy is that it distinguishes the number of days over a week in which the student engaged in a school-related activity.

For performance q_t, I construct a weekly performance index using assessment information from OULAD (assessments, studentAssessment). Each assessment has a recorded date, which I convert into course weeks. I then compute, for each student and week, the mean rescaled assessment score across all assessments recorded in that week, pooling tutor-marked assignments (TMA), computer-marked assignments (CMA), and exams. Scores are rescaled to the unit interval before aggregation.

To ensure that the performance measure is not mechanically driven by differences in engagement, I residualize weekly performance with respect to engagement. Specifically, I regress the weekly performance index on weekly engagement, proxied by the number of active days, together with week fixed effects and course fixed effects. The residual from this regression captures each student's weekly performance beyond what would be predicted by engagement, common week-specific shocks (week 1 different than week 5, etc.), and persistent differences across courses (Biology different to Mathematics, etc.). I then average these weekly residuals across the weeks in which performance is observed to obtain a student-level residualized performance measure q_i, which is standardized for use in the empirical models:

$$q_{it}^{eff} = q_{it} - \hat{q}_{it}, q_i = \frac{1}{T_i} \sum_{t=1}^{T_i} q_{it}^{eff} .$$

The purpose of residualizing Performance is to separate execution quality from the amount of observed engagement. For example, consider two students enrolled in the same course and observed in the same week. Suppose both students are active in the VLE on four days during that week, but one receives a substantially higher assessment score than the other. The raw activity measure treats them as equally consistent, because both engaged with the course on the same number of days. The residualized Performance measure instead captures the difference in assessment outcomes that remains after accounting for their level of weekly engagement, the timing of the assessment, and course-level differences. In this sense, residualized Performance is interpreted as a proxy for how well project-consistent activity is executed, rather than how often the student engages with the project. This measure should still be interpreted cautiously, because assessment scores are part of the academic process that ultimately determines course success; the residualization reduces mechanical overlap with engagement, but it does not make Performance independent of final academic outcomes. In further robustness checks, I attempt to overcome this concern (Table 8).

I include a set of student-level controls sourced from studentInfo: age band, gender, highest prior education, imd_band (capturing local socio-economic background), an indicator for reported disability, and the number of previous attempts at the same course. I also include registration timing from studentRegistration.

The first of the two models - final-success logit model - includes these controls together with course assessment-type controls (e.g., homework, mid-term exams, etc.) and a random intercept for courses. The second of the two models - hazard model - uses the same residualized performance measure but is estimated at the student-week level, includes week fixed effects to capture the baseline hazard, and uses a random intercept for courses. In the hazard model, intertemporal consistency is measured differently: rather than course-average consistency, it is proxied by lagged cumulative consistency up to the week of risk. Course assessment controls are examined there as a robustness check rather than included in the preferred baseline specification.

3.2.2 Educational project pursuit. Logit model

This specification examines how PP proxies relate to course passing. The outcome is the binary indicator Y_i of course pass. The key predictors are Intertemporal Consistency b_i^{mean} and Performance q_i^{mean}, standardised to have mean zero and unit variance. I estimate a two-level logistic mixed-effects model with a logit link using glmmTMB, allowing for heterogeneity across courses via random intercepts:

$$\text{logit}[\Pr(Y_{ij} = 1)] = (\beta_0 + u_{0j}) + \beta_b\, b_{ij}^{\text{mean}} + \beta_q\, q_{ij}^{\text{mean}} + \beta_{bq}\, b_{ij}^{\text{mean}} q_{ij}^{\text{mean}} + \sum_k \beta_k\, X_{k,ij},$$

where:

- i indexes students, j indexes courses
- $u_{0j} \sim N(0, \sigma_u^2)$is a class-level random intercept
- $X_{k,ij}$are the environmental variables and student-level controls (demographics, deprivation band, prior attempts, registration timing).

The interaction term $b^{\text{mean}} q^{\text{mean}}$ allows me to test the PP prediction that Intertemporal Consistency and Performance are complements in determining project realization: a positive β_{bq} implies that the impact of IC grows with Performance, and vice versa. The model accounts for between-course differences through random intercepts and course-level assessment environment.

As previously described, the binary outcome Y in the dataset indicates whether the student completed the course (Pass or Distinction) or not (Fail or Withdrawn). The overall pass rate is around 60.9%, with 15,347 completions and 9,859 failures or withdrawals. Intertemporal consistency, b_i^{mean}, is defined as the average share of days per week with at least one VLE click over all weeks.

Table 5 summarizes the main variables used in the education logit model. Course success is the binary realization outcome. Intertemporal consistency is the average weekly share of activity in the Virtual Environment (VLE). Residualized performance is the student-course average of weekly assessment performance after removing variation associated with active days, week fixed effects, and course-level fixed effects (Biology, Mathematics, etc). The interaction term is the product of the standardized consistency and standardized residualized-performance measures. The table also reports previous attempts and registration timing, both of which are included as controls in the model.

Table 5. Summary statistics – education project pursuit. Logit

Table 5. Summary statistics — education model sample only

Variable	N	Mean	Median	SD	Min	Max
Course success (1/0)	25,206	0.609	1.000	0.488	0.000	1.000
Intertemporal Consistency (IC)	25,206	0.375	0.340	0.152	0.143	0.976
Performance	25,206	-0.020	0.009	0.159	-0.801	0.332
IC x Performance	25,206	0.129	-0.093	0.981	-1.364	4.003
Previous attempts	25,206	0.149	0.000	0.457	0.000	6.000
Registration timing (days)	25,206	-66.447	-53.000	47.538	-311.000	124.000

Note: Model sample corresponds to observations retained in the education logit specification (panel_eff_all). N = non-missing.

Table 5. Summary statistics education project pursuit, logit. Own elaboration (2026). Note: The sample corresponds to observations retained in the education logit specification. Intertemporal consistency is the average weekly share of active VLE days. Residualized performance is assessment performance net of active days, week fixed effects, and course fixed effects. The interaction term is calculated as the product of standardized consistency and standardized residualized performance. Registration timing is measured in days relative to the course start date; negative values indicate registration before the start of the course

Table 5. Summary statistics education project pursuit, logit. Own elaboration (2026).

Together, these descriptive statistics indicate that the OULAD sample provides variation both in course realization outcomes and in the PP proxies of Intertemporal Consistency and Performance, while covering a heterogeneous set of students and course environments.

3.2.3 Results

Table 6 reports estimates from the mixed-effects logistic regression of successful course completion on PP proxies

Table 6. Education project pursuit. Results

Table 6. Regression results for education project pursuit: mixed-effects logit model.						
Term	**Coef.**	**2.5% CI**	**97.5% CI**	**SE (log-odds)**	**z**	**p**
Constant	1.43***	1.02	1.84	0.21	6.82	0.000
Intertemporal consistency	0.75***	0.71	0.79	0.02	36.84	0.000
Performance	0.91***	0.88	0.95	0.02	48.30	0.000
Age band: 35-55	-0.05	-0.12	0.01	0.03	-1.54	0.124
Age band: 55<=	-0.26	-0.66	0.13	0.20	-1.31	0.192
Gender: M	-0.01	-0.08	0.07	0.04	-0.24	0.809
Highest education: HE Qualification	-0.03	-0.12	0.06	0.05	-0.63	0.529
Highest education: Lower Than A Level	-0.50***	-0.57	-0.44	0.03	-14.88	0.000
Highest education: No Formal quals	-0.50**	-0.81	-0.18	0.16	-3.07	0.002
Highest education: Post Graduate Qualification	-0.19	-0.51	0.13	0.16	-1.18	0.240
Imd band: 0-10%	-0.82***	-1.02	-0.63	0.10	-8.32	0.000
Imd band: 90-100%	-0.27**	-0.47	-0.08	0.10	-2.71	0.007
Disability: Y	-0.29***	-0.39	-0.19	0.05	-5.66	0.000
Previous attempts	-0.11***	-0.14	-0.08	0.02	-7.55	0.000
Registration timing	-0.03	-0.06	0.00	0.02	-1.66	0.097
Assess pattern: TMA+Exam	0.06	-0.52	0.64	0.30	0.22	0.829
Intertemporal consistency × Performance	0.24***	0.20	0.28	0.02	11.10	0.000

Note: Performance is residualized with respect to active days, week fixed effects, and course fixed effects before aggregation to the student-course level.
Observations: 25,206 courses: 22
Log Likelihood: -13,285.35 AIC: 26,622.70 BIC: 26,834.21
RE SD — course intercept: 0.68
*** p<0.001, ** p<0.01, * p<0.05

Table 6. Regression results education project pursuit, logit. Own elaboration (2026).

Table 6 reports estimates from the mixed-effects logistic regression of course success on the PP proxies and controls. The model includes a random intercept for course offering, where a course offering refers to a specific course taught in a specific presentation period. The estimated random-effect standard deviation is 0.68, indicating meaningful heterogeneity in baseline pass rates across course offerings after accounting for student characteristics, registration timing, assessment-type structure, and the PP variables.

The main PP results are strongly consistent with the course-realization prediction. Intertemporal Consistency is positive and highly statistically significant $(\hat{\beta} = 0.75, p < 0.001)$. Since the variable is standardized, this means that a one standard deviation increase in consistency is associated with a 0.75 increase in the log-odds of course success, holding other variables constant. This corresponds to an odds ratio of approximately $e^{0.75} = 2.12$. Residualized Performance is also positive and highly significant $(\hat{\beta} = 0.91, p < 0.001)$, corresponding to an odds ratio of approximately $e^{0.91} = 2.49$. Thus, students who engage more regularly and students who perform better than expected given their engagement intensity are substantially more likely to pass or receive a distinction.

The interaction between IC and Performance is also positive and statistically significant $(\hat{\beta} = 0.24, p < 0.001)$. This supports the PP complementarity prediction. The positive interaction implies that the association between IC and success is stronger when Performance is higher, and conversely, that Performance matters more when engagement is consistent rather than sporadic. In substantive terms, course realization appears most likely when students combine sustained engagement with effective execution.

Several control variables also behave as expected. Prior education is strongly associated with course success. Compared with the reference education group, students whose highest qualification is below A-level have substantially lower odds of success $(\hat{\beta} = -0.50, p < 0.001)$, and students with no formal qualifications also have lower odds of success $(\hat{\beta} = -0.50, p < 0.01)$. This suggests that prior academic preparation remains important even after controlling for engagement and performance during the course.

Socioeconomic background is also related to course outcomes. Students in the most deprived IMD band have lower odds of course success $(\hat{\beta} = -0.82, p < 0.001)$, and students in the least deprived band also show a smaller negative coefficient $(\hat{\beta} = -0.27, p < 0.01)$relative to the omitted IMD category. The disability indicator is negative and statistically significant $(\hat{\beta} = -0.29, p < 0.001)$, indicating that students reporting a disability have lower predicted success, conditional on the other covariates. These associations should not be interpreted causally, but they show that background inequalities remain visible in the course-success model.

Previous attempts are negatively associated with success $(\hat{\beta} = -0.11, p < 0.001)$, consistent with the idea that students repeating or reattempting a course face greater academic difficulty. Registration timing is weakly negative $(\hat{\beta} = -0.03, p = 0.097)$, suggesting that later registration may be associated with slightly lower success, although this effect is only marginally significant. The assessment-type structure indicator is not statistically significant, suggesting that after controlling for course-offering heterogeneity and student characteristics, the difference between the displayed assessment structures does not explain additional variation in course success.

Overall, Table 6 shows that both PP dimensions are strongly associated with educational project realization, and that their interaction is positive and robust. The control variables indicate that these associations coexist with meaningful differences by prior education, deprivation, disability status, and previous attempts. The results therefore support the PP interpretation while also showing that course success remains shaped by student background and prior academic experience.

Table 9 reports robustness checks. The first adds the standardized number of weeks with observed performance data. This is a demanding control because it captures an important exposure/persistence dimension: students with more observed Performance weeks are, by construction, present and active in the course for longer and therefore have more opportunities both to be assessed and to succeed. Reassuringly, the interaction between Intertemporal Consistency and Performance remains positive and highly significant ($\hat{\beta}_{bq} = 0.21, p < 0.001$). Although the main effect of Intertemporal Consistency becomes smaller once this variable is included, this is not surprising, since observed Performance weeks absorbs part of the persistence/exposure variation that would otherwise load onto the consistency margin.

The second robustness check allows for nonlinearities by adding quadratic terms in IC and Performance. This tests whether the complementarity result is merely an artifact of imposing a linear interaction structure. It is not. The interaction term remains positive and highly significant ($\hat{\beta}_{bq} = 0.19$, $p < 0.001$), while both squared terms are negative and statistically significant. This indicates diminishing marginal returns in both dimensions: increases in IC and Performance continue to raise the probability of success, but their marginal payoff becomes smaller at higher levels. The quadratic plot in the appendix confirms this pattern, showing rising but flattening predicted probabilities, especially at lower levels of performance.

Table 7. First robustness checks for the logit model of course success.

Table 7. Robustness checks for the logit model of course success			
Term	**(1) Main**	**(2) +Weeks**	**(3) Quad.**
IC	0.749***	0.158***	0.804***
	(0.020)	(0.026)	(0.023)
Performance	0.914***	1.089***	0.832***
	(0.019)	(0.026)	(0.020)
IC × Performance	0.237***	0.206***	0.193***
	(0.021)	(0.027)	(0.022)
Obs. perf. weeks		2.377***	
		(0.033)	
IC^2			-0.117***
			(0.014)
$Performance^2$			-0.383***
			(0.017)
N	25,206	25,206	25,206
AIC	26,622.705	16,664.697	25,968.683

Note: All models include the same controls and a random intercept for each course.

Performance is residualized with respect to active days, week fixed effects, and course level fixed effects.

SEs in parentheses. *** p<0.001, ** p<0.01, * p<0.05

Table 7. First run of robustness check for the education project pursuit, logit. Own elaboration (2026).

The robustness checks show that the core interaction term remains positive and statistically significant across specifications, while the quadratic model further indicates diminishing marginal returns in both intertemporal consistency and performance.

A remaining concern is that the Performance measure is partly assessment-based e.g., based on mid-term exam and homework results, while the main course-success outcome is defined as Pass/Distinction versus Fail/Withdrawn. This raises a possible mechanical-overlap concern: students with higher assessment results are, by construction, more likely to pass the course. The residualization procedure used in the main model removes variation in Performance associated with active days, week fixed effects, and course level fixed effects (e.g., Biology, Mathematics, etc.), but it does not fully eliminate the fact that assessment scores contribute to final academic outcomes. I therefore estimate an additional set of robustness checks focused on this issue.

Table 8 reports these checks. Column (1) reproduces the main specification using full-course residualized Performance. Column (2) reconstructs Performance using only the first two observed assessment periods. This is the most direct test of the mechanical-overlap concern, because early Performance is measured before the final course outcome is fully realized and therefore cannot simply summarize end-of-course grading.

Table 8. Second robustness checks for the logit model of course success.

Table 8. Robustness checks 2: logit models of course realization outcomes				
Term	**(1) Full q**	**(2) First 2 q**	**(3) No-final q**	**(4) Pass/fail**
Intertemporal consistency	0.749***	0.802***	0.711***	1.077***
	(0.020)	(0.020)	(0.022)	(0.029)
Performance	0.914***	0.800***	0.764***	0.820***
	(0.019)	(0.018)	(0.019)	(0.022)
Intertemporal consistency × Performance	0.237***	0.217***	0.211***	0.248***
	(0.021)	(0.020)	(0.021)	(0.025)
Outcome	Success	Success	Success	Pass vs fail
Performance measure	Full course	First two assessments	Excludes final observed assessment	First two assessments
Controls	Yes	Yes	Yes	Yes
Assessment pattern controls	Yes	Yes	Yes	Yes
Course-run random intercept	Yes	Yes	Yes	Yes
N	25,206	25,206	22,138	20,765
AIC	26,622.705	27,201.718	22,609.960	18,901.244

Note: Columns (1)–(3) use the main course-success outcome, equal to one for Pass/Distinction and zero for Fail/Withdrawn.
Column (4) restricts the sample to non-withdrawers and compares Pass/Distinction against Fail.
Performance is residualized with respect to active days, week fixed effects, and course level fixed effects before aggregation.
All models include student background controls, previous attempts, registration timing, assessment pattern controls, and a random intercept for courses.
AIC values are reported for reference but should not be compared across columns with different samples or dependent variables.
Standard errors in parentheses. *** $p<0.001$, ** $p<0.01$, * $p<0.05$

Table 8. Second run of robustness check for the education project pursuit, logit. Own elaboration (2026).

The results remain very similar to the main specification. Intertemporal Consistency remains positive and statistically significant $(\hat{\beta} = 0.802, p < 0.001)$, Performance remains positive and statistically significant $(\hat{\beta} = 0.800, p < 0.001)$, and the interaction between the two remains positive and highly significant $(\hat{\beta}_{bq} = 0.217, p < 0.001)$. This suggests that the complementarity result is not driven only by using full-course assessment Performance to predict final course success. In simple words, the result is not driven only by using all of the course assessment (homeworks, mid term exams, etc.).

Column (3) provides a second check by excluding each student's final observed assessment from the Performance measure. This addresses the concern that the main result may be driven by the assessment observation closest to the final pass/fail classification. Again, the results remain stable. Both main effects are positive and statistically significant, and the interaction remains positive and highly significant $(\hat{\beta}_{bq} = 0.211, p < 0.001)$. The sample is smaller because students with only one observed Performance period cannot contribute to this specification, but the coefficient pattern remains very similar.

Column (4) further separates academic success from course abandonment by restricting the sample to students who did not withdraw and estimating Pass/Distinction versus Fail. This check is useful because the main success outcome combines two different forms of non-realization: withdrawal and academic failure. Among non-withdrawers, the results continue to support the PP interpretation. Intertemporal Consistency $(\hat{\beta} = 1.077, p < 0.001)$, Performance $(\hat{\beta} = 0.820, p < 0.001)$, and their interaction $(\hat{\beta}_{bq} = 0.248, p < 0.001)$ all remain positive and statistically significant. Thus, the PP variables are not only associated with remaining in the course, but also with academic realization conditional on not withdrawing.

Taken together, these checks substantially reduce the concern that the main logit results are purely tautological. The performance variable is still related to course assessment outcomes, and the estimates remain descriptive rather than causal. However, the core findings persist when Performance is measured early, when the final observed assessment is excluded, and when pass/fail outcomes are examined only among non-withdrawers. The evidence therefore supports the interpretation that course realization is associated with the joint presence of sustained engagement and higher-quality execution, rather than being merely an artifact of using full-course assessment scores to predict final course success.

To visualize complementarity in educational project realization, Figure 2 plots model-implied predicted probabilities of course success from the preferred mixed-effects logit specification. Using the estimation sample, I construct a prediction grid that varies standardized intertemporal consistency (b_z)over its observed range and evaluates predictions at three empirical levels of standardized residualized performance (q_z), corresponding to the 20th, 50th, and 80th percentiles of its distribution. All other covariates are held at typical values from the estimation sample, using modal categories for categorical variables and medians for continuous variables. Predictions are computed from the fitted model using the fixed-effects component only, with the random intercept set to zero. Accordingly, the figure should be interpreted as showing the expected relationship for an average course offering.

Figure 2. Predicted probability of course success by intertemporal consistency and performance.

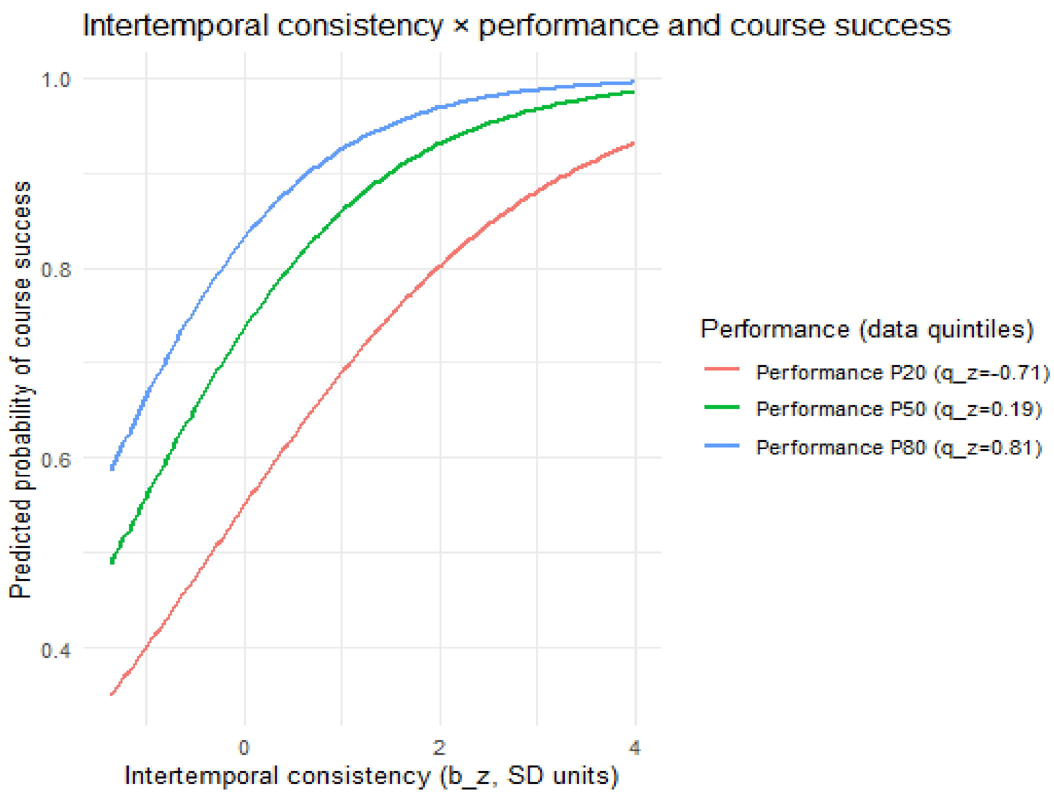

Figure 2. Predicted probability of course success. Source: own elaboration (2026). Note: The figure reports model-implied predicted probabilities of course success over the observed

range of intertemporal consistency, evaluated at the 20th, 50th, and 80th percentiles of residualized performance ($q_z = -0.71$, 0.19, and 0.81, respectively). Since q_z is standardized, negative values indicate below-average residualized performance relative to the estimation sample. Residualized performance is obtained by removing variation associated with active days, week fixed effects, and course-offering fixed effects before aggregation to the student-course level. All other covariates are held at typical sample values, and the random intercept is set to zero.

Figure 2 shows that predicted course success rises with intertemporal consistency at all three levels of residualized performance. However, the slope is clearly steeper at higher values of performance. This means that the positive association between consistency and course success is stronger for students whose performance is higher. Equally, the vertical distance between the curves becomes larger as consistency increases, indicating that the association between performance and course success is stronger when students engage more consistently. This pattern is consistent with complementarity between the two PP dimensions in the estimated model.

The estimated model is

$$\Pr\left(Y_i = 1 \mid X_i, u_j\right) = \Lambda\left(\beta_0 + \beta_b b_{zi} + \beta_q q_{zi} + \beta_{bq}(b_{zi} q_{zi}) + X_i' \gamma + u_j\right),$$

where $Y_i = 1$ indicates course completion, b_{zi} is standardized intertemporal consistency, q_{zi} is standardized residualized performance, X_i is the vector of controls, u_j is the random intercept for course offering j, and $\Lambda(z) = \frac{e^z}{1+e^z}$ is the logistic function.

For the figure, predicted probabilities are computed as

$$\hat{p}(b, q) = \Lambda\left(\hat{\beta}_0 + \hat{\beta}_b b + \hat{\beta}_q q + \hat{\beta}_{bq}(bq) + \tilde{X}' \hat{\gamma}\right),$$

where b varies over the observed range of standardized intertemporal consistency, q is fixed at one of three empirical values, $q_z = (-0.71,\ 0.19,\ and\ 0.81)$, $\tilde{X}$ denotes the vector of typical covariate values, and the random intercept is set to zero. Each curve in the figure is obtained by evaluating this expression repeatedly as $b$changes.

The figure reinforces the regression results by showing that the two PP dimensions are associated with course realization in a multiplicative rather than purely additive way. Students with higher Intertemporal Consistency have higher predicted success probabilities, and students with higher residualized Performance also have higher predicted success probabilities, but the gains from one dimension are larger when the other dimension is also high. Thus, students who are both more consistent in their engagement and stronger in residualized Performance have the highest predicted probabilities of course success. This visual pattern matches the positive and statistically significant interaction term in the main model and is consistent with the PP framework's complementarity prediction

Next, I test the key PP proxies in a reverse setup: how well my PP constructs of Intertemporal Consistency and Performance affect quitting and withdrawal decisions.

3.2.4 Educational pursuit project – Project abandonment using a Hazard model.

The second specification of the educational project pursuit examines how PP variables relate to the timing of project abandonment. Although quitting is the inverse of project realization, modeling the hazard of withdrawal is central to the PP mechanism because realization and abandonment are two sides of the same process. A project can fail either because individuals never initiate it or because they abandon it before completion. The PP framework predicts that sustained project-consistent behavior and high performance should not only increase the likelihood of ultimate realization but also lower the risk of quitting the project at any point in time. Thus, studying dropout provides a dynamic test of the same conceptual inputs introduced in Section 3, focusing on the continuation margin rather than the final realization endpoint.

In this event-history setting, I interpret the mapping $p_t = f(m_t, x)$ through a discrete-time hazard framework in which withdrawal within a period is modeled as a Bernoulli event induced by an underlying Poisson arrival. Let λ_{it}^{quit} denote the weekly intensity of unregistration for student i in week t. Consistent with the PP premise that Intertemporal Consistency and Performance increase the probability of project success I allow the dropout intensity to decline with these dimensions. Same as in the logit specification, in this setting Intertemporal Consistency varies week to week, while Performance is captured by a student-level residualized measure that isolates execution quality net of engagement. A convenient reduced-form parameterization is

$$log\lambda_{it}^{quit} = \alpha_t - \kappa logb_{i,t-1} - \eta logq_{i,t-1} - \rho logb_{i,t-1}logq_{i,t-1} + x'_i\delta + u_{0j}, \quad \kappa, \eta > 0,$$

where α_t captures the baseline hazard through week-specific intercepts and u_{0j} allows for course-level heterogeneity. Under the PP continuation prediction, $\gamma_b < 0$ and $\gamma_q < 0$, indicating that greater IC and higher Performance reduce the hazard of dropout; a negative γ_{bq} would further suggest that these dimensions reinforce each other in lowering abandonment risk. This specification implies the discrete-time probability of withdrawal

$$h_{it} = 1 - \exp(-\lambda_{it}^{quit}),$$

so that increases in recent intertemporal consistency and higher performance shift the hazard of abandonment downward over time.

To study withdrawal dynamics, I construct a weekly person-period dataset in which each row is a student-course week during which the student is still enrolled and therefore at risk of unregistering. The binary outcome h_{it} equals 1 if student i formally unregisters in week t, and 0 otherwise. Students who never unregister are treated as right-censored at their last observed week of activity. I estimate a discrete-time hazard model with a complementary log-log link and week fixed effects. This provides a binary-response approximation to a continuous-time proportional hazards model while allowing the baseline hazard to vary flexibly by course week.

The estimated equation is:

$$\begin{aligned} &\log\left[-\log\left(1 - \Pr\left(h_{it} = 1\right)\right)\right] \\ &\qquad = \alpha_t + \gamma_b \log\left(b_{i,t-1} + \varepsilon\right) + \gamma_q q_{i,t-1}^{eff} + \gamma_{bq} \log\left(b_{i,t-1} + \varepsilon\right) q_{i,t-1}^{eff} \\ &\qquad + \gamma_n NoPriorQ_{it} + \sum_k \gamma_k X_{ki} + u_{0j}. \end{aligned}$$

Here, α_t are week fixed effects capturing the baseline withdrawal hazard, and u_{0j} is a random intercept for course runs. The Intertemporal Consistency measure is constructed dynamically: for each student-week, I compute the cumulative average share of active days using only engagement observed up to week $t - 1$. Because IC can be close to zero, I apply a logarithmic transformation with a small offset. Performance is also constructed dynamically. Rather than using full-course average Performance, which would use future information to predict earlier withdrawal risk, I measure Performance as the cumulative average of residualized assessment Performance observed up to week $t-1$. Weeks before a student's first observed course assessment are retained using a separate indicator for having no prior course assessment information.

This specification therefore ensures that both behavioral predictors are temporally ordered: withdrawal in week t is predicted only using information available before week t.

Table 9 reports the hazard results. Since the dependent variable equals one when the student withdraws, negative coefficients indicate lower weekly withdrawal risk.

Table 9. Education project pursuit. Weekly hazard. Results

Table 9. Education project pursuit: Discrete-time hazard model of course exit

Term	**Coef.**	**2.5% CI**	**97.5% CI**	**SE**	**z**	**p**
Constant	-5.81***	-6.81	-4.82	0.51	-11.48	0.000
Lagged cumulative intertemporal consistency (log)	-0.29*	-0.53	-0.04	0.13	-2.28	0.023
Lagged cumulative performance	-0.75***	-1.16	-0.34	0.21	-3.58	0.000
No prior assessment observed	0.58*	0.14	1.03	0.23	2.56	0.010
Age band: 35-55	0.01	-0.30	0.31	0.16	0.04	0.970
Age band: 55<=	-0.35	-2.33	1.64	1.01	-0.34	0.732
Gender: M	-0.04	-0.34	0.25	0.15	-0.27	0.786
Highest education: HE Qualification	0.06	-0.35	0.47	0.21	0.28	0.781
Highest education: Lower Than A Level	0.35*	0.05	0.66	0.16	2.27	0.023
Highest education: No Formal quals	0.61	-0.55	1.78	0.60	1.03	0.303
Highest education: Post	-0.98	-2.98	1.02	1.02	-0.96	0.336

Table 9. Education project pursuit: Discrete-time hazard model of course exit						
Term	**Coef.**	**2.5% CI**	**97.5% CI**	**SE**	**z**	**p**
Graduate Qualification						
Imd band: 0-10%	-0.06	-0.85	0.73	0.40	-0.14	0.887
Imd band: 90-100%	-0.35	-1.19	0.48	0.42	-0.84	0.403
Disability: Y	0.06	-0.42	0.53	0.24	0.23	0.818
Previous attempts (z)	0.01	-0.12	0.14	0.07	0.14	0.887
Registration timing (z)	-0.08	-0.21	0.05	0.07	-1.21	0.226
Assess pattern: TMA+Exam	-0.40*	-0.75	-0.05	0.18	-2.24	0.025
Lagged cumulative IC × lagged cumulative performance	-0.11	-0.44	0.22	0.17	-0.65	0.517

Note: The model is a mixed-effects discrete-time hazard model estimated with a complementary log-log link.
Intertemporal Consistency is measured as lagged cumulative consistency up to week t−1.
Performance is measured as lagged cumulative residualized course assessment performance observed up to week t−1.
Residualized Performance is obtained from a model of weekly performance on active days, week fixed effects, and course level fixed effects.
Weeks before the first observed assessment are retained using a no-prior-assessment indicator.
The negative coefficients on consistency and performance indicate lower weekly withdrawal risk.
Weekly observations: 79,146 Course runs: 22
Log Likelihood: -1,372.15 AIC: 2,852.30 BIC: 3,353.37
RE SD — course-run intercept: 0.0004
Week fixed effects are included in the model but omitted from the table.

h = 1 if the student quits the course in that week.

*** p<0.001, ** p<0.01, * p<0.05

Table 9. Regression results education project pursuit, hazard model. Own elaboration (2026).

The coefficient on lagged cumulative IC is negative and statistically significant $(\hat{\gamma}_b = -0.29, p = 0.023)$, suggesting that students with more consistent prior engagement are less likely to unregister in the following week. The coefficient on lagged cumulative Performance is also negative and highly significant $\left(\hat{\gamma}_q = -0.75, p < 0.001\right)$. This indicates that students who performed better in prior assessments, relative to what would be predicted by their engagement, face a lower weekly risk of withdrawal.

The no-prior-assessment indicator is positive and statistically significant ($\hat{\gamma} = 0.58, p = 0.010$). This suggests that weeks before any prior assessment information is available are associated with higher withdrawal risk, consistent with the idea that early-course uncertainty or weak course attachment may contribute to dropout.

The interaction between lagged IC and lagged Performance is negative, as predicted by the PP framework for a withdrawal outcome, but it is not statistically significant $\left(\hat{\gamma}_{bq} = -0.11, p = 0.517\right)$. Therefore, the corrected hazard model does not provide clear evidence that IC and Performance reinforce each other in reducing weekly withdrawal risk. Instead, the hazard evidence should be interpreted as supporting the separate continuation effects of the two PP dimensions: both sustained engagement and prior performance are associated with lower abandonment risk.

Among the controls, most demographic coefficients are modest once the PP variables and week fixed effects are included. One notable exception is prior education: students whose highest qualification is below A-level have higher withdrawal risk ($\hat{\gamma} = 0.35, p = 0.023$). The course assessment-type control is also significant: students in TMA-plus-exam course structures have lower withdrawal risk than the reference assessment structure ($\hat{\gamma} = -0.40, p = 0.025$). The estimated course level random-intercept standard deviation is very small, suggesting that after including week fixed effects, assessment type controls (e.g., homeworks, mid-term exams, etc.), and student covariates, little residual between-course-run variation remains in the weekly withdrawal hazard.

Overall, the corrected hazard model strengthens the dynamic interpretation of the PP framework by showing that both lagged IC and lagged prior Performance reduce the risk of abandoning the educational project. However, unlike the course-success logit model, the hazard model does not provide statistically significant evidence of complementarity. The results therefore suggest that complementarity is more visible in final course-realization outcomes than in the week-to-week timing of withdrawal.

To assess whether the corrected hazard-model results depend on specific measurement choices, Table 10 reports two robustness checks. Since the corrected main specification already uses only information available before the week of risk and includes course assessment type controls, the robustness checks focus on two remaining issues.

First, Column (2) adds the standardized number of prior course assessment observations. This is a demanding control because students with more prior course assessments have, by construction, remained enrolled long enough to accumulate more Performance information. The variable therefore captures part of the exposure and assessment-history dimension that may otherwise be confounded with prior performance. Second, Column (3) replaces cumulative prior Performance with the most recent prior assessment Performance. This tests whether the results depend on averaging all prior course assessment information or whether they also hold when Performance is measured using the latest available course assessment signal.

Table 10. Robustness checks for the hazard of course withdrawal.

Table 10. Robustness checks for the discrete-time hazard model of course exit

Term	**(1) Main**	**(2) +Assess. N**	**(3) Last q**
Lagged cumulative IC (log)	-0.286*	-0.292*	-0.286*
	(0.125)	(0.125)	(0.125)
Lagged prior performance (z)	-0.749***	-0.735***	-0.791***
	(0.209)	(0.209)	(0.211)
Lagged IC × lagged prior performance	-0.108	-0.097	-0.140
	(0.167)	(0.166)	(0.168)
Prior assessments observed (z)		-0.204	
		(0.251)	
No prior assessment observed	0.582*	0.114	0.582*
	(0.227)	(0.609)	(0.227)
Week fixed effects	Yes	Yes	Yes
Assessment pattern controls	Yes	Yes	Yes
Course-run random intercept	Yes	Yes	Yes
Performance measure	Cumulative prior q	Cumulative prior q	Last prior q
N	79,146	79,146	79,146
AIC	2,852.304	2,853.489	2,851.983

Note: The dependent variable equals one if the student quits the course in that week.
All models use a complementary log-log link and are estimated on the weekly risk set up to week 33.
Intertemporal consistency and performance are lagged and use only information available before the week of risk.

Table 10. Robustness checks for the discrete-time hazard model of course exit			
Term	**(1) Main**	**(2) +Assess. N**	**(3) Last q**

Performance is residualized with respect to active days, week fixed effects, and course level fixed effects.
Column (2) controls for the standardized number of prior assessment observations.
Column (3) uses the most recent prior assessment performance instead of cumulative prior performance.
Week fixed effects are included in all models but omitted from the coefficient block.
Standard errors in parentheses. *** p<0.001, ** p<0.01, * p<0.05

Table 10. Robustness check for the hazard education project withdrawal. Own elaboration (2026).

Table 10 shows that the main effects are stable across specifications. In the corrected main model, lagged cumulative Intertemporal Consistency is negatively associated with weekly withdrawal risk $(\hat{\beta} = -0.286, p < 0.05)$, and lagged prior Performance is also negative and highly significant $(\hat{\beta} = -0.749, p < 0.001)$. Adding the number of prior course assessment observations leaves both coefficients essentially unchanged: IC remains negative and significant $(\hat{\beta} = -0.292, p < 0.05)$, and prior Performance remains strongly negative $(\hat{\beta} = -0.735, p < 0.001)$. The coefficient on the number of prior course assessments is itself not statistically significant, suggesting that the Performance result is not simply capturing the amount of prior assessment exposure.

Column (3) shows a very similar pattern when Performance is measured as the most recent prior assessment rather than cumulative prior Performance. Lagged IC remains negative and significant $(\hat{\beta} = -0.286, p < 0.05)$, and last prior Performance is negative and highly significant $(\hat{\beta} = -0.791, p < 0.001)$. This supports the interpretation that prior Performance reduces withdrawal risk regardless of whether it is measured cumulatively or using the latest available signal.

However, the interaction between IC and Performance is not statistically significant in any specification. The interaction remains negative in all columns, which is directionally consistent with the PP complementarity prediction for a withdrawal outcome, but the estimates are imprecise. Therefore, the corrected hazard robustness checks do not support the claim that IC and Performance jointly reduce withdrawal risk more than additively.

Taken together, the robustness checks support a more cautious interpretation of the hazard evidence. The dynamic withdrawal models provide robust evidence that both lagged IC and lagged prior Performance reduce the weekly risk of course exit. They do not, however, provide robust evidence of complementarity in the timing of withdrawal. This contrasts with the course-success logit models, where the complementarity result is stronger and more stable. The hazard results therefore validate the continuation dimension of the PP framework, while suggesting that complementarity is more evident in final realization outcomes than in week-to-week withdrawal decisions.

To visualize the implications of the discrete-time hazard model for course withdrawal, Figure X plots model-implied cumulative probabilities of withdrawal over time. The figure is based on the preferred hazard specification with a complementary log-log link. Predicted weekly withdrawal hazards are generated over the observed course weeks for four stylized profiles defined by low and high values of lagged cumulative Intertemporal Consistency and lagged residualized Performance, using the 20th and 80th percentiles of each distribution. All other covariates are held at typical values from the estimation sample, using modal categories for categorical variables and medians for continuous variables. Predictions are computed from the fitted model using the fixed-effects component only, with the random intercept set to zero, so the figure should be interpreted as referring to an average course offering.

Figure 3. Model implied cummulative withdrawal risk.

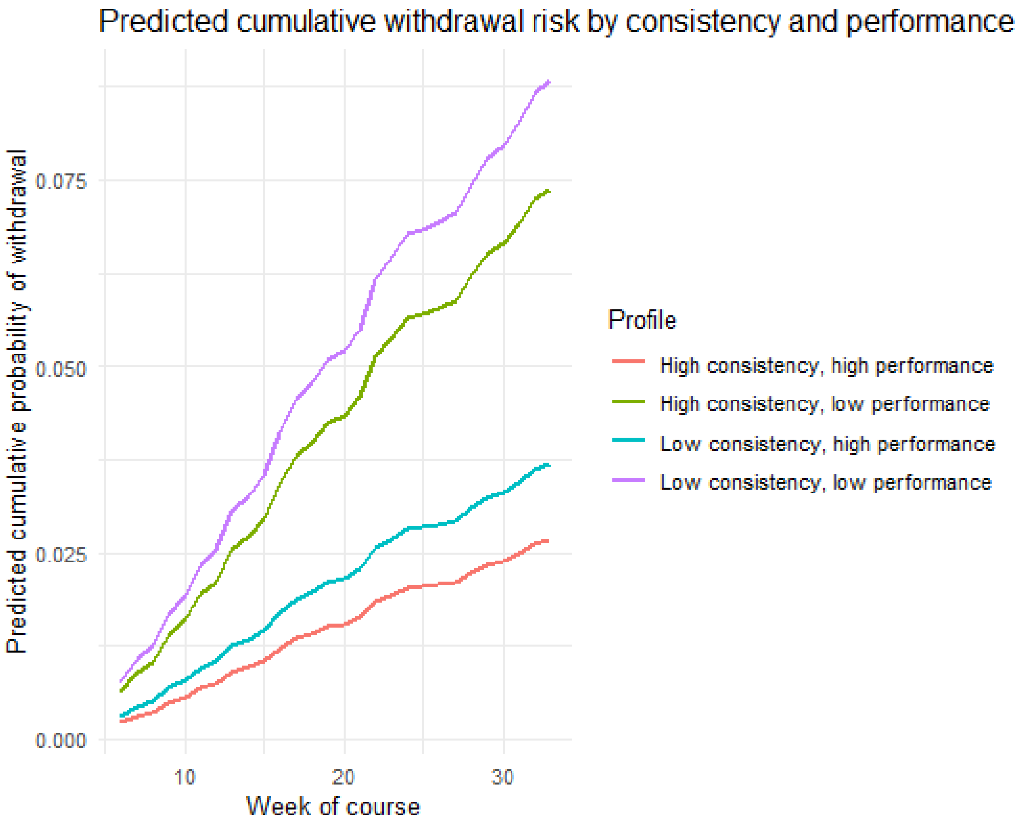

Figure 3. Predicted hazard of unregistering course. Source: own elaboration (2026). Note: The figure reports model-implied cumulative probabilities of withdrawal from the preferred discrete-time hazard model. Weekly hazards are predicted over the observed course weeks for four profiles defined by low and high values of lagged cumulative Intertemporal Consistency and lagged residualized Performance, using the 20th and 80th percentiles of each distribution. All other covariates are held at typical sample values, and the random intercept is set to zero. Predicted weekly hazards are then converted into cumulative withdrawal probabilities. Since lagged performance is standardized, low values indicate below-average prior performance relative to the estimation sample, not negative performance in an absolute sense. Because the interaction term is not statistically significant, the figure should be interpreted as illustrating the joint main effects of the two PP dimensions rather than robust evidence of complementarity in dropout timing.

Figure 3 shows an economically intuitive ordering of the profiles. Students with both high consistency and high performance have the lowest cumulative withdrawal risk throughout the course, whereas students with both low consistency and low performance have the highest. The two mixed profiles lie in between, indicating that each dimension is associated with lower withdrawal risk on its own. Thus, the figure reinforces the substantive interpretation of the hazard model: sustained engagement and stronger prior performance are both associated with lower probability of course exit over time. However, because the interaction term in the corrected hazard model is not statistically significant, the figure should be interpreted primarily as illustrating the joint implications of the estimated main effects rather than as strong evidence of complementarity.

The discrete-time hazard model is

$$\Pr\left(h_{it} = 1 \mid X_{it}, u_j\right) = 1 - \exp\left[-\exp\left(\alpha_t + \theta_b \log\, b_{i,t-1} + \theta_q q_{i,t-1} + \theta_{bq}(\log\, b_{i,t-1} \cdot q_{i,t-1}) + X_i'\delta + u_j\right)\right],$$

where $h_{it} = 1$indicates that student $i$withdraws in week t, $\alpha_t$denotes week-specific baseline hazard terms, $\log b_{i,t-1}$is lagged cumulative intertemporal consistency up to the week of risk, $q_{i,t-1}$is lagged residualized performance, $X_i$is the vector of controls, and $u_j$is the random intercept for course offering j.

To construct the figure, I define four project-pursuit profiles using low and high values of lagged cumulative consistency and lagged performance. Specifically, I set both variables at the 20th and 80th percentiles of their empirical distributions, yielding four cases:

1. low consistency, low performance;
2. low consistency, high performance;
3. high consistency, low performance;
4. high consistency, high performance.

For each week $t$and profile (b, q), the fitted weekly hazard is

$$\hat{h}_t(b, q) = 1 - \exp\left[-\exp\left(\hat{\alpha}_t + \hat{\theta}_b \log\, b + \hat{\theta}_q q + \hat{\theta}_{bq}(\log\, b \cdot q) + \tilde{X}'\hat{\delta}\right)\right],$$

where $\tilde{X}$denotes the vector of typical covariate values and the random intercept is set to zero.

These weekly hazards are converted into cumulative withdrawal probabilities. Let $\hat{h}_s(b, q)$denote the predicted hazard in week s. The predicted survival probability up to week $t$is

$$\hat{S}_t(b, q) = \prod_{s=1}^{t} \left(1 - \hat{h}_s(b, q)\right),$$

and the corresponding cumulative probability of withdrawal by week $t$is

$$\hat{F}_t(b, q) = 1 - \hat{S}_t(b, q).$$

Thus, each curve in the figure reports the model-implied cumulative withdrawal probability over time for one of the four project-pursuit profiles.

The hazard figure complements the regression table by translating the weekly hazard estimates into cumulative withdrawal risk over time. The figure shows that students with stronger consistency and stronger prior performance face lower predicted withdrawal risk, and that the profile combining both features performs best throughout the observed course weeks. This ordering is substantively informative because it shows that the two PP dimensions point in the same direction in the continuation margin: students who engage more consistently and perform better are less likely to leave the course. At the same time, because the estimated interaction term is not statistically significant in the corrected hazard model, the figure should not be read as establishing robust complementarity in withdrawal behavior. Rather, it shows that the combination of the two favorable dimensions yields the lowest model-implied dropout risk, even though the incremental cross-effect between them is estimated imprecisely.

Taken together, the hazard results complement the static logit findings. Whereas Model 1 shows that consistency and quality jointly are associated with an increased probability of final realization, with evidence of complementarity; the hazard model reveals that each dimension separately reduces dropout rates, making students less likely to abandon the project in any given week. The absence of a strong interaction on the hazard scale suggests that the PP complementarity is most pronounced in determining whether the project is ultimately realized, while the timing of dropout is governed more by additive effects of sustained engagement and adequate performance.

3.2.5 Summary of the educational project pursuit empirical model

In the first specification, I estimated a two-level mixed-effects logit model of successful course completion, defined as Pass or Distinction versus Fail or Withdrawn, using OULAD. Because all students in the sample have already initiated the project by enrolling, the model focuses on the continuation margin of Intertemporal Consistency and on Performance. I constructed Intertemporal Consistency as the average weekly share of active days in the VLE, and I measured Performance using assessment scores aggregated to the week level and residualized with respect to engagement, week fixed effects, and course fixed effects. This residualization is intended to isolate execution quality beyond what would be mechanically implied by activity alone. In the multilevel logit model, with random intercepts by course, both IC and Performance are positively associated with passing, and the interaction between them is positive and statistically significant. This is consistent with the PP complementarity prediction in final educational project realization.

The robustness checks for the course-completion model support this interpretation. First, the results remain stable when I control for the number of weeks with observed performance data. This is a demanding check because the number of observed performance weeks partly captures exposure and persistence in the course. Although the main IC coefficient becomes smaller, the interaction between IC and Performance remains positive and highly significant. Second, the results are robust to allowing nonlinearities through quadratic terms in IC and Performance. The interaction remains positive and significant, while the squared terms suggest diminishing marginal returns: consistency and performance continue to increase the probability of success, but their marginal contribution becomes smaller at higher levels.

A second set of robustness checks addresses the concern that Performance is assessment-based while course success is also partly determined by assessment outcomes. The core results remain similar when Performance is constructed using only the first two observed assessment periods, which reduces the risk that the variable simply summarizes end-of-course grading. They also remain stable when each student's final observed assessment is excluded from the Performance measure. Finally, when the sample is restricted to non-withdrawers and the outcome is Pass/Distinction versus Fail, IC, Performance, and their interaction all remain positive and statistically significant. These checks do not eliminate the fact that Performance is related to academic assessment, and the results remain descriptive rather than causal. However, they reduce the concern that the main completion results are purely mechanical. The evidence supports the interpretation that course realization is associated with both sustained engagement and higher-quality execution, and that the two dimensions reinforce each other in the final course outcome.

To test the PP approach from the perspective of project abandonment, I also model course withdrawal using a discrete-time hazard framework. I construct a student-course-week panel and estimate a complementary log-log model with week fixed effects and a course-level random intercept. The weekly probability of withdrawal depends on lagged cumulative IC, lagged cumulative Performance, their interaction, and student controls. In this setting, both lagged IC and residualized Performance are negatively associated with the hazard of withdrawal. This indicates that students who have been more consistently engaged, and students who have performed better relative to their level of engagement, are less likely to unregister in a given week. The interaction term is negative, as predicted by the PP framework for a withdrawal outcome, but it is not statistically significant. Therefore, the hazard model provides evidence that both PP dimensions separately reduce abandonment risk, but it does not provide clear evidence that they reinforce each other in determining the week-to-week timing of dropout.

The robustness checks for the hazard model support this more cautious interpretation. The negative associations of lagged IC and lagged Performance with withdrawal risk remain stable when controlling for the number of prior assessment observations. They also remain stable when Performance is measured using the most recent prior assessment rather than cumulative prior performance. These checks are important because the hazard model uses only information available before the week of risk, so the specification is temporally stronger than the course-completion logit. However, the interaction between lagged IC and lagged Performance remains statistically insignificant across these hazard specifications. Thus, the dynamic withdrawal models provide robust evidence that sustained engagement and prior performance separately reduce course-exit risk, but they do not provide robust evidence of complementarity in the timing of withdrawal.

Taken together, the two education specifications provide complementary evidence on educational project pursuit in OULAD. The course-completion model links higher Intertemporal Consistency and higher residualized Performance to higher realization probabilities, with a positive and statistically stable interaction consistent with complementarity in the final course outcome. The hazard model, by contrast, shows that both dimensions are associated with lower abandonment risk over the course timeline, but without statistically significant evidence of interaction in weekly withdrawal timing. This pattern suggests that complementarity between consistency and performance is more visible in final project realization than in the week-to-week decision to remain enrolled.

4 Discussion

This thesis introduced Project Pursuit as a framework for interpreting project realization through three behavioral margins: initiation, continuation, and performance. The framework is grounded in the idea that many projects require individuals to translate intentions into action, sustain project-consistent behavior over time, and execute project-related actions effectively. The two main economic concepts underlying the framework are intertemporal consistency and performance. Intertemporal consistency captures whether individuals act in line with forward-looking project goals rather than delaying or abandoning them, while performance captures the quality or effectiveness of project-consistent actions.

The empirical models were designed to test these ideas in two complementary data environments. In the entrepreneurship application, based on GEM, the main constraint is that the data are repeated cross-sections and do not follow the same individuals over time. As a result, the model cannot directly observe continuation after initiation. Instead, it focuses on the initiation margin: whether individuals who report entrepreneurial intentions also report taking concrete steps toward starting a business. This initiation proxy is interpreted as an empirical manifestation of intertemporal consistency at the intention-action margin. Performance is proxied by perceived entrepreneurial skills, which should be interpreted cautiously because it captures self-assessed capability rather than observed execution quality.

The entrepreneurship results are consistent with the main predictions of the PP framework. Both the Initiation proxy and perceived entrepreneurial skills are positively associated with early-stage entrepreneurial activity. The interaction between them is also positive and statistically significant in the preferred specification, suggesting that an initiation-conducive environment is more strongly associated with entrepreneurial realization among individuals who report higher entrepreneurial capability. However, this complementarity result is less stable across robustness checks than the main associations. The entrepreneurship application should therefore be interpreted as strongest evidence for the separate relevance of initiation and perceived capability, and as suggestive evidence for complementarity.

The entrepreneurship model also reveals meaningful cross-country heterogeneity. Countries differ not only in baseline levels of early-stage entrepreneurial activity, but also in the strength of the relationship between Initiation and entrepreneurial realization. This heterogeneity may reflect differences in institutions, culture, opportunity structures, financing conditions, or measurement. At this stage, the thesis does not identify the source of this heterogeneity. It instead shows that the PP framework can organize part of the variation in entrepreneurial realization while also pointing to the importance of country-level context.

The education application provides a stronger setting for observing continuation. In OULAD, all students in the sample have already initiated the project by registering for a course, so initiation is not the relevant empirical margin. Instead, the data allow student behavior to be observed repeatedly over the duration of the course. I therefore construct Intertemporal Consistency from weekly VLE activity and Performance from assessment outcomes residualized with respect to engagement, week, and course structure. This setting maps more directly onto the continuation margin of the PP framework than the entrepreneurship application does.

The course-completion model provides the clearest evidence for the PP framework. Both Intertemporal Consistency and residualized Performance are positively associated with successful completion, and their interaction is positive and statistically significant. This suggests that students are more likely to realize the educational project when they both engage consistently and perform well conditional on engagement. The robustness checks support this interpretation: the results remain stable under alternative constructions of Performance, controls for observed performance weeks, nonlinear specifications, exclusion of final assessments, and a pass-versus-fail specification among non-withdrawers. These checks reduce the concern that the education results are purely mechanical, although the performance measure remains related to academic assessment and should not be interpreted as exogenous.

The withdrawal model provides a complementary dynamic perspective. In the discrete-time hazard specification, lagged Intertemporal Consistency and lagged Performance are both associated with a lower weekly risk of withdrawal. This indicates that students who have been more consistently engaged, and students who have performed better relative to their engagement, are less likely to abandon the course in subsequent weeks. However, the interaction between lagged consistency and lagged performance is not statistically significant. Thus, the hazard model supports the separate importance of the two PP dimensions for reducing abandonment risk, but it does not provide clear evidence that they reinforce each other in the week-to-week timing of withdrawal.

Taken together, the two empirical applications show how the PP framework can be adapted to different data environments. GEM allows the initiation margin to be studied but not continuation within individuals. OULAD allows continuation and performance to be observed over time but does not study initiation, since students have already enrolled. Despite these differences, both settings show that the proposed PP proxies are associated with realization outcomes in the expected direction. The evidence for complementarity is strongest in the education completion model and more mixed in the entrepreneurship and withdrawal analyses.

The main limitation of the PP approach is measurement feasibility. The framework requires credible empirical proxies for initiation, continuation, or performance, and many datasets do not contain such measures. Some datasets observe intentions but not subsequent actions; others observe final outcomes but not the behavioral path leading to them. Even when behavioral traces are available, they may capture activity only imperfectly. For example, VLE clicks indicate engagement with the course platform, but they do not capture all forms of studying. Similarly, perceived entrepreneurial skills may reflect actual capability, but also confidence, optimism, or cultural response patterns. The PP framework is therefore most informative in settings where the data record repeated project-relevant actions, clear realization outcomes, and meaningful indicators of execution quality.

At the same time, the PP approach has a clear advantage as a conceptual organizing framework. It separates project pursuit into interpretable behavioral margins and encourages researchers to ask whether realization differences arise from failure to initiate, failure to continue, weak execution, or some combination of these. This decomposition can help structure empirical work that might otherwise rely on broad measures such as motivation, effort, or engagement without distinguishing the behavioral channels through which they matter.

Future research could apply the PP framework in other project settings. Job search is one natural application: individuals form intentions to find employment, take search actions, continue or stop searching over time, and vary in the quality of their applications or interviews. The National Longitudinal Surveys are especially promising for this purpose because they include longitudinal information on job-search methods, search intensity, and search outcomes. Online education provides another direct extension. Datasets such as HarvardX-MITx/edX, which contain de-identified information on online-course participation and outcomes, could be used to test whether the PP framework travels beyond OULAD. Business and management settings are also relevant. For example, the Kauffman Firm Survey follows new businesses over their early years and could be used to study continuation, survival, and performance after business formation. Establishment-level datasets such as the Management and Organizational Practices Survey could also be useful for studying how management practices relate to performance outcomes, although their mapping to individual project pursuit would require more care (Buffington et al., 2017). Research and development is another possible setting. Romer's discussion of technological change emphasizes that aggregate discovery depends on actions people take, rather than on calendar time alone (Romer, 1994. Page 12). This makes innovation a potentially relevant domain for PP, although the mapping would need to be developed carefully: more people engaging in research may raise aggregate discovery rates, but this does not automatically imply that additional effort by the same individuals has the same effect.

Cross-country applications are also possible, and existing comparative datasets provide measures that map closely onto the PP framework. The Global Preferences Survey provides cross-country measures of time preferences, including patience, which are directly relevant to the intertemporal-consistency dimension of PP (Falk et al., 2018). Hofstede's long-term orientation dimension captures cultural differences in future-oriented attitudes and preparation for the future, while the GLOBE project includes future orientation and performance orientation, with the latter explicitly capturing the extent to which a society encourages and rewards performance improvement and excellence (House et al., 2004). These measures can be interpreted as aggregate PP-related constructs: future-oriented measures correspond to the consistency side of the framework, while performance orientation corresponds to the performance side. The main empirical challenge is that these measures are broad and usually measured at the country level. They may describe the behavioral environment in which project pursuit occurs, but they do not by themselves show how specific individuals pursue specific projects. Future cross-country work would therefore need careful measurement, attention to within-country heterogeneity, and designs that reduce the risk of ecological interpretation.

Overall, this thesis was aimed at introducing and testing a conceptual framework for studying project realization outcomes through the behavioral margins of initiation, continuation, and performance. The empirical applications provide descriptive evidence that the framework is implementable and that its main dimensions are associated with project realization in the expected direction. The results should not be interpreted as causal, and the framework remains at an early stage of development. Nevertheless, the thesis provides a first implementation of the Project Pursuit approach and shows that distinguishing intertemporal consistency from performance can be useful for organizing variation in realization outcomes. Future research can refine the theoretical framework, improve the measurement of its components, and test it in additional settings with richer longitudinal data and stronger empirical designs.

5 Conclusion

This thesis introduced the Project Pursuit framework as a way to analyze project realization outcomes. The framework distinguishes three behavioral margins: the translation of project intentions into action, the continuation of project-consistent behavior over time, and the performance with which project-consistent actions are executed. The central idea is that project realization depends not only on whether individuals want to achieve a goal, but also on whether they act consistently toward it and how effectively they perform the actions required by the project.

The thesis leads to two main conclusions. First, the framework is empirically implementable. Although intertemporal consistency and performance are not always directly observed, they can be operationalized using context-specific proxies. In the entrepreneurship application, the initiation margin is measured through the share of entrepreneurial intenders who take concrete steps toward starting a business, while performance is proxied by perceived entrepreneurial skills. In the education application, intertemporal consistency is measured through repeated engagement with the Virtual Learning Environment, while performance is measured using residualized assessment outcomes.

Second, the empirical results suggest that the two Project Pursuit dimensions are informative for understanding realization outcomes. In the entrepreneurship model, both Initiation and perceived entrepreneurial skills are positively associated with early-stage entrepreneurial activity. In the education model, Intertemporal Consistency and Performance are positively associated with course success, and both are negatively associated with withdrawal risk in the hazard model. The evidence for complementarity is strongest in the course-completion model, where the interaction between consistency and performance is positive and statistically stable across robustness checks. In the entrepreneurship model and the withdrawal hazard model, the evidence for complementarity is more mixed and should be interpreted as suggestive rather than definitive.

The evidence in this thesis is descriptive rather than causal. The empirical models show that the proposed Project Pursuit proxies are associated with realization outcomes, but they do not identify causal effects of consistency or performance. The approach is also constrained by data availability. In particular, the entrepreneurship data do not follow the same individuals over time, so the model captures the initiation margin but not continuation through later stages of entrepreneurial pursuit. The education data provide a stronger setting for observing continuation, but the performance measure remains closely related to academic assessment outcomes.

Overall, the thesis provides an initial conceptual and empirical foundation for the Project Pursuit approach. Its main contribution is to separate project pursuit into interpretable behavioral margins and to show that these margins can be studied empirically across different settings. Future research could develop the framework more formally e.g., include a formal model of project pursuit, apply it to data that observe individuals over longer project trajectories, and use research designs better suited for causal interpretation. As a first application, the results suggest that distinguishing consistency from performance is a useful way to organize variation in why some projects are realized while others are not.

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Appendix

Alternative specifications for the Djankov test.

To test the relevance and specificity of the key PP proxy (Initiation) in entrepreneurship, I used the replication package by Djankov and colleagues (2010), who studied how corporate taxes rates affect investment and entrepreneurial activity across 85 countries. They used a cross-country panel data from 85 countries between 2003 and 2005 to analyze the effective corporate tax rate and its impact on four economic outcomes: 1) investment as a share of GDP; 2) foreign direct investment; 3) business density; 4) and business entry rate) on one tax rate at a time plus the log of annual tax payment same as in the standard model.

I extend each baseline specification by adding the Initiation key PP proxy, interpreted here as a country-level intention to action conversion measure. This extension serves two purposes. First, focusing on the business entry rate provides a test of whether the proxy predicts a conceptually related but distinct entrepreneurial outcome relative to GEM-based early-stage entrepreneurship (TEA). Second, the presence of three non-entry outcomes (investment, FDI, and business density) provides a test of specificity: if Initiation is primarily associated with entry rather than broader investment activity or the stock of firms, this pattern is consistent with a project-realization mechanism specific to entrepreneurial entry.

The main limitation of this exercise is that I use an average measure of Initiation from years 2011, 2014, 2015, 2016 and 2017, because earlier versions of the GEM dataset did not allow to unify a consistent Initiation dataset, due to data revisions by GEM. However, within country variance for Initiation was relatively stable during the 2011-2017 period. Using yearly values from the 2011-2017 instead of an average was unpractical because Djankov and colleague also used average value across three years (2003-2005) for their covariates.

$$Y_j = \alpha + \beta Tax_j + \theta \log\left(TaxPayments_j\right) + \delta Doer_j + \varepsilon_j$$

For each outcome and tax measure, Tables A1–A4 report the baseline replication estimate alongside the augmented estimate that includes Initiation. Columns (1), (3), and (5) reproduce the Djankov et al. specification for the statutory, first-year effective, and five-year effective tax rate, respectively. Columns (2), (4), and (6) add Initiation to the corresponding baseline.

Table A1: Taxes and Investment

Variable	(1)	(2)	(3)	(4)	(5)	(6)
Statutory corporate tax rate	-0.072 (0.076)	-0.104 (0.083)				
1st-year effective tax rate			-0.217*** (0.074)	-0.276*** (0.090)		
5-year effective tax rate					-0.247*** (0.080)	-0.285*** (0.091)
Initiation		-0.055 (0.606)		0.167 (0.575)		0.235 (0.577)
Constant	23.547*** (2.274)	24.512*** (2.490)	25.239*** (1.385)	26.402*** (1.693)	26.269*** (1.627)	27.070*** (1.868)
Observations	85	63	85	63	85	63
R-squared	0.011	0.025	0.093	0.136	0.104	0.140

*Standard errors in parentheses. * p<0.10; ** p<0.05; *** p<0.01.*

Table A1. Regression results investment specification. Own elaboration (2026).

In table A1 I present the original Djankov et al. (2010) investment specification with three types of taxes as covariates: 1) statutory corporate tax rate, 2) 1st-year effective rax rate, and 3) 5-year effective tax rate, and the PP proxy, consistency. The original Djankov specification is un every odd column (1, 3 and 5), and the extension in every even column (2, 4, and 6). The inclusion of the PP proxy increases the coefficients of all the tax variables and improves model fit; however, the PP proxy has a small effect size and is not statistically significant.

Table A2: Taxes and FDI

Variable	(1)	(2)	(3)	(4)	(5)	(6)
Statutory corporate tax rate	-0.195*** (0.046)	-0.175*** (0.049)				
1st-year effective tax rate			-0.226*** (0.045)	-0.207*** (0.056)		
5-year effective tax rate					-0.223*** (0.050)	-0.221*** (0.056)
Initiation		0.176 (0.358)		0.342 (0.358)		0.400 (0.356)

Variable	(1)	(2)	(3)	(4)	(5)	(6)
Constant	9.044*** (1.378)	8.382*** (1.469)	7.292*** (0.845)	6.982*** (1.054)	7.718*** (1.023)	7.617*** (1.153)
Observations	84	63	84	63	84	63
R-squared	0.180	0.177	0.233	0.189	0.196	0.207

*Standard errors in parentheses. * p<0.10; ** p<0.05; *** p<0.01.*

Table A2. Regression results FDI specification. Own elaboration (2026).

When FDI is the dependent variable, adding Initiation modestly attenuates the estimated tax coefficients. The Initiation coefficient is positive but imprecisely estimated and not statistically distinguishable from zero. Overall, the results do not suggest a robust association between Initiation and cross-country FDI once taxes and baseline controls are included.

Table A3: Taxes and Business density

Variable	(1)	(2)	(3)	(4)	(5)	(6)
Statutory corporate tax rate	-0.153** (0.063)	-0.122* (0.066)				
1st-year effective tax rate			-0.193*** (0.062)	-0.211*** (0.073)		
5-year effective tax rate					-0.200*** (0.068)	-0.194** (0.075)
Initiation		-0.639 (0.481)		-0.470 (0.467)		-0.442 (0.476)
Constant	9.473*** (1.864)	8.819*** (1.975)	8.394*** (1.162)	9.005*** (1.374)	8.913*** (1.375)	9.054*** (1.540)
Observations	80	63	80	63	80	63
R-squared	0.071	0.080	0.109	0.146	0.101	0.125

*Standard errors in parentheses. * p<0.10; ** p<0.05; *** p<0.01.*

Table A3. Regression results business density specification. Own elaboration (2026).

For business density, the Initiation coefficient turns negative and remains statistically insignificant, with comparatively large standard errors. This pattern suggests that the PP proxy is not strongly related to the stock of registered firms once taxes and baseline controls are accounted for.

Table A4: Taxes and Business entry

Variable	(1)	(2)	(3)	(4)	(5)	(6)
Statutory corporate tax rate	-0.127** (0.060)	-0.144** (0.060)				
1st-year effective tax rate			-0.137** (0.057)	-0.189*** (0.063)		
5-year effective tax rate					-0.136** (0.061)	- 0.197* ** (0.063)
Initiation		0.888* (0.457)		1.045** (0.447)		1.128* * (0.448)
Constant	11.812*** (1.790)	12.252*** (1.812)	10.452*** (1.048)	11.394*** (1.198)	10.771*** (1.262)	11.940* ** (1.323)
Observations	62	49	62	49	62	49
R-squared	0.070	0.170	0.089	0.218	0.076	0.228

Standard errors in parentheses. * p<0.10; ** p<0.05; *** p<0.01.

Table A4. Regression results business entry specification. Own elaboration (2026).

The business entry rate is the entrepreneurship outcome in Djankov et al. (2010). Here, adding Initiation yields a positive and statistically significant association across all three tax specifications. The magnitude is economically meaningful: a one standard deviation increase in Initiation is associated with substantially higher business entry rates, conditional on the tax measure and baseline controls. This is the only outcome among the four specifications for which Initiation shows a robust relationship.