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Rationality, socioeconomic stratum, and educational lag in Mexico

Racionalidad, estrato socioeconómico y rezago educativo en México

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Article information	**Abstract**

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Keywords: rationality, socioeconomic stratum, human capital, complementary *log-log* model.

Objective: Educational lag (EL) affects human capital and significantly limits economic growth and development.
Methodology: Using a cloglog model, we prove the theoretical hypothesis that individuals' rationality differs across socioeconomic strata: while individuals from lower strata are more likely to experience EL (4.3%), the opposite occurs for higher strata individual (-15.5%).
Results: We also found that, in the absence of any other variables, the probability of EL is as high as 20%; having children 24.3% (the highest in the model); and being male increases it by 9%.
Limitations: This work focuses on the factors that "pull" students away from formal educational institutions and the model only includes data from 2018.
Main findings: With scenario analysis, we demonstrate that a male from lower socioeconomic stratum, without access to healthcare and with children, faces 61% probability of EL, contrary to 37% for males with the same characteristics in the upper stratum.

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Información del artículo	Resumen
Recibido: 12 junio 2024 Aceptado: 23 mayo 2025 Clasificación JEL: C25, D01, J24, D91. Palabras clave: racionalidad, estrato socioeconómico, capital humano, modelo log-log complementario.	**Objetivo:** El rezago educativo (RE) afecta al capital humano y limita significativamente el crecimiento y el desarrollo económicos. **Método:** Utilizando un modelo cloglog, demostramos la hipótesis teórica de que la racionalidad de los individuos difiere según el estrato socioeconómico: mientras que los individuos de estratos más bajos son más propensos a experimentar RE (4,3%), ocurre lo contrario con los individuos de estratos más altos (-15,5%). **Resultados:** También descubrimos que, en ausencia de otras variables, la probabilidad de RE es del 20 %; tener hijos, el 24,3 % (la más alta del modelo); y ser hombre la aumenta en un 9%. **Limitaciones:** Este trabajo se centra en los factores que "alejan" a los estudiantes de las instituciones educativas formales y el modelo solo incluye datos de 2018. **Principales hallazgos:** Mediante análisis de escenarios, demostramos que un hombre de un estrato socioeconómico bajo, sin acceso a la atención médica y con hijos, tiene un 61% de probabilidades de sufrir RE, frente al 37 % de los hombres con las mismas características del estrato superior.

Introduction

Educational lag (*EL*) is a key indicator of social deprivation, for individuals born between 1998 and 2003 here analyzed, and affects a country's human capital, productivity and wages, potentially condemning it to slow long-term economic growth.

EL also applies to individuals who have not attained the mandatory level of education and are not enrolled in a formal educational institution (CONEVAL, 2021, 3).[1] On a national scale, according to the OECD (2023), 60% of the adult population in Mexico completed less than 12 years of education in 2018. However, the situation has worsened since then. Between 1990 and 2016, *EL* decreased from 26.6% to 18.5%, but the trend has since reversed, rising to 19.4% in 2022 (CONEVAL, 2021 and 2023). According to our results, our forecast, and recent available data, it is expected to increase further.

Identifying the variables that influence the decision to either not pursue education or drop out of school is crucial, because they significantly limit

[1] According to the National Institute for the Evaluation of Education (INEE, 2018), in 1993 the secondary education became mandatory in Mexico, with later reforms introducing the mandatory preschool education in 2004 and the high school education in 2012.

an individual's productivity and therefore their ability to earn higher incomes and to enhance economic growth and development. The Mincer equation (Mincer, 1974: 84) illustrates the positive linear association between education and wages.

High *EL* results in poor human capital, defined as the set of skills, knowledge, and other capabilities that negatively affect income, as well as both the quantity and the quality of life (Schultz, 1961). The theory of human capital (Schultz, 1961; Becker, 1993; Sobel, 1978) posits that education should be viewed as an investment, determined by a cost-benefit analysis.

While education undeniably has significant positive effects on economic growth and development, perceptions of its value differ across socioeconomic strata, which helps explain the varying outcomes of *EL*.

Becker and Mulligan (1997) argue that individuals vary in their abilities, desires, and, above all, their willingness to invest in education. They claim that low-socioeconomic strata individuals often prioritize immediate utility (high impatience) derived from work that provides instant income and consumption, whereas higher-socioeconomic individuals are more inclined to sacrifice short-run consumption and invest more years in education. These individuals, not burdened by immediate survival needs, are able to invest in education due to the support of their families, allowing them to wait longer for higher long-term returns.

We argue that, in both cases, the assumption of economic rationality holds, meaning that individuals make optimal decisions based on their expectations and information available to them. These factors, influenced by their socioeconomic status, lead individuals to perceive education as a distinct good or asset. Individuals from lower socioeconomic strata tend to prioritize securing employment at early ages and allocate most of their resources to immediate consumption, which limits their ability to invest in education. They generally perceive education as a highly uncertain investment, akin to a volatile asset with unpredictable returns. Schultz (1961) pointed out that, in underdeveloped regions, individuals with low incomes typically prioritize an early entry into the workforce and the accumulation of physical capital over investing in human capital, thereby limiting their educational opportunities in the short run and reducing the potential of improved living conditions in the long run.

It has been demonstrated that the initial socioeconomic and cultural conditions of a household have intertemporal consequences on work, education, accumulation of human capital, and preference for present consumption utility. All these factors may influence the intergenerational transmission of current socioeconomic strata (Schmelkes, 2022; Coughlin, 1989; Loría and Licona, 2022) and help explain the poverty traps that affect large lower socioeconomic groups in both developed and developing countries. In this way, when a household's socioeconomic conditions are low, the probability of not attending or dropping out of school early increases and is higher compared to upper socioeconomic strata.

Despite the adoption of educational reforms to expand compulsory education and official regulatory measures implemented in recent years to prevent school dropout;[2] idiosyncratic, socioeconomic, and geographical factors contribute more to the increase in *EL* in Mexico, Lizardo and Guzmán (1999). In addition to these factors, deeply ingrained socioeconomic narratives also influence people's behavior, potentially sustaining their living conditions over time, as noted by Shiller (2021).

Based on the classification by Doll *et al*. (2013) and on our findings, we claim the hypothesis that the socioeconomic stratum of a household, along with other characteristics of family heads, play a crucial role in shaping investment decisions in education, influencing individuals' likelihood of either remaining in school or dropping out, and ultimately contributing to *EL*. This is because rationality differs across socioeconomic strata. For individuals in lower strata, education may be perceived as a burden, whereas those in higher strata view it as an asset that enables social mobility in the long run. In this paper, we use socioeconomic stratification from ENIGH (2018: 36), which classifies households into four strata: low, lower-middle, upper-middle, and high, based on 24 indicators derived from the 2010 Population and Housing Census. Thus, we not only consider income levels but also a broader set of variables that collectively shape the behaviors of different socioeconomic strata.

We estimated a *complementary log-log* (*cloglog*) *model* for the year 2018, using 29,930 observations from the National Survey of Household Income and Expenditure (ENIGH, 2018). Our findings show that the probability of individuals born between 1998 and 2003 experiencing *EL* varies across socioeconomic strata.

[2] In the 2021-2022 academic year, giving failing grades to elementary and secondary school students was prohibited as a measure to mitigate school dropouts (DOF, 2022).

The factors that increase the probability of *EL*, in descending order, are: having children (24.3%), lacking access to healthcare (20.3%), being male (9.06%), belonging to a low socioeconomic stratum (4.31%), and age (1.47% for every year). Conversely, the probability of *EL* decreases for individuals belonging to high socioeconomic stratum households (-15.54%) and with each additional level of formal education attained by the head of the household (-4.08%).

Through scenario analysis, in which several variables are combined, we estimate that for males from low socioeconomic strata, who lack access to medical services and have children, the probability of *EL* increases to 61.30%. In contrast, for males from high socioeconomic strata with the same characteristics is 37.38%.

Although data for 2020 and 2022 are available, we chose not to conduct estimations for those years due to significant disruptions in information and in household perceptions caused by the pandemic and by the subsequent recovery, which substantially impacted households' economic situation and life expectations.

According to our hypothesis, 2018 can be considered the last year of a representative period in terms of school enrollment, as subsequent years have seen a declining trend in student registration. This phenomenon may be linked to the implementation of government programs such as *Jóvenes Construyendo el Futuro* (*Youth Building the Future*), which, while aimed at promoting youth employment, could have (unintended) effects on educational continuity.

Moreover, the COVID-19 pandemic was marked by multiple waves of high transmission rates that persisted until early 2023. The peak of daily confirmed cases (approximately 80,000) was recorded on January 17, 2022, followed by around 44,000 cases on July 11 of the same year (Secretaría de Salud, 2025).

According to the United Nations Development Programme (UNDP, 2022) and the OECD (2023), the pandemic had heterogeneous effects on school dropout rates, educational attrition, time devoted to studying, participation in extracurricular activities, and even the estimated returns on education. Furthermore, UNESCO (2022) highlights that schools in Mexico remained closed for 71 weeks, only gradually resuming in-person instruction. These impacts were heavily mediated by households' socioeconomic conditions, both pre- and post-pandemic—a finding that substantiates our hypothesis.

Such unprecedented disruptions complicated the collection of reliable statistical data and posed challenges for robust econometric inference. Consequently, we argue that data from 2020 and 2022 may reflect atypical agent behavior amid uncertainty, economic recovery, and adaptation to hybrid work-education models—a phenomenon whose full analysis falls beyond the scope of this study.

In effect, while estimating for those years, it generated atypical statistical and economic results that hindered reliable statistical inference. Therefore, we consider that the estimation for 2018 may best address our research problem, as it reflects long-term structural features.

The age range of the sample (individuals born between 1998 and 2003) was defined based on the recent increase in *EL*, the drop in school enrollment, and the limited attention historically given to young people, as noted by Currie (2019).

Although our estimate is based on 2018 data, our results allow for accurate forecasts, as supported by recent OECD (2025) data, which indicate a significant decline in school enrollment between 2019 and 2022: pre-primary (-13%), primary (-3.5%), and secondary (-7.5%).

The article is organized as follows. Section 1 addresses theoretical issues. In section 2, we review the relevant literature. Sections 3 and 4 present the econometric analysis along with the discussion. Finally, section 5 concludes and provides additional insights.

1. Theoretical Issues

Schultz's (1961: 1) seminal work defines human capital as the accumulation of "useful skills and knowledge" that individuals possess, enabling them to perform tasks more efficiently, increase their income, and, ultimately, achieve better living conditions. Formal education plays a crucial role in these outcomes, allowing individuals to develop and adopt more efficient production processes, which, in turn, leads to higher productivity and greater remuneration.[3] Therefore, in general terms, allocating resources to attend an educational institution should be

[3] Other factors that the author takes into account include access to healthcare services, on-the-job training, and adult education programs.

considered an economically rational decision and viewed as an investment in human capital.

In economics, education has long been a central topic of interest due to its positive developmental effects at both individual and collective levels. Herrero and Loaiza (2021), Hanushek and Wößmann (2010), Heckman (2011), and Delalibera and Ferreira (2019) point out that education drives long-term productivity gains, making it a positive structural factor in economic growth and development. At the individual level, Becker (1962) introduced the concept of rationality derived from the rate of return on investment in education. Subsequently, Mincer (1974) popularized this idea by estimating a wage function that positively correlates years of education and work experience (Heckman *et al*. 2006). According to Becker's (1993) hypothesis of economic rationality, individuals choose to invest in education when they perceive that the expected future benefits (returns) outweigh the associated costs. These direct costs include the expenses related to attending an educational institution, along with the opportunity cost of forgoing potential short-term earnings in the labor market, while allocating time and resources to education.

However, the issue lies in the existence of different rationalities depending on an individual's socioeconomic stratum, which leads to varying investment calculations and, more importantly, distinct perceptions of the profitability of education. Becker and Mulligan (1997) demonstrate that preferences and uncertainty vary among individuals and countries, as they are shaped by an array of factors such as culture, wealth, mortality, among many others.[4]

Therefore, rationality cannot be considered homogeneous; rather, it is shaped by diverse socioeconomic conditions and individuals' perceptions. Specifically, individuals from lower socioeconomic strata perceive education as a potential burden, viewing it as an investment in a highly uncertain asset, both in terms of returns and time, and one that deprives them of a stable income in the short term. On the other hand, individuals in more favorable circumstances view education as an asset (a normal good) with lower uncertainty regarding its long-term returns. In contrast, the calculation of investment costs is more straightforward, as it involves

[4] Lawrence (1991) found that the preference for current utility among low-income households is 3% to 5% higher than that of high-income households.

a clearer estimation of the resources required to obtain different academic degrees.

For the sake of clarity, we formalize a theoretical model that integrates two distinct types of rationalities, which form the basis of our entire conceptual and empirical framework. Starting from the workers' optimalization condition ($w_t = PMgL_t$) and by assuming that, from the initial period ($t = 0$), an individual invests all their time in academic training, they incur opportunity costs –such as the utility lost associated to income and leisure– to which direct training expenses are added.[5]

Therefore, investment in education hinges on the subjective estimation of uncertain variables, particularly future returns. If preferences satisfy the assumptions of completeness, reflexivity, transitivity, monotonicity, and convexity, different socioeconomic groups' choices can be explained by factors such as budget constraints, short-term household needs, expectations, and varying intertemporal calculations, which largely depend on their conditions of origin, de Jonge (2012: 9).

Given the above and their lower uncertain returns on education, individuals from higher socioeconomic strata view education as a normal good. This leads them to prioritize high levels of education, as they can afford greater expenses and endure longer waits before entering the labor market, thanks to their more favorable family circumstances. Conversely, individuals from more disadvantaged backgrounds face greater daily needs and uncertainty when calculating future returns from education. As a result, they tend to prioritize current utility over greater uncertainty. Viewed through the lens of the microeconomic theory (Varian 2010: 251), education could be considered a highly uncertain asset for these individuals compared to their basic immediate needs. Consequently, their expected returns (R) exhibit higher variance and uncertainty. Rationally, they are more likely to opt for assets that have more immediate and secure returns compared to individuals in better socioeconomic conditions. All the above can be expressed as follows:

$$\sum_{t=0}^{n} \frac{R_t}{(1+i)^t} = \sum_{t=0}^{n} \frac{C_t}{(1+i)^t} \tag{1}$$

The term on the left represents the sum of future total labor income *(R)* discounted by the interest rate, while the one on the right represents total costs *(C)* over t periods.

[5] This accounts for the essential expenses of an individual to attend school, including tuition and other fees, uniforms, school supplies, food, and transportation.

We can easily incorporate expectation and uncertainty (θ), rather than interest rate to discount the calculated returns on education investment and, thus, have an expression more aligned with our hypothesis:

$$E\left[\sum_{t=0}^{n}\frac{R_t}{(1+\theta)^t}\right]=\sum_{t=0}^{n}\frac{C_t}{(1+\theta)^t} \tag{2}$$

By doing so, the term on the left now represents the mathematical expectation of future returns (R_t), adjusted by a discount rate (θ) that reflects the subjective perception of risk, impatience and uncertainty. This discount rate is not easily estimated and depends on a set of "pull" factors, which we will explore shortly. On the other hand, the right side represents the updated total costs of investment in education, which is much more predictable and quantifiable than the first.

The basic idea of equation (2) is that the decision to drop out is rational, meaning that reduced expectations, increased costs, or greater impatience are key determinants of school dropout.

If we consider the arguments proposed in equation (2), in the early stages of education, income expectations and costs are lower, making economic support more effective in preventing dropout. However, as students' progress through the education system, educational costs increase, and if the quality of education fails to improve either their human capital or their income expectations, then support programs will no longer be able to restore the equilibrium in equation (2), leading to higher dropout rates.

In this way, we can understand why Oreopoulos (2007) found that each additional year of schooling reduces the probability of receiving public assistance. This suggests that gains in productivity and income resulting from education make individuals less dependent on long-term transfers to meet their needs. Alternatively, the level of support required to keep students in school becomes increasingly higher, making such resources scarcer over time. Eckstein and Wolpin (1999) show that a deterioration in future income expectations raises the probability of school dropouts.

To integrate these ideas, and assuming there are only two lifetime periods, individuals' lifetime utility can be expressed as:

$$U_V=\theta U_t+[1-\theta]U_{t+1} \tag{3}$$

Following Becker and Mulligan (1997), individuals from lower socioeconomic strata tend to prioritize immediate consumption due to higher impatience, making θ close to 1. Conversely, individuals from higher socioeconomic households experience less uncertainty and, therefore, greater patience, which results in a lower θ.

Haushofer and Fehr (2014) argue that individuals from lower socioeconomic strata experience significant psychological effects, leading to limited future vision (short-sightedness) and increased impatience when individuals make intertemporal choices. As a result, they become less inclined to pursue "risky" long-term investments, such as education. Unfortunately, if this happens, it perpetuates and widens the inequality in education and income across different income groups over time, which hinders social mobility, potentially leading to a poverty trap, Loría and Licona (2022), Loría (2020: 278).

Cárdenas and Zúñiga (2017: 84-89) show that adverse out-of-school factors linked to socioeconomic conditions have strong impacts on *EL*. They found that parents with low levels of education that have jobs located far from their homes and work long hours with low wages provided little support for children's school activities. As a result, by prioritizing short-term attention to basic needs to subsist, low-income parents often exhibit limited incentives and interest in their children's school attendance and academic achievement. Domestic violence, family breakdown, addictions, and lack of access to medical attention are also cited as additional factors influencing *EL*. Mendoza and Zúñiga (2017) identified both intra- and extra-school factors that increase *EL*, especially those related to parents' educational attainment and income, as well as their children's academic interest.

2. Literature Review

Watt and Roessingh (1994), Jordan *et al*. (1996) and Doll *et al*. (2013) point out that factors influencing school dropout rates can be categorized into three main groups. The first category includes "push" factors, which are determined within the classroom environment. These include relationships between peers and teachers, infrastructure, teaching models, human resources available within the institution, and disciplinary measures implemented to address inadequate performance. The second group–"pull" factors– include household income and household conditions, the educational level of the household head and additional responsibilities beyond school, such as employment, caring for family members, marital status, and parenthood. Finally, the third group consists of "falling out" factors, including students' behavior related to their academic activities and grades, which may result in disinterest and, ultimately, failing. Due to the availability of official data and the focus of our research, our attention is exclusively directed towards "pull" factors, which relate to socioeconomic strata and rationality of households as estimated in our *cloglog* model.

In terms of our hypothesis, we found several key references. For urban households in Argentina, Boniolo and Najmias (2018) demonstrated that children from lower-middle and unskilled working-class children have a 29% and 73% higher likelihood of experiencing *EL* than those in higher-stratum families. They also found that female children have 44.7% less probability of experiencing *EL* than male children. On the other hand, the authors noted that young people whose parents have incomplete upper secondary education are twice as likely to have *EL* than those with parents who have attained higher levels of education.[6]

To show that higher-income individuals perceive greater returns from education, Harmon *et al*. (2003:149) demonstrated that, in the UK, individuals in the highest deciles earn higher incomes for each additional year of education compared to those in the lowest deciles.

Hu (2021) argued that in China lower-income households have fewer incentives and allocate fewer resources toward human capital accumulation. The author emphasized that this phenomenon also prevails in developing economies, where household incomes are the primary source of education funding and where credit constraints are more pronounced.

In Ecuador, Barrionuevo (2022) used a comprehensive set of variables[7] and discovered that, in single-parent households, the likelihood of *EL* occurrence increases, while parental educational attainment reduces it.
Ali *et al.* (2021) showed that the probability of primary school dropout in Pakistan depends on the age and gender of the household head, the family's income level, and the number of income earners. When a man heads a household, the probability of school dropout decreases by 15.8%, because men tend to have higher incomes.

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[6] These results are fully consistent with our econometric estimates.
[7] Such as education, age, sex, ethnicity, and household head characteristics. Other additional important variables are per capita income, housing infrastructure, and a social program beneficiary status.

For Mexico, Alcaraz (2020) found that parental education was the most significant variable in determining the probability of high school dropouts, followed by the household income. The study showed that high school students —whose parents had completed the same level of education— were 35% less likely to drop out prematurely compared to those whose parents had only completed primary or secondary education. Similarly, young individuals whose parents attained higher levels of education exhibited a 58% lower probability of dropping out compared to those whose parents completed only primary education or less. Mora (2010) argued that, in addition to the socioeconomic status of the household, factors such as students' health status, access to healthcare services, and social security also play a crucial role.

3. Econometric Issues

We used microdata from the National Household Income and Expenditure Survey (ENIGH, 2018), which provides individual-level information relevant to our research focus. After filtering for age, we obtained 29,930 observations.

Standard qualitative binary response models are estimated using maximum likelihood, with the most used being logistic regression (*logit*), probit regression (*probit*), and complementary *log-log* regression (*cloglog*). The difference between these models lies in their cumulative distribution function. The *cloglog model* assumes an asymmetric distribution of the dependent variable, Cameron and Trivedi (2009: 446). The probability function of a *cloglog model* is defined as:

$$C(x'\beta) = 1 - exp\{-exp(x'\beta)\} \tag{4}$$

where $C(\cdot)$ is the asymmetric cumulative distribution function and β represents the estimated parameters that enable the calculation of the marginal effects of changes in the regressors on the conditional probability, based on the following function:

$$\frac{\partial y}{\partial x_i} = exp\{-exp(x'\beta)\}exp(x'\beta)\beta_j \tag{5}$$

Explanatory variables are expressed in vector X (x_i) of dimension $k \times 1$; $F(\cdot)$ is a cumulative distribution function of $x'\beta$. The dependent variable y_i is defined as:

$$y_i = \{1,\ 0, i - nth\ person\ has\ EL; i - nth\ person\ does\ not\ have\ EL\} \tag{6}$$

Table 1
Variables description

Variable	Definition	
el[1]	1: Educational lag 0: No educational lag	
age[2]	15-20 years old	
sex	1: Male 0: Female	
medatt	1: No medical attention 0: Medical attention	
strat_l[3]	1: Low socioeconomic household stratum 0: Lower-middle, upper-middle, and high socioeconomic household stratum	
strat_h	1: High socioeconomic household stratum 0: Low, lower-middle, and upper-middle socioeconomic household stratum	
educ_j[4]	1: No schooling 2: Preschool 3: Incomplete primary education 4: Complete primary education 5: Incomplete secondary education 6: Complete secondary education	7: Incomplete high school 8: Complete high school 9: Incomplete professional education 10: Complete professional education 11: Postgraduate
children	1: Has children 0: Does not have children	

[1] According to CONEVAL (2021), *EL* is defined as a situation in which a person lacks "a compulsory educational level and does not attend a formal educational institution."
[2]. A discrete non-binary variable indicating the age of the individual.
[3] This classification was defined based on socioeconomic characteristics of individuals, as well as physical characteristics and household amenities, represented by 24 indicators derived from the 2010 Population and Housing Census. This stratification was conducted using multivariate statistical methods, INEGI (2018: 36), classifying households into four strata: low, lower-middle, upper-middle, and high. For our purposes, we classify the first stratum as low, and the other three as high.
[4]. A discrete non-binary variable representing the educational level of the head of the household.
Own elaboration with data from INEGI (2018).

By incorporating the independent variables, we obtain the following conditional expression:

$$C = 1 - exp[(-exp\ (\beta_0 + \beta_1 age_i + \beta_2 sex_i + \beta_3 medatt_i + \beta_4 strat\_l_i + +\beta_5 strat\_h_i + \beta_6 educ\_l_{\mathrm{i}} + \beta_7 children_i)] + \varepsilon_i \tag{7}$$

Initially, we estimated a *logit* model, which revealed distributional problems according to the Hosmer-Lemeshow (Hosmer *et al*. 2013) and Stukel (1988) tests.[8] It should be noted that both *logit* and *probit* models

[8] The Hosmer-Lemeshow test is used to assess the goodness-of-fit for logistic regression models. It is calculated using a chi-squared test that compares the observed and the expected counts of 1's in the dependent variable across deciles of the data. A *p-value* below 0.05 indicates that the model does not fit properly. Therefore, the Stukel test serves as an alternative goodness-of-fit measure for the logit model and shows if the predicted probabilities significantly differ from the observed event frequencies. It compares the deviance of residuals from the fitted logistic model to a chi-squared distribution and is more reliable than the Hosmer-Lemeshow test, as it is less sensitive to the size of the sample. In this case, a small *p-value* also indicates that the model's predictions do not align with the observed outcome (Hosmer *et al*. 2013: 157-160, 438-439).

assume a symmetric cumulative distribution function. Given the frequency distribution of our dependent variable (Table 2) and the results of the Hosmer-Lemeshow and Stukel tests, their application is not suitable.

Although the approach proposed by Dong and Lewbel (2015) allows for addressing endogeneity issues in binary choice models, it yields less precise estimates due to its more flexible assumptions compared to other correction techniques, such as two-stage least squares, maximum likelihood, and control functions (Baum *et al*. 2012). Therefore, considering the results of the Hosmer-Lemeshow and Stukel tests, we find that the *cloglog* model yields more precise and robust estimates for calculating marginal effects and scenario analysis.

The choice of a *cloglog* specification is theoretically and empirically justified in this context for the following reasons:

1. Asymmetry in the response curve. Unlike *logit* or *probit* models, which assume symmetric distributions (logistic and normal, respectively), the *cloglog* link accounts for asymmetry in the probability of the outcome. This is particularly suitable when the underlying process reflects a natural imbalance –for example, when the probability of the event is inherently low or increases more sharply under certain thresholds.
2. Failure of Standard Binary Models (*logit/probit*). The *logit* model's poor performance in Hosmer-Lemeshow and Stukel tests indicates a misspecification in the link function, likely due to unaccounted nonlinearities or asymmetry in the data-generating process. The *cloglog* model, with its skewed distribution, often provides a better fit in such cases, especially when the outcome is rare or tied to an underlying hazard process (Prentice, 1976).
3. Count Data Alternatives (Poisson/Negative Binomial). While Poisson and negative binomial regressions are standard for count data, they are unsuitable here. These models require non-negative integer outcomes, whereas the dependent variable is binary. Moreover, overdispersion (addressed by the negative binomial model) is irrelevant for binary outcomes (Cameron and Trivedi, 2013:10). In contrast, the *cloglog* model, derived from continuous-time hazard models, is better suited for duration-dependent processes, such as the cumulative "risk" of dropout over time.
4. Theoretical alignment with duration processes. If the outcome (*EL*) is influenced by time-dependent covariates or unobserved

thresholds (temporary disruptions), the *cloglog*'s foundation in extreme-value theory (Gumbel distribution) makes it ideal for modeling "rare events" or latent triggering mechanisms (Collett, 2003).

5. Empirical Precedents. Similar applications in economics (Heckman, 1979) and epidemiology favor *cloglog* when the data reflect underlying cumulative risks –consistent with this study's focus on determinants like income shocks or cost constraints.

Table 2 shows that the distribution of the dependent variable is asymmetric, with 28% of observations with $y_i = 1$, making the *cloglog model* the most appropriate estimation method, as it assumes an asymmetric cumulative distribution function. Estimation results and the calculated marginal effects are presented in Tables 3 and 4.

Table 2
Proportion of the dependent variable

	Frequency	Proportion
$y_i = 0$	21,547	72%
$y_i = 1$	8,383	28%

Table 3
Estimation results

logit

Variable	Coef.	Std. Err.	z	*p*
age	.0978847	.0088616	11.05	0.00
sex	.553178	.0312136	17.72	0.00
medatt	1.187118	.0342055	34.71	0.00
strat_l	.2867407	.0322374	8.89	0.00
strat_h	-.7646969	.1125371	-6.80	0.00
educ_j	-.2685264	.0075567	-35.53	0.00
children	1.742514	.0542081	32.14	0.00
c	-2.598684	.1625983	-15.98	0.00

R^2 = 0.1852, HL = 58.27(0.00), Stukel* = 99.42 (0.00)

*Where za = $(x'\beta)2 \geq 0$ is the extreme right-hand value and zb = $(x'\beta)2 < 0$ is the extreme left-hand value.

cloglog

Variable	Coef.	Std. Err.	z	*p*
age	.0722535	.006921	10.44	0.00
sex	.4454887	.0254146	17.53	0.00
medatt	.9992961	.0298834	33.44	0.00
strat_l	.2120158	.0242814	8.73	0.00
strat_h	-.7638945	.1042592	-7.33	0.00
educ_j	-.2007683	.0057054	-35.19	0.00
children	1.194369	.0361582	33.03	0.00
c	-2.463463	.1279644	-19.25	0.00

In both cases, all parameters are significant at 99% and exhibit correct signs. Given the previously mentioned distribution issues, we calculated the marginal effects exclusively from the *cloglog model*.

4. Discussion

The marginal effects show that the probability of *EL* increases in the following order: a) having children (24.3%), b) lacking access to healthcare (20.3%), c) being male (9.06%), d) belonging to a low socioeconomic stratum (4.31%), and e) increasing age (1.47% for each additional year). Conversely, the probability of *EL* decreases under two conditions: when an individual belongs to a household of a high socioeconomic stratum (-15.54%) and with each additional level of formal education attained by the head of household (-4.08%), Table 4.

All these results are consistent with both our hypothesis and literature review.

Table 4
Marginal effects of the *cloglog model*

el	$\frac{\partial y}{\partial x}$	St. err.	z	p
age	.0147021	.0014023	10.48	0.00
sex	.0906476	.005104	17.76	0.00
medatt	.2033358	.0058751	34.61	0.00
strat_l	.0431408	.0049205	8.77	0.00
strat_h	-.1554365	.0212181	-7.33	0.00
educ_j	-.0408521	.0011024	-37.06	0.00
children	.243029	.0069471	34.98	0.00

Specifically, the value of the parameters $strat\_l$ (0.0431) > $strat\_h$ (-0.1554) clearly supports our hypothesis that socioeconomic stratum conditions, which are associated with other key variables, reflect the rationality of the two selected socioeconomic groups.

Finally, we performed a scenario analysis to evaluate the varying probabilities of *EL* based on different combinations of independent variables for both socioeconomic strata, Table 5.

The *baseline* scenario indicates that, without accounting for any other variable, the probability of *EL* for both sexes is 22%, which demonstrates the high inherent likelihood of not entering or dropping out of the formal education system. However, when additional variables are incorporated to build several scenarios, we obtain surprising outcomes, particularly in terms of notable marginal deterioration. For instance, scenario (4) –which combines being male from a low socioeconomic stratum, having children, and having no access to medical services– raises the probability of EL to 61%, significantly above the 37% observed for males from a high socioeconomic stratum (scenario 7).

Table 5
Scenario analysis, by socioeconomic stratum

Scenario Low stratum	$\frac{\partial y}{\partial x}$	Difference from base scenario
(1) *Base line*	21.75%	-
(2) $age + sex + strat\_l$	15.01%	-6.74
(3) $age + sex + strat\_l + medatt$	32.42%	10.67
(4) $age + sex + strat\_l + medatt + children$	61.30%	39.55
High stratum		
(5) $age + sex + strat\_h$	6.24%	-15.51
(6) $age + sex + strat\_h + medatt$	15.31%	-6.44
(7) $age + sex + strat\_h + medatt + children$	37.38%	15.63

We observe that in scenarios (5)-(7), men from high socioeconomic stratum households exhibit a lower probability of EL. This confirms our hypothesis that differences in socioeconomic strata lead to vastly different –and in our case, opposing– outcomes driven by rational choice.

This point is crucial as it highlights that, in all cases, being male increases the probability of EL. Granados (2020: 43-46) found that in Mexico, the lower incidence of EL among women can be attributed to their being better covered by social programs and by their caregiving responsibilities for other family members. Almås *et al*. (2016) found that in Norway young women are better informed about the labor market and are more likely to continue their studies to better integrate into it. On the other hand, while men tend to be more competitive in the labor market, they also exhibit more rebellious traits that can affect their academic performance. According to Cavaco *et al.* (2021: 6) both in Norway and in other EU countries, the men/women gap is: 7.5% in Latvia, 7.1% in Cyprus, 6.6% in Malta, 6.9% in Estonia, and 6.9% in Portugal. Boniolo and Najmias (2018) also confirm that gap for Argentina.

Finally, Suberviola-Ovejas (2024) claim that the early school dropout rate for males in Spain was 16.5%, while for females it was 11.2% in 2023. She explains that this gap reflects the stronger intention of young women to continue their studies because they perceive obtaining an academic degree as the key to unlocking better professional opportunities. This, in turn, enables them to develop an independent life plan, distancing themselves from gender-based violence.

5. Conclusion and Further Comments

After a prolonged decline from 1990 to 2014, official data from CONEVAL (2023) indicate that *EL* began to increase again after 2016, reflecting an already significant deterioration in human capital accumulation, which, in turn, contributed to low productivity and stagnant wages.

Based on our analysis, investing in human capital is a rational choice, whereby behaviors vary based on socioeconomic strata. Individuals who do not allocate resources to invest in education do so because they deal with immediate survival needs and perceive the potential future higher income after accumulating more human capital as highly uncertain. This stands in contrast with individuals from higher strata, who view education as a normal good and do not have immediate survival needs. The important part of this hypothesis is that, in both cases, these outcomes stem from rational decisions made by individuals based on their specific circumstances.

We estimated a *cloglog model* for the year 2018, due to the years 2020 and 2022 were highly contradictory, both statistically and economically. These inconsistencies can be attributed to disruptions in data collection and to shifts in households' perceptions and expectations due to the pandemic and the subsequent recovery of activities. Hence, we selected 2018 as the most reliable year to test our hypotheses.

We filtered and refined the entire sample –based on age criteria– from the 2018 National Household Income and Expenditure Survey (ENIGH, 2018), resulting in 29,930 individuals.

To ensure precision, we present the most relevant econometric results:

1. We extensively prove our hypothesis that individuals from lower socioeconomic strata have a higher probability of experiencing *EL* (4.3%), compared to those from more advantaged backgrounds, who even exhibit a negative probability (-15.5%). We attribute these differences to rational decision-making.
2. When calculating the marginal effects, we find that, in the absence of other variables, there is a high baseline probability of *EL* (20%), underscoring the significant socioeconomic strata outcome.

3. We found men are 9% more likely to experience *EL* than women, which can be attributed to the need to enter the labor market early and the fact that they have less access to social programs compared to women. The same occurs for some other countries here mentioned but might be attributed to some other reasons.
4. The stratum condition is also reflected in the educational level of the head of the household, which reduces the probability of *EL* by 4.08%. This may help explain the intergenerational effects of *EL*, as discussed by Alcaraz (2020) and Loría and Licona (2022) for the case of poverty.
5. Having children is associated with the highest probability of *EL* in the model (24.3%).

Given our main goal, as well as the availability of survey data, one of the limitations of this work might be that it only focuses on the "pull" factors as well as we only use data for the year 2018. Nevertheless, we included a broad set of variables that allows us to focus on the most relevant factors to test our hypothesis, while minimizing the risk of omitted variables and "unobserved factors".

By taking these steps, we attained robust statistical representation. We selected 29,930 individuals from the 2018 National Household Income-Expenditure Survey after filtering for age (born 1998-2003) to accurately reflect the characteristics of the target population relevant to our hypothesis. Furthermore, the ENIGH (2018) is representative at the national and state levels, which ensures that the characteristics of the population are accurately reflected within the sample.

Our results are both statistically and economically robust, and furthermore they are highly concerning because the literature suggests that *EL* limits productivity, income, and economic growth, potentially leading to a low-development trap.

While the results are based on a young population, it is important to note that, according to the OECD (2023), in 2018, 60% of Mexican adult population attained less than 12 years of education. This reflects the limited human capital, which, in turn, explains low wages and high levels of poverty and inequality, which prevail across large segments of the Mexican population.

Our estimates for 2018 provide a strong explanation (forecast) for the increase in *EL* by 2022, because of the impact of all socioeconomic variables here analyzed and estimated, during the 2020 pandemic, and, most importantly, due to its long-term effects.

UNDP (2022) reports that during the pandemic school attendance among individuals aged 12 to 22 decreased in Mexico, as men increasingly assumed the role of the household provider, while women faced greater burdens of domestic and caregiving responsibilities, further exacerbating *EL*. Recent OECD data (2025) indicate a significant decline in school enrollment for 2019-2022: pre-primary (-13%), primary (-3.5%), and secondary (-7.5%). This recent development is consistent with our analysis and econometric results. Accordingly, the following recommendations are made: a) allocate institutional resources to public, sexual, and reproductive health initiatives in areas with a high concentration of young individuals from low socioeconomic backgrounds; b) make targeted efforts to reintegrate young people who dropped out of the education system due to the 2020 lockdown, thereby mitigating the risk of intergenerational recurrence of this issue.

While the positive effects of education are evident in the long term, *EL* is a pressing issue that also has short-term implications and reflects the significant constraint for economic growth due to the lack of capacity and quality within the Mexican workforce.

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