

UNIVERSIDAD LOYOLA ANDALUCÍA



TESIS DOCTORAL

“Lab-in-the-field experiments on inconsistency,
delay discounting, and homophily”

Doctorando/a: Gladis Herminia Gonzales Aguilar

Directores: Pablo Brañas-Garza

Antonio Alfonso Costillo

Tutor/a de Doctorado: Diego Andrés Jorrat

- Mención de Doctorado Internacional

Córdoba, 2025

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Lab-in-the-field experiments on inconsistency, delay discounting, and homophily

Gladis Herminia Gonzales Aguilar

A dissertation submitted in fulfillment
of the requirements for the degree of
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April 17, 2025

I, Gladis Herminia Gonzales Aguilar, confirm that the work presented in this thesis is my own. Where information has been derived from other sources, I confirm that this has been indicated in the work.

*Lo que antes era un sueño imposible de alcanzar,
hoy se materializa con la entrega de esta tesis.*

Para mis padres,
Gladys Aguilar y Andrés Gonzales

“El futuro pertenece
a quienes creen en la
belleza de sus sueños.”

- Eleanor Roosevelt

Abstract

This thesis contributes to the literature on adolescent preferences through field experiments, exploring their relationship with personal characteristics such as cognitive skills, academic performance, and educational expectations. Additionally, certain aspects of their school environment are explored, which may or may not influence their decision-making process. A particularly relevant aspect is the role of social interactions, and the relationships adolescents form within their school environment. In this regard, part of this thesis focuses on the phenomenon of link formation, analyzing how they form links with those who share similar characteristics. This process of forming links with those who are more similar is known as homophily, a key factor in the dynamics of social relationships within the school environment.

The studies are based on data collected in two countries, Spain and El Salvador, during the years 2022 and 2023, using a “Lab-in-the-field” methodology. The sample focuses on adolescents from 33 schools in Spain and 12 in El Salvador. The data was collected following the same protocols for gathering, tasks, and tools¹. It is important to highlight the use of tasks traditionally used to elicit economic preferences and aspects of decision-making in adult populations, adapted with strong visual components to collect these data in adolescents. In addition to tasks related to economic preferences, cognitive skills, academic performance, and social interaction, sociodemographic data and other complementary tasks were obtained.

¹See Chapter 2 for more details.

In Chapters 3, 4, and 5, sub-samples of the available data are used to address specific aspects of economic preferences and network formation among adolescents.

Below is a summary of each chapter:

Chapter 3: This chapter analyzes the *inconsistency* of responses when completing two tasks traditionally used to elicit temporal discounting and risk preferences. A sample of 2,248 Salvadoran adolescents is used to explore how factors such as age, cognitive abilities, and task repetition influence decision-making consistency and how these inconsistencies may affect their educational expectations. The results show that only 27% of the sample was consistent in both tasks, and those with better performance in cognitive skills and probability measures were less likely to make inconsistent decisions. In our sample, task repetition, in general, does not improve consistency. Additionally, it was found that those who were more inconsistent had worse short- and long-term educational expectations than their more consistent peers.

Chapter 4: This chapter focuses on the relationship between *delayed gratification* and *work ethic* among 4,005 Spanish adolescents. Experimental tasks are used to assess how delayed gratification correlates with performance on tasks that require effort. Temporal preferences are elicited to measure delayed gratification, and the alternative uses task of Guilford is used as an effort task. Furthermore, this analysis sheds light on how cognitive traits such as academic performance and reflection influence work ethic, particularly in relation to delayed gratification. The results show that individuals who delay gratification not only perform better on the task, providing more uses but also perform better by proposing more unique uses and avoiding repetition in their responses.

Chapter 5: This chapter explores *social network formation* in El Salvador, using 7,419 observations collected over three different periods on 3,726 students. These data were used to create potential links that could form in a school network. This study explores how homophily – in terms of both observable and unobservable traits

– shapes peer relationships in a school environment, examining observable characteristics (e.g., gender, class) and unobservable characteristics (e.g., risk preferences, future educational aspirations) in the formation of positive (friendships) and negative (enmities) links. For this analysis, Bayesian Model Averaging (BMA) is used. The study finds that both for friendships and enmities, observable characteristics remain robust, specifically having been friends/enemies in a previous period, having the same gender, and being in the same class. For friendships, other unobservable factors are relevant, such as having a similar income, risk preferences, aspirations to work in a technical profession in the future, as well as a shared desire to attend university and achieve good results in science, technology, engineering, or mathematics (STEM) disciplines. Regarding negative links, only the fact of having doctor as the same expected future profession might play a role, as it loses significance. Therefore, at least in our sample, negative links appear to be influenced by mechanisms distinct from homophily.

In conclusion, the integration of findings from the various areas mentioned in this study contributes to the design of educational interventions that have the potential to improve long-term outcomes, both in terms of academic performance and social integration.

Resumen

La presente tesis contribuye a la literatura sobre las preferencias de los adolescentes mediante experimentos económicos en campo, explorando su relación con características personales como habilidades cognitivas, rendimiento escolar y las expectativas educativas. Además, se exploran ciertos aspectos de su entorno escolar, que pueden influir, o no, en su forma de tomar decisiones. Un aspecto particularmente relevante es el papel de las interacciones sociales y las relaciones que los adolescentes forman en su entorno escolar. En este sentido, parte de esta tesis se centra en el fenómeno de la formación de vínculos, analizando como crean vínculos con aquellos que comparten características similares. Este proceso de formar vínculos con aquellos más similares se conoce como homofilia, un factor clave en la dinámica de las relaciones sociales dentro del entorno escolar.

Los estudios se basan en datos recolectados en dos países, España y El Salvador, durante los años 2022 y 2023, utilizando una metodología “lab-in-the-field”. La muestra se enfoca en adolescentes de 33 centros educativos en España y 12 en El Salvador. Los datos se recopilaron siguiendo los mismos protocolos de recolección, tareas y herramientas². Es relevante destacar el uso de tareas tradicionalmente utilizadas para elicitación de preferencias económicas y aspectos sobre la toma de decisiones en poblaciones adultas, adaptadas con fuertes componentes visuales para obtener estos datos en adolescentes. Además de las tareas relacionadas con preferencias económicas, habilidades cognitivas, desempeño escolar e interacción social, se obtuvieron datos sociodemográficos y otras tareas complementarias.

En los capítulos 3, 4 y 5, se emplean submuestras de los datos disponibles para abordar aspectos específicos de las preferencias económicas y la formación de redes en los adolescentes.

A continuación, se presenta un resumen de cada capítulo:

²Ver capítulo 2 para más detalles.

Capítulo 3: Analiza la *inconsistencia* de las respuestas al completar dos tareas que tradicionalmente se utilizó para elicitarse el descuento temporal y las preferencias de riesgo. Usamos una muestra de 2,248 adolescentes salvadoreños con la que se explora cómo factores como la edad, las capacidades cognitivas y la repetición de tareas influyen en la consistencia de la toma de decisiones y cómo estas inconsistencias pueden afectar a sus expectativas educativas. Los resultados muestran que solo un 27% de la muestra fue consistente en ambas tareas, aquellos que tienen un mejor desempeño en las medidas de habilidades cognitivas y de probabilidad son menos propensos a hacer decisiones inconsistentes. En nuestra muestra, la repetición de la tarea, en general, no mejora la consistencia. Además, se encontró que aquellos más inconsistentes tienen peores expectativas educativas a corto y largo plazo que sus compañeros más consistentes.

Capítulo 4: Se enfoca en la relación entre el *retraso de la gratificación* y la *ética del trabajo* entre 4,005 adolescentes españoles. Se emplean tareas experimentales para evaluar cómo el retraso de la gratificación se correlaciona con el rendimiento en tareas que requieren esfuerzo. Para medir el retraso de la gratificación se elicitan sus preferencias temporales y como tarea de esfuerzo la tarea de usos alternativos de Guilford. Además, este análisis arroja luz sobre cómo rasgos cognitivos como el rendimiento académico y la reflexión influyen en la ética del trabajo, particularmente en relación con el retraso de la gratificación. Los resultados muestran que los individuos que retrasan la gratificación no sólo obtienen mejores resultados en la tarea, proporcionando más usos, sino que también presentan un rendimiento superior al proponer más usos únicos y evitar la repetición en sus respuestas.

Capítulo 5: Explora la *formación de redes sociales* en El Salvador, utilizando 7,419 observaciones recolectadas en tres diferentes periodos sobre 3,726 estudiantes. Estos datos se usaron para crear los diferentes vínculos potenciales que podrían formarse en la red de un centro escolar. Este estudio explora cómo la homofilia - tanto en términos de rasgos observables como inobservables - da forma a las relaciones entre iguales en un entorno escolar, examinando características observables

(por ejemplo, género, clase) y no observables (por ejemplo, preferencias de riesgo, aspiraciones educativas futuras) en la formación de vínculos positivos (amistades) y negativos (enemistades). Para este análisis, se utiliza el promediado bayesiano de modelos (Bayesian Model Averaging, BMA). Encontrando que tanto para amistades como enemistades, las características observables se mantienen robustas, específicamente el haber sido amigos/enemigos en un periodo anterior, tener el mismo género y estar en la misma sección. Mientras que para amistades otros factores no observables son relevantes. Específicamente, tener una renta similar, preferencias por el riesgo, expectativas de trabajar en una profesión técnica en el futuro, así como un deseo similar de asistir a la universidad y obtener buenos resultados en disciplinas científicas, tecnológicas, de ingeniería o matemáticas (STEM, por sus siglas en inglés) son factores relevantes. En cuanto a la formación de vínculos negativos, solo el hecho de tener médico como la misma profesión futura esperada, podría desempeñar un papel ya que pierde significancia. Por lo tanto, al menos en nuestra muestra, los vínculos negativos parecen estar influenciados por mecanismos distintos a la homofilia.

En conclusión, la integración de los hallazgos de las diversas áreas mencionadas en este estudio contribuye al diseño de intervenciones educativas que tienen el potencial de mejorar los resultados a largo plazo, tanto en términos de rendimiento académico como de integración social.

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Lo que antes era un sueño imposible de alcanzar, hoy se materializa con la entrega de esta tesis.

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Honduras se caracteriza por muchas cosas, como su gente linda y paisajes preciosos, sin embargo, también destaca por la violencia y el empobrecimiento de la mayor parte de la población. En donde el salario con suerte es el mínimo y no se compara con el precio de la canasta básica. Todos estos factores, hacen que la formación superior se convierta en solo un sueño para la mayoría que anhelan tenerla.

Sin darme cuenta, al entrar al mundo laboral ya estaba absorta en extensas jornadas laborales que desgastan física y emocionalmente, poco a poco parece que te quedas sin tiempo para nada más. Recuerdo como quería obtener una maestría, cuando acudí por información me di cuenta de que, en ese momento para mí, equivalía a 2 años y 8 meses de ahorrar mi salario completo, por una maestría que ni siquiera sabía si me gustaba y que al final de cuentas, no cambiaría mi situación laboral a mejor, por esto, lo más sensato fue dejar ese anhelo como un sueño inalcanzable y seguir adelante.

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Chapter 1

Introducción

Los experimentos económicos que implican muestras de poblaciones no adultas (por ejemplo, niñez y adolescencia), cada vez son más comunes y han tomado relevancia por dos razones fundamentales: En primer lugar, se necesita comprender cómo se forman las preferencias económicas a lo largo del periodo madurativo (Fehr et al., 2013; Brocas and Carrillo, 2020a,b), y, en segundo lugar, cómo estas preferencias influyen en otros aspectos de la vida adulta, tanto aquellos relacionados con la formación de capital humano como otras cuestiones incorreladas con la educación (Sutter et al., 2013; Castillo et al., 2011, 2019). Es importante destacar que si estas preferencias se pudiesen intervenir, en especial a edades tempranas, se podrían obtener resultados positivos para el bienestar de las personas (Lührmann et al., 2018). Por ejemplo, es conocido que la paciencia y el autocontrol indíciden en el rendimiento educativo y que ambas son “manipulables”. Una intervención encaminada a moldear la paciencia tendría por tanto impacto en el rezago educativo.

Al estudiar la forma en la que los adolescentes toman decisiones en entornos escolares, hay que tener en cuenta que los alumnos pasan una enorme cantidad de horas en los centros educativos y que además forman - y aprenden a formar - relaciones con otros individuos. Resulta inevitable preguntarse cómo son las interacciones sociales, y en particular, en cómo crean vínculos con aquellos que comparten características similares (edad, género, gustos, valores, estatus socioeconómico, prefe-

rencias económicas, etc.). El fenómeno de formar vínculos con aquellos que son similares a uno mismo, es conocido como *homofilia* y es uno de los aspectos de redes sociales que ha sido estudiado con mayor profundidad en todas las disciplinas (Lazarsfeld et al., 1954; McPherson et al., 2001; Moody, 2001; Kossinets and Watts, 2009). La homofilia es tan poderosa que las interacciones humanas terminan casi siempre en una situación de segregación, ya sea por el color, por los hábitos o las creencias religiosas. Al final, la homofilia termina impactando en cosas tan diversas como, la difusión de ideas, el comportamiento, la desigualdad y la movilidad social (Glaeser et al., 2000; Ruef et al., 2003; Centola, 2011; Bramoullé et al., 2012; Jackson et al., 2017; Zeltzer, 2020). Por ello, es esencial entender los orígenes, la naturaleza y las repercusiones de la homofilia.

En la presente tesis se busca contribuir con el avance del conocimiento sobre cómo *los jóvenes toman decisiones* ya sea económicas o sociales y cómo sus habilidades cognitivas impactan en sus decisiones o en la forma que las toman. Todos los participantes de nuestros experimentos son alumnos de centros escolares con edades comprendidas entre 10 y 24 años¹. Para ello se analizan datos de dos muestras de dos países, España y El Salvador. Los datos de España provienen de proyectos coordinados por Loyola Behavioral Lab (LoyolaBehLab) desarrollados dentro del TeensLab, un consorcio de universidades de diferentes regiones, principalmente España². Los datos de El Salvador los recogió la autora de esta tesis.

Respecto a las preferencias económicas, existen diversos matices y una amplia variedad de variables que pueden ser exploradas. Por lo que es relevante especificar que en esta tesis se analizan ciertos aspectos de las preferencias económicas en las dos muestras. Inicialmente, se analizó la *inconsistencia* en las tareas para medir descuento temporal y aversión al riesgo en la muestra de estudiantes salvadoreños. Posteriormente, se analizó la ética del trabajo en la muestra española, utilizando sus preferencias temporales (paciencia), entendidas como una medida de *retraso de*

¹Las observaciones de 10 años y de más de 22 años son infrecuentes en los datos.

²Ver el capítulo 2 para más detalles. Los datos de TeensLab están accesibles en Vasco et al. (2025)

gratificación, con su *desempeño* en una tarea de esfuerzo. Finalmente, se estudió la homofilia en la muestra salvadoreña, evaluando el rol de características observables e inobservables mediante un enfoque de modelos bayesianos de promedio ponderado (BMA por sus siglas en inglés) tanto en redes de links positivos (*amistades*) como negativos (*enemigos*³.) En todos los estudios se toman en cuenta aspectos como habilidades cognitivas, desempeño escolar entre otras que serán detalladas en cada capítulo. La tesis se organiza en tres partes: I Metodología, II Artículos derivados de la tesis y III Conclusiones generales.

La primera parte presenta la metodología “lab-in-the-field” utilizada para la recolección de dos bases de datos de adolescentes en contextos diferentes entre un país latinoamericano de renta media baja (El Salvador) y otro europeo de renta alta (España). Se presentan los aspectos comunes entre ambos procesos de recolección de datos, seguido de una breve descripción de las tareas utilizadas para generar los datos analizados en los capítulos 3, 4 y 5. Además, se presentan experiencias específicas vividas durante la recolección de datos en campo en El Salvador, con el objetivo de proporcionar al lector una visión más completa y por ende, una comprensión más profunda de las diferencias contextuales entre las muestras. Adicionalmente, se proporciona una descripción inicial de las submuestras utilizadas en cada uno de los capítulos.

La segunda parte de la tesis analiza los datos obtenidos, enfocándose en diferentes aspectos relacionados con los adolescentes españoles y salvadoreños. En primer lugar, en el capítulo 3 exploramos la inconsistencia en dos tareas clásicas para elicit preferencias por el riesgo y tiempo, con parte de la muestra de adolescentes salvadoreños. En segundo lugar, en el capítulo 4 se explora la ética de trabajo relacionada al retraso de la gratificación en una muestra de adolescentes españoles. Finalmente, en el capítulo 5 se analiza cómo las características observables e inobservables influyen en la formación de redes sociales. Explorando tanto la creación de vínculos positivos como negativos en redes de adolescentes salvadoreños. Cada

³Es relevante mencionar que se llama enemigos por simplicidad. Para ver detalles de cómo se obtienen estas medidas ver la sección 5.2 del capítulo 5.

capítulo explica en detalle la muestra específica utilizada, los resultados y las conclusiones.

Finalmente, la tercera parte presenta las conclusiones generales de la tesis, donde se sintetizan los hallazgos y se ofrecen perspectivas para futuras investigaciones.

1.1 Objetivos

La Parte II de esta tesis se organiza en tres objetivos generales, los cuales son desarrollados, analizados y discutidos en detalle en cada capítulo.

En el capítulo 3, el objetivo general es “*Analizar la inconsistencia de una muestra de estudiantes salvadoreños en las dos tareas experimentales tradicionales para medir descuento temporal y aversión al riesgo*”. Para lograr este objetivo, se establecieron los siguientes objetivos específicos:

OE1₁: Analizar si determinados factores asociados al desarrollo, como la edad, las habilidades cognitivas y la repetición de tareas mejoran la consistencia en estas decisiones.

OE1₂: Analizar si la inconsistencia en este tipo de decisiones determina de algún modo sus expectativas educativas inmediatas y a largo plazo.

Para cumplir con este objetivo, se utilizó la muestra de datos salvadoreños, que, a diferencia de los datos españoles, abarca tres periodos distintos para los mismos sujetos. Esta característica permite evaluar los cambios en la *inconsistencia* de los participantes en diferentes periodos. Por lo tanto, se utilizó la muestra correspondiente al primer y segundo periodo. Con estos datos, se analizó la *inconsistencia* en las decisiones tomadas en dos tareas experimentales, especialmente adaptadas a adolescentes, con el fin de medir el descuento temporal (*Truck*) y la aversión por el riesgo (*Gumball*)⁴. Asimismo, se analizaron los factores asociados a estas inconsistencias y si las mismas afectan las expectativas de continuar sus estudios tanto en el corto, como en el largo plazo.

⁴Más detalles en la sección 3.2.2 del capítulo 3.

Los principales hallazgos sugieren altos niveles de *inconsistencia*, que son significativamente más altos que en estudios similares realizados en *España con adultos*. Estudios como el de Brañas-Garza et al. (2021, 2023), que analiza datos de experimentos de *laboratorio* en España obtuvo una consistencia aproximada del 80%, mientras que en el *campo* de Honduras y Nigeria reportan una consistencia aproximadamente del 70% y 90%. Es importante destacar que si bien se usaron instrucciones similares la población no era de adolescentes sino de adultos y además, en los estudios de campo mencionados se usan entrevistadores que claramente pueden “ayudar” a los entrevistados. Sin embargo, en el artículo de Alfonso et al. (2023) con adolescentes españoles - con una edad media de 13 años - que usa exactamente los mismos procedimientos e imágenes para elicitación las preferencias de tiempo y riesgo se obtienen porcentajes de consistencia similares.

Encontramos una serie de resultados relevantes: No encontramos diferencias sustanciales en la *inconsistencia* entre hombres y mujeres, sin embargo, las mujeres son más proclives a manifestar inconsistencias en la tarea que implica probabilidades (riesgo). Asimismo, aquellos con mejores habilidades cognitivas se asocian con una menor *inconsistencia* en ambas tareas. En línea con previos estudios como el de Brañas-Garza et al. (2012), quienes encontraron que puntajes más altos en la prueba de reflexión cognitiva⁵ (CRT por sus siglas en inglés) está relacionado con la toma de decisiones más racionales. Desafortunadamente, la repetición de la tarea no hace que lo hagan mejor. Por último, los estudiantes inconsistentes tienen un peor rendimiento escolar y menores expectativas de continuar sus estudios el próximo año y un interés aún más bajo de asistir a la universidad. Podemos decir que de modo general la falta de consistencia en las decisiones nos está indicando que el alumno muestra problemas de elección básicos y que eso puede implicar rezago en diversos ámbitos educativos.

El capítulo 4 tiene como objetivo “*Analizar el efecto de la paciencia sobre el rendimiento en la realización de una tarea en adolescentes*”. Desarrollando el

⁵Es usada como una de las dos tareas complementarias para medir habilidades cognitivas. Ver la Sección 3.2.3 para más detalles.

siguiente objetivo específico:

OE2: Analizar cómo factores adicionales como la edad, las habilidades cognitivas y el género afectan el rendimiento (*performance*) en la realización de una tarea.

Utilizando la base de datos de España, se analizaron los resultados de las tareas de descuento temporal (*retraso de la gratificación*) y su desempeño en la tarea de usos alternativos propuesta por Guilford (1967) donde los participantes debían enumerar usos inusuales para un ladrillo, tarea que normalmente se utiliza para medir el pensamiento divergente. Sin embargo, al ser la última tarea de un experimento “lab-in-the-field” de 50 minutos aproximadamente, sumado al hecho de que no se proporcionó ninguna motivación extrínseca, es utilizada para obtener dos medidas: *rendimiento* y *rendimiento superior* en la tarea.

Los hallazgos sugieren que los adolescentes que más *retrasan la gratificación* tienen un mejor *desempeño* en esta tarea ya que, proporcionaron más usos únicos y evitaron repetir respuestas, lo que se relaciona con una ética del trabajo más fuerte. Además, encontramos que ser mujer, presentar un mejor rendimiento escolar y una mayor capacidad de reflexión cognitiva impactan positivamente con el *desempeño*. Sin embargo, sólo estas últimas se mantienen significativos para un *rendimiento superior*, es decir no hay diferencias de género. Por último, el efecto del *retraso de la gratificación* en el *desempeño* es de mayor magnitud en jóvenes de mayor edad (grados 9 y 10).

Trabajos como los de Corgnet et al. (2015) señalan que, incluso en un entorno de laboratorio con poblaciones adultas, el establecimiento de objetivos puede mejorar el rendimiento al crear una sensación de ganancia. Lo que sugiere que, en el contexto de adolescentes, incluso sin incentivos extrínsecos, las metas personales podrían potenciar su rendimiento en tareas que requieren esfuerzo cognitivo.

Finalmente, el capítulo 5 está orientado a cumplir con el objetivo de “Analizar los determinantes de la formación de amistades y enemistades en redes sociales emergentes en El Salvador” mediante un enfoque de modelos bayesianos de promedio

ponderado (BMA). Realizando el siguiente objetivo específico:

OE3: Analizar la importancia relativa de las preferencias económicas (inobservables) versus otras variables observables utilizadas en la literatura en la determinación de vínculos sociales.

Este análisis se basó en la muestra salvadoreña, recolectada en El Salvador durante los años 2022-2023, en la que se participó activamente como coordinadora de campo, recopilando un total de 7,419 observaciones en tres períodos distintos sobre 3,726 sujetos. Se realizó un análisis de los determinantes de la formación de *amistades* y *enemistades* usando un enfoque de modelos bayesianos de promedio ponderado (BMA) para abordar la incertidumbre en el modelo. Este enfoque permite medir la importancia relativa de las características *observables* (y que se usan comúnmente en la literatura) y las preferencias económicas que se midieron en nuestro experimento pero que en general son *inobservables* para los estudiantes y los investigadores⁶.

Para este análisis tomamos en cuenta solo relaciones recíprocas (donde el sujeto *i* nombra al *j* y el *j* nombra al *i*). Este es un criterio establecido por Granovetter (1973) para considerar que un vínculo es fuerte. Para el modelo, utilizamos la similitud o diferencia en las características (in)observables entre pares de sujetos que potencialmente podrían formar un vínculo tanto de amistad como de enemistad.

Los principales hallazgos sugieren que tanto para relaciones de amistad como las de enemistad las características observables se mantienen robustas. Estas características son: haber sido amigo/enemigo en el periodo anterior, tener el mismo género y pertenecer a la misma sección (clase). De las características inobservables, en las relaciones de amistad destacan aquellos aspectos en los que ser similares aumenta la probabilidad de formar este vínculo. Estas características son: ingreso, aversión al riesgo, querer trabajar en una profesión técnica, deseo de ir a la universidad y haber obtenido buena nota en clases relacionadas con disciplinas de Ciencia,

⁶La tabla 5.3 enumera los potenciales determinantes en la formación de vínculos.

Tecnología, Ingeniería o Matemáticas (STEM por sus siglas en inglés). Mientras que para la formación de relaciones de enemistad, de todas las características inobservables solo destaca el que ambos quieran ser doctores, sin embargo, al ver la submuestra de solo aquellos estudiantes que estuvieron presentes en los tres periodos de recolección de datos, pierde significancia.

1.2 Conclusiones

La investigación presentada en esta tesis aborda aspectos específicos de un tema de creciente relevancia: las preferencias económicas de poblaciones no adultas, y su posible relación con características específicas de los sujetos tales como habilidades cognitivas, desempeño escolar, entre otras. Se plantean tres objetivos generales diferenciando cada uno con una de las muestras disponibles.

El primer objetivo explora en la muestra de El Salvador las inconsistencias mientras se elicit el descuento temporal y la aversión al riesgo, con posibles factores asociados al desarrollo. Se estudian principalmente los datos recolectados durante el primer periodo y de forma adicional se exploran los datos del segundo periodo para determinar si, al menos en nuestra muestra, la repetición mejora la inconsistencia en sus decisiones.

Por otro lado, para el desarrollo del segundo objetivo, se utiliza la muestra de España, enfocándose en la relación del retraso de la gratificación sobre el rendimiento en la realización de una tarea que requiere esfuerzo. Mientras que, para el tercer objetivo, se utilizan todas las observaciones disponibles de los datos recolectados durante tres periodos en El Salvador para explorar los determinantes de la formación de amistades y enemistades en redes sociales emergentes.

La tesis se organiza en tres partes. La primera, metodología, detalla la recolección de los datos en ambos contextos, describiendo las diferencias y similitudes entre las muestras. La segunda parte presenta los artículos derivados del análisis de los datos, donde se exploran diferentes aspectos del comportamiento económico y social de los adolescentes. Finalmente, la tercera parte ofrece las conclusiones generales,

resumiendo los hallazgos más relevantes y sugiriendo direcciones para futuras investigaciones.

Estos estudios no solo contribuyen a la literatura existente, sino que además la obtención de este tipo de datos ha demostrado que puede proporcionar información valiosa a instituciones educativas que no suelen medir estos aspectos en sus estudiantes, ya sea por la falta de instrumentos para hacerlo o porque no se aborda como parte de las actividades a desarrollar durante un año escolar. En este sentido, por ejemplo, investigaciones previas sobre experimentos de redes sociales en escuelas han servido para el lanzamiento de programas preventivos, como los de consumo de alcohol y drogas (Paluck et al., 2016; Starkey et al., 2009; Valente et al., 2007).

Diversos autores destacan como el uso de métodos experimentales en la evaluación de políticas sociales facilita conocer cuales funcionan y cuáles no (por ejemplo, Brañas-Garza and Cabrales, 2015; Vázquez and Estepa, 2024). Otros autores también ponen de manifiesto las complejidades asociadas a recoger datos de campo, los problemas propios de la logística, los incentivos y las unidades de medida (ver también Rivera-Garrido et al., 2022).

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I

METHODOLOGY

Chapter 2

Methodology

In this chapter, the general methodology will be described. There are several common elements, as the dataset is part of two projects that share the same procedures, albeit in different contexts. One dataset originates from Spain, and the other from El Salvador. Understanding these shared aspects will help avoid redundancy in the information presented. First, the general study design will be outlined, followed by a detailed description of the specific challenges encountered when collecting data in the field, particularly in a developing country like El Salvador. Lastly, the general statistics of the sample used will be presented.

2.1 Experiments in schools

The studies in Spain and El Salvador are part of projects coordinated by Loyola Behavioral Lab (LoyolaBehLab) within the TeensLab, a consortium of universities from different regions, mainly Spain. The aim is the study of economic behavior among adolescents¹. The studies are about 50-minute lab-in-the-field experiments, approved by the Universidad Loyola Andalucía Ethical Committee. Furthermore, for the Spain dataset in the primary level² (10-year-olds), it was also approved by the Bioethics Commission of the University of Barcelona.

The Spain dataset counts 33 educational centers representing various educational

¹Visit: <https://loyolabehlab.org/teenslab/> for more details.

²This data was not used in this thesis.

levels, such as primary school, secondary school, sixth form, and vocational training, and collects 5,890 observations of students from 10 to 23 years old. This dataset has already been published by Vasco et al. (2025). The El Salvador dataset counts 12 educational centers³ located in five districts. The educational levels represented are secondary and high school. A relevant difference between the dataset of Spain and El Salvador is that, for El Salvador, we have data from three different periods: March to June 2022 (2,600 observations), March to May 2023 (2,649 observations), and August to October 2023 (2,100 observations). Summarizing 7,419 observations collected over 3,726 subjects who participated in at least one period (see 5.1 for participation distribution of subjects).

Each project was led by a field coordinator in the respective country. One of the principal functions of the field coordinator was to program the SAND⁴ platform for the experiments. The SAND platform was developed by Kampal under the specifications of the TeensLab, which aims to offer superior data privacy control and flexibility. We mainly used tablets to collect data in the school classrooms under the supervision of the field coordinator. In the case of El Salvador, we counted on a local partner with an established network of public schools across the country. This local team also participated in collecting data (including the adaptation of tasks) under the guidance of the field coordinator, who, in turn, was under the supervision of the LoyolaBehLab team in Spain.

The experimental tasks were designed explicitly for the non-adult population and adapted for subjects with the help of a local pedagogical team. The payoffs were hypothetical since, at least for risk and time preferences, they elicited similar results to monetary payments (Alfonso et al., 2023). It is worth mentioning that the collection data process in Spain started at least 6 months before El Salvador, and El Salvador followed the same processes as Spain did with all the challenges of the context that will be described in detail in the next section.

³For more details about the school, see Sections 3.2.4 and more details in A.6.

⁴Acronym for Social Analysis and Network Data, offered by Kampal (<https://sand.kampal.com>)

2.2 Experimental tasks

The studies included several experimental tasks to measure different aspects of the students. In this thesis, not all tasks were used, and the ones used are described in detail in each chapter. Therefore, we will briefly describe the tasks in this section to avoid repetition. It is relevant to mention that each task has its own instructions. For simplicity, we could divide the experiment setup into three blocks: social networks, preferences, and other tasks.

2.2.1 Social networks

We took several measures of social networks to elicit different aspects of the network at individual level, group (class) level, cycle level (third cycle: 7th, 8th, 9th grades, and high school: 1st, 2nd, 3rd years), and school level. Figure 2.1 shows an example⁵ of the list where students are asked to select their friends. Note that SAND was designed to let students select friends in other classes that are different from their current class (see tabs on the top). Every time a student clicks on a tab, a new screen with the list of the names of the students of that group would appear.

¿Quién crees que te marcará como "amiga/o"?

1º ESO - F 1º ESO - E 1º ESO - D 1º ESO - C 1º ESO - B 1º ESO - A

☐ Ana Isabel Sacristán Hernández - 1º ESO A	☐ José Lomas Gómez - 1º ESO A
☐ Perla Rozas Cortés - 1º ESO A	☐ Cándido Iñiguez Caparrós - 1º ESO A
☐ Alexandra Roselló Estévez - 1º ESO A	☐ Jaime Hurtado Zurita - 1º ESO A
☐ Claudia Rodríguez Alfonso - 1º ESO A	☐ Claudia Huerta Arnal - 1º ESO A
☐ Teodosio Ramírez Cordero - 1º ESO A	☐ Gabriel González Camacho - 1º ESO A
☐ Alejandra Puga Ros - 1º ESO A	☐ Pablo Fernández González - 1º ESO A
☐ Víctor Pou Peña - 1º ESO A	☐ Natividad Estepa Brañas - 1º ESO A
☐ Gonzalo Polo Pastor - 1º ESO A	☐ Toribio Español Ojeda - 1º ESO A
☐ Lara Pavón Fernández - 1º ESO A	☐ Úrsula Carpio Cerezo - 1º ESO A
☐ Basilio Palau Murillo - 1º ESO A	☐ Urbano Camino Pacheco - 1º ESO A
☐ Amaro Nieto Cid - 1º ESO A	☐ Américo Calatayud Manjón - 1º ESO A
☐ Tomasa Nieto Amat - 1º ESO A	☐ Antonio Betanzos Lobo - 1º ESO A
☐ Isafas Montoya González - 1º ESO A	☐ Roberta Bellido Lluch - 1º ESO A
☐ Pedro Montero García - 1º ESO A	☐ María Manuela Balaguer Español - 1º ESO A

Figure 2.1: Example of selection screen on social network task (Spain)

⁵The names are fictitious.

From the lists, we ask them to select to who they consider his *friends*, then on the next screen, a list with the prior selection of friends was shown, and they could select those they consider his *best friends*. Similarly, we asked “*With which colleagues do you not have a good relationship or do you not like them?*”, for simplicity, we call this variable *enemy*. From that previously selected list (a subset of the original list), we asked “*With which of them do you have a particularly bad or problematic relationship?*”, this variable is called *worst enemy*.

Besides, we also asked for other aspects such as their beliefs “*Who do you think will select you as a friend?*”, and the same with best friends, enemies, and worst enemies.⁶

We also ask about the group’s most *popular* and *central* subject. To do so, we asked “*Who do you think will be the person most often selected as ‘best friend’ in your class?*” and then “*Send a message: If you had to send a message and wanted it to reach the entire class but could only contact one person, who would you send it to? Who do you think is the classmate that can spread the information to the most people?*”.

The data gathered along this experiment allow us to elicit positive (friendship) and negative (enmity) links in networks, considering relevant aspects such as position within the network, e.g., *centrality*, *popularity* or *isolation*, as described in Brañas-Garza et al. (2024a).

2.2.2 Preferences

To measure both time and risk preferences, we utilize two graphical tasks specifically adapted for an adolescent population (see Figure 3.1): *The Truck* task, a visual modification of the Multiple Price List task proposed by Collier and Williams (1999) to assess *time preferences*, developed by Alfonso et al. (2023), and *The Gumball Machine*, a graphical adaptation of the risk preference test from Holt and Laury (2002), introduced by Vasco and Vázquez De Francisco (2025). These tasks are

⁶See Brañas-Garza et al. (2024b)

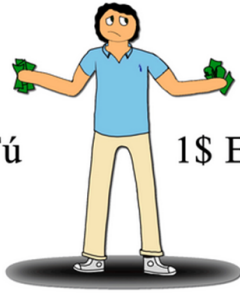
described in detail in Chapter 3.

In addition, we use an adaptation of the Dictator Game (DG), as in Brañas-Garza (2024), where the students decide how to split an amount of money between them and others – options A was always egalitarian, and B varies across the game (see Figure 2.2). We used two versions of the task, one with six decisions and the other with three. We define *altruistic behavior* as the number of times the subject chooses the altruist option.

¿Qué prefieres?

☐ | A)

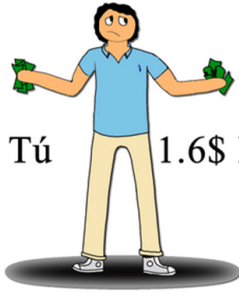
Opción A



 1\$ Tú 1\$ El otro

☐ | B)

Opción B



 0.8\$ Tú 1.6\$ El otro

Figure 2.2: Social preferences

2.2.3 Other tasks

The Alternative Uses Task (AUT) from Guilford (1967) was used. This is a well-known task for measuring divergent thinking as suggested by Attanasi et al. (2021). We provide 5 minutes to complete the task: “*Write down all the alternative uses you can imagine with a brick.*” (see Figure 2.3). This task was located almost at the end of the 50-minute lab-in-the-field experiment in some of the studies. For that reason and others explained in chapter 4, we also use it as an effort task (more details about the task in Appendix B.1.2).

On the other hand, we ask students about their educational expectations and aspirations, especially about the likelihood of continuing their studies the next year and attending university (see questions 7 and 9 in Appendix A.1.5).

Moreover, authors like Corgnet et al. (2016) highlight the role of cognitive abilities in explaining outcomes in economic experiments. In line with this, we use an adapted version of the Cognitive Reflection Test (*CRT*), as in Alfonso et al. (2023), three *financial* questions (see A.1.4), and an extended version of Delavante test to know the ability of adolescents to comprehend probabilities (Brañas-Garza et al., 2021). Besides, we also asked them to *self-report* their grades or GPA for the previous year.

4:59



Escribe todos los usos alternativos que puedas imaginar con un ladrillo. Recuerda separar cada idea que escribas con un punto y coma (;):

Introducir texto

2000 caracteres restantes.

Figure 2.3: The Alternative Uses Task

2.3 In the field: El Salvador

This project was coordinated by the LoyolaBehLab (Universidad Loyola Andalucía) and the ETEA Foundation⁷. They established an alliance with a local partner from El Salvador, Fe y Alegría, who had an established network with schools and played a key role in the entire logistics process.

Three measurements (periods) were taken to gather information about lag and social isolation among students from educational centers in five districts: San Miguel, San Salvador, Ahuachapán, Sonsonate, and Santa Ana, with the participation of seven urban and five rural schools.

⁷The Loyola University Development Institute, for more details visit: <https://fundacionetea.org/>

To detect lag, we measured several student skills (such as cognitive and financial skills, and creativity, for example) and used network mechanisms to understand the students' position in the class's social network. The first measurement was conducted in 2022, and the remaining two in 2023.

2.3.1 Coordination among partners

The three data collection processes were conducted using the same methodology: The team in Spain, through the field coordinator in El Salvador (Gladis Gonzales), designed and programmed the tool in SAND. The local partner team coordinated the tool's contextual adaptations with a local pedagogical team and coordinated visits to the educational centers to carry out the measurements. On the scheduled day, the field coordinator and a local team would travel to the center, equipped with tablets, internet, and temporary users generated from information provided by the educational centers. Students were organized into groups, and measurements were taken. Once the information was gathered, the researchers analyzed the data to generate various reports shared with the participant centers.

The activities were developed as follows: In the first year of the intervention, several limitations⁸ affected the planned dates for the first data collection process. However, necessary adjustments were made to ensure the planned activities for the school year were carried out.

Despite the initial delays, the recruitment of the local project team was initiated. At the same time, efforts were made to acquire the necessary equipment for the project, including 250 tablets. However, the availability of devices from local suppliers forced a staggered acquisition process, and ultimately, 171 tablets were purchased. Despite this, with some adjustments to the schedule, all three planned measurements were completed. At the end of the first measurement, 50 tablets were available. The process included material preparation, coordination with school directors to schedule visits, pilot testing of the tool, and generating temporary users from student enrolment lists provided by the schools.

⁸For more details, see Section 2.3.2.

For staff training, the field coordinator of El Salvador received specific training on using and programming the SAND platform for data application, collection, and report generation. She was also trained in the protocols for performing measurements. Additionally, for the initial training of the local partner staff, the field coordinator from Spain and a volunteer with expertise in working with children with special needs were involved. The tablets were configured, and a protocol was developed to adapt to the context of the schools.

As the next step in the project, the focus shifted to ensuring the appropriation and continuity of the project, so full training was provided to the local partner team. The training included eight modules on the methodology used for measurements, project information, and report generation. The field coordinator in El Salvador designed and delivered a training plan. During the first measurement of cognitive skills and networks, teachers assisted the technical team but did not directly participate in the measurements. Once the first data collection process was completed, teacher training was carried out, and 121 teachers from the 12 educational centers in the study completed it, participating more actively in the subsequent measurements.

Thus, in the first year, efforts were made to acquire the necessary equipment for the measurements, complete the tool's design, programming, and validation, and implement it online. Training for the local partner team and selected teachers was also carried out, alongside creating tailored reports for the schools' needs.

The second year of execution focused on increasing teacher involvement in schools, conducting two measurements, disseminating results, and developing and implementing an action plan based on prior identification of each center.

In January and February 2023, some adaptations and system programming were made to launch the second measurement process. The field coordinator assisted in this process, but the local partner took the lead with support from the teachers at the centers, who had already received training on the measurement and analysis tool. Simultaneously, the local partner continued to acquire more tablets. Due to the

availability of the teaching staff and incidents that initially delayed the schedule, it was decided to begin the third measurement in August 2023. The local team took the entire leadership role in the process with support from the teachers at the educational centers. The field coordinator supported the process remotely due to possible incidents.

As a result of these activities, and following the completion of each data collection process, various reports with different objectives were generated and adapted to the needs of the educational centers, as well as general reports on skills, competencies, social preferences, and student networks. Additionally, each center received a report detailing students at risk of social exclusion or with more significant lag in skills and competencies⁹.

Finally, on-site expatriate personnel from the ETEA Foundation accompanied the entire process, especially in monitoring and administrative justification according to the funding agency regulations, mediation with the local partner, an adaptation of the tool, and capacity transfer to the local partner. For the three measurements carried out over the two years, instruments were applied in 12 educational centers in the local partner's school network, prioritizing attention to children in the third cycle (7th, 8th, 9th grades) and high school (1st, 2nd, 3rd years), reaching a total of 3,726 students to whom the measurement instrument.

2.3.2 Limitations

In the first year, 2022, the limitations included the late start of classes due to the COVID-19 pandemic. A semi-presential mode was implemented as a preventive measure in schools, unlike in 2021, when classes were completely virtual. As a result, the Ministry of Education of El Salvador delayed the start of classes by one month, affecting the initial planning of school activities and, therefore, the starting date for the first data collection process. Another consequence of this mode was the division of each group's attendance, resulting in more visits to complete the data collection process. Additionally, due to constraints from local suppliers, we

⁹More details in Section 2.3.3.

could not obtain more than 30 tablets during the first data collection in at least six schools, limiting the number of students who could participate and slowing down the process. This was further exacerbated by the state of emergency (suspension of fundamental rights such as mobility, expression, association, and privacy of communications) to address the social violence situation was declared on March 27, 2022, which led to the closure of schools and local partner activities during March and April 2022.

To understand the state of emergency implemented in El Salvador in March 2022, which continues to this day, it is relevant to mention that El Salvador had some of Central America's most notorious street gangs¹⁰. For many years, these criminal organizations instilled fear across the country and were notorious for recruiting young people. Their primary activities included extortion, domestic drug trafficking, and kidnapping, along with other more unusual but specific roles, such as working as hitmen or carrying out particular tasks. As a result, El Salvador remained one of the countries with the highest homicide rates globally. By the end of 2015, the nation had a homicide rate exceeding 100 per 100,000 inhabitants, according to Insight Crime (2024). The state of emergency was declared amid a surge of violence that resulted in at least 92 fatalities from March 24 to 27, 2022, where over 73,000 people were put into jail until the beginning of November 2023, according to a report of the Comisión Interamericana de Derechos Humanos (CIDH) (2024). The schools are located in some of the "territories" of these gangs. Therefore, all the programmed visits to the schools and activities of the students were delayed until May 2022.

Another limitation occurred in June 2022. The Ministry of Education and the Ministry of Health suspended classes due to increased COVID-19 cases. These circumstances led to schedule adaptations, which allowed us to reschedule activities with the schools and adjust group sizes to meet health requirements. This way, we could reach the first collection data process. In 2023, the Ministry of Education deter-

¹⁰Locally known as "Maras".

mined that classes would be entirely in-person, and students were no longer divided into groups; however, the organization of the return to classes caused the ministry's decision to start the school year a few weeks later than initially planned.

Additionally, a technical limitation in all three measurements was the lack of internet in most schools, particularly those in more remote areas. To address this, some tablets were used as modems, and internet services from different phone companies were contracted, ensuring sufficient coverage.

2.3.3 Reports and action plans

Reports were delivered to the schools to provide relevant information about the students and develop an action plan to prevent or reduce social exclusion of children identified as at risk and those with learning problems.

All reports follow a structure based on indicators, as presented in Table 2.1, which include networks, cognitive skills, and academic-related indicators. Each indicator encompasses various variables, with the findings most relevant for tutoring and counseling highlighted. The information was presented for school, and “cycle”, following the educational classification of El Salvador (third cycle comprising 7th, 8th, and 9th grades, and high school comprising 1st, 2nd, and 3rd years for technical baccalaureates).

The reports included a general or preliminary report, with normalized averages presented in graphs according to the cycle averages for the 12 educational centers. Additionally, more specific reports were generated at the request of the schools, called “individual reports”.

Additionally, for the cases described below, *prioritized* case reports were provided (containing the student code, gender, cycle, and grade). These cases were classified into:

- Possible bullying cases, including self-reported, reported by another student, or confirmed cases, i.e., students who self-reported and were also reported by

a peer as a possible bullying victim.

- Possible social isolation cases, reporting students lacking social friendship bonds and those with more enmity.

Table 2.1: Report structure

Category	Subcategory
Networks	Unrecognized bullying Bullying type 1 (self) Bullying type 2 (others) Recognized bullying (type 1 and 2) Reciprocity Friendship Enmity General mood state Altruism
Cognitive Skills	Reflective thinking Probability errors Financial skills Creativity
Expectations	Expectations of continuing studies Next year In university Patience

As a complement to the first measurement, a network report was provided, where each individual is represented by a node, and their interactions, whether friendship or enmity, are represented by a link connecting the nodes. A general report for centers was also provided, summarizing the quantities and percentages of each variable.

In summary, the reports delivered to schools were three general reports, 24 individual reports, and two prioritized case reports (corresponding to the first and third measurements).

An analysis was carried out using the reports from the first measurement to develop and validate an approved action protocol addressing backlog and social isolation. The local team participated in identifying those centers where addressing one aspect

of the backlog was more urgent than others. It is also important to note that all reports of prioritized cases were considered for later analysis and evaluation with the psychologist. With this prior identification and assessment of the capacity installed in each school, an initial proposal of actions to be carried out within the schools was created.

The process of identifying problems was carried out in collaboration with the management of the educational centers, who participated in monthly meetings with the coordination team from the local team and the psychologist assigned to the project, both before, during, and after the implementation of the action plans.

After these meetings, new activities were held with the teaching committees formed in the educational centers of the project, which were more involved in its execution. The management of the centers was also present at these meetings. The proposed actions to be taken in the action plan were presented, and teachers and management, knowing their context, proposed inputs to elaborate the action plans that were eventually implemented.

In particular, each center designed between 5 and 9 concrete actions. Six participating schools required external support to complement their capacities and resources. The local team provided this support: A new psychologist was hired to attend six centers without these services.

Between June and November 2023, interventions by psychology professionals were carried out for 103 prioritized cases identified across 12 educational centers, as well as the implementation of pilot measures.

2.4 Sample

This thesis uses a sample from two countries: Spain and El Salvador. As described earlier, the Spanish sample targets students aged 10 to 23, spanning various educational levels. Data were collected from 19 locations in Cádiz, Sevilla, Córdoba, Granada, and Málaga in Andalusia and Barcelona in Catalonia. Of the 33 schools,

20 are public, and the rest are semi-private.

The target population in El Salvador consists of students aged between 12 and 18 years —the age range allowed in the regular school system for the prioritized grades. Data were collected from 12 public schools in five different districts. Seven schools are urban, and the rest are rural. This population comes from communities with high levels of displacement and stigmatization, and they experience limited exercise of human rights due to poverty and violence. The state has a minimal presence, *machismo* prevails, social cohesion is lacking, economic opportunities are scarce, and, in many cases, criminal structures are in control.

Following the general description of the sample, the specific sub-samples and their corresponding statistics are presented in each chapter. Therefore, in this section, we will briefly describe the self-reported variables *female*, *age*, and *distribution across grades*.

First, in Chapter 3, a sub-sample from El Salvador is used, focusing on Period 1, due to the selection criteria¹¹ 2,248 observations out of 2,600 were used from the 12 schools. Descriptive statistics are presented in Table 2.2, where 49% were female, the mean age was 15.46 years old, and the 7th, 8th and 9th grade represent the 73% of the total sample. The complete descriptive statistics are presented in Table 3.2. In the same chapter, a cohort of students who completed the task and met the selection criteria in Period 2 was also included (see Subsection 3.3.6 for details).

¹¹Described in detail in Section 3.2.6.

Table 2.2: Sample in Chapter 3 (El Salvador)

Variables	n	Mean	Min.	Max.
<i>Female</i>	2,248	0.49		
<i>Age</i>	2,248	15.46	12	20
Distribution across grades:				
7 th grade	573	25.49%		
8 th grade	540	24.02%		
9 th grade	528	23.49%		
10 th grade	310	13.79%		
11 th grade	297	13.21%		
Total	2,248			

Second, a sub-sample from Spain is used in Chapter 4. The selection criteria are described in Section 4.2. Therefore, a sub-sample of 4,005 observations from 4,344 recruited participants from 18 secondary schools in Andalusia and Catalonia is used.

Table 2.3 shows the statistics. As in the previous sample, 49% of participants are females. The mean age is 13.83 years old, and the observations are from grades 7th to 10th, with the most significant proportion coming from 7th and 8th grades, representing a combined total of 58.53% of the sample.

Table 2.3: Sample in Chapter 4 (Spain)

Variables	n	Mean	Min.	Max.
<i>Female</i>	4,005	0.49		
<i>Age</i>	4,005	13.83	12	17
Distribution across grades:				
7 th grade	1,171	29.24%		
8 th grade	1,173	29.29%		
9 th grade	854	21.32%		
10 th grade	807	20.15%		
Total	4,005			

Finally, in Chapter 5, the three-period sample from El Salvador is used due to the methodology employed. The descriptive statistics are present in Table 2.4. In all periods, 49% of the sample are females, and the mean age across periods is 15.12 years old. The 7th, 8th and 9th grades represent the 70.38%, 70.93%, and 72.34%,

Table 2.4: Sample in Chapter 5 (El Salvador)

Variables	Period 1		Period 2		Period 3	
	n	Mean	n	Mean	n	Mean
<i>Female</i>	2555	0.49	2627	0.49	2161	0.49
<i>Age</i>	2593	15.61	2648	14.88	2093	14.86
Distribution across grades:						
7 th grade	654	25.15%	759	28.65%	599	27.60%
8 th grade	592	22.77%	561	21.18%	515	23.73%
9 th grade	584	22.46%	559	21.10%	456	21.01%
10 th grade	339	13.04%	406	15.33%	322	14.84%
11 th grade	326	12.54%	287	10.83%	228	10.51%
12 th grade	105	4.04%	77	2.91%	50	2.30%
Total	2600		2649		2100	

Note: *Female* and *Age* are self-reported, and therefore the sample size varies.

respectively, while the less representative grade is 12th with an average of 3.08% in the full sample. Complete descriptive statistics of the participants are presented in Table 5.2.

2.5 Conclusions

This chapter describes the general methodology employed in the data collection of Spain and El Salvador data sets and briefly introduces the experimental tasks described in detail in the chapters below. We noted the need for some logistic adaptations and challenges in a different context out of the standard samples from European and developed countries, particularly in El Salvador, where issues such as limited resources and socio-political factors are present.

The objective is to provide a broader view of the overall data set; this helps to understand the samples' shared aspects and differences. One of the most relevant aspects is the shared design of the experimental tasks, which were adapted for adolescents, with minimal specific adaptations for El Salvador, as the symbol of dollars instead of euros. Both studies provided valuable insights into adolescents' behavioral preferences, social dynamics, and abilities, among other relevant aspects not addressed in this thesis.

In summary, the execution of the two projects in different contexts, one in Spain and

the other in El Salvador resulted in a combined potential sample of 13,309 observations of 9,616 students aged between 10 and 24 years old¹², across 45 educational centers. Given the specific research focus of this thesis, we apply selection criteria to work with sub-samples. The Spanish dataset is analyzed in Chapter 4, which focuses on the delay of gratification and work ethics. The El Salvador dataset is explored in Chapters 3 to study the inconsistent behavior over time and risk preference tasks. In Chapter 5, we analyze the role of the observable and unobservable characteristics in friendship and enmity formation.

Moving forward, the findings from these datasets could be used to develop more targeted interventions and educational strategies, particularly in addressing issues such as social isolation and disparities in educational outcomes.

¹²The El Salvador sample includes four observations from 22-year-olds, and one each from 23 and 24-year-olds (see Table 5.2).

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Chapter 6

Future research

The work carried out to complete this doctoral thesis has been an incredible opportunity to learn about things that, honestly, I knew very little about five years ago.

First, I have learned to think scientifically, to articulate questions, and to seek evidence that supports or refutes them. Second, I have acquired technical skills for analyzing individual and network data. From the former, what has left the biggest impression on me is that a simple analysis is always better than a complex one; from the latter, that sometimes simple analyses are impossible.

In this final chapter, I will outline some of the ideas I am currently working on and wish to continue pursuing after completing my doctoral thesis. I have divided this chapter into two parts. The first focuses on a new project I have recently started working on directly related to my current research. The second centers on new areas I want to explore once my thesis allows me the time to investigate subjects that are still unfamiliar to me.

6.1 Network position and creativity

This project was born during my stay with Prof. Roberto Hernán at the Burgundy School of Business (BSB) in Dijon, France. We began working on this topic during this period, and it has since evolved into a joint paper that we are writing together with Prof. Jaromír Kovářík.

The paper aims to test the theoretical hypotheses proposed by Perry-Smith and Shalley (2003) regarding the relationship between social networks and creativity. To test these hypotheses, we use the Spanish adolescents dataset (see Vasco et al., 2025).

The idea behind Perry-Smith and Shalley (2003) is that individual creativity should be related to her social environment. In fact, there is evidence that creativity can be elicited from a young age and, more importantly, it is influenced by the environment and interactions of the subject or group (Sternberg and Lubart, 1991; Plucker et al., 2004; Fernández-Batanero et al., 2012). Interestingly, creativity can be a predictor of success in adult life (Torrance, 1972; Fernández-Díaz et al., 2021).

The model proposed by Perry-Smith and Shalley (2003) is framed from an organizational perspective; our intention is to adapt these hypotheses to the educational context, particularly the school environment.

Perry-Smith and Shalley (2003) hypotheses

The model proposed by Perry-Smith and Shalley (2003) has two separate sets of hypotheses: social ties and network position.

Network ties

H1a: “Weak ties should facilitate creativity at work compared to strong ties.”

H1b: “Relatively many weak ties and fewer strong ties should correspond with higher creativity at work than many strong ties and fewer weak ties.”

H1c: “A larger number of weak ties should correspond with higher creativity at work, up to a point; beyond this point, there is less benefit realized from larger numbers of weak ties, and they may constrain creativity at work.”

Network position

H2: “Holding constant ties outside the network, individuals with greater closeness centrality are likely to have higher creativity at work through some moderate level of closeness centrality; beyond this level, greater closeness centrality

may constrain creativity.”

Metrics

Consequently, we will focus on two specific aspects of the (class) networks: *i) Ties: Weak and strong.* A weak tie is when only one of the two subjects mentions the other as a friend, but it does not happen in the other sense (*i* calls *j* but *j* does not call *i*). On the contrary, a strong tie is a reciprocal relationship in which both select each other as friends (*i* calls *j* and *j* does call *i*), as in Chapter 5 in this thesis. *ii) Position: Closeness.* The average distance of a node (e.g., a subject) from the others in the network is defined by Freeman (1979) as a centrality measure. Additionally, other aspects of the network will be included.

To measure the creativity within our Spanish sample, we use the Alternatives Used Task (AUT) of Guilford (1967). This task let us obtain the four components of Creativity proposed by Guilford (1950):

- *fluency*: Refers to the ease or ability to generate many ideas.
- *flexibility*: The ability through which one transforms, changes, rethinks, or reinterprets while solving a problem or formulating it.
- *originality*: A characteristic that defines the idea or proposed solution as a unique, novel, and far from the usual or predetermined.
- *elaboration*: The level of complexity of the proposed creative idea, meaning the amount of detail, development, or how a specific response is enhanced or refined.

Dataset and data cleaning

Using an initial sample of 4,574 observations of subjects in Spain who completed the AUT from 18 schools in Spain (Andalusia and Catalonia). Data arising from the AUT need to be cleaned. After a “human” cleaning process, we obtained 13,520 uses. The cleaning includes grammatical error correction and translating usages

from Catalan to Spanish.

To compute the measurements defined before, we use a parallel process. *i)* With the help of R, we were able to compute *fluency* (amount of valid answers) and *elaboration* (amount of words by use). After aggregating the repetitive uses, we have a final sample of 5,284 uses.

ii) With a team of 15 adolescents (aged 15.9 on average), we compute *originality* and *flexibility*. Each use was assigned to two human judges, who evaluated them for originality (from 1 = not original at all to 5 = very original) and flexibility (9 categories predefined¹). On average, they earned €34. This payment was conditional on their performance. Judges' responses and agreement levels were evaluated using proper statistical tests.

Potential Extensions

We plan to extend the analysis in two ways besides the direct test of Perry-Smith and Shalley (2003) hypotheses. First, we are planning to explore how the conflict within the class may have an impact on the use of the language. As a measure of *Conflict*, we may use an enmity index (based on bad peer relationships) and bullying within the classroom. For the *use of language*, we use the responses in the AUT task.

Second, we are also interested in the capacity of ChatGPT 4 to classify originality and flexibility – compared to human judges. To address this question, we will use the previous *originality* and *flexibility* measure from human judges; we will ask ChatGpt 4 to be a judge with the exact instructions.

6.2 Continuing previous studies

Regarding the things I want to continue working on, there are two topics that I need to keep exploring.

Cultural differences: In Chapter 3, we explored the inconsistency in the sample of

¹They were also given the opportunity to add new categories.

Salvadoran students without directly comparing it with the Spanish sample's performance. We know context differences; hence, one potential avenue for future research could involve simultaneously analyzing both samples to examine the varying degrees of inconsistency within each, leveraging identical procedures and task designs. This approach may uncover key distinctions in the performance of other tasks and characteristics between the samples, enhancing our understanding of inconsistency within the Salvadoran cohort.

Homophily: The methodology used in Chapter 5, Bayesian Model Averaging (BMA) - which allows us to address uncertainty and analyze both observable and unobservable characteristics for link formation - could be applied to new datasets to verify the generalizability of our results. This would help determine whether observable characteristics are the primary factors driving homophilous interactions. Similarly, another important area for future research is the analysis of stronger relationships beyond reciprocity. For instance, our data includes information about *best friends*, which could provide a richer understanding of the dynamics at play.

New Network Metrics: Related to previous work, I am also interested in exploring other network metrics, such as the subject's popularity, centrality, or isolation based on the number of received mentions in the network, which could offer further insights.

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III

GENERAL CONCLUSIONS

This thesis is organized into three parts, each addressing a distinct aspect of the research. Part I details the general methodology employed in the data collection in 2022 and 2023, involving two datasets of adolescents in Spain and El Salvador, with students aged between 10 and 24 years. It also describes the sub-samples used in Part II. Additionally, it provides an overview of the overall datasets, highlighting the shared procedures and experimental task design.

Part II analyzes the data using a variety of statistical methods, including OLS regressions and Bayesian Model Averaging (BMA), to address the principal objectives of this thesis:

*GO*₁ To analyze the inconsistency of a sample of Salvadoran students in two traditional experimental tasks designed to measure temporal discounting and risk aversion.

Chapter 3 focuses on this aspect, using a sample of 2,248 students of the first period collected in El Salvador, across the 12 schools. It analyzes how these students make decisions regarding time and risk.

First, to determine if students in El Salvador can perform the tasks satisfactorily, we explored their inconsistencies. Our findings suggest that the answer to this question is negative since only 27% of the sample was consistent in both tasks. Then, we analyze our sample, segregating cognitive and probability abilities, finding that those who perform better are less likely to be inconsistent. Using the data of the second period collected in El Salvador across the same students, we examined if repetition improves inconsistency, and we found that, at least in our sample, repetition does not always result in subjects making more consistent decisions. Therefore, over-

all inconsistency remains, which means they are presenting a serious problem with the basics. Finally, we explore using Cumulative Distribution Functions (CDFs) over the immediate and long-term implications related to their educational performance, expectations (next year and going to university) and desire to attend university. Finding that in all cases, the inconsistent students have worse expectations and even less interest in attending university.

GO₂ Analyzing the effect of patience on adolescent task performance.

Chapter 4 uses a sample of 4,005 Spanish students from 18 schools in Andalusia and Catalonia. It investigates the impact of patience, also known as delay of gratification, on performance, which can provide insights into the work ethics of the sample. We use the truck task to measure students' delay of gratification and the AUT (Guilford, 1967) as a real-effort task to assess performance. Each task allows us to go deeper into our measures, having for delay of gratification those present or future oriented and for the effort task performance and outperformance. Our results suggest that the delay of gratification impacts performance and, further, on outperformance. Corroborating the existing relation between delay of gratification and work ethics.

GO₃ Analyzing the determinants of friendship and enmity formation in emerging social networks of students in El Salvador using a Bayesian Model Averaging (BMA) modeling approach.

Chapter 5 uses the complete three-period sample from El Salvador, comprising a potential sample of 7,419 observations taken from 3,726² students aged 11 to 24 years across 12 public schools. All subjects were used to build the possible pairs within the network, but the model only included pairs without missing values, excluding subjects with a single participation. We applied the Bayesian Model Averaging (BMA) to address the model uncertainty over 37 observable and unobservable characteristics and compared the (dis)similarity between pairs.

²More than one observation per some of the students.

We examined positive links (friendship), followed by negative ones (enmity). Our results suggest that those more robust determinants are observable for both kinds of link formation. The observable determinants include having a prior relationship, common gender, and being in the same section. When examining unobservable determinants for friendship, we find that similarity is important. Specifically, similarity in income, risk preferences, expectations about a future tech profession, desire to attend university, and academic performance in the scientific track all play a role. In addition, there are other, less stable determinants. Meanwhile, for enmity formation, we only found having the same expected future profession as being a doctor could play a role but is less stable since his estimated posterior inclusion probability (*PIP*) value diminishes when we look for only those who participated in the three periods.

Finally, Chapter 6 presents future research, building on the studies in this thesis and investigating additional aspects of the samples.

APPENDICES

Appendix A

Chapter 3

A.1 Experimental tasks

This section describes the tasks as they were presented to subjects. In schools 1 to 8, they completed the tasks in the following the order: truck + CRT + Fin + gumball + Delavande. In schools 9 to 12, the order of the truck and gumball tasks was inverted.

A.1.1 The Truck task

Screen 1

Throughout the next 6 screens, you will have to make 6 decisions (one per screen) about **how you want to receive a hypothetical amount of money**. Your task is to choose which option you prefer, knowing that if you choose one you will receive the money **tomorrow**, and if you choose the other you will receive it **next week**. As you progress through the decisions, the amount of money you will receive for waiting will get **larger and larger**.

¿Qué prefieres?

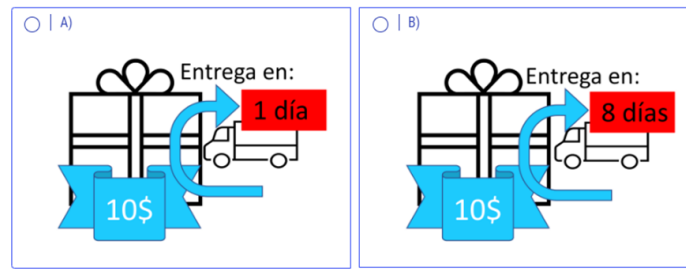


Figure A.1: Screen 2

¿Qué prefieres?

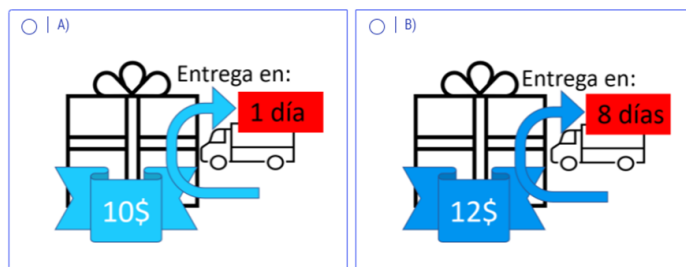


Figure A.2: Screen 3

¿Qué prefieres?

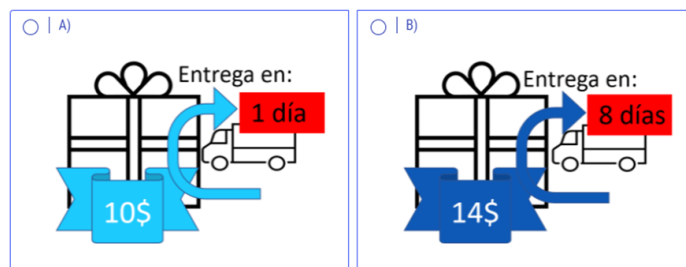


Figure A.3: Screen 4

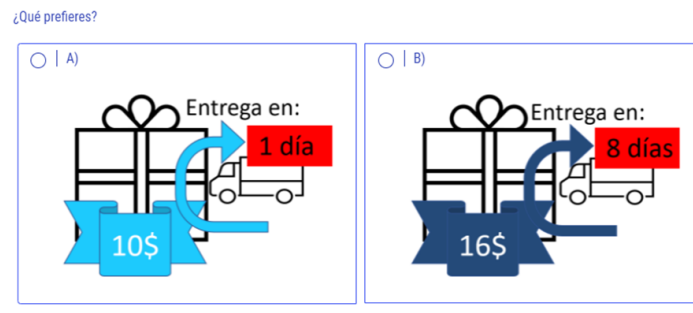


Figure A.4: Screen 5

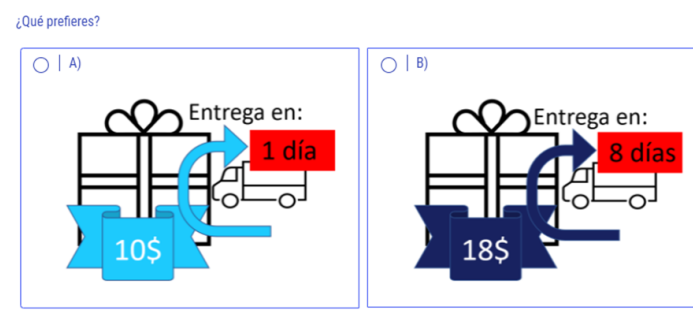


Figure A.5: Screen 6

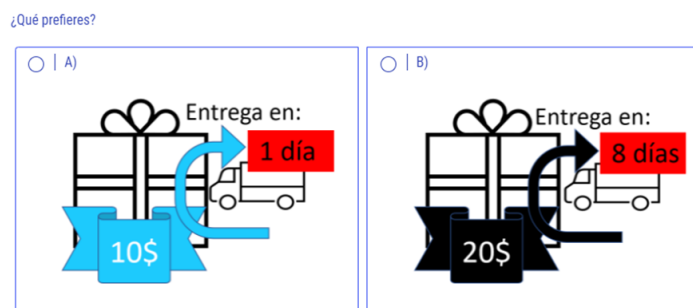


Figure A.6: Screen 7

A.1.2 The Gumball task

Screen 1

In this task you are going to make decisions about **probabilities**. Probability is the possibility of something happening, that is, how someone is sure what is going to happen.

In each decision **you will have to choose between two options** where you can win fictitious money: in both you will win, but you can be luckier and win more, or you can be less lucky and win less. **The probabilities of winning change** from one decision to another.

Below, you are presented with **6 different questions**. Your task is to choose option **A)** or option **B)** in all questions.

To complete the task, proceed to the **next screen**.

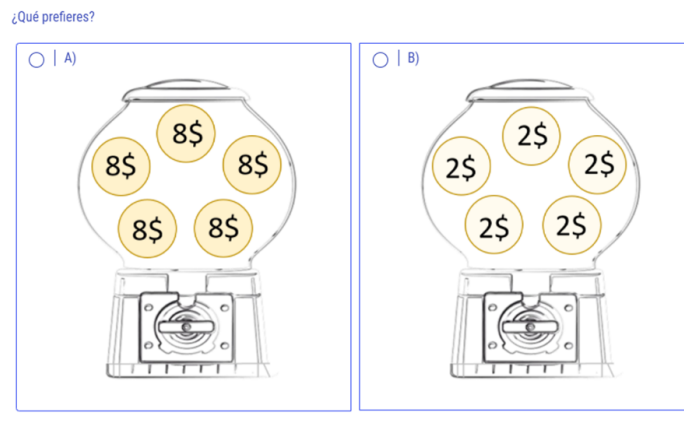


Figure A.7: Screen 2

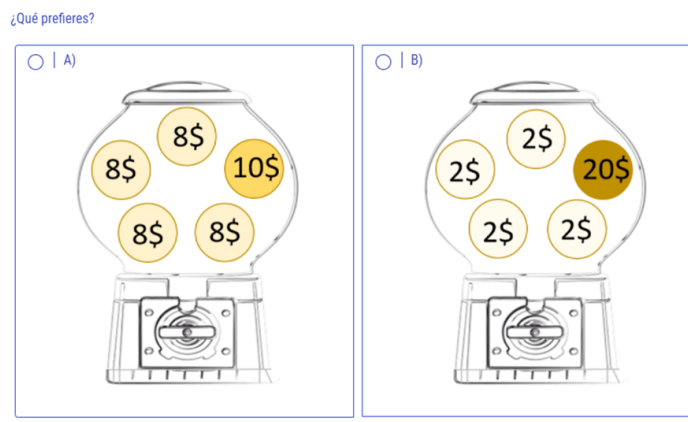


Figure A.8: Screen 3

¿Qué prefieres?

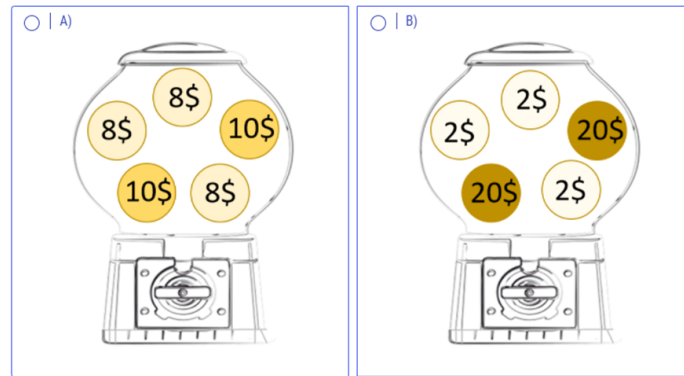


Figure A.9: Screen 4

¿Qué prefieres?

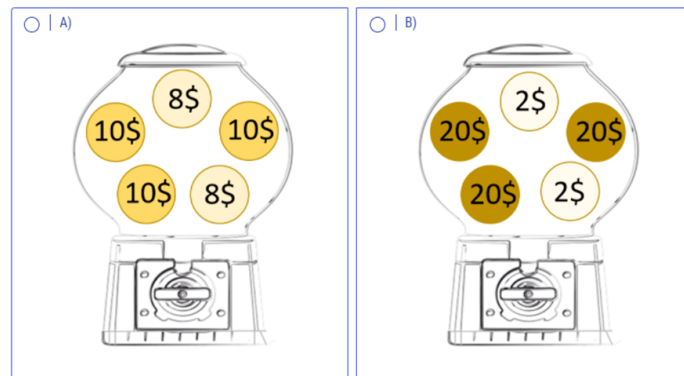


Figure A.10: Screen 5

¿Qué prefieres?

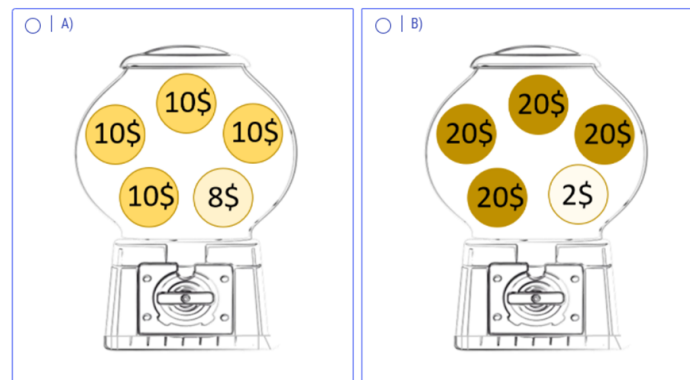


Figure A.11: Screen 6

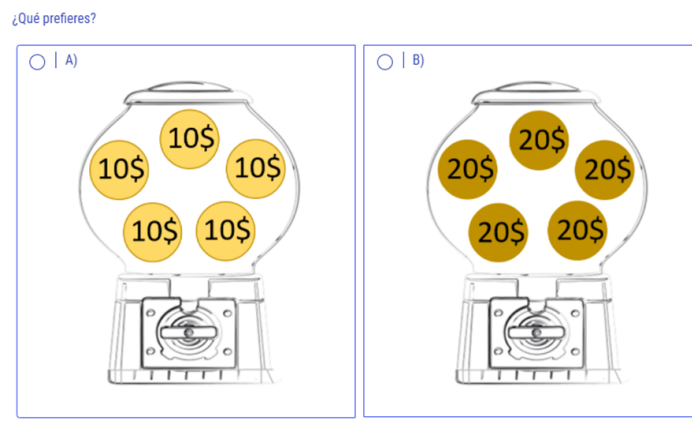


Figure A.12: Screen 7

A.1.3 Cognitive Reflection Test

Screen 1

Please answer the following questions. **There are** correct and incorrect answers to these questions.

Screen 2

Randomly ordered questions:

1. In a library, the number of books doubles every month. If the library takes 48 months to fill, how long will it take to fill it halfway? Indicate with a number. (reflective: 47; intuitive: 24).
2. If you are running a race and you pass the person in second place, what place are you in? Indicate with a number. For example: 1 (first), 2 (second), etc. (reflective: second; intuitive: first).
3. The father of Emilia has 3 daughters. The first two are named April and May. What is the name of the third daughter? (reflective: Emilia; intuitive: June).

A.1.4 Financial abilities

Screen 1

NOTE: In case you **do NOT know how** to answer or you think this question is not for you, please answer with this question is not for you, answer with: **00**

1. If there are 5 people who possess the winning ticket of a lottery and the prize to be shared is 2 million dollars, how much money will each person receive? Indicate with numbers without periods or commas. (correct: 400000).
2. Imagine that you have \$100 in a savings account. The account accumulates an interest rate of 10% by year. How much money will you have in the account after 2 years? (correct: 121).
3. Imagine you have \$100 in a savings account and the interest rate you earn on the savings is 2% by year. If you keep the money in the account for 5 years, how much money will you have at the end of 5 years? (This question had options to select as an answer: Less than \$102, Exactly \$102, More than \$102 or 00. I don't know) (correct: More than 102).

A.1.5 Delavande

Note that participants in schools 1 to 8 responded to the task by entering a number, while in schools 9 to 12 half of the sample entered numbers and the other half moved a slider (see Figure A.13). The instructions and questions were maintained in both versions.

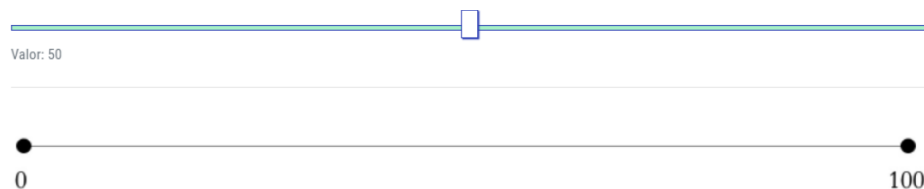


Figure A.13: Slider

Screen 1

In the next screen, we **will ask you** about the **probability** that certain things could

happen. In each question, you should **write down** how **likely you think** it is that these things will happen in reality.

If you think something will happen for **sure**, you should write **100**. If you are fairly but not completely sure, write a number close to 100 (but less than 100). If you think it is something that will **never** happen, write **0**. If you think it is unlikely, write a number close to 0 (but greater than 0). If you think it is **equally likely** to happen or not to happen, write **50**.

Screen 2

EXAMPLES:

- If it is a sunny day and I ask you how likely it is that it will be sunny within 1 hour, you would typically say 100 or numbers very close to 100.
- If it is 12 o'clock at night, the most reasonable thing to say is that the probability that it will be sunny in 1 hour is 0.
- If I flip a coin, the probability that it will come up heads is 50.

Screen 3

(First question format schools 1 to 8: how likely from 0 to 100 do you think it is possible to GET the GREEN apple?)

1. Imagine I have a basket with 5 APPLES: 1 GREEN and 4 RED. If I ask you to pick ONE of the apples WITHOUT LOOKING inside the basket, how likely is it that you will get the GREEN apple from 0 to 100?
2. Imagine I have a basket with 10 APPLES: 1 GREEN and 9 RED. If I ask you to pick ONE of the apples WITHOUT LOOKING inside the basket, how likely is it that you will get the GREEN apple from 0 to 100?
3. How likely are you to EAT RICE in THE NEXT WEEK from 0 to 100 (including today)?

4. How likely are you to EAT RICE in THE NEXT MONTH from 0 to 100 (including today)?

Screen 4

5. How likely is it that you will NOT ATTEND your school any time in the NEXT MONTH from 0 to 100 (including today)?
6. How likely is it that you will take a bath at least once during the NEXT MONTH from 0 to 100 (including today)?

Screen 5¹

(First question format center 1 to 8: How likely from 0 to 100 is it that you will still be STUDYING in 1 YEAR?)

7. How likely are you to CONTINUE your STUDIES next year from 0 to 100?
9. How likely are you to go to UNIVERSITY from 0 to 100?

A.2 Distribution of individual abilities

Table A.1: Cognitive and Probability abilities

Index	CogAb						ProbAb					
	CRT + FinAb		CRT		FinAb		Accuracy + No violations		Accuracy		No violations	
	n	Cumul%	n	Cumul%	n	Cumul%	n	Cumul%	n	Cumul%	n	Cumul%
0	450	20.02%	698	31.05%	1,287	57.25%	139	6.18%	713	31.72%	196	8.72%
1	761	53.87%	858	69.22%	835	94.40%	440	25.76%	791	66.90%	1,035	54.76%
2	613	81.14%	674	99.20%	124	99.91%	612	52.98%	533	90.61%	1,017	100%
3	341	96.31%	18	100%	2	100%	520	76.11%	139	36.80%		
4	76	99.69%					350	91.68%	72	100%		
5	7	100%					115	96.8%				
6	0	100%					72	100%				
Total	2,248						2,248					

¹Question 8 is not of interest for this study.

Table A.2: School performance

Self-reported school score	n	Cum. %
0	117	5.2%
1	1,061	52.4%
2	501	74.7%
3	266	86.5%
4	109	91.4%
5	86	95.2%
6	14	95.8%
7	38	97.5%
8	14	98.1%
9	13	98.8%
10	14	99.3%
11	12	99.9%
12	3	100.00
Total	2,248	

A.3 Robustness checks

In this section we present results from the following robustness checks²:

Adjustment in the standard errors. In Table A.3 we replicate Table 3.3 with clustering at the individual level to account for potentially correlated decisions across tasks. Note that in Table 3.3 we included clustering at the class level. We found that the results described in the paper are substantially the same with both kinds of clustering.

Numerical and non-numerical dimensions of CogAb. Given that: (i) our measure of cognitive abilities *CogAb* is constructed by adding subjects' scores in two different tests: the *CRT*, which reflects their ability to think deliberately and carefully, and the and financial abilities test (*FinAb*), which measures analytical skills, particularly in financial maths; and (ii) provided that reflection (*CRT*) differs from numeracy (*FinAb*), a valid question is whether math literacy is driving the inconsistencies described in the paper. In Table A.4 we compare the overall effect of *CogAb* (Models 1-3) with its numerical (Models 7-9) and non-numerical dimensions (Models 4-6)

²We thank our reviewers for suggesting these checks.

explored individually. Our findings suggest that both measures have similar effects in terms of the magnitude of the coefficient and statistical significance. Therefore, we do not find evidence that math literacy is the only driver of the inconsistencies described in the paper, as reflection seems to play a similar role.

Table A.3: Determinants of inconsistency (clustering at the individual level)

Vars.	(1) <i>Time</i>	(2) <i>Risk</i>	(3) <i>Both</i>	(4) <i>Time</i>	(5) <i>Risk</i>	(6) <i>Both</i>	(7) <i>Time</i>	(8) <i>Risk</i>	(9) <i>Both</i>
<i>Female</i>	-0.006 (0.021)	0.057*** (0.021)	0.026 (0.016)	-0.008 (0.021)	0.047** (0.021)	0.020 (0.016)	-0.011 (0.021)	0.043** (0.021)	0.016 (0.016)
<i>Year</i>	-0.011 (0.010)	-0.030*** (0.010)	-0.020*** (0.007)	-0.010 (0.010)	-0.024** (0.010)	-0.017** (0.007)	-0.008 (0.010)	-0.020** (0.010)	-0.014* (0.007)
<i>CogAb</i>				-0.008 (0.010)	-0.032*** (0.010)	-0.020*** (0.008)			
<i>ProbAb</i>							-0.020** (0.008)	-0.052*** (0.008)	-0.036*** (0.006)
School 1	0.017 (0.050)	0.029 (0.049)	0.023 (0.036)	0.015 (0.050)	0.021 (0.049)	0.018 (0.036)	0.008 (0.050)	0.005 (0.049)	0.007 (0.035)
School 2	0.059 (0.060)	0.021 (0.060)	0.040 (0.047)	0.053 (0.061)	-0.003 (0.061)	0.025 (0.047)	0.042 (0.060)	-0.024 (0.059)	0.009 (0.047)
School 3	0.041 (0.053)	0.099* (0.052)	0.070* (0.039)	0.037 (0.053)	0.083 (0.052)	0.060 (0.039)	0.028 (0.053)	0.065 (0.052)	0.047 (0.039)
School 4	-0.061 (0.048)	0.030 (0.049)	-0.015 (0.036)	-0.061 (0.048)	0.027 (0.049)	-0.017 (0.036)	-0.065 (0.048)	0.018 (0.049)	-0.023 (0.036)
School 5	-0.098* (0.059)	0.182*** (0.059)	0.042 (0.044)	-0.105* (0.060)	0.156*** (0.060)	0.026 (0.045)	-0.116* (0.061)	0.134** (0.061)	0.009 (0.046)
School 6	0.029 (0.077)	0.123* (0.073)	0.076 (0.057)	0.025 (0.077)	0.107 (0.073)	0.066 (0.057)	0.016 (0.077)	0.088 (0.071)	0.052 (0.057)
School 7	-0.043 (0.039)	0.136*** (0.038)	0.046 (0.029)	-0.046 (0.039)	0.123*** (0.038)	0.038 (0.029)	-0.058 (0.039)	0.095** (0.038)	0.019 (0.029)
School 8	-0.040 (0.046)	-0.031 (0.046)	-0.035 (0.035)	-0.042 (0.046)	-0.037 (0.046)	-0.039 (0.035)	-0.047 (0.046)	-0.048 (0.046)	-0.047 (0.035)
School 9	0.026 (0.045)	0.071 (0.044)	0.048 (0.033)	0.022 (0.045)	0.057 (0.044)	0.040 (0.034)	0.014 (0.044)	0.040 (0.043)	0.027 (0.033)
School 10	0.000 (0.047)	0.074 (0.046)	0.037 (0.035)	-0.004 (0.047)	0.059 (0.046)	0.028 (0.035)	-0.008 (0.047)	0.053 (0.046)	0.022 (0.035)
School 12	0.029 (0.037)	0.079** (0.037)	0.054* (0.029)	0.028 (0.037)	0.077** (0.037)	0.053* (0.029)	0.026 (0.037)	0.071* (0.037)	0.049* (0.028)
Constant	0.428*** (0.079)	0.617*** (0.079)	0.522*** (0.059)	0.440*** (0.081)	0.663*** (0.081)	0.551*** (0.060)	0.478*** (0.081)	0.749*** (0.081)	0.614*** (0.061)
Observations	2,248	2,248	2,248	2,248	2,248	2,248	2,248	2,248	2,248
R-squared	0.009	0.023	0.016	0.010	0.028	0.019	0.012	0.044	0.033

Robust standard errors in parentheses (clustering at the individual level)

*** p<0.01, ** p<0.05, * p<0.1

Accuracy and consistency dimensions of ProbAb. Given that our measure of Probability abilities *ProbAb* is composed of the number of correct probability estimations (*accuracy*) and the consistent decisions between sets (*noviolations*), in Table A.5 we compare the overall effect of *ProbAb* (Models 1-3) with its *accuracy* (Models 4-6) and *noviolations* dimensions (Models 7-9) explored individually. Regarding inconsistencies in *time* preferences, we found that the effect of *ProbAb* is mainly driven by *accuracy*, as the *noviolations* coefficient is not statistically significant for

this task (Model 7). For *risk*, both dimensions are statistically significant and effect sizes are similar (Models 5 and 8).

Table A.4: Determinants of inconsistency (*CogAb*, *CRT* and *FinAb*)

Vars.	(1) <i>Time</i>	(2) <i>Risk</i>	(3) <i>Both</i>	(4) <i>Time</i>	(5) <i>Risk</i>	(6) <i>Both</i>	(7) <i>Time</i>	(8) <i>Risk</i>	(9) <i>Both</i>
<i>Female</i>	-0.008 (0.021)	0.047** (0.021)	0.020 (0.014)	-0.007 (0.021)	0.052** (0.021)	0.023 (0.015)	-0.008 (0.021)	0.051** (0.020)	0.022 (0.014)
<i>Year</i>	-0.010 (0.009)	-0.024*** (0.009)	-0.017** (0.007)	-0.011 (0.009)	-0.026*** (0.009)	-0.019*** (0.007)	-0.010 (0.008)	-0.026*** (0.009)	-0.018*** (0.007)
<i>CogAb</i>	-0.008 (0.010)	-0.032*** (0.010)	-0.020*** (0.007)						
<i>CRT</i>				-0.006 (0.013)	-0.035** (0.014)	-0.021** (0.009)			
<i>FinAb</i>							-0.014 (0.016)	-0.038** (0.016)	-0.026** (0.012)
School 1	0.015 (0.053)	0.021 (0.048)	0.018 (0.037)	0.016 (0.053)	0.022 (0.050)	0.019 (0.037)	0.016 (0.053)	0.027 (0.048)	0.022 (0.036)
School 2	0.053 (0.083)	-0.003 (0.052)	0.025 (0.049)	0.056 (0.083)	0.003 (0.052)	0.029 (0.049)	0.056 (0.083)	0.012 (0.053)	0.034 (0.049)
School 3	0.037 (0.045)	0.083 (0.058)	0.060 (0.039)	0.039 (0.044)	0.084 (0.057)	0.061 (0.038)	0.040 (0.044)	0.096 (0.058)	0.068* (0.038)
School 4	-0.061 (0.043)	0.027 (0.042)	-0.017 (0.028)	-0.061 (0.043)	0.026 (0.043)	-0.018 (0.028)	-0.060 (0.042)	0.031 (0.042)	-0.014 (0.027)
School 5	-0.105*** (0.038)	0.156*** (0.056)	0.026 (0.032)	-0.102*** (0.038)	0.160*** (0.057)	0.029 (0.033)	-0.101*** (0.037)	0.175*** (0.056)	0.037 (0.031)
School 6	0.025 (0.048)	0.107*** (0.040)	0.066** (0.033)	0.028 (0.047)	0.113*** (0.039)	0.071** (0.032)	0.026 (0.047)	0.114*** (0.042)	0.070** (0.033)
School 7	-0.046 (0.047)	0.123*** (0.028)	0.038* (0.023)	-0.044 (0.046)	0.126*** (0.027)	0.041* (0.022)	-0.044 (0.047)	0.131*** (0.028)	0.043* (0.022)
School 8	-0.042 (0.045)	-0.037 (0.044)	-0.039 (0.037)	-0.042 (0.046)	-0.039 (0.044)	-0.040 (0.037)	-0.040 (0.045)	-0.029 (0.044)	-0.035 (0.037)
School 9	0.022 (0.028)	0.057 (0.052)	0.040 (0.033)	0.024 (0.027)	0.062 (0.052)	0.043 (0.033)	0.023 (0.027)	0.065 (0.053)	0.044 (0.033)
School 10	-0.004 (0.038)	0.059 (0.037)	0.028 (0.024)	-0.002 (0.038)	0.063* (0.036)	0.030 (0.023)	-0.002 (0.038)	0.068* (0.037)	0.033 (0.023)
School 12	0.028 (0.034)	0.077*** (0.028)	0.053** (0.021)	0.028 (0.034)	0.075*** (0.028)	0.052** (0.021)	0.029 (0.034)	0.080*** (0.028)	0.055** (0.021)
Constant	0.440*** (0.067)	0.663*** (0.071)	0.551*** (0.051)	0.435*** (0.067)	0.653*** (0.072)	0.544*** (0.051)	0.434*** (0.066)	0.632*** (0.070)	0.533*** (0.050)
Observations	2,248	2,248	2,248	2,248	2,248	2,248	2,248	2,248	2,248
R-squared	0.010	0.028	0.019	0.009	0.026	0.018	0.010	0.025	0.018

Robust standard errors in parentheses (clustering at the class level)

*** p<0.01, ** p<0.05, * p<0.1

Table A.5: Determinants of inconsistency (*ProbAb*, *Accuracy* and *Noviolations*)

Vars.	(1) <i>Time</i>	(2) <i>Risk</i>	(3) <i>Both</i>	(4) <i>Time</i>	(5) <i>Risk</i>	(6) <i>Both</i>	(7) <i>Time</i>	(8) <i>Risk</i>	(9) <i>Both</i>
<i>Female</i>	-0.011 (0.021)	0.043** (0.020)	0.016 (0.014)	-0.012 (0.021)	0.043** (0.020)	0.016 (0.014)	-0.006 (0.021)	0.052** (0.021)	0.023 (0.014)
<i>Year</i>	-0.008 (0.009)	-0.020** (0.009)	-0.014** (0.006)	-0.007 (0.009)	-0.020** (0.009)	-0.014** (0.006)	-0.011 (0.009)	-0.026*** (0.009)	-0.018*** (0.006)
<i>ProbAb</i>	-0.020** (0.008)	-0.052*** (0.008)	-0.036*** (0.006)						
<i>Accuracy</i>				-0.033*** (0.011)	-0.073*** (0.010)	-0.053*** (0.008)			
<i>No violations</i>							-0.010 (0.017)	-0.064*** (0.016)	-0.037*** (0.013)
School 1	0.008 (0.053)	0.005 (0.049)	0.007 (0.037)	0.007 (0.053)	0.008 (0.050)	0.007 (0.037)	0.015 (0.053)	0.020 (0.049)	0.017 (0.037)
School 2	0.042 (0.085)	-0.024 (0.049)	0.009 (0.051)	0.040 (0.084)	-0.021 (0.045)	0.009 (0.049)	0.056 (0.083)	0.004 (0.055)	0.030 (0.052)
School 3	0.028 (0.044)	0.065 (0.059)	0.047 (0.040)	0.026 (0.044)	0.066 (0.057)	0.046 (0.038)	0.039 (0.044)	0.087 (0.059)	0.063 (0.039)
School 4	-0.065 (0.042)	0.018 (0.044)	-0.023 (0.028)	-0.064 (0.042)	0.022 (0.045)	-0.021 (0.028)	-0.062 (0.043)	0.023 (0.042)	-0.019 (0.028)
School 5	-0.116*** (0.037)	0.134** (0.052)	0.009 (0.028)	-0.117*** (0.037)	0.141** (0.055)	0.012 (0.030)	-0.102*** (0.037)	0.160*** (0.053)	0.029 (0.029)
School 6	0.016 (0.048)	0.088** (0.042)	0.052 (0.034)	0.017 (0.048)	0.095** (0.041)	0.056* (0.033)	0.026 (0.047)	0.105** (0.042)	0.065* (0.034)
School 7	-0.058 (0.049)	0.095*** (0.027)	0.019 (0.025)	-0.060 (0.049)	0.096*** (0.027)	0.018 (0.025)	-0.045 (0.047)	0.121*** (0.028)	0.038 (0.023)
School 8	-0.047 (0.045)	-0.048 (0.045)	-0.047 (0.037)	-0.046 (0.045)	-0.043 (0.046)	-0.045 (0.038)	-0.042 (0.045)	-0.041 (0.044)	-0.041 (0.037)
School 9	0.014 (0.027)	0.040 (0.050)	0.027 (0.031)	0.012 (0.028)	0.041 (0.051)	0.026 (0.032)	0.024 (0.027)	0.060 (0.051)	0.042 (0.031)
School 10	-0.008 (0.038)	0.053 (0.036)	0.022 (0.023)	-0.007 (0.038)	0.057 (0.036)	0.025 (0.023)	-0.002 (0.037)	0.063* (0.036)	0.031 (0.023)
School 12	0.026 (0.034)	0.071** (0.028)	0.049*** (0.021)	0.025 (0.034)	0.070** (0.027)	0.048** (0.020)	0.028 (0.034)	0.077*** (0.028)	0.053** (0.021)
Constant	0.478*** (0.067)	0.749*** (0.074)	0.614*** (0.053)	0.465*** (0.066)	0.697*** (0.072)	0.581*** (0.051)	0.443*** (0.068)	0.707*** (0.075)	0.575*** (0.053)
Observations	2,248	2,248	2,248	2,248	2,248	2,248	2,248	2,248	2,248
R-squared	0.012	0.044	0.033	0.014	0.044	0.036	0.010	0.030	0.020

Robust standard errors in parentheses (clustering at the class level)

*** p<0.01, ** p<0.05, * p<0.1

A.4 Inconsistency types and intensity

The measure of inconsistency in our paper is constructed by considering three types of inconsistent behavior: subjects who make wrong choices in *time*, *risk* and *both* ($time \cup risk$). Within each domain, inconsistencies are defined as follows:

Time: refers to multiple switching along the temporal discounting task.

Risk: refers to choosing dominated strategies and/or multiple switching along the risk task.

For simplicity, in the paper, we report inconsistency results by considering individuals who made at least one inconsistent choice in the respective domain. In

this section, we extend the analysis by examining the *intensity* of inconsistencies, defined as the number of inconsistencies within the same task. Furthermore, considering previous studies have shown the importance of analyzing the differences between different *types* of inconsistency³, for *risk* we distinguish between *switching* and *dominated* strategies. These are referred to as lack of understanding (hereafter, LoU) and inattention, respectively (see Amador-Hidalgo et al., 2021).

In the first row of Table A.6 we report the proportion of subjects who made at least one inconsistent choice in each task (as presented in Figure 3.2 in the main text). In the lower panels, we break down these results to assess the *intensity* of inconsistency for both tasks and the inconsistency *types* for *risk*.

Table A.6: Inconsistency types and intensity

	Time	Risk	Both	
At least one inconsistency	45.37%	56.54%	72.78%	

Intensity				
	1	35.23%	26.38%	27.14%
	2	9.74%	19.93%	22.29%
	3	0.40%	10.23%	14.59%
	4 or more			8.79%

Types				
	LoU		27.62%	
	Inattention		23.98%	
	Switching		45.33%	
	Multiple types		30.16%	

Note: All percentages are calculated over total sample. For *types*, each category reflects the proportion of subjects exhibiting that specific type of inconsistency, regardless of them having committed other types as well. Therefore, the percentages reported for types do not sum to 100%. Subjects who exhibited more than one type of inconsistency *Multiple types* are 30.16% over the total sample.

We first analyze *intensity*. Among the inconsistent subjects in *time* (45% of total sample), most of them made only one inconsistent choice (35% of total sample). The proportion of subjects who made two or three inconsistent choices is much smaller (9.7% and 0.4% of total sample, respectively). In Figure A.14 we explore

³For example, Chew et al. (2022) argue that multiple switching is driven by stochastic preferences or a deliberate preference for randomization.

this result by gender, finding that the *intensity* of inconsistency in *time* is almost identical for boys and girls. Models 1, 4 and 7 in Table A.7 show that there are no statistically significant gender differences. The *intensity* of inconsistency is higher for *risk*. Table A.6 shows that, among inconsistent subjects (57% of total sample), almost half made only one inconsistent choice (26% of total sample), whereas 20% made two inconsistent choices and 10% made three inconsistencies.

Figure A.14 shows that the 5% gender gap in inconsistency in *risk* reported in the main text is explained by girls who made one mistake. Models 2, 5 and 8 in Table A.7 show that the gender difference in the *intensity* of inconsistency in *risk* weakens as we include *CogAb* to the regression ($p < 0.1$) and disappears when we include *ProbAb* ($p > 0.1$).

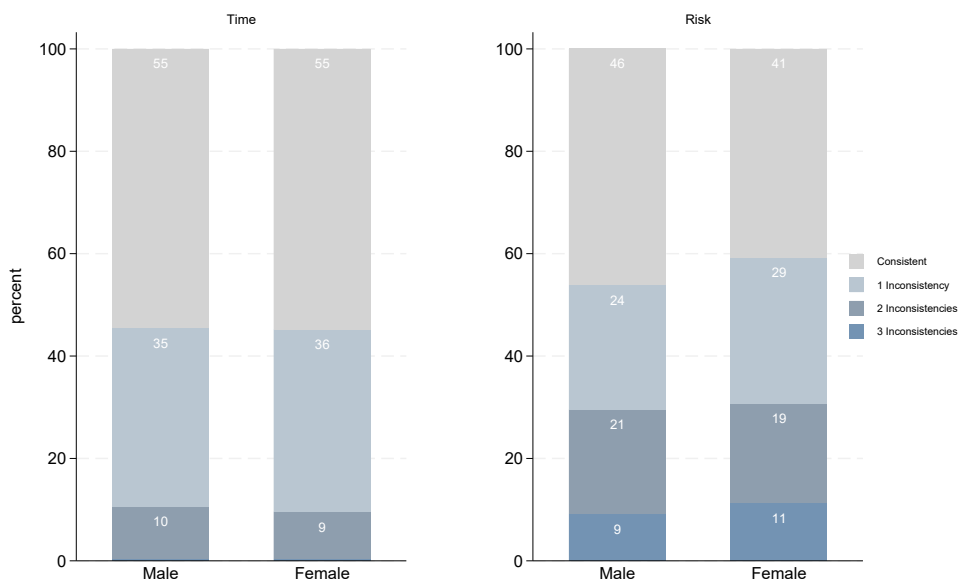


Figure A.14: Intensity of inconsistency by gender

Note: The percentage of males and females with 3 inconsistencies in *Time* is not displayed on the figure as it is very small (0.44% and 0.36%, respectively).

We now turn to inconsistency *types* in *risk*. Table A.6 shows the proportion of subjects exhibiting each *type* of inconsistency, regardless of whether they also exhibited other inconsistencies. As a result, the percentages for all *types* do not sum to 100%. A first important finding is that most inconsistent subjects made multiple

types of inconsistencies (30% of total sample). In fact, the proportion of subjects who made only one type of inconsistency is rather low (switching (15%) and dominated⁴ (11%)).

In Figure A.15 we see that the only *type* in which we observe gender differences is *switching* (13% of boys versus 18% of girls). Accordingly, Models 3 and 7 in Table A.8 show that girls are more likely to do *switching* ($p < 0.01$). Models 2 and 6 in Table A.8 show that both *CogAb* and *ProbAb* have a negative effect on the probability of choosing *dominated* strategies ($p < 0.05$ and $p < 0.01$, respectively). For *switching*, *ProbAb* has a negative effect ($p < 0.01$) (Model 7), but the effect of *CogAb* is not significant (Model 3). For multiple types (*Dom+Swb*), both *CogAb* and *ProbAb* have a negative and statistically significant effect ($p < 0.01$).

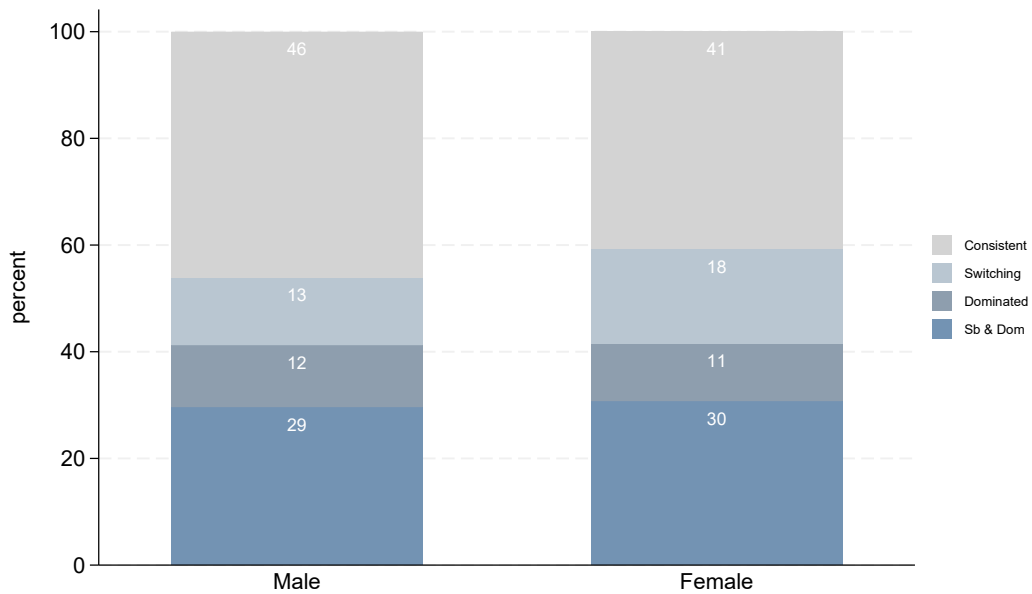


Figure A.15: Types of inconsistency in risk by gender

⁴For simplicity, in Figure A.15 we aggregate *LoU* (6.5%) and *Inattention* (4.7%) into the category *Dominated*.

Table A.7: Intensity of inconsistency

Vars.	(1) <i>Time</i>	(2) <i>Risk</i>	(3) <i>Both</i>	(4) <i>Time</i>	(5) <i>Risk</i>	(6) <i>Both</i>	(7) <i>Time</i>	(8) <i>Risk</i>	(9) <i>Both</i>
<i>Female</i>	-0.017 (0.029)	0.091** (0.043)	0.068 (0.053)	-0.018 (0.029)	0.072* (0.043)	0.047 (0.054)	-0.023 (0.029)	0.067 (0.043)	0.038 (0.053)
<i>Year</i>	-0.017 (0.014)	-0.061*** (0.020)	-0.076*** (0.025)	-0.016 (0.014)	-0.050** (0.021)	-0.063** (0.026)	-0.012 (0.014)	-0.044** (0.020)	-0.054** (0.025)
<i>CogAb</i>				-0.005 (0.014)	-0.060*** (0.020)	-0.068*** (0.025)			
<i>ProbAb</i>							-0.025** (0.011)	-0.089*** (0.015)	-0.112*** (0.020)
School 1	-0.020 (0.065)	-0.082 (0.096)	-0.095 (0.119)	-0.021 (0.066)	-0.098 (0.096)	-0.113 (0.119)	-0.031 (0.065)	-0.122 (0.096)	-0.146 (0.117)
School 2	0.043 (0.078)	-0.076 (0.118)	-0.046 (0.150)	0.039 (0.079)	-0.121 (0.120)	-0.096 (0.152)	0.022 (0.079)	-0.152 (0.118)	-0.142 (0.150)
School 3	0.071 (0.074)	0.073 (0.106)	0.136 (0.132)	0.068 (0.074)	0.042 (0.107)	0.101 (0.132)	0.054 (0.074)	0.015 (0.106)	0.062 (0.131)
School 4	-0.076 (0.067)	-0.063 (0.098)	-0.148 (0.120)	-0.076 (0.067)	-0.068 (0.099)	-0.155 (0.120)	-0.081 (0.067)	-0.083 (0.097)	-0.173 (0.120)
School 5	-0.144* (0.075)	0.226* (0.125)	0.075 (0.152)	-0.149* (0.076)	0.177 (0.126)	0.020 (0.154)	-0.167** (0.077)	0.145 (0.127)	-0.027 (0.157)
School 6	0.015 (0.100)	0.102 (0.156)	0.102 (0.199)	0.013 (0.100)	0.072 (0.156)	0.067 (0.200)	-0.001 (0.100)	0.043 (0.154)	0.027 (0.198)
School 7	-0.064 (0.053)	0.158** (0.080)	0.108 (0.098)	-0.066 (0.053)	0.134* (0.080)	0.081 (0.098)	-0.083 (0.054)	0.090 (0.081)	0.022 (0.099)
School 8	-0.035 (0.065)	-0.180** (0.089)	-0.211* (0.113)	-0.036 (0.065)	-0.192** (0.089)	-0.225** (0.113)	-0.043 (0.065)	-0.209** (0.089)	-0.248** (0.113)
School 9	0.081 (0.065)	0.076 (0.092)	0.120 (0.115)	0.079 (0.065)	0.050 (0.093)	0.091 (0.115)	0.067 (0.065)	0.023 (0.091)	0.054 (0.113)
School 10	0.032 (0.067)	0.124 (0.098)	0.152 (0.123)	0.029 (0.067)	0.096 (0.098)	0.121 (0.123)	0.022 (0.067)	0.088 (0.098)	0.107 (0.123)
School 12	0.025 (0.051)	0.187** (0.079)	0.212** (0.099)	0.024 (0.051)	0.184** (0.079)	0.209** (0.099)	0.021 (0.051)	0.174** (0.079)	0.196** (0.098)
Constant	0.516*** (0.113)	1.204*** (0.164)	1.699*** (0.204)	0.523*** (0.115)	1.291*** (0.166)	1.796*** (0.207)	0.579*** (0.116)	1.428*** (0.168)	1.981*** (0.210)
Observations	2,248	2,248	2,248	2,248	2,248	2,248	2,248	2,248	2,248
R-squared	0.011	0.019	0.018	0.011	0.023	0.021	0.013	0.033	0.032

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Note: In models (1), (4) and (7) the dependent variable corresponds to the number of inconsistent choices made in *time*. In models (2), (5) and (8) we add the number of inconsistent choices in *risk*, regardless of the type (dominated or switch-back). In models (3), (6) and (9) we add subjects' inconsistencies in both tasks.

Table A.8: Determinants of inconsistency types in *risk*

Vars.	(1) <i>Any</i>	(2) <i>Dom</i>	(3) <i>Swb</i>	(4) <i>Dom+Swb</i>	(5) <i>Any</i>	(6) <i>Dom</i>	(7) <i>Swb</i>	(8) <i>Dom+Swb</i>
<i>Female</i>	0.047** (0.021)	0.004 (0.025)	0.088*** (0.023)	0.030 (0.025)	0.043** (0.020)	0.001 (0.025)	0.077*** (0.021)	0.028 (0.025)
<i>Year</i>	-0.024*** (0.009)	-0.016* (0.009)	-0.009 (0.013)	-0.029*** (0.009)	-0.020** (0.009)	-0.014 (0.009)	-0.003 (0.013)	-0.025*** (0.009)
<i>CogAb</i>	-0.032*** (0.010)	-0.021** (0.010)	-0.017 (0.011)	-0.034*** (0.012)				
<i>ProbAb</i>					-0.052*** (0.008)	-0.029*** (0.008)	-0.043*** (0.007)	-0.047*** (0.008)
School 1	0.021 (0.048)	0.101* (0.057)	0.067 (0.050)	-0.066 (0.046)	0.005 (0.049)	0.091 (0.056)	0.048 (0.051)	-0.075 (0.047)
School 2	-0.003 (0.052)	0.113* (0.064)	-0.011 (0.055)	-0.073 (0.061)	-0.024 (0.049)	0.105 (0.065)	-0.035 (0.052)	-0.081 (0.062)
School 3	0.083 (0.058)	0.130* (0.067)	0.052 (0.065)	0.048 (0.061)	0.065 (0.059)	0.121* (0.066)	0.035 (0.065)	0.037 (0.062)
School 4	0.027 (0.042)	0.110*** (0.036)	0.059 (0.054)	-0.063 (0.039)	0.018 (0.044)	0.103*** (0.036)	0.053 (0.057)	-0.070* (0.040)
School 5	0.156*** (0.056)	0.278*** (0.064)	0.069 (0.061)	0.097 (0.062)	0.134** (0.052)	0.261*** (0.063)	0.031 (0.061)	0.080 (0.059)
School 6	0.107*** (0.040)	0.213*** (0.050)	0.105 (0.071)	0.037 (0.056)	0.088** (0.042)	0.205*** (0.055)	0.089 (0.074)	0.026 (0.055)
School 7	0.123*** (0.028)	0.239*** (0.043)	0.056 (0.047)	0.061* (0.032)	0.095*** (0.027)	0.224*** (0.043)	0.027 (0.047)	0.042 (0.031)
School 8	-0.037 (0.044)	0.067*** (0.022)	0.013 (0.053)	-0.121*** (0.042)	-0.048 (0.045)	0.058** (0.022)	-0.002 (0.054)	-0.128*** (0.044)
School 9	0.057 (0.052)	0.087* (0.044)	0.070 (0.060)	0.016 (0.055)	0.040 (0.050)	0.081* (0.042)	0.053 (0.059)	0.005 (0.053)
School 10	0.059 (0.037)	0.029 (0.029)	0.035 (0.060)	0.064 (0.047)	0.053 (0.036)	0.021 (0.028)	0.020 (0.061)	0.060 (0.045)
School 12	0.077*** (0.028)	0.014 (0.031)	0.035 (0.046)	0.095*** (0.027)	0.071** (0.028)	0.009 (0.029)	0.032 (0.046)	0.091*** (0.026)
Constant	0.663*** (0.071)	0.226*** (0.070)	0.207** (0.100)	0.607*** (0.071)	0.749*** (0.074)	0.271*** (0.071)	0.297*** (0.102)	0.672*** (0.072)
Observations	2,248	1,229	1,318	1,655	2,248	1,229	1,318	1,655
R-squared	0.028	0.059	0.023	0.033	0.044	0.066	0.040	0.045

Robust standard errors in parentheses (clustering at the class level)

*** p<0.01, ** p<0.05, * p<0.1

Note: In each model, we compare subjects who committed each type of inconsistency with the consistent group. Therefore, the number of observations varies across models because those committing other types of inconsistencies are not included. For comparison, we include models (1) and (5) in which the dependent variable considers subjects who committed *any* inconsistency, thus using the full sample.

Inconsistency types across waves

For *risk* we also explored the role of inconsistency types across waves. In Table A.9 we report the proportion of subjects who were consistent and who committed each type of inconsistency in the first and second waves. The percentages are calculated over the sub-sample of students who participated in both waves⁵ and considering

⁵Recall that a total of 1,960 students from wave 1 repeated the experiment of which 1,322 met the same selection criteria as wave 1.

subjects' behavior in wave 1 as denominator. For example, among consistent subjects in wave 1, in wave 2 we find that 64% were consistent, 18% committed LoU, 16% inattention, and 30% switching. Since 30% of subjects committed more than one inconsistency (see Table A.6), percentages in Table A.9 do not sum to 100%.

We focus on the role of inattention and LoU in the transition from consistency to inconsistency and vice versa. In the first case, we could expect that inattention explains why consistent subjects in wave 1 become inconsistent in wave 2. In other words, these subjects understood the task well the first time, but were inattentive the second time. Likewise, LoU in wave 1 could explain why a subject becomes consistent in wave 2, assuming that she understood the task better the second time.

Our data does not suggest that inattention and LoU played a significant role in these transitions. This may be because a high proportion of subjects in our sample exhibited multiple types of inconsistencies (30%, as reported in Table A.6), making it difficult to isolate the role of a specific *type*. Table A.9 shows that, among subjects who transitioned from consistency to inconsistency, the most common *type* of inconsistency was switching (30%), which is almost twice as frequent as LoU and inattention (18% and 16%, respectively). For subjects who transitioned from inconsistency to consistency, the table shows that 30% of those who exhibited LoU became consistent. This proportion is similar for subjects who committed inattention in wave 1 but were consistent in wave 2 (30%), and slightly lower for those who made switching in wave 1 but became consistent in wave 2 (36%).

Table A.9: Inconsistency types in *risk* across waves

		<i>W1</i>			
		Consistent	LoU	Inattention	Switching
W2	Consistent	64.16%	29.72%	30.41%	36.27%
	LoU	17.92%	44.17%	40.64%	35.13%
	Inattention	16.13%	34.72%	36.84%	31.70%
	Switching	29.75%	59.72%	57.31%	54.74%

Note: The percentages do not sum to 100% because each category reflects the proportion of subjects exhibiting that specific type of inconsistency. Subjects who exhibited more than one type of inconsistency are included in multiple categories.

A.5 Strategies

Replacement strategies and elicitation of preferences

In this section we describe our replacement strategy for switching back decisions and discuss why it involves non-trivial assumptions that could distort the elicitation of subjects' preferences. Recall that the strategy that we adopted replaced subject's switching back decision to the one she had made immediately before. Take the case of a subject whose decision pattern was ABABBB. In this case, the switching back took place in the third decision "A" and the replacement consisted in changing it to the one she had made immediately before (second decision) "B". The underlying assumption of this replacement strategy is that subject's mistake was switching back from "B" to "A" in the third decision. However, an alternative interpretation of subject's decision pattern could be that the mistake was choosing "B" in the second decision. Under this assumption, an alternative replacement strategy would be to replace subject's second decision from a "B" to an "A".

Different assumptions about subject's inconsistent choices have non-trivial implications in the elicitation of their preferences. For *risk* preferences, the implications of the example above are straightforward: the first replacement strategy leads to the new decision pattern ABBBBB and the subject is classified as *risk lover*. Instead, with the alternative replacement, the resulting decision pattern is AAABBB and the subject is classified as *risk averse*.

Table A.10: Replacement strategies and risk preferences

Decision	Original pattern	Pattern with replacement	Pattern with alternative replacement
1	A	A	A
2	B	B	A
3	A	B	A
4	B	B	B
5	B	B	B
6	B	B	B
Classification	Inconsistent	Lover	Averse

As illustrated in A.10, alternative replacement strategies in *The Gumball* task lead to different classifications that could potentially distort the elicitation of subjects' preferences.

For *time* preferences, the different replacement strategies would not make a difference within the (*Interior*) dummy category. Nonetheless, if we compute the measure of time preferences in terms of the *number* of future allocations ($\#Future$, from 0 to 6 choices of one week later), it obviously matters whether we are changing a “B” to an “A” or an “A” to a “B”.

A.6 Background information about schools

In this section, we provide background information on the geographical distribution and performance of the schools included in the sample. Green dots in the map⁶ Figure A.16 represent the approximate geographical location.



Figure A.16: Approximate location of schools

Source: Map derived from a production by the United Nations Cartographic Section (UNCS), in the public domain. Accessible at Wikimedia Commons.

⁶ Accessible at Wikimedia Commons url: <https://commons.wikimedia.org/wiki/File:Un-el-salvador.png>.

The schools cover 5 of the 14 departments (i.e. states) of the country, three of which are located in the West Zone (Ahuachapán, Santa Ana y Sonsonate), one in the Central Zone (San Salvador), and one in the Eastern Zone (San Miguel).

Figure A.17 shows each school's performance in terms of average grades, according to official data from the Ministry of Education, Science, and Technology. The latest available update of this data is February, 2020. The dataset includes grades from the following subjects: Science, Health and Environment, Natural Sciences, Physical Education, Social Studies, Civics, Foreign Language, Computer Science, Educational Computing, English, Language and Literature, Mathematics, and Life Guidance.

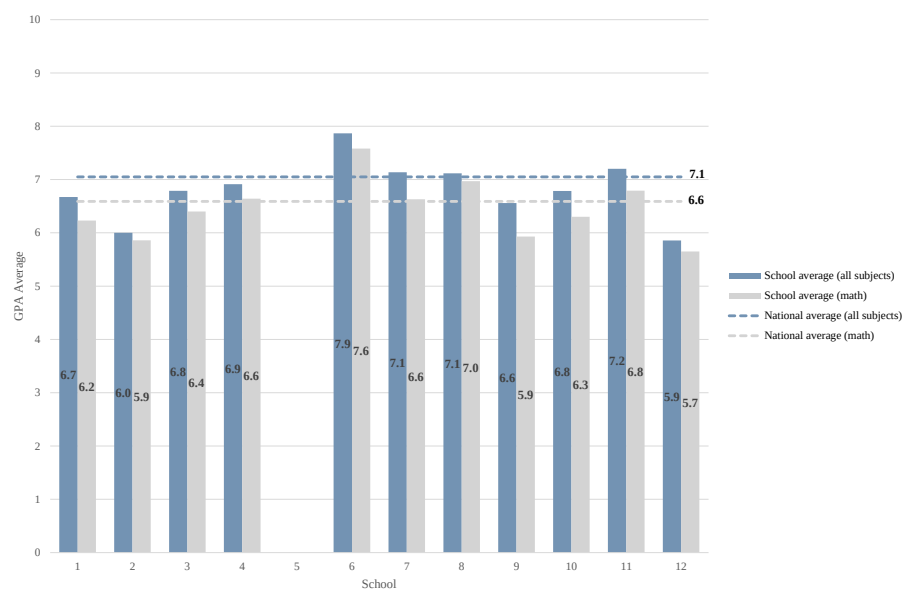


Figure A.17: School and national average

Source: Authors' calculations based on data from the information system for educational management of El Salvador (SIGES, in Spanish) by the Ministry of Education, Science, and Technology, 2019.

Given that our study focuses on students from 7th to 11th grade, we extracted data from 3,699 schools offering these grade levels. For these grades, we computed the

overall and the math average for each of the schools of our sample, only excluding school 5, where there was no available data. For comparison, we also computed the overall and math national average. The blue dotted line in Figure A.17 shows the overall national average and the blue bars show each school's average. For all subjects, the national average is 7.1 out of 10. In our sample, half of the schools have an overall average between 6.0 and 7.0, and the lowest and highest scores are 5.9 (school 12) and 7.9 (school 6). For Mathematics, the national score was 6.6 and 7 out of the 12 schools in our sample have an average between 6.0 and 7.0, with the lowest and highest scores of 5.7 (school 12) and 7.9 (school 6). Based on these comparisons, we conclude that, relative to the national average, the performance of the schools in our sample is neither systematically above nor below the national standard.

A.7 Inconsistent Choices and Educational Outcomes

Following the approach of Jacobson and Petrie (2009), we extend our analysis to examine how riskiness and the propensity to make mistakes influence educational expectations.⁷ First, we employed an error choice model to estimate the error rate in our sample using maximum likelihood estimation. Our estimated error rate, $\varepsilon = 0.227$, closely aligns with the 0.222 error rate for the gain lottery reported by Jacobson and Petrie (2009). Using this error rate, we then calculated the probability of making at least one mistake for each observed choice pattern in our sample.

We begin by analyzing whether our naïve measure of riskiness, *risky*,⁸ and the tendency to make mistakes can explain decision-making. Table A.11 presents the results of OLS regressions with bootstrapped standard errors.⁹ Models 1, 3, 5, and 7

⁷We replicated Jacobson and Petrie (2009)'s analysis as it closely aligns with the focus of our paper. We acknowledge that alternative approaches could have been used, such as those by Harrison et al. (2009) and Espinosa and Ezquerro (2022) to incorporate stochastic error using constant relative risk aversion (CRRA).

⁸*Risky* counts the number of risky allocations (option B vs A) from 0 to 6. The distribution is reported in Table A.12.

⁹As in Jacobson and Petrie (2009), we avoided standard OLS since we are using the estimated probability of making at least one mistake as an independent variable, creating a generated regressor. The estimates were obtained by sampling with replacement 10,000 times to generate bootstrapped estimates and standard errors.

show that neither riskiness nor the probability of making mistakes is significantly correlated with any of our immediate or long-term educational expectations measures.

Table A.11: Educational expectations with inconsistency measure OLS regression with bootstrapped errors

Vars.	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	<i>Self-reported</i>		<i>Likelihood of</i>		<i>Likelihood of</i>		<i>Wants to go</i>	
	<i>GPA</i>		<i>studying next year</i>		<i>going to university</i>		<i>to university</i>	
<i>Risky</i>	0.012	0.021	-0.003	0.010	-0.002	0.008	0.009	0.018**
	(0.035)	(0.038)	(0.008)	(0.009)	(0.007)	(0.008)	(0.007)	(0.008)
<i>Estimated probability of mistake</i>	4.164	8.862	0.832	7.707***	0.635	5.941***	0.076	4.891**
	(3.468)	(12.754)	(0.592)	(2.356)	(0.623)	(2.151)	(0.567)	(1.997)
<i>Risky x Estimated probability of mistake</i>		-1.023		-1.508***		-1.155**		-1.056**
		(2.623)		(0.512)		(0.460)		(0.436)
<i>Female</i>	-0.112	-0.110	0.027*	0.028*	0.059***	0.061***	0.078***	0.078***
	(0.076)	(0.076)	(0.015)	(0.014)	(0.014)	(0.014)	(0.013)	(0.013)
<i>Year</i>	0.099***	0.098***	-0.009	-0.010	-0.004	-0.004	0.005	0.004
	(0.038)	(0.038)	(0.007)	(0.007)	(0.007)	(0.007)	(0.006)	(0.006)
Constant	1.607***	1.577***	0.970***	0.934***	0.522***	0.489***	0.728***	0.703***
	(0.455)	(0.457)	(0.095)	(0.096)	(0.082)	(0.083)	(0.080)	(0.082)
Observations	2,248	2,248	1,160	1,160	2,248	2,248	1,160	1,160
R-squared	0.028	0.028	0.027	0.035	0.077	0.080	0.046	0.051

Standard errors in parentheses (clustering at the subject level)

*** p<0.01, ** p<0.05, * p<0.1

Note: Standard errors reported in parentheses. The estimates are bootstrapped 10,000 times. All regressions include the following control variables: gender, year, class size, device and school-level fixed effects. There are fewer observations for the questions on likelihood of studying next year and wanting to go to university because they were included during data collection.

However, the interaction between riskiness and the propensity to make mistakes is statistically significant for three of our four measures. Conditional on a higher likelihood of making mistakes, risky individuals are less likely to believe that they will study next year, attend university, or even desire to attend university. Nevertheless, their school performance, as captured by their self-reported GPA, is not significantly correlated with riskiness, the tendency to make mistakes, or the interaction between the two.

Table A.12: Risky distribution

<i>Risky</i>	Freq.	Percent
0	105	4.67%
1	129	5.74%
2	285	12.68%
3	522	23.22%
4	688	30.60%
5	372	16.55%
6	147	6.54%
Total	2,248	100%

A.7.1 Acknowledgements

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Appendix B

Chapter 4

B.1 Experimental tasks

B.1.1 DoG (*Patience*)

To measure time preferences, we used the *truck task* of Alfonso et al. (2023), where monetary payoffs are represented as gifts with a blue ribbon indicating their value and waiting times by a van. The blue ribbon gets dark as the interest rate increases. Subjects clicked on a button to indicate which gift of indicated monetary value they wanted to choose. Subjects made six hypothetical decisions: they could obtain the payoff at the early date of tomorrow by choosing the left option, or they could receive the payoff at a later date of one week (right option). The amount corresponding to the “A option” (left) is always € 10, and the corresponding amount of money in the later date “B option” (right) increases by 2 euros from decision to decision (€ 10, € 12, € 14, € 16, € 18, and € 20). Figure B.1 provides an example of the decision screen for the second time preference decision.

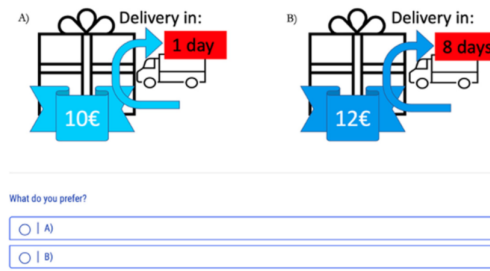


Figure B.1: Time preferences: screen decision 2.

Task screen

*Throughout the next six screens, you must make six decisions (one per screen) about how you want to receive a hypothetical amount of money. Your task is to **choose which option you prefer**, knowing that, if you choose one, you will receive the money **tomorrow**, and if you choose the other, you will receive it **next week**. As you progress through the decisions, the amount of money you will receive for waiting will increase.*¹

B.1.2 AUT (Performance and Outperformance)

The final component of the experiment is Guilford's Alternative Uses Task (AUT) (Guilford, 1967). This assessment is commonly used to measure divergent thinking and is well-known in the creative thinking literature. Participants are asked to think of as many different and unusual uses for a common object within a given time frame. In this particular case, the object is a brick (see Figure B.2), and they have up to 5 minutes to complete the task.

¹The original version of the task in Spanish reads as follows: A lo largo de las siguientes 6 pantallas, tendrás que tomar 6 decisiones (una por pantalla) sobre **cómo quieres recibir una cantidad de dinero** hipotética. Tu tarea es **elegir qué opción prefieres**, sabiendo que, si eliges una recibirás el dinero **mañana**, y si eliges la otra lo recibirás **la semana que viene**. Conforme vayas avanzando en las decisiones, la cantidad de dinero que recibirás por esperar será cada vez mayor.

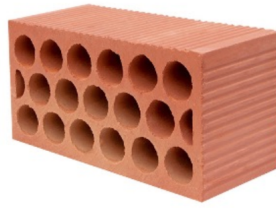


Figure B.2: Depiction of a Brick

Example screen

*In the following screen, you will find an object. We ask you to **list** in your response **ALL the uses** that come to your mind with it. **Separate** each use you mention with a semicolon (;).*

*This **IS AN EXAMPLE** of the question we are going to ask you.*

*Imagine we ask you: **List all the alternative uses you can think of with a paperclip**. Your answers could be: make a hook; make a bracelet; make a fishing hook.*

Time screen

*You can take **5 minutes** for the following question.*

Task screen

Write down all the alternative uses you can imagine for a brick (Figure B.2 is also shown in the task). Remember to separate each idea you write with a semicolon (;).²

²The original version of the example of the task in Spanish reads as follows: En la siguiente pantalla encontrarás un objeto. Te pedimos que **incluyas** en tu respuesta **TODOS los usos** que se te ocurran con él. **Separa** cada uso que menciones con un punto y coma (;). Esto **ES UN EJEMPLO** de la pregunta que vamos a realizar. Imagina que te preguntamos: **Escribe todos los usos alternativos que puedas imaginar con un clip**. Tus respuestas podrían ser: hacer un gancho; hacer una pulsera; hacer un anzuelo de pesca. The original version of the task in Spanish reads as follows: **Puedes tomarte 5 minutos** para la siguiente pregunta. Escribe todos los usos alternativos que puedas imaginar con un ladrillo. Recuerda separar cada idea que escribas con un punto y coma (;).

B.1.3 Cognitive Reflection Test (*Reflective*)

We use the Cognitive Reflection Test (CRT) adapted to teenagers to measure cognitive abilities (see Alfonso et al., 2023). We used the following questions:

CRT1: In a library, the number of books doubles every month. If the library takes 48 months to fill, how long would it take to fill it halfway? Indicate with a number. (reflective: 47; intuitive: 24).

CRT2: If you are running a race and you pass the person running in second place, what place are you in? Indicate with a number. For example: 1 (first), 2 (second), etc. (reflective: second; intuitive: first).

CRT3: Emilia's father has 3 daughters. The first two are named April and May. What is the name of the third daughter? (reflective: Emilia; intuitive: June).

The participants had the CRT prompts on a unified display. The sequence of questions was randomly assigned for each participant³.

- *CRT*: Number of correct answers in CRT normalized between 0 to 1.

B.1.4 Other variables (*female, grade, #A marks*)

- *Female*: Students self-identify as male, female, other, or prefer not to answer. The variable is 1 if the response is female, 0 if male, and NA in other cases. NA cases are disregarded from the analysis.
- *Grade*: The experiment is conducted as a school activity, and we have information on the grade level the student is currently in (ranging from 7 to 10).
- *GPA*: Students are asked whether they achieved outstanding grades in Math-

³The original version of the task in Spanish is the following: (First screen) Por favor, responde las preguntas siguientes. En estas preguntas **sí** hay respuestas correctas e incorrectas. (Second screen) 1. En una biblioteca, todos los meses se duplica el número de libros. Si la biblioteca tarda 48 meses en llenarse, ¿cuánto tardaría en llenarse a la mitad? Indica con un número. 2. Si estás corriendo una carrera y pasas a la persona que está en segunda posición, ¿en qué posición estás? Indica con un número. Por ejemplo: 1 (primero), 2 (segundo), etc. 3. El padre de Emilia tiene 3 hijas. Las dos primeras se llaman Abril y Mayo. ¿Cuál es el nombre de la tercera hija?

ematics, Language (Spanish), or the study of a secondary language (English) in the previous academic year. The variable is normalized between 0 to 1 based on the number of outstanding grades received.

B.2 Additional Tables

Table B.1: Regression analysis on performance and outperformance (allpresent)

	<i>performance</i>			<i>outperformance</i>		
	(1)	(2)	(3)	(4)	(5)	(6)
allpresent	-0.015*** (0.003)	-0.013*** (0.003)	-0.009*** (0.003)	-0.019*** (0.004)	-0.016*** (0.004)	-0.012*** (0.004)
grade		0.007*** (0.001)	0.008*** (0.001)		0.010*** (0.002)	0.011*** (0.002)
female		0.007*** (0.003)	0.006** (0.003)		-0.001 (0.004)	-0.001 (0.004)
#As		0.031*** (0.004)	0.033*** (0.004)		0.039*** (0.005)	0.041*** (0.005)
reflexive		0.036*** (0.005)	0.030*** (0.005)		0.026*** (0.007)	0.022*** (0.007)
Constant	0.104*** (0.002)	0.018* (0.010)	0.029*** (0.011)	0.136*** (0.002)	0.027* (0.014)	0.027* (0.015)
N	4005	4005	4005	2779	2779	2779
Adj R^2	0.005	0.049	0.093	0.006	0.045	0.076
Control	NO	YES	YES	NO	YES	YES
Fixed Effect	NO	NO	YES	NO	NO	YES

Note: Robust standard errors are presented in parentheses. *** $p < 0.01$; ** $p < 0.05$; * $p < 0.1$.

Table B.2: Regression analysis on performance and outperformance (allfuture)

	<i>performance</i>			<i>outperformance</i>		
	(1)	(2)	(3)	(4)	(5)	(6)
allfuture	0.016*** (0.005)	0.015*** (0.005)	0.009** (0.004)	0.021*** (0.007)	0.021*** (0.006)	0.017*** (0.006)
grade		0.007*** (0.001)	0.008*** (0.001)		0.010*** (0.002)	0.011*** (0.002)
female		0.007*** (0.003)	0.007*** (0.003)		-0.000 (0.004)	-0.001 (0.004)
#As		0.031*** (0.004)	0.034*** (0.004)		0.039*** (0.005)	0.041*** (0.005)
reflexive		0.036*** (0.005)	0.030*** (0.005)		0.026*** (0.007)	0.023*** (0.007)
Constant	0.100*** (0.001)	0.011 (0.010)	0.025** (0.011)	0.130*** (0.002)	0.018 (0.014)	0.020 (0.015)
N	4005	4005	4005	2779	2779	2779
Adj R^2	0.003	0.049	0.092	0.004	0.045	0.077
Control	NO	YES	YES	NO	YES	YES
Fixed Effect	NO	NO	YES	NO	NO	YES

Note: Robust standard errors are presented in parentheses. *** $p < 0.01$; ** $p < 0.05$; * $p < 0.1$.

Table B.3: Regression analysis for highest degree

	(1) performance	(2) outperformance
DoG	0.021*** (0.008)	0.037*** (0.011)
female	0.005 (0.006)	-0.001 (0.009)
GPA	0.047*** (0.009)	0.063*** (0.014)
CRT	0.038*** (0.010)	0.036** (0.017)
constant	0.074*** (0.010)	0.096*** (0.017)
N	807	607
Adj R^2	0.101	0.103

Note: *** $p < 0.01$; ** $p < 0.05$; * $p < 0.1$.

Appendix C

Chapter 5

C.1 Variables

Observable characteristics

Body mass index (BMI). They select first a gender between female, male or prefer not to specify or other. Then, they select the number of the figure that, according to them, looks more like them.

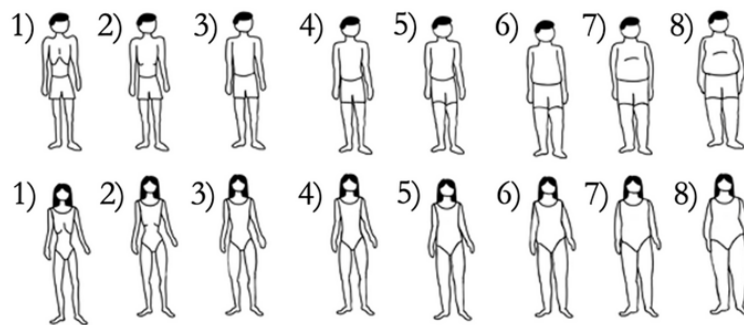


Figure C.1: Figure to select BMI

Unobservable characteristics

Common interests.

1. Expected Future Professions

Table C.1: List of expected Future Professions

Variable	Period 1			Period 2			Period 3			Original	
	n	Mean	Std. Dev.	n	Mean	Std. Dev.	n	Mean	Std. Dev.	Min.	Max.
Lawyer	1267	0.26	0.44	2644	0.27	0.44	2161	0.26	0.44	0	1
Security Agent (Police, Firefighter, Military, etc.)	1267	0.14	0.35	2644	0.21	0.41	2161	0.19	0.40	0	1
Farmer	1267	0.02	0.14	2644	0.04	0.20	2161	0.04	0.19	0	1
Face to the public in the service sector (waiter/waitress, sales clerk, etc.).	1267	0.03	0.16	2644	0.02	0.13	2161	0.03	0.17	0	1
In an NGO helping others.	1267	0.08	0.27	2644	0.05	0.23	2161	0.04	0.21	0	1
Influencer/Youtuber/Streamer	1267	0.16	0.37	2644	0.12	0.32	2161	0.11	0.31	0	1
Mechanic	1267	0.12	0.32	2644	0.11	0.32	2161	0.13	0.33	0	1
Doctor	1267	0.23	0.42	2644	0.21	0.41	2161	0.22	0.41	0	1
Entrepreneurship (Own business)	1267	0.15	0.36	2644	0.14	0.34	2161	0.15	0.35	0	1
Tech profession (IT specialist, engineer, etc).	1267	0.21	0.41	2644	0.15	0.36	2161	0.16	0.37	0	1
Teacher	1267	0.08	0.27	2644	0.08	0.27	2161	0.08	0.27	0	1
Veterinarian	1267	0.13	0.34	2644	0.11	0.32	2161	0.11	0.31	0	1
Other	1267	0.15	0.36	2644	0.14	0.35	2161	0.13	0.33	0	1

2. Climate change: How concerned are you personally about climate change?
Subjects indicate their level of concern using a slider ranging from 0 to 100.
3. Expectation: They had to select from 0 to 100, where closing to 0 was something that for sure would not happen, 50 they did not know if it would happen, and finally, closer to 100, it was sure that it would happen. **uniwantdiff**, Indicate from 0 to 100 if you would like to go to University in the future.
delavande_unidiff: How likely are you to go to UNIVERSITY from 0 to 100?

Prosocial attitudes. An example of a screen decision is presented in Figure C.2. only the amount changed between screens and is used to measure *Altruism*.

1. This version was employed in period 1. Subjects performed six times between A and B answering “What do you prefer?”. The value of option A in the six decisions is \$1 for you and \$1 for the other.
The option B was:
(screen 1) \$0.8 for you and \$1.6 for the other.
(screen 2) \$1.2 for you and \$0.4 for the other.
(screen 3) \$1 for you and \$1.8 for the other.
(screen 4) \$1 for you and \$0.6 for the other.
(screen 5) \$1.6 for you and \$0.4 for the other.

(screen 6) \$1.1 for you and \$1.9 for the other.

2. This version was employed in periods 2 and 3. Subjects performed three times between A and B answering “What do you prefer?”. The value of option A in the three decisions is \$10 for you and \$10 for the other.

The option B was:

(screen 1) \$10 for you and \$0 for the other.

(screen 2) \$10 for you and \$20 for the other.

(screen 3) \$20 for you and \$0 for the other.

The order of the decisions was aleatoric, generating six different paths.

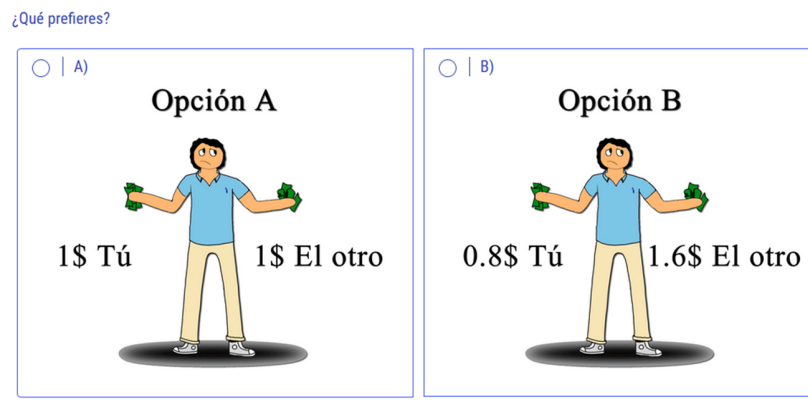


Figure C.2: Social preferences (version 1)

Emotional and Social Well-Being.

1. Self-reported happiness: Participants responded to three questions about their experiences in the past week:
 - (q1) Have you ever felt lonely?
 - (q2) Have you had fun with your friends?
 - (q3) Have you been doing well at school?

C.2 Gender results

In this section, we explore the results when we segregate male, female, and mixed couples for friend and enemy.

C.2.1 Friends

Table C.2: Friend male couples

Variable	PI prob.	Pt. Mean	Pt. Std.
Friends_{t-1}	1.000	0.290	0.004
Common Section	1.000	0.101	0.002
Tech profession	1.000	0.017	0.002
Risk diff.	0.973	-0.015	0.004
Income diff.	0.945	-0.013	0.004
Inconsistent risk	0.115	-0.001	0.002
CRT diff.	0.095	0.001	0.003
Wants to go to university diff.	0.036	-0.000	0.002
NGO helping others	0.039	0.002	0.010
Reflective	0.022	-0.000	0.001
Delavande violations diff.	0.015	-0.000	0.001
Happiness last week diff.	0.011	-0.000	0.001
Constant		0.009	0.002
Observations		49,129	

Notes: Column 1 presents the (un)observable characteristics. Column 2 displays the posterior inclusion probability (*PIP*). Robust determinants are those with $PIP \geq 0.8$ in bold. Column 3 shows the posterior mean. Column 4 reports the posterior standard deviation. The dependent variable equals 1 if i and j are friends in Period 2 and similarly for Period 3. It equals 0 otherwise. The results are obtained by using a betabinomial prior for the prior model probability and a benchmark prior for the hyperparameter that measures the degree of prior uncertainty on the coefficients, with $g = \max(N, p^2)$. Baseline: 1,375 (2.80%).

Table C.3: Friend female couples

Variable	PI prob.	Pt. Mean	Pt. Std.
Friends_{t-1}	1.000	0.252	0.004
Common Section	1.000	0.067	0.002
Income diff.	0.999	-0.014	0.003
Wants to go to university diff.	0.145	-0.001	0.003
STEM best	0.121	0.000	0.001
Constant		0.006	0.001
Observations		49,866	

Notes: Column 1 presents the (un)observable characteristics. Column 2 displays the posterior inclusion probability (*PIP*). Robust determinants are those with $PIP \geq 0.8$ in bold. Column 3 shows the posterior mean. Column 4 reports the posterior standard deviation. The dependent variable equals 1 if i and j are friends in Period 2 and similarly for Period 3. It equals 0 otherwise. The results are obtained by using a betabinomial prior for the prior model probability and a benchmark prior for the hyperparameter that measures the degree of prior uncertainty on the coefficients, with $g = \max(N, p^2)$. Baseline: 951 (1.91%).

Table C.4: Friend mix couples

Variable	PI prob.	Pt. Mean	Pt. Std.
Friends_{t-1}	1.000	0.218	0.003
Common Section	1.000	0.053	0.001
Wants to go to university diff.	0.905	-0.006	0.002
Risk diff.	0.859	-0.006	0.003
Happiness last week diff.	0.797	-0.007	0.004
Income diff.	0.366	-0.002	0.003
STEM best	0.305	0.001	0.001
Face to the public in the service sector	0.133	0.009	0.024
Inconsistent risk	0.029	-0.000	0.000
Altruism diff.	0.029	-0.000	0.000
CRT diff.	0.022	0.000	0.001
Inconsistent time	0.015	-0.000	0.000
Constant		0.005	0.002
Observations		98,221	

Notes: Column 1 presents the (un)observable characteristics. Column 2 displays the posterior inclusion probability (*PIP*). Robust determinants are those with $PIP \geq 0.8$ in bold. Column 3 shows the posterior mean. Column 4 reports the posterior standard deviation. The dependent variable equals 1 if i and j are friends in Period 2 and similarly for Period 3. It equals 0 otherwise. The results are obtained by using a betabinomial prior for the prior model probability and a benchmark prior for the hyperparameter that measures the degree of prior uncertainty on the coefficients, with $g = \max(N, p^2)$. Baseline: 1,196 (1.22%).

C.2.2 Enemies

Table C.5: Enemies male couples

Variable	PI prob.	Pt. Mean	Pt. Std.
Enemies_{t-1}	1.000	0.031	0.004
Common Section	1.000	0.007	0.000
Doctor	0.014	0.000	0.000
Constant		0.0001	0.0002
Observations		49,129	

Notes: Column 1 presents the (un)observable characteristics. Column 2 displays the posterior inclusion probability (*PIP*). Robust determinants are those with $PIP \geq 0.8$ in bold. Column 3 shows the posterior mean. Column 4 reports the posterior standard deviation. The dependent variable equals 1 if i and j are enemies in Period 2 and similarly for Period 3. It equals 0 otherwise. The results are obtained by using a betabinomial prior for the prior model probability and a benchmark prior for the hyperparameter that measures the degree of prior uncertainty on the coefficients, with $g = \max(N, p^2)$. Baseline: 63 (0.13%).

Table C.6: Enemies female couples

Variable	PI prob.	Pt. Mean	Pt. Std.
Enemies_{t-1}	1.000	0.084	0.004
Common Section	1.000	0.019	0.001
Doctor	0.016	0.000	0.000
Constant		0.0011	0.0003
Observations		49,866	

Notes: Column 1 presents the (un)observable characteristics. Column 2 displays the posterior inclusion probability (*PIP*). Robust determinants are those with $PIP \geq 0.8$ in bold. Column 3 shows the posterior mean. Column 4 reports the posterior standard deviation. The dependent variable equals 1 if i and j are enemies in Period 2 and similarly for Period 3. It equals 0 otherwise. The results are obtained by using a betabinomial prior for the prior model probability and a benchmark prior for the hyperparameter that measures the degree of prior uncertainty on the coefficients, with $g = \max(N, p^2)$. Baseline: 206 (0.41%).

Table C.7: Enemies mix couples

Variable	PI prob.	Pt. Mean	Pt. Std.
Enemies_{t-1}	1.000	0.038	0.003
Common Section	1.000	0.005	0.000
Influencer/Youtuber/Streamer	0.421	0.001	0.002
Tech profession	0.149	0.000	0.001
Bullying intersection	0.113	0.002	0.004
Delavande violations diff.	0.019	0.000	0.000
Constant		0.0002	0.0001
Observations		98,221	

Notes: Column 1 presents the (un)observable characteristics. Column 2 displays the posterior inclusion probability (*PIP*). Robust determinants are those with $PIP \geq 0.8$ in bold. Column 3 shows the posterior mean. Column 4 reports the posterior standard deviation. The dependent variable equals 1 if i and j are enemies in Period 2 and similarly for Period 3. It equals 0 otherwise. The results are obtained by using a betabinomial prior for the prior model probability and a benchmark prior for the hyperparameter that measures the degree of prior uncertainty on the coefficients, with $g = \max(N, p^2)$. Baseline: 104 (0.11%).

C.3 Robustness different priors

C.3.1 Friends

Table C.8: Robustness Friend binomial

Variable	PI prob.	Pt. Mean	Pt. Std.
Friends_{t-1}	1.000	0.258	0.002
Income diff.	1.000	-0.010	0.001
Risk diff.	1.000	-0.007	0.001
Common Gender	1.000	0.007	0.001
Common Section	1.000	0.069	0.001
Tech profession	1.000	0.011	0.001
Wants to go to university diff.	0.998	-0.006	0.001
STEM best	0.968	0.003	0.001
Inconsistent Risk	0.929	-0.002	0.001
Happiness last week diff.	0.917	-0.006	0.002
CRT diff.	0.397	0.002	0.002
Inconsistent diff.	0.249	-0.001	0.001
Veterinarian	0.032	-0.000	0.001
NGO helping others	0.030	0.000	0.002
Delavande violations diff.	0.021	-0.000	0.000
Influencer/Youtuber/Streamer	0.020	0.000	0.001
Reflective	0.013	-0.000	0.000
Constant		0.0035	0.0013
Observations		197,216	

Notes: Column 1 presents the (un)observable characteristics. Column 2 displays the posterior inclusion probability (*PIP*). Robust determinants are those with $PIP \geq 0.8$ in bold. Column 3 shows the posterior mean. Column 4 reports the posterior standard deviation. The dependent variable equals 1 if i and j are friends in Period 2 and similarly for Period 3. It equals 0 otherwise. The results are obtained by using a binomial 0.5 prior for the prior model probability and a benchmark prior for the hyperparameter that measures the degree of prior uncertainty on the coefficients, with $g = \max(N, p^2)$. Baseline: 3,522 (1.79%).

Table C.9: Robustness Friend uniform

Variable	PI prob.	Pt. Mean	Pt. Std.
Friends_{t-1}	1.000	0.258	0.002
Income diff.	1.000	-0.009	0.001
Risk diff.	1.000	-0.007	0.001
Common Gender	1.000	0.007	0.001
Common Section	1.000	0.069	0.001
Tech profession	1.000	0.011	0.001
Wants to go to university diff.	0.997	-0.006	0.001
STEM best	0.977	0.003	0.001
Inconsistent Risk	0.928	-0.002	0.001
Happiness last week diff.	0.919	-0.006	0.002
CRT diff.	0.391	0.002	0.002
Inconsistent diff.	0.240	-0.001	0.001
Veterinarian	0.032	-0.000	0.001
NGO helping others	0.029	0.000	0.002
Delavande violations diff.	0.022	-0.000	0.000
Influencer/Youtuber/Streamer	0.015	0.000	0.001
Reflective	0.014	-0.000	0.000
Constant		0.0035	0.0013
Observations		197,216	

Notes: Column 1 presents the (un)observable characteristics. Column 2 displays the posterior inclusion probability (*PIP*). Robust determinants are those with $PIP \geq 0.8$ in bold. Column 3 shows the posterior mean. Column 4 reports the posterior standard deviation. The dependent variable equals 1 if i and j are friends in Period 2 and similarly for Period 3. It equals 0 otherwise. The results are obtained by using a uniform prior for the prior model probability and a benchmark prior for the hyperparameter that measures the degree of prior uncertainty on the coefficients, with $g = \max(N, p^2)$. Baseline: 3,522 (1.79%).

C.3.2 Enemies

Table C.10: Robustness Enemies binomial

Variable	PI prob.	Pt. Mean	Pt. Std.
Enemies_{<i>t</i>-1}	1.000	0.061	0.002
Common Gender	1.000	0.001	0.000
Common Section	1.000	0.009	0.000
Doctor	0.997	0.002	0.000
Security Agent	0.281	-0.000	0.001
Influencer/Youtuber/Streamer	0.160	0.000	0.001
Risk diff.	0.131	-0.000	0.001
Likelihood of going to university diff.	0.013	-0.000	0.000
Constant		-0.0003	0.0002
Observations		197,216	

Notes: Column 1 presents the (un)observable characteristics. Column 2 displays the posterior inclusion probability (*PIP*). Robust determinants are those with $PIP \geq 0.8$ in bold. Column 3 shows the posterior mean. Column 4 reports the posterior standard deviation. The dependent variable equals 1 if i and j are enemies in Period 2 and similarly for Period 3. It equals 0 otherwise. The results are obtained by using a binomial (0.5) prior for the prior model probability and a benchmark prior for the hyperparameter that measures the degree of prior uncertainty on the coefficients, with $g = \max(N, p^2)$. Baseline: 373 (0.19%).

Table C.11: Robustness Enemies uniform

Variable	PI prob.	Pt. Mean	Pt. Std.
Enemies_{<i>t</i>-1}	1.000	0.061	0.002
Common Gender	1.000	0.001	0.000
Common Section	1.000	0.009	0.000
Doctor	0.997	0.002	0.000
Security Agent	0.279	-0.000	0.001
Influencer/Youtuber/Streamer	0.157	0.000	0.001
Risky diff.	0.128	-0.000	0.000
Constant		-0.0003	0.0002
Observations		197,216	

Notes: Column 1 presents the (un)observable characteristics. Column 2 displays the posterior inclusion probability (*PIP*). Robust determinants are those with $PIP \geq 0.8$ in bold. Column 3 shows the posterior mean. Column 4 reports the posterior standard deviation. The dependent variable equals 1 if i and j are enemies in Period 2 and similarly for Period 3. It equals 0 otherwise. The results are obtained by using a uniform prior for the prior model probability and a benchmark prior for the hyperparameter that measures the degree of prior uncertainty on the coefficients, with $g = \max(N, p^2)$. Baseline: 373 (0.19%).

C.4 Different periods

In this section, we explore the results for independent periods. The tables by periods are presented as follows: Periods 1-2, Periods 2-3, and Periods 1-3. The results

are presented for friends and for enemies. This approach relaxes the assumption that the same determinants have equal weight in all periods test whether the identified determinants remain consistent across different periods or if their influence is contingent on specific periods.

C.4.1 Friends

We segregate by Periods: 1-2 (see Table C.12), 2-3 (see Table C.13), and finally 1-3 (see Table C.14). This decreases the number of potential pairs to 35,246 in Periods 1-2, and 1-3¹. For Periods 2-3, we have a potential pairs sample of 161,970.

Table C.12: Friends all (Only Periods 1 and 2)

Variable	PIP	Pt. Mean	Pt. Std.
Friends_{<i>t</i>-1}	1.000	0.290	0.005
Common Gender	1.000	0.012	0.001
Common Section	1.000	0.093	0.002
Tech profession	0.994	0.015	0.003
NGO helping others	0.485	0.019	0.021
Wants to go to university diff.	0.422	-0.005	0.007
Face to the public in the service sector	0.056	0.008	0.033
Reflective	0.044	0.000	0.001
Inconsistent risk	0.029	-0.000	0.001
Constant		-0.001	0.002
Observations		35,246	

Notes: Column 1 presents the (un)observable characteristics. Column 2 displays the posterior inclusion probability (*PIP*). Robust determinants are those with $PIP \geq 0.8$ in bold. Column 3 shows the posterior mean. Column 4 reports the posterior standard deviation. The dependent variable equals 1 if i and j are friends in Period 2. It equals 0 otherwise. The results are obtained by using a betabinomial prior for the prior model probability and a benchmark prior for the hyperparameter that measures the degree of prior uncertainty on the coefficients, with $g = \max(N, p^2)$. Baseline: 951 (2.70%).

Friends_{*t*-1}, Common Gender, and Common Section consistently show high *PIP* values of 1.000, indicating their strong relevance in all periods. Tech profession remains significant but with a slightly lower *PIP* in Period 3 (0.942). New variables like Happiness last week (0.977), STEM best (0.959), and Altruism (0.125) emerge in Periods 2 and 3, reflecting their increasing relevance. On the other hand, Income,

¹This sample is influenced by the change of academic year and other factors described in Section 5.2.1. Since the model only takes those present in more than one Period.

Risk, and Inconsistent risk show a decline in PIP across periods, indicating a decrease in their relevance. Other new variables, such as others_bullying (0.028) and Farmer (0.015), appear in Period 3. While core variables remain stable, the results show shifts in the importance of certain variables over time, with some, like Income and Risk, becoming less relevant.

Table C.13: Friends all (Only Periods 2 and 3)

Variable	PIP	Pt. Mean	Pt. Std.
Friends_{t-1}	1.000	0.248	0.002
Income diff.	1.000	-0.011	0.001
Risk diff.	1.000	-0.008	0.001
Common Gender	1.000	0.006	0.001
Common Section	1.000	0.063	0.001
Tech profession	1.000	0.009	0.002
Happiness last week diff.	0.977	-0.008	0.002
STEM best	0.959	0.003	0.001
Altruism diff.	0.125	-0.000	0.000
Inconsistent risk	0.116	-0.000	0.001
Wants to go to university diff.	0.100	-0.000	0.001
Inconsistent time	0.022	-0.000	0.000
Constant		0.003	0.001
Observations		161,970	

Notes: Column 1 presents the (un)observable characteristics. Column 2 displays the posterior inclusion probability (*PIP*). Robust determinants are those with $PIP \geq 0.8$ in bold. Column 3 shows the posterior mean. Column 4 reports the posterior standard deviation. The dependent variable equals 1 if *i* and *j* are friends in Period 3. It equals 0 otherwise. The results are obtained by using a betabinomial prior for the prior model probability and a benchmark prior for the hyperparameter that measures the degree of prior uncertainty on the coefficients, with $g = \max(N, p^2)$. Baseline: 2,571 (1.59%).

Table C.14: Friends all (Only Periods 1 and 3)

Variable	PIP	Pt. Mean	Pt. Std.
Friends_{t-1}	1.000	0.212	0.005
Common Gender	1.000	0.007	0.001
Common Section	1.000	0.073	0.002
Wants to go to university diff.	0.997	-0.016	0.003
Income diff.	0.967	-0.014	0.004
Tech profession	0.942	0.011	0.004
Face to the public in the service sector	0.374	0.056	0.077
NGO helping others	0.081	0.002	0.008
others_bullyingint	0.028	-0.000	0.001
Inconsistent risk	0.017	-0.000	0.001
Reflective	0.016	0.000	0.001
Farmer	0.015	0.002	0.016
Constant		0.007	0.002
Observations		35,246	

Notes: Column 1 presents the (un)observable characteristics. Column 2 displays the posterior inclusion probability (*PIP*). Robust determinants are those with $PIP \geq 0.8$ in bold. Column 3 shows the posterior mean. Column 4 reports the posterior standard deviation. The dependent variable equals 1 if i and j are friends in Period 3. It equals 0 otherwise. The results are obtained by using a betabinomial prior for the prior model probability and a benchmark prior for the hyperparameter that measures the degree of prior uncertainty on the coefficients, with $g = \max(N, p^2)$. Baseline: 746 (2.12%).

C.4.2 Enemies

As in friends, we explored the results for Periods 1-2 (see Table C.15), 2-3 (see Table C.16), and 1-3 (see Table C.17). The observations is reduced to 35,246 in Periods 1-2 and 1-3, while in Periods 2-3 the observations are 161,970.

Enemies_{t-1}, Common Gender, and Common Section consistently show high relevance across all periods with *PIP* values of 1.000. Common Gender's relevance slightly decreases in Periods 1-3, with a low *PIP* of 0.017. Periods 2-3 introduce new variables like Doctor (*PIP* = 0.972) and Risk (*PIP* = 0.069), though its influence is minimal. Security Agent and Influencer/Youtuber/Streamer show low *PIPs* across periods, indicating they are not significant predictors.

The analysis across the combination of Periods shows high consistency for core variables like Enemies_{t-1}, Common Gender, and Common Section, but introduces some variability with new variables like Doctor in Period 2-3. The influence of

Common Gender decreases in Period 1-3, and the relevance of certain variables such as Risk and Security Agent remains minimal throughout the periods. This suggests that while some variables maintain their importance over time, others have less stable influence depending on the period.

Table C.15: Enemies all (Only Periods 1 and 2)

Variable	PIP	Pt. Mean	Pt. Std.
Enemies_{t-1}	1.000	0.052	0.007
Common Gender	1.000	0.003	0.000
Common Section	1.000	0.010	0.001
delavande_uni_ndiff L1.	0.044	0.000	0.001
Constant		-0.001	0.000
Observations		35,246	

Notes: Column 1 presents the (un)observable characteristics. Column 2 displays the posterior inclusion probability (*PIP*). Robust determinants are those with $PIP \geq 0.8$ in bold. Column 3 shows the posterior mean. Column 4 reports the posterior standard deviation. The dependent variable equals 1 if i and j are enemies in Period 2. It equals 0 otherwise. The results are obtained by using a betabinomial prior for the prior model probability and a benchmark prior for the hyperparameter that measures the degree of prior uncertainty on the coefficients, with $g = \max(N, p^2)$. Baseline: 78 (0.22%).

Table C.16: Enemies all (Only Periods 2 and 3)

Variable	PIP	Pt. Mean	Pt. Std.
Enemies_{t-1}	1.000	0.063	0.002
Common Gender	1.000	0.001	0.000
Common Section	1.000	0.009	0.000
Doctor	0.972	0.002	0.001
Risk diff.	0.069	-0.000	0.000
Security Agent	0.028	-0.000	0.000
Influencer/Youtuber/Streamer	0.013	0.000	0.000
Constant		-0.001	0.000
Observations		161,970	

Notes: Column 1 presents the (un)observable characteristics. Column 2 displays the posterior inclusion probability (*PIP*). Robust determinants are those with $PIP \geq 0.8$ in bold. Column 3 shows the posterior mean. Column 4 reports the posterior standard deviation. The dependent variable equals 1 if i and j are enemies in Period 3. It equals 0 otherwise. The results are obtained by using a betabinomial prior for the prior model probability and a benchmark prior for the hyperparameter that measures the degree of prior uncertainty on the coefficients, with $g = \max(N, p^2)$. Baseline: 295 (0.18%).

Table C.17: Enemies all (Only Periods 1 and 3)

Variable	PIP	Pt. Mean	Pt. Std.
Enemies_{<i>t</i>-1}	1.000	0.054	0.006
Common Section	1.000	0.009	0.001
Common Gender	0.017	0.000	0.000
Constant		0.001	0.000
Observations		35,246	

Notes: Column 1 presents the (un)observable characteristics. Column 2 displays the posterior inclusion probability (*PIP*). Robust determinants are those with $PIP \geq 0.8$ in bold. Column 3 shows the posterior mean. Column 4 reports the posterior standard deviation. The dependent variable equals 1 if i and j are enemies in Period 3. It equals 0 otherwise. The results are obtained by using a betabinomial prior for the prior model probability and a benchmark prior for the hyperparameter that measures the degree of prior uncertainty on the coefficients, with $g = \max(N, p^2)$. Baseline: 66 (0.19%).

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Appendix D

Documentación adicional

1. Artículo JCR
2. Certificados de congresos internacionales
3. Aprobación del comité de ética de la investigación
4. Documento justificativo mención internacional
5. Participación en proyecto de investigación



Inconsistent Choices Among Adolescents in El Salvador

Gladis Gonzales*

Adriana Gaviria[†]

Submission received: January 16, 2024

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Published: January 24, 2025

Abstract

This paper examines inconsistencies in the decision-making of a sample of 2,248 adolescents from El Salvador when completing two classic experiments: temporal discounting and risk preferences. Inconsistency in responses is a significant issue when collecting experimental data because it implies a loss of the sample, as these data come from subjects who do not respond to the task as they should and could indicate, for instance, a lack of understanding of the task. To mitigate this problem, we reduced the number of decisions, designed tasks with a strong visual component, and adapted them to the context with the assistance of a local pedagogical team. Despite these adaptations, we first observe participants' significant difficulties in avoiding errors such as multiple switching. Secondly, we investigate whether developmental factors (age), cognitive skills, and task repetition improve consistency. Lastly, we explore whether inconsistency in decision-making somehow shapes their immediate and long-term educational expectations.

Keywords: El Salvador, teenagers, inconsistencies, developmental decision-making, field experiment.

JEL codes: C91, D81.

*Loyola Behavioral Lab, Universidad Loyola Andalucía, email: ghgonzales@uloyola.es

[†]Loyola Behavioral Lab, Universidad Loyola Andalucía, email: agaviria@uloyola.es

V AJICEDE

La comunicación titulada:

ANÁLISIS DEL PENSAMIENTO DIVERGENTE EN ADOLESCENTES DE EL SALVADOR: UNA PROPUESTA METODOLÓGICA

**Gladis Herminia Gonzales Aguilar
Pablo Ernesto Brañas Garza
María del Pino Ramos Sosa
Antonio Alfonso Costillo**

Ha sido presentada en el marco del **V Congreso Iberoamericano de Jóvenes Investigadores en Ciencias Económicas y Dirección de Empresas**, celebrado en Córdoba del 14 al 16 de diciembre de 2022.

Y para que así conste, se expide la siguiente certificación a 15 de diciembre de 2022.

Fdo.: María del Mar Ortiz Gómez
Co-Chair del Congreso

Fdo.: Laura Serrano Mendoza
Co-Chair del Congreso

Fdo.: Elena Moreno Ureba
Secretaria General de AJICEDE





PROOF OF ATTENDANCE

This certificate is presented to

Gladis Gonzales

For attending the “**Workshop on Market, Cooperation and Votes**”

hosted by Universidad Carlos III de Madrid

The conference took place on 13-14 June 2024.

Work presented: “Inconsistent choices among adolescents in El Salvador”

A handwritten signature in black ink, appearing to be 'Antonio Cabrales', written in a cursive style.

Antonio Cabrales
Organizing Committee

A continuación, se detalla en estado de la evaluación del comité de Ética de la Universidad Loyola Andalucía para la Tesis de Doctorado “Lab-in-the-field experiments on inconsistency, delay discounting, and homophily” realizada por la alumna Gladis Herminia Gonzales Aguilar (Pasaporte: E0015397).

1. Experimentos en campo en España: se utilizan datos secundarios del proyecto “*Estudio de competencias y habilidades sociales del alumnado de origen migrante en educación secundaria que informen sobre desigualdades y brecha educativa causadas por el covid19*” en España. Los datos fueron anonimizados y tratados por los requerimientos de confidencialidad para poder ser utilizados. Estos procedimientos fueron aprobados por el comité de Ética de la Universidad Loyola Andalucía en la fecha 16 de diciembre de 2021.
2. Experimentos en campo en El Salvador: se utilizan datos secundarios de proyecto “*Estudio de competencias y habilidades sociales del alumnado de origen migrante en educación secundaria que informen sobre desigualdades y brecha educativa causadas por la covid19*” en El Salvador. Los datos fueron anonimizados y tratados según los requerimientos de confidencialidad para poder ser utilizados. Estos procedimientos fueron aprobados por el comité de Ética de la Universidad Loyola Andalucía en la fecha 29 de marzo de 2022.

Se adjuntan los documentos que acreditan dichas aprobaciones.

El Comité de Ética de la Universidad Loyola Andalucía ha emitido valoración relativa al Proyecto *Estudio de competencias y habilidades sociales del alumnado de origen migrante en educación secundaria que informen sobre desigualdades y brecha educativa causadas por el covid19* remitido por el investigador Lorenzo Estepa Mohedano para su valoración ética.

El Comité de Ética de la Universidad Loyola Andalucía ha valorado, por unanimidad, que el proyecto cumple con los criterios éticos necesarios para su desarrollo.

Resolución: **INFORME FAVORABLE**

Sevilla, 16 de diciembre de 2021

Vº Bº El Presidente

SEPULVEDA DEL RÍO, JUAN IGNACIO (AUTENTICACIÓN)

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Fdo. Ignacio Sepúlveda del Río

El Comité de Ética de la Universidad Loyola Andalucía ha emitido valoración relativa al proyecto titulado *Estudio de competencias y habilidades sociales del alumnado de origen migrante en educación secundaria que informen sobre desigualdades y brecha educativa causadas por la covid19 (01008/2020)* remitido por el Sr. Pablo Brañas para su valoración ética.

El Comité de Ética de la Universidad Loyola Andalucía ha valorado, por unanimidad, que el proyecto cumple con los criterios éticos necesarios para su desarrollo.

Resolución: **INFORME FAVORABLE**

Sevilla, 29 de marzo de 2022

La Vicepresidenta

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El Secretario

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Fdo. Alejandro Tapia Frade

Dr. Guillaume BIOT-PAQUEROT

Associate Dean of Research
Burgundy School of Business
29, rue Sambin – BP 50608
21006 DIJON Cedex
France

Gladis Herminia GONZALES AGUILAR

Universidad de Loyola
Calle Escritor Castilla Aguayo, 4
14004 Córdoba
Spain

Dijon, October 16, 2024

Dear Gladis Herminia Gonzales Aguilar,

We would be delighted to welcome you to Burgundy School of Business (BSB) for a full-time exchange for the period between **November 1, 2024, and January 31, 2025**, to:

- Participate in data analysis and write an academic paper stemming from that research working alongside with Roberto Hernán González, Full Professor at BSB and member of the Organizational Transformation, Behaviors and Decisions Research Axis
- Organize a presentation as part of the Organizational Transformation, Behaviors and Decisions seminars to present research activities and progress on the doctoral thesis.

We look forward to welcoming you to BSB and hope you have a productive and rewarding experience at our institution.

Yours sincerely,

Dr. Guillaume BIOT-PAQUEROT

Associate Dean of Research

CAMPUS BSB DIJON

29 rue Sambin - BP 50608 - 21006 Dijon Cedex - France
Tél. +33 (0) 380 725 900

CAMPUS BSB LYON

37 rue Saint Romain - 69008 Lyon - France
Tél. +33 (0)428 297 720

CERTIFICATE OF ATTENDANCE

Home University: UNIVERSIDAD LOYOLA ANDALUCÍA

Name of the host institution / enterprise: on Burgundy School of Business

This document certifies that:

El presente documento certifica que:

ARRIVAL

The student **GLADIS HERMINIA GONZALES AGUILAR** has started

El estudiante (name and surname)

ha comenzado

an ERASMUS internship at our organisation on **01/11/2024**
unas prácticas Erasmus en nuestra organización con fecha

Signature of the Responsible person
at the receiving organisation
Firma de un representante de la organización

Signed on **04/11/2024**
Firmado a

Seal of the institution
Sello de la Institución

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B.P. 50608 - 21006 DIJON Cedex
Tél. (+33) (0) 380 725 900
N° Formateur : 27 21 03685 21
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au capital social de 10 448 000 € - RCS Dijon 823 945 753 00015

The date of signature must be completed on, or after the date of arrival and verified by the host Institution/Organisation.

DEPARTURE

The student **GLADIS HERMINIA GONZALES AGUILAR** has finished

El estudiante (name and surname)

ha finalizado

an ERASMUS internship at our organisation on **31/01/2025**

unas prácticas Erasmus en nuestra organización con fecha

Signature of the Responsible person
at the receiving organisation
Firma de un representante de la organización

Signed on **05/02/2025**
Firmado a

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BSB | DIJON
LYON
PARIS
BURGUNDY SCHOOL OF BUSINESS
B.P. 50608 - 21006 DIJON Cedex
Tél. (+33) (0) 380 725 900
N° Formateur : 27 21 03685 21
ESC Dijon-Bourgogne, EESC à directoire et conseil de surveillance
au capital social de 10 448 000 € - RCS Dijon 823 945 753 00015

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La doctoranda Gladis Herminia Gonzales Aguilar ha participado activamente como coordinadora en campo desde enero 2022 en el proyecto “Fortalecimiento de la capacidad de analizar la integración social y habilidades cognitivas para una educación más inclusiva en los centros educativos de Fe y Alegría en El Salvador” financiado por la Agencia Andaluza de Cooperación Internacional para el Desarrollo (AACID) [2021UI004].

Los principales logros alcanzados por la doctoranda bajo lo planificado en el proyecto durante los meses de septiembre 2022 a mayo 2023 son:

Resultado 1: *Formados los equipos del proyecto de FyA en metodologías de estudio y uso de las herramientas tecnológicas y puesta en marcha del proyecto.*

- A4.R1. Capacitar a socio local con el objetivo de que lleven a cabo autónomamente el proceso de recogida de datos en un tercer proceso, este se encuentra programado en las actividades del proyecto.

Resultado 2: *Realizados estudios individuales sobre la red social, competencias y preferencias sociales entre alumnado de secundaria que evidencie problemas de integración, rezago o fracaso escolar.*

- A1.R2. Modificación de cuestionario en plataforma SAND para la segunda recogida de datos.
- A2.R2. Llevar a cabo segundo proceso de recogida de datos con socio local en 12 centros de El Salvador, obteniendo 2,649 observaciones.
- A2.R2. Proveer asistencia y resolución de conflictos en procesos de recogida de datos a socio local.
- A3. R2. Manejo de bases de datos.
- A3.R2. Elaboración de informes individuales para cada centro con base en 2,600 observaciones obtenidas en el primer proceso de recogida de datos realizado durante el año 2022.
- A3.R2. Elaboración de informe global adaptado al socio local del primer proceso de recogida de datos.
- A3.R2. Realizar proceso de socialización de resultados del primer proceso de recogida de datos con socio local.
- A3.R2. Realizar procesos de socialización de resultados del primer proceso de recogida de datos con docentes en los 12 centros.

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GARZA

PABLO

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BRAÑAS GARZA

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Pablo Brañas Garza
Investigador Principal



Tesis depositada en Universidad Loyola
Córdoba, 2025

