The desperation threshold: a model to explain decisions in poverty

De wanhoopsdrempel: een model om beslissingen in armoede te begrijpen

Benoît de Courson

June 25, 2025

À ma maman, qui a la classe
À mon papa, qui m'a subtilement transmis sa soif de comprendre des trucs

Table of contents

Summary

In this dissertation, I propose the desperation threshold model, which seeks to explain decisions in situations of poverty as rational ones. The model assumes that people in poverty aim at staying above a "desperation threshold" – a critical amount of resources that represents their basic needs. Throughout the dissertation, I show that this assumption can explain several behavioral patterns associated with poverty – and with economic inequality at the population level. I then try to assess its empirical validity. I explore this idea in two modelling chapters, one empirical chapter using secondary data, and an integrative literature review chapter. In the first modeling chapter (Chapter 2), I show that the desperation threshold can account not only for the high proportion of property crime in deprived or unequal populations, but also for the frequency of violent crime, as a toughness signal to deter exploitation. In the second modeling chapter (Chapter 3), I show that the desperation threshold generates elevated time discounting when basic needs are on the line. Chapter 4 aims at testing the model's prediction empirically. I show that the empirical literature is currently split, with studies predicting and finding either an increase or a decrease of risk taking in situations of poverty. I propose that the desperation threshold model can reconcile these seemingly contradictory findings. I derive testable predictions from the model, and test them on secondary survey data from France and the UK. I obtain partial support for a U-shape between resources and risk taking, but a clear polarizing effect: both risk taking and risk avoidance are more frequent among the poorer participants. In the integrative review chapter (Chapter 5), I give more perspective on the desperation threshold. I first state the model in its purest form, highlight and justify its core assumptions. I then review the empirical evidence from diverse fields and methods, relevant to test the validity desperation threshold model. I find that similar models – under different names – have been proposed and tested across several social and biological science disciplines, though their full implications and explanatory potential have rarely been recognized. I conclude that the desperation threshold model, along its intellectual antecedents, has promising empirical support, and is already a fruitful paradigm for the study of poverty.

Samenvatting

In dit proefschrift stel ik het wanhoopsdrempelmodel voor, dat probeert beslissingen in situaties van armoede te verklaren als rationele beslissingen. Het model gaat ervan uit dat mensen in armoede ernaar streven om boven een "wanhoopsdrempel" te blijven – een kritische hoeveelheid middelen die hun basisbehoeften vertegenwoordigt. Door het proefschrift heen laat ik zien dat deze aanname verschillende gedragspatronen kan verklaren die geassocieerd worden met armoede – en met economische ongelijkheid op het niveau van de bevolking. Vervolgens probeer ik de empirische geldigheid ervan te beoordelen. Ik verken dit idee in twee modelleringshoofdstukken, een empirisch hoofdstuk met secundaire gegevens en een integratief hoofdstuk over literatuuronderzoek. In het eerste modelleringshoofdstuk (hoofdstuk 2) laat ik zien dat de wanhoopsdrempel niet alleen het hoge aandeel van vermogenscriminaliteit in achtergestelde of ongelijke bevolkingsgroepen kan verklaren, maar ook de frequentie van geweldsdelicten, als een hardheidssignaal om uitbuiting af te schrikken. In het tweede modelleringshoofdstuk (hoofdstuk 3) laat ik zien dat de wanhoopsdrempel een verhoogde tijddiscontering genereert wanneer basisbehoeften op het spel staan. Hoofdstuk 4 richt zich op het empirisch testen van de voorspelling van het model. Ik laat zien dat de empirische literatuur op dit moment verdeeld is, met studies die ofwel een toename of een afname van het nemen van risico's in situaties van armoede voorspellen en vinden. Ik stel voor dat het wanhoopsdrempelmodel deze schijnbaar tegenstrijdige bevindingen met elkaar kan verzoenen. Ik leid testbare voorspellingen uit het model af en test ze op secundaire onderzoeksgegevens uit Frankrijk en het Verenigd Koninkrijk. Ik krijg gedeeltelijke ondersteuning voor een U-vorm tussen middelen en risicobereidheid, maar een duidelijk polariserend effect: zowel risicobereidheid als risicovermijding komen vaker voor bij de armere deelnemers. In het integrerende overzichtshoofdstuk (hoofdstuk 5) geef ik meer perspectief op de wanhoopsdrempel. Eerst geef ik het model in zijn meest zuivere vorm weer, waarbij ik de belangrijkste aannames benadruk en rechtvaardig. Vervolgens bekijk ik het empirisch bewijs uit verschillende velden en methoden die relevant zijn om de geldigheid van het wanhoopsdrempelmodel te testen. Ik ontdek dat soortgelijke modellen - onder verschillende namen - zijn voorgesteld en getest in verschillende disciplines van de sociale en biologische wetenschappen, hoewel hun volledige implicaties en verklarend potentieel zelden zijn erkend. Ik concludeer dat het wanhoopsdrempelmodel, samen met zijn intellectuele antecedenten, veelbelovende empirische ondersteuning heeft en al een vruchtbaar paradigma is voor de studie van armoede.

1 Introduction

”Money is better than poverty, if only for financial reasons.”

– *Woody Allen, Without Feathers (1975)*

1.1 Poverty is unpleasant

Explaining a joke is bad taste: it generally ruins it. But allow me, just this once, to lead into my dissertation by explaining why the quote above is, objectively, funny. First, it seems to make a new and profound statement, but just states something that is so obvious that it is never verbalized: poverty is unpleasant. Second, the quote is such a blatant understatement. Poverty is not merely a matter of being unable to afford organic vegetables. According to the Cambridge Dictionary, poverty is, instead, ‘the state of not having enough money to buy basic things’. The ‘basic’ adjective is eloquent. Metaphorically, ‘basic things’ are things that form the basis of a normal life. When they can not be bought, the metaphor implies, the structure risks collapsing.

Intuitively, we thus see poverty as a point where the lack of money has catastrophic effects on life. Implicitly, we think of poverty as a ‘cliff’, a point where losing little resources causes an abrupt decline in wellbeing. This intuition of a discontinuity is reflected in common language: low-income people are said to ‘live on the edge’, to be in ‘tight’ situations, to ‘fall into poverty’, or to be ‘trapped in poverty’. These phrases suggest that poverty is not a matter of degree, but a distinct category. This is also reflected in measures: while wealth is often measured by counting money (e.g. through the median income), poverty is measured as a rate, by counting people below a certain ‘poverty line’, or those who cannot satisfy certain needs (Blasco, 2023).

In turn, when people with little economic resources behave in a certain way – and they do behave in striking ways (Pepper & Nettle, 2017) – academics often attribute it to a fear of the poverty cliff. After all, if being poor is that awful, it is reasonable to expect that people adapt their decisions to avoid it. More precisely, decisions typical of people on low incomes are often explained as attempts to reduce the risk of not meeting certain basic needs. Examples are countless and span all fields of social sciences. Let us consider a few classical examples. When subsistence populations are observed to help each other and share, as in Kropotkin’s classical ethnography of Siberian populations during winters, it is seen as a form of ‘collective insurance’ against starvation (Kropotkin, 1902). When people in situations of poverty refuse to specialize in one profession, and instead keep one foot in agriculture and one in industry and earn a lower income as a result, this is seen as a “risk-spreading” technique to be protected from bad harvests (A. V. Banerjee & Duflo, 2007). When they show reluctance to innovation, for instance in agriculture, this is explained by the lack of a buffer: if the innovation does not work, one could not bear the losses (Schultz, 1964). When people save, it is seen as a way to build a ‘buffer’, to avoid catastrophic consequences in case something bad happens in the future (Collins et al., 2009). This principle is even used to explain institutional arrangements in subsistence societies: Scott (1977) claims that such societies develop a 'subsistence ethic': "elites had a positive moral obligation to provide for the maintenance needs of their subjects in time of dearth" (p33).

Yet, not all people show carefulness or solidarity in situations of poverty. Excessive borrowing, gambling, migration, revolts, prostitution and crime are all more frequent in low-income populations (Dobbie & Skiba, 2013; Gurr, 2015; Hsieh & Pugh, 1993; Monroe, 2005; Wardle et al., 2014). And the thing is, we spontaneously understand these behaviours as 'desperate' actions, that stem from the very same cliff: a person needs a minimal amount of resources, and if he lacks resources, he might have no choice but to take risks to get them. Examples of such reasoning pervade not only in common conversations, but also in social sciences. The most classical example is Merton's 'strain theory' (Merton, 1938): when someone can not achieve culturally valued goals (e.g. wealth and status) with legitimate means, they resort to 'innovation', that is, to alternative, potentially illegitimate, means, such as crime. It is often used in criminology, with a clearer link with poverty: in an ethnography of offenders, Rossmo & Summers (2022) observed that "[the person] needs a specific amount of money such that anything less has limited value; for example...a debt with an impending payment due or [the requirement to] come up with the rent in order to avoid eviction. For these individuals, it is a matter of all or nothing" (p.7). Put otherwise, the offenders have too much to gain in the crime. Another, closely related way to frame this reasoning is to say that in dire poverty, people have too little to lose: they are miserable anyway, their situation could not be much worse, so they might as well try something. The phrase 'little to lose' is often used to justify risky behaviours in situations of poverty: for instance, Holdsworth et al. (2020) explains gambling among homeless populations this way: "With little to lose and a desire to change life circumstances, gambling may appear to be desirable for the hope it provides to win money." (p.14).

We face a double paradox. First, at an empirical level, how can people be both risk takers and risk avoiders in situations of poverty? Second, at a theoretical level: how can the concept of a poverty cliff be used to explain both risk taking and risk avoidance? This ambivalence has been pointed out before by Banerjee in an essay entitled "The two poverties": he observed that "There are at least two distinct and, prima facie, inconsistent views of poverty in these models" (p. 59), conceptualising poverty respectively as having too much to lose and too little to lose. This does not just question the coherence of the concept, it also questions its scientific value: if any empirical pattern can be accommodated to the idea of 'poverty as a cliff', then it is unfalsifiable and therefore unscientific.

As we will see, the paradoxes disappear when the situation is properly formalised. In Fig. 1.1, I translate the representation of poverty that I have verbally sketched into a 'utility function', that represents the satisfaction of the person depending on its level of resources. Importantly, the function features a cliff, that I henceforth call the 'desperation threshold' (DT): at some point, losing little resources has catastrophic consequences on satisfaction, as basic needs can no longer be met. Below the cliff, utility levels out: people have 'little left to lose'. The consequences are visible on the figure. Above the DT, you have more to lose than to gain, so you avoid risk. This makes sense: you do not dance on a tightrope. Below the threshold, you have more to gain than to lose. This also makes sense: if you are falling from the tightrope, you have to try something, get out of your way. Thus, the paradoxes disappear: poverty can imply both 'too much to lose' and 'little to lose' situations. Depending on whether they barely make ends meet or not, people in situations of poverty should thus either take, or avoid, risks. The central aim of my PhD is to formalise this 'desperation threshold model'

(DTM), looking at which social phenomena it can help explain, both at the individual and the population level, and test empirically whether it is a reasonable explanation.

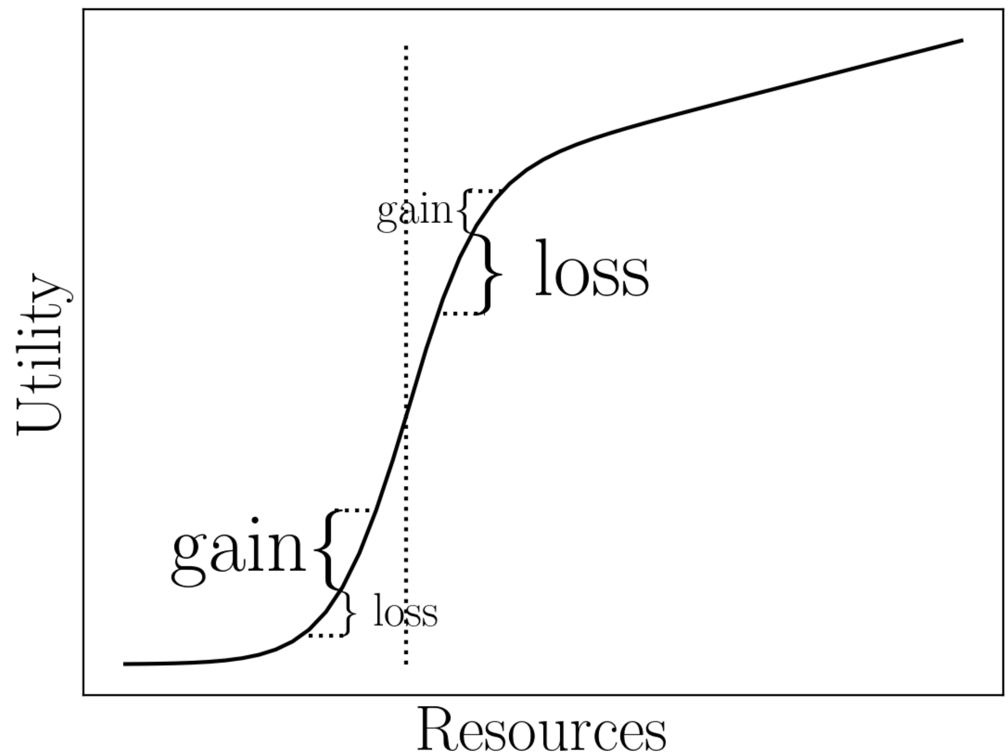

Figure 1.1: Graphical representation of the desperation threshold model.

I coined the phrase 'desperation threshold' with Daniel Nettle in 2019, before I started my PhD. At the time, we were not sure why. It just sounded right. We stuck with it, and until now, we have had no regrets: it still corresponds to what we want to say, and people spontaneously understand it, even without grasping the underlying mathematics. After six years of scratching my head on this idea, I finally understood why 'desperation' was the right word. 'Desperation' comes from the latin dēspērāre, which means literally 'losing hope'. This meaning is still present in the older word 'despair', which shares the same etymology, and that the Cambridge dictionary defines it as "the feeling that there is no hope and that you can do nothing to improve a difficult or worrying situation". It is usually associated with passivity, and with a sense of resignation. 'Desperation', however, came to refer to opposite behaviours: the same dictionary defines it as "the feeling that you have when you are in such a bad situation that you are willing to take risks in order to change it".

Why would one try something if one is losing hope? Our model, I hope, illustrates why. Like many words (e.g. awesome or astonished), desperation has likely undergone 'semantic bleaching': it lost some of its intensity over time, and started to be used to describe still extremely bad situations, but where there still is a glimmer of hope. Likewise, the DT marks the point at which meeting basic needs becomes unlikely. It is a point where one is not just worried, but actually expecting a catastrophe as a plausible outcome. Resignation results in a sure catastrophe, while taking a risk maintains a possibility of making it. If the situation further degrades, then the catastrophe becomes surer, and one needs to take even bigger risks to keep hope. At some point, no hope is left, and 'desperation' turns into 'despair'. Thus, our model not only reconciles Banerjee's "two poverties", it also reconciles the modern sense of desperation with its etymological sense: economic misery can bring about caution (above the DT), risk taking (below the DT) and resignation (well below the DT).

In this introduction, I state the goals and the means of my dissertation. In the first section, I discuss the value of formal modeling in social sciences. In the second section, I present and defend my particular use of modeling, insisting on my commitment to rational choice and methodological individualism. In the third section, I trace the intellectual history of the desperation threshold across the social sciences. Finally, I give an outline of the chapters to come.

1.2 Why model

If I have leaned heavily on colloquial phrases and etymologies, it is because I am convinced that the core predictions of the desperation threshold model are already present in the collective unconscious. It is not exactly breaking news that extreme situations give rise to extreme behaviours. So, why shall we bother mathematicising the whole thing? Why translate something so intuitive into a language of Greek letters and obscure symbols?

Many people – including academics – are confused about the role of formal models in social sciences (Tiokhin, 2021). In the papers that form this dissertation, I did not have the space to make general epistemological points to avoid confusion. I hope this introduction can serve as the right place to situate the work epistemologically — so that readers understand how to approach the chapters that follow.

1.2.1 "Models do not investigate nature"

A naive reader might think that having a model will help us make predictions, just like weather forecasts are more accurate than folk sayings. At parties, I used to boastfully present myself as a PhD student in criminology who models crime in situations of poverty. Most people spontaneously assumed that I was building tools to predict who will commit a crime, based on what is left on people's bank accounts. At the risk of being even more distressing (or, depending on your political awareness, slightly reassured), the models that I will present do not make quantitative predictions. Or, at least, not useful ones.

In fact, except in Chapter 4, no data has been directly involved in my dissertation. The models are built on assumptions: that people have particular options, that they make decisions by optimizing certain criteria, and that they interact in specific patterns. As they are quite abstract, the assumptions are not validated by empirical data: they are minimal axioms that simply sound reasonable and intellectually exciting.

The results of a model depend entirely on the assumptions. This is the source of two frequent critiques. First, a model is tautological. Second, you can obtain any result by tweaking the assumptions. Both critiques are entirely accurate. Unless all the assumptions are true – which is not realistic in social sciences – the results of a model do not teach us anything about the real world. As Kokko (2007) puts it "models do not investigate nature" (p. 7). This point is fundamental and must be hammered: most readers wrongly understand formal models as proving something about reality. For instance, the first chapter finds that in our model, inequality produces more crime. About a hundred papers have cited it, most of them to claim that inequality does produce crime. I wish they heard me: models are not about the real world, but the world of ideas. They only teach us that a set of conclusions logically follow from a set of assumptions.

1.2.2 We are all modelers

So, why model, then? In response to this very question, J. Epstein (2008) responds that every social scientist with even the slightest theoretical ambition is a modeler. "Anyone who ventures a projection, or imagines how a social dynamic—an epidemic, war, or migration—would unfold is running some model" (p. 1). The choice is not whether to model, but whether to state the model verbally or formally. Verbal models are simpler to elaborate and to communicate, but they have critical limitations that formal models help overcome.

1.2.3 Verbal models are vague

The first flaw of verbal models is their vagueness: they leave many details unspoken. At best, their assumptions are implicit. At worst, assumptions are ambiguous and open to multiple interpretations. This gives the model a dangerous room for maneuver, and it can then be stretched to fit a wide range of empirical patterns. The problem is not just practical, but fundamental: social sciences, and psychology in particular, currently go through a 'theory crisis' (Eronen & Bringmann, 2021; Muthukrishna & Henrich, 2019; Scheel et al., 2021), as it becomes increasingly evident that there is little or no cumulative progress in theoretical work. Two pitfalls strike me. First, many projects pretend to test theories, when they are actually only based on vague frameworks. Daniel Nettle calls this tendency "Calling It Theory for Effect": to exaggerate their contributions, authors often dress their confused thoughts as a theory. This plague does not spare criminology (Ducate et al., 2024; Walters & Mandracchia, 2017): the most influential theories in the field have been deemed "too imprecise and discursive to yield meaningful tests of theories" (Ducate et al., 2024, p. 5). It has recently been proposed that authors might make their verbal models vague on purpose, due to the incentive structure in academia. Slippery models are moving targets: they are hard to refute, as they can be interpreted in so many ways, and shape-shift to match data.

In contrast, formal models are written in formal languages – mathematics or computer code – that, by design, do not tolerate ambiguity. Unlike humans, computers cannot interpret vague instructions; they require explicit, fully specified instructions to function. Thus, formal modeling is, first and foremost, an exercise in making theories entirely explicit. It is also an exercise in intellectual humility: it often makes it visible that the assumptions are simplistic, the scope narrow, and the model itself a caricature. Yet this transparency is necessary for cumulative progress in theoretical social science.

1.2.4 Verbal models are fallible

The second flaw of verbal models is that they can be actively misleading. Some theories 'sound' true, but turn out to be logically inconsistent upon further inspection. Chapter 3 gives an example: many authors argue that in situations of high need ('I need to eat today'), people should prefer to obtain resources sooner. Through a cumbersome mathematical model, we show that this is not necessarily true, and that one needs further conditions to justify it.

Formal logic is the only way to prove that a set of conclusions follow from a set of conclusions. As Kokko (2007) puts it, formal models "investigate the validity of our own thinking, i.e. whether the logic behind an argument is correct." (p. 7). In some cases, the result is quite obvious, and verbal models are in practice a good replacement for formal models. In other cases, we face problems that are too complex to be grappled by simple intuition. During my PhD, I often found that my intuitions were wrong—or that the models produced results I hadn't anticipated. In such cases, modeling serves as a cognitive aid, a "telescope of the mind, multiplying human powers of analysis and insight just as a telescope does our powers of vision" (Bouchaud, 2009, p. 32). This is the way I feel about mathematics: it is simply empowering.

1.2.5 Poverty and risk taking need formalisation

Risk taking in poverty actually exemplifies the risk of vague theories, and the merits of specification. As discussed earlier, the intuition behind the desperation threshold can be used to predict both more risk taking and less risk taking in situations of poverty. Put otherwise, the verbal model is flexible, because it is underspecified.

There is a central ambiguity in the verbal argument: even if we agree on a utility cliff at some point, what happens below that cliff? Does utility continue to fall, or does it level off? Metaphorically, is poverty a utility pit, or an abyss? I have realised that the first option – assuming that there is a 'rock bottom' on utility – is necessary to capture the intuition of 'desperation'. This assumption represents the idea that at some point, people have 'little to lose', and is the only way to generate risk taking below the threshold.

Once we formally specify what we mean by a desperation threshold (Fig. 1), surprising conclusions emerge. Whereas verbal models yield monotonic predictions—poverty either increases or decreases risk taking—the specified model reveals a non-monotonic relationship. Poverty has no consistent directional effect, but a polarizing one: individuals avoid risk just above the threshold and embrace it below. This result offers a guide to test our model empirically: unlike most previous studies, we do not fit the data with linear function, but with a broken-stick pattern (Chapter 4).

1.3 What is a good model?

To sum up, a formal model is an explicit and internally consistent representation of a candidate explanation for a phenomenon. This definition applies generally to formal modeling in social sciences. But there are countless ways to explain a phenomenon that do not necessarily contradict each other. Take crime rates in deprived neighbourhoods, the simplest explanation would be: people commit crime because they are in poverty. A slightly more elaborate would be: poverty is frustrating, so people commit crime. These are explanations, just not particularly satisfying ones.

What kind of explanation does this dissertation aim to provide? I am not a philosopher, and the project did not begin with a clear epistemological framework. That said, I believe I have implicitly followed principles that have been articulated by philosophers. What follows is a kind of retrospective epistemology, a post-hoc attempt to clarify and justify the approach I have taken.

1.3.1 Abductive reasoning

Scientific reasoning is often described as either deductive or inductive. Deductive reasoning starts with assumptions and derives predictions from them. This is the case, historically, of neoclassical economics. From axioms of rationality and market equilibrium, economists derive all sorts of consequences, from the effect of a minimum wage to the effect of trade tariffs. In inductive reasoning, scientists accumulate findings, and a general law emerges. This has, for a large part, been the case of experimental psychology.

Both approaches have important limitations in social sciences. As humans are quite messy, induction tends to never produce a clear theory. Discussing the state of psychological research, Muthukrishna & Henrich (2019) cite Poincaré to illustrate the problem: 'an accumulation of facts is no more a science than a heap of stones is a house' (p. 4). Deductive social sciences have also reached a dead end. For instance, neoclassical economics yielded elegant predictions on every aspect of the economy, but little predictive power. Many predictions are out of touch with reality: at equilibrium, no firm makes any profit and there is no involuntary unemployment. In the last decades, the field has pivoted toward applied research, at the expense of theory (Backhouse & Cherrier, 2017). More broadly, I believe that a purely deductive social science is unattainable, as we lack proper axioms about human behaviour.

Formally, the models in this dissertation are deductive: I prove that the DT and other assumptions have several implications. However, my thinking process is not a deduction, but rather an 'abduction', also called 'inference to the best explanation' (P. Lipton, 2017). In each chapter, I start from macro-level empirical patterns, and argue that the DT is capable of explaining them. In other words, I do not claim that the DT was a priori an obvious assumption. Otherwise, neoclassical economists would likely have thought of it. My claim is that the DT is able to account for many social phenomena, which makes it a posteriori plausible. Abduction is not unusual in theoretical social sciences (Muthukrishna & Henrich, 2019), but it is rarely acknowledged. Some of the results of my dissertation were also made deductively, in particular, Chapter 4 where I investigate the consequences of the DT on time discounting. In those cases, I followed the thread of the DT and looked for interesting consequences. However, I also framed those cases as abductions, starting from known empirical phenomena. This choice reflects my conviction that the value of the model is not predictive, but explanatory: the DT is only interesting insofar it helps us to understand existing findings.

Abduction has a strong shortcoming: it does not show that the model is the true explanation for a phenomenon. Again, models do not investigate nature. Rather, abductive models humbly show that an assumption is a 'candidate explanation' (J. M. Epstein, 2012) for these phenomena: the DT is sufficient to explain crime in deprived populations, but whether it is the mechanism at play remains to be proven. This is just a step in the scientific process, but a crucial, and rarely made step.

1.3.2 State-dependent rational choice

I now turn to concrete theoretical frameworks that have guided my work. The central one is rational choice: in all four chapters, I have aimed to explain social phenomena as the result of cost-benefit analysis. The DT itself is formulated as a utility function. I also use game theoretical arguments in Chapter 2 and 4.

Rational choice theory is, of course, widely discredited empirically (Kahneman, 2011). However, I would argue that its bad name is due to its use in a deductive fashion, with the aim of making quantitative predictions. Here, I instead use it in an abductive fashion (see above). Instead of assuming rationality, I start from empirical phenomena, and wonder what rationality can explain. In Boudon's terms, I look for 'good reasons' behind people's actions.

Rational choice has also been criticised for its flexibility and lack of falsifiability: for a very wide range of behaviours, one can build an aptly shaped utility function accounting for the findings. In these cases, rational choice theory is almost tautological. The desperation threshold, however, is not an arbitrarily shaped utility function. It aligns with the intuition of 'basic needs', and resonates with experiences of people in situations of poverty. It also has plausible evolutionary roots. Rubin & Paul (1979) argue that there is a "minimum income needed in order to support a mate and offspring" (p. 593). In other words, reproductive value is plausibly very small below some level of resources, and can of course not be negative.

I should nonetheless stress that my use of rational choice theory is not a commitment to its realism. Nor do I claim that rationality accounts for most social phenomena. However, when applicable, I find rational accounts particularly satisfying: they are 'self-sufficient' (Boudon, 2003). Most explanations beg further questions – for instance, emotional explanations beg the question of why the emotion occurs in such contexts. In contrast, rational explanations can bring the scientific inquiry to a close: people behave this way because they have good reasons to do so, period.

I believe rational choice theory is especially valuable for analysing decision making in contexts of poverty. Since Malthus (1798), a long-standing tradition in the social sciences has portrayed the poor as irresponsible. Today, one of the most influential paradigms — 'scarcity theory' — attributes behaviour under poverty to what Vohs (2013) calls the 'Poor's Poor Mental Power.' According to scarcity theory, people in poverty take risks or act impulsively because they fail to take into account the negative consequences of their actions, as poverty disrupts their decision making (Shah et al., 2012). Despite its limited empirical support (O'Donnell et al., 2021), scarcity theory has had immense influence.

More broadly, behaviours in situations of poverty are almost always framed as bad decisions. This framing is particularly evident in discussions of risk taking. When people in poverty take risks, they are accused of endangering themselves and those around them. When they avoid risk, they are said to refuse profitable opportunities, thus perpetuating their poverty (Haushofer & Fehr, 2014).

In this dissertation, I take the opposite track: following the work of Daly & Wilson (2001) and of Pepper

& Nettle (2017), I analyse such behaviours in poverty as attempts to manage in a bad situation. Putting it more politically, I try to see the world through the eyes of a person in poverty, and to take their decisions as seriously as we take the decisions of the well-off. My interest in rationality is not absolute, but state-dependent: we are not interested in what behaviour is optimal in general, but only in how the context – level of resource and the social environment – shapes the optimal decision. However, I do not study the reverse causality – the role of behaviour in generating poverty. This reverse causality clearly exists, but is beyond the scope of the PhD.

1.3.3 Methodological individualism

A good explanation is not a simple paraphrase. Saying that poverty causes crime is just restating an empirical phenomenon, without adding much light. This amounts to saying that a car advances because fuel makes it go forward. An explanation is more satisfying when it 'opens the black box', that is, proposes a mechanism by which the micro-level entities of the system generate the macro-level ones. This 'reductionism' is not always feasible: to explain global conflicts, molecules are of little help. It is also sometimes not desirable: to explain the existence of poverty, the individual scale might be a distraction (Brady, 2023).

In the case of the phenomena that my dissertation studies, however, I believe individual decisions cannot be ignored. Groups do not have an independent will, and in cases like violent crime rates, it is not plausible that a centralised decision making is happening. Of course, the mapping between individual decisions and macro-level outcomes is not trivial. Structural factors (economic inequality, the penal system) play a role, and strategic interactions between individuals generate non-trivial effects. In Chapter 2, I use an agent-based model to investigate such effects. I found an interesting and unexpected hysteresis phenomenon: the level of violence in a group depends not only on the current economic conditions, but also on the past. Put otherwise, the group has properties of its own – but those properties are maintained through individual decisions.

1.3.4 Toy models

Last, the models I will present belong to the class of 'toy models', also called 'conceptual' (Kokko, 2007) or 'explanatory' (J. Epstein, 2008) models. Toy models are models that do not aim at being as realistic as possible, but to be as simple as possible while remaining interesting, non-trivial and explanatory. Kokko (2007) defends this approach by drawing a comparison with maps. The first reason that maps are simplified versions of reality is that reality is too complex. Just like the fractal-shaped coast of Brittany is impossible to cartography, we could never measure everything that is relevant in social reality, as too many variables (culture, landscape, economies, family structures...) are relevant. And even if we had data, the models could not handle the complexity of computations, as all the variables interact with one another. The second reason is that a realistic map would be terribly unhelpful to orient: 'if lost in a forest, [a hiker] would not become any wiser by looking at a too vastly detailed map than by staring at the original forest' (p. 4). What the hiker needs is a highly simplified version of the forest, that highlights the paths and the contour lines. The same way, a perfect social simulation like The Matrix would be less useful to a sociologist than Schelling (1971) model of segregation (see below).

Toy models shall not be used to make useful quantitative predictions. At best, they make qualitative predictions: for instance, in deprived neighbourhoods, we expect more crime than in richer ones. However, just like 'scale models' are good at showing children how catapults work, toy models are very good at illuminating the core dynamics of a proposed explanation. Ideally, they should find the minimal conditions for a phenomenon to emerge. This justifies our unapologetic use of rational choice theory: integrating bounded rationality or biases would vastly increase the realism of our models, but in our cases, such assumptions were not needed to obtain the results.

1.3.5 What for?

If the models that I present here make no quantitative predictions, are they just elegant mind games? Well, not entirely. In most cases, explaining a phenomenon is more intellectually satisfying than being able to predict the consequences of an intervention, but less useful. In some cases, however, an explanatory model can be more useful than an empirically-informed model. This argument is usually known as the 'Lucas critique'. Lucas (1976) argued that statistical models that rely solely on historical correlation often fail to predict the effect of structural changes, because they ignore how people adapt their expectations and behavior in response to new rules. An explanatory model, however, can be used to approach unprecedented situations or new rules. Understanding the system helps to generalize to situations that do not exist in the empirical record. Harford (2015) gives the following example: "Fort Knox has never been robbed, so we can save money by sacking the guards." This is of course absurd, hence the conclusion: "You can't look just at the empirical data, you need also to think about incentives" (p. 182). A model that opens the black box and proposes a rudimentary cost-benefits analysis for the guards' behaviour would – correctly – predict that sacking the guards would result in a Fort Knox robbery. Lucas applied this reasoning to macro-economic models: providing micro-foundations does not help to better fit historical data, but it can plausibly help to better predict the effects of policy changes.

I believe the Lucas critique applies to the DTM in several places. Proposing rational motivations for risk taking in situations of poverty does not help to predict the crime rate in Paris next year. However, the flexibility and the generality of my models can make them suitable instruments to approach the effects of radical public policies. For instance, crime rates are often observed to be insensitive to the severity of punishment (Nagin, 2013), and the DTM proposes an explanation for it (Courson & Nettle, 2021). However, no one has ever observed the effect of a complete abolition of the criminal justice system. The DTM can make a qualitative prediction: below a certain threshold of severity, crime rates would explode. More importantly, the DTM can inform us on the behavioural consequences of an unprecedentedly protective welfare, that would guarantee that every citizen can meet its basic needs. I discuss the consequences of the DTM in that regard at the end of each chapter.

1.4 The desperation threshold: an old, simple, but radical idea

With a clearer view of the aim and value of this scientific enterprise, I now turn back to introducing concretely what this dissertation consists of. The aim of this dissertation is to propose a new way to explain certain behaviours in situations of poverty and social outcomes in deprived or unequal populations. The model I propose is simple and intuitive: in poverty, people try first and foremost to make ends meet. This idea is so simple that I am of course not the first to propose it. Actually, I found instances in many disciplines – instances that in most cases ignored each other, even though they proposed models that are formally equivalent. Most of the instances, however, failed to grasp the full consequences and radicality of the model. In particular, they rarely thought about the two aspects of the threshold at once, that is, the fact that it produces risk aversion above and risk taking below.

As I mentioned in the first page, a threshold is implicitly present in many verbal models of decisions in poverty, for instance in Merton's strain theory. To our knowledge, the oldest explicit presentation comes from the Soviet economist Chayanov (1926), who considered that "in a natural economy, human economic activity is dominated by the requirement of satisfying the needs of each production unit" (p. 4). Chayanov put this principle at the center of his analysis of the "peasant economy", and studied the many ways that peasants minimized the risk of not meeting their needs: for instance by growing crops that one can directly consume, by working insanely hard or by selling cattle in bad years. However, Chayanov was not interested in what happens when ruin is likely. Interestingly, his principle came to be known as the 'safety first' principle, which connotes prudence and not risk taking.

This principle was later formally modeled in several disciplines, independently. Let us review, by disciplines, how models analogous to the DTM have been proposed.

1.4.1 Agricultural economics

The first, historically, is agricultural economics. Roumasset (1971) built a formal model to explain the choice of technique of peasants in the Philippines. He assumes that agents have 'lexicographic preferences': they first try to make sure that they are above a 'disaster level', and only if the probability of falling below is very small, optimise average production. When one gets closer to the threshold, agents switch to safer actions, but then 'reswitch' to risk taking when they dip below the threshold. This result seems not to have been understood at the time: in reviews of Roumasset's later book, Lundahl (1977) concludes that "This result runs contrary to all conventional wisdom" and "casts some doubt on Roumasset's methods" (p. 392), while M. Lipton (1977) argued that "it is not clear how it withstands more usual, and in farming more plausible, assumptions" (p. 826).

The idea was simultaneously developed by Kunreuther (1971) who also found this result puzzling: "It is thus conceivable that extremely rich farmers and poor farmers will follow a similar cropping pattern [i.e. risk-taking] but for entirely different reasons" (p. 7). Masson (1974) proposed a model closer to the DTM, representing 'disaster level' as a jump in the utility function. Again, the model produced the same result, but Masson discarded it as largely irrelevant empirically: "[being below the threshold] should be rare because these imply that even to remain at the current income level would be disastrous. Most people with discontinuities to the right of the zero point would in fact not remain in farming and thus would not show up in the sample" (p. 562). Overall, the literature on agricultural economics has focused almost entirely on risk aversion above the threshold, and scarcely on risk seeking below. For instance, McCloskey (1976) used this principle to explain scattering in English open fields as risk minimization, but did not explore the fact that when times are dire enough, the model prediction reverses.

1.4.2 Development economics

After a hiatus, the principle was rediscovered in development economics. It was first explored by A. V. Banerjee & Newman (1994), who pointed out that if poverty is best represented as having 'nothing to lose' – formally, if individuals in poverty are close to a lower bound in their utility function – then they should take risks. In this case, an individual who received a loan would have no reason to repay it as long as he has a chance to get away with it. No one would therefore be willing to loan money to individuals in poverty, and this 'credit constraint' might generate poverty traps.

Lybbert & Barrett (2007) took the opposite point of view. They showed that if a poverty trap exists, then individuals around it should alter their risk taking. The poverty trap can be modelled as a point at which wealth dynamics 'bifurcate': above, individuals tend to accumulate wealth, whereas below, they tend to fall into poverty. Individuals should therefore avoid risks just above the bifurcation level: any risk taken increases one's chance of ending up in poverty. Below the threshold, they should on the contrary take risks, to get a chance to break out of poverty. While the justifications are different, the result emerges the same way as in our model: around the poverty trap, the long-term utility of wealth is sigmoid-shaped (Lybbert & Barrett, 2007). Unlike Banerjee, they made a connection with the agriculture economics literature, presenting their model as "conceptually indistinguishable from the safety-first, lexicographic preferences popular in the 1970s" (p. 414).

1.4.3 Evolutionary biology and psychology

Meanwhile, Caraco et al. (1980) and Stephens (1981) independently introduced the idea of a 'starvation threshold' in behavioural ecology. This resulted in a large empirical literature in animal behaviour, known under the name 'energy budget rule', or 'risk-sensitive foraging'. This literature stayed very separate, even though the model is equivalent: in both cases, a sigmoid-shaped utility function generates risk-taking below a critical level of resources, and risk aversion above it. The principle then diffused to evolutionary approaches of human behaviour, in anthropology (Kuznar, 2001; Mace & Houston, 1989; Winterhalder et al., 1999) and psychology (Mishra & Lalumière, 2010; Nettle, 2009; Pietras & Hackenberg, 2001; Rode et al., 1999). These fields interpreted the threshold in a looser way, not in terms of starvation, but of 'subsistence' in anthropology, and 'need' in psychology. Both in biology and psychology, however, authors focused on the right side of the threshold: they merely predicted – and tested – an increase in risk taking in dire situations.

It is remarkable that different fields have independently converged on analogous ideas, sharing a desperation threshold as a common denominator. It highlights how general the mechanism is, and how he can apply across various domains. Though, it is unfortunate that these models have rarely crossed disciplinary boundaries, and that the same idea had to be rediscovered multiple times. It is also striking that most authors – with the exception of Travis & Lybbert – had interest in only one side of the threshold: they looked at behaviour either above or below the threshold, but rarely both at once. With this simplification, the DTM makes a linear prediction that is easily testable: poverty either increases or decreases risk taking. This simplification is very problematic: it makes the DTM non-falsifiable, since both a positive and a negative correlation between resources and risk taking can be predicted.

Despite the many intellectual forerunners, I believe however that most authors have not grasped the radicality of the desperation threshold. The DTM predicts that poverty has a complex effect on risk taking: people take less risk up to a point, then much more risk. The DTM predicts a 'behavioural switch' at the threshold: a little loss in resources can trigger a massive change in behaviour. At the population level, it predicts a polarization: a deprived population will be a mixture of people avoiding risk, and people taking risks. Chapter 4 clarifies these predictions and presents an empirical test on survey data.

1.5 Dissertation outline

The four chapters of my thesis are connected by the desperation threshold. They are part of a larger project, some parts of which are not included in this dissertation, as I took part in them before starting my PhD. The first (Courson & Nettle, 2021) is a modeling paper, where we showed that the DT could explain "Why do inequality and deprivation produce high crime and low trust?". The second, led by Setayesh Radkani, was a test of these predictions in experimental games (Radkani et al., 2023). We show that when faced with an artificial threshold, participants broadly conform to the model's prediction.

1.5.1 Chapter 2: Why is violence high and persistent in deprived communities? A formal model

The second chapter in this dissertation stems from these two projects. It extends the previous model, allowing for the possibility to use violence to deter exploitation. I show that under these conditions, the DT can account not only for the effect of poverty on property crime, but also on violent crime. The effect of the DT is indirect: some individuals are desperate and therefore take risks, which triggers a need for protection among the rest of the population. The model also reproduces two important stylised facts about violence. First, the fact that homicide rates are so variable over time and space. Second, the model features hysteresis: violence can persist even if the economic conditions triggering it have disappeared – which can explain violence 'neighbourhood effects'.

This chapter is co-authored with Willem Frankenhuis, Daniel Nettle and Jean-Louis van Gelder. It has been published in journal Proceedings of the Royal Society B. The full citation is:

de Courson, B., Frankenhuis, W. E., Nettle, D., & Van Gelder, J. L. (2023). Why is violence high and persistent in deprived communities? A formal model. Proceedings of the Royal Society B, 290(1993), 20222095.

1.5.2 Chapter 3: Why does poverty increase time discounting? Present needs and uncertain future

In this chapter, I extend the desperation threshold model to the study of time discounting. I argue that current models of time discounting in situations of poverty are not sufficient to explain empirical findings, and that the verbal theory that one should prioritize present needs in situations of urgent needs has not been appropriately modeled. I present four different scenarios of the desperation threshold, varying the consequences of the threshold on future utility. My model predicts high discounting around the threshold, and high patience at intermediate levels of resources. In contrast with the risk-centered DTM, the effect is predicted to occur on both sides of the DT. I show that, unlike existing accounts, our explanation does not depend on assuming a future improvement, but predicts a U-shaped effect of future expectations.

This chapter is co-authored with Willem Frankenhuis and Daniel Nettle.

1.5.3 Chapter 4: Poverty is associated with both risk avoidance and risk taking: empirical evidence for the desperation threshold model from the UK and France

This chapter provides an empirical test of the desperation threshold model. I derive and preregister distinctive predictions of the model on the relationship between poverty and risk taking, and test them against data from the UK and France. I obtain the predicted V-shape with our subjective resource measure, but not the objective one. In line with the model, I observe that risk taking is unambiguously polarized among people with low income: variance in risk taking is higher, and both extreme risk avoidance and extreme risk taking are more frequent. I cast out alternative explanations, by showing that income is not correlated with coherence in the risk task, and that there is no polarization on the similarly phrased time discounting task.

This chapter is co-authored with Willem Frankenhuis and Daniel Nettle. It has been published in journal Proceedings of the Royal Society B. The full citation is:

de Courson, B., Frankenhuis, W. E., & Nettle, D. (2025). Poverty is associated with both risk avoidance and risk taking: empirical evidence for the desperation threshold model from the UK and France. Proceedings B, 292(2040), 20242071.

1.5.4 Chapter 5: Explaining the paradoxical effects of poverty on decision making: The Desperation Threshold Model

In this chapter, I expose the desperation threshold model in its most general form and highlight the minimal necessary assumptions. I trace back the different versions of this model that have been previously proposed in economics, biology and social sciences, and that have ignored each other until recently. I review a wide range of evidence from different methods and disciplines, to evaluate the model validity. I discuss the consequences of the DTM at the population level, to explain the effect of inequality, welfare states and deterrence. I spell out the critical open issues of the DTM: whether the threshold is objective or subjective, absolute or relative, and whether it is falsifiable. I conclude by setting an agenda for DTM research in the future.

This chapter is co-authored with Willem Frankenhuis, Jean-Louis van Gelder and Daniel Nettle. Daniel Nettle and I have contributed equally. It has been published as a preprint, and is under review at *Behavioral and Brain Sciences*. The full citation is:

de Courson, B., Frankenhuis, W., van Gelder, J., & Nettle, D. (2025). Explaining the paradoxical effects of poverty on decision making: The Desperation Threshold Model. https://doi.org/10.31234/osf.io/bdvpa_v1.

2 Why is violence high and persistent in deprived communities? A formal model

This chapter is based on: de Courson, B., Frankenhuis, W. E., Nettle, D., & Van Gelder, J. L. (2023). Why is violence high and persistent in deprived communities? A formal model. Proceedings of the Royal Society B, 290(1993), 20222095.

2.1 Abstract

There is massive variation in rates of violence across time and space. These rates are positively associated with economic deprivation and inequality. They also tend to display a degree of local persistence, or 'enduring neighbourhood effects'. Here, we identify a single mechanism that can produce all three observations. We formalise it in a mathematical model, which specifies how individual-level processes generate the population-level patterns. Our model assumes that agents try to keep their level of resources above a 'desperation threshold', to reflect the intuitive notion that one of people's priorities is to always meet their basic needs. As shown in previous work, being below the threshold makes risky actions, such as property crime, beneficial. We simulate populations with heterogeneous levels of resources. When deprivation or inequality is high, there are more desperate individuals, hence a higher risk of exploitation. It then becomes advantageous to use violence, to send a "toughness signal" to exploiters. For intermediate levels of poverty, the system is bistable and we observe hysteresis: populations can be violent because they were deprived or unequal in the past, even after conditions improve. We discuss implications of our findings for policy and interventions aimed at reducing violence.

2.2 Introduction

There is massive variation in neighbourhood levels of interpersonal violence across time (Eisner, 2003) and space (Glaeser et al., 1995). For instance, homicide rates varied more than 100-fold between Chicago neighbourhoods in the 1988-93 period (Wilson & Daly, 1997). This variation is partially explained by macro-level factors (Pratt & Cullen, 2005), such as economic conditions, poverty and inequality in particular (Daly, 2017; Fajnzylber et al., 2002; Hsieh & Pugh, 1993; Kelly, 2000; Pratt & Cullen, 2005; M. Wilson & Daly, 1997), with extremely disadvantaged neighbourhoods having an unusually high level of violent crime (Krivo & Peterson, 1996). Violence is also a locally persistent phenomenon, subject to enduring neighbourhood effects (Sampson, 2012). That is, violent places tend to remain violent to some degree, despite continuous population flux and even when economic conditions improve (Sampson, 2012; Shaw & McKay, 1942; Weisburd et al., 2004) .

Different bodies of research have offered explanations of these observations at different scales. At the population level, several criminological theories view poverty as interfering with the normal functioning of a community, creating 'strain' (Agnew, 1992; Messner & Rosenfeld, 1994). Other criminological theories propose that poverty renders neighbourhoods deficient in social organisation (Shaw & McKay, 1942) or social efficacy (Sampson, 2012), promoting violence and crime. A separate body of work has focused on the role of inequality, arguing that inequality creates a fiercer competition for symbolic and material resources, resulting in higher violence (Daly, 2017; R. Wilkinson, 2004; R. G. Wilkinson et al., 1998; R. Wilkinson & Pickett, 2010).

At the individual and psychological levels, several authors have pointed to the role of time preferences (Brezina et al., 2009; M. Wilson & Daly, 1997). Poverty (Bolte et al., 2010; Lantz et al., 1998) and inequality (M. Wilson & Daly, 1997) are related to poorer future prospects, including higher mortality and morbidity rates. This can result in a sense of futurelessness, which in turn leads to steep future discounting and choosing actions that can lead to immediate payoffs, such as crime (Brezina et al., 2009; Daly & Wilson, 2001). Yet, other authors report that violence is a signal that serves to communicate a toughness reputation and avoid being victimised. This idea has been proposed independently in a variety of fields: ethnography (Anderson, 2000; Brezina et al., 2016), sociology (Gambetta, 2009), cultural psychology (D. Cohen & Nisbett, 2016) and evolutionary psychology (Fessler et al., 2014). On this view, violence also has long-term benefits, and does not necessarily qualify as a short-term strategy. Therefore, time preferences alone can not explain the social gradient of violence.

In this article, we show that a single mechanism is able to generate all three key observations: violence is higher in deprived or unequal populations, varies considerably between populations, and can persist in a community despite economic improvement. Whereas the theories mentioned above are stated verbally, we articulate our explanation in a formal model. This serves two purposes. The first is to prove that the mechanism we propose is indeed able to reproduce the empirical observations at a qualitative level (i.e. the model's generative sufficiency (J. M. Epstein, 2012). If it is, our model can be considered as a valid candidate explanation (J. M. Epstein, 2012, 2012). Second, formalisation eliminates the ambiguity inherent in natural language (Frankenhuis et al., 2023) and compels the provision of a fully explicit mechanism (Smaldino, 2017; Smaldino, 2020). In particular, the process of formalisation forces the specification of how interactions at the individual level produce group-level outcomes, which in turn shape individual behaviour. Thus, our approach aligns with the key aim of criminology and the social sciences generally to integrate micro- and macro-level processes (Box-Steffensmeier et al., 2022; Matsueda, 2017). This model uses ideas from complexity science. In that field, several models have studied crime (for a review, see D'Orsogna & Perc, 2015) – yet without engaging with the role of material circumstances.

That violence is a social problem (Heeks et al., 2018) does not imply that it reflects a dysfunction at the individual level. Here, we propose that violence is a 'contextually appropriate response', meaning it can be understood as a response to the costs and benefits associated with living in a particular context – as opposed to, for instance, a psychopathology or failure of willpower (Pepper & Nettle, 2017). In our model, individuals make decisions based on their level of resources and other individuals' behaviours. This game-theoretical feature creates the possibility that optimal strategies at the individual level produce suboptimal outcomes for the population, such as high rates of community violence, analogously to a 'tragedy of the commons' (Hardin, 1968).

Analysing violence as a contextually appropriate response requires first the specification of its possible costs and benefits for an individual. Violence is commonly assumed – for instance, in the classic Hawk-Dove model (Maynard Smith, 1982) – to allow an agent to take a resource by force, while facing a physical risk. In addition to these assumptions, we incorporate the idea that violence has reputational consequences as a 'toughness signal' (Anderson, 2000; Brezina et al., 2016; D. Cohen & Nisbett, 2016; Fessler et al., 2014; Gambetta, 2009), reducing the probability of being exploited. We thus focus on interpersonal violence involving physical harm to others for instrumental or reputational motives, rather than other forms of violence, like self-harm, child abuse, intimate partner violence, or warfare. Our question then becomes "why would it be more appropriate to send such signals in deprived or unequal neighbourhoods?". These neighbourhoods can be characterised as having a larger number of 'desperate individuals', without enough resources to meet their basic needs. They can be compared to drowning individuals, who would do anything to try to get their head out of the water, including dragging others down. Despite the high potential costs (Courson & Nettle, 2021), exploiting others can be the most direct way to get resources quickly and jump back "above water". We argue that the risk of being exploited by desperate individuals, in turn, triggers an incentive to send toughness signals – i.e., violent displays – among non-desperate individuals, to protect themselves from being targeted.

To formalise this intuition, we make two main assumptions. To represent the 'signal effect' of violence, we assume that being violent makes one less likely to be selected as a target of property crime. To represent financial desperation, we assume that agents are defined by a dynamic level of resources and have a 'desperation threshold', below which it is harmful to fall. In other words, agents are trying to always meet their basic needs and keep their head above water. The assumption of a threshold is a theoretically innovative idea in the social sciences (Courson & Nettle, 2021) that we believe to be reasonable. It is inspired by optimal foraging theory in ethology (Stephens, 1981), where models commonly include a 'starvation threshold' below which fitness rapidly declines. In humans, there are ethnographic descriptions of such thresholds (Du Bois, 2010; Nettle, 2015; Scott, 1977), involving both physiological needs (e.g., hunger) and social needs (e.g., being respected), thus more generally the ability to meet basic needs. In the Philadelphia community he studied, Du Bois described the poorest individuals as a "submerged tenth", who are more likely to engage in dangerous actions (Du Bois, 2010). Scott (1977) later observed among South Asian farmers a "subsistence crisis level—perhaps a 'danger zone' rather than a 'level' would be more accurate [...] a threshold below which the qualitative deterioration in subsistence, security and status is massive and painful" (p. 17). Experimental games have found that humans adjust their levels of risk taking in response to such thresholds (Mishra & Lalumière, 2010; Pietras & Hackenberg, 2001), including by stealing resources from other participants (Radkani et al., 2023). Here, we assess the explanatory power of the desperation threshold for the socio-economic gradient of violence.

2.3 Model

The model is more thoroughly described in the Supplementary Materials. The Python code can be found here: https://github.com/regicid/model

2.3.1 Structure of the model

Our model combines an individual-level optimal decision model and a population structure. The individual-level component is a state-dependent optimisation algorithm, implemented by stochastic dynamic programming (Houston et al., 1999; Mangel & Clark, 1988). Agents are defined by a dynamic 'state variable' that represents their level of resources. It is affected by the agent's actions and by random fluctuations, following an AR(1) process with autocorrelation r. The model assumes a 'desperation threshold', a value below which agents are heavily penalised. They have access to several strategies, defined by probabilistic consequences on their level of resources, conditional on other agents' strategies. Agents choose the strategy associated with the highest 'fitness', a maximand criterion that represents the agents' goal. We allow the chosen strategy to depend on (i) the agent's level of resources and (ii) the frequencies of strategies in the population. In other words, agents pick the strategy which is optimal for their current level of resources and social environment.

The individual-level model identifies the optimal action an individual should choose for any given distribution of strategies in the surrounding population. It is not sufficient for revealing how that distribution will evolve. To address this population-level question, we simulate large populations of interacting agents with different levels of resources. By varying the initial distribution of those resource levels – in particular their mean and variance, representing economic affluence and inequality, respectively – we can test how the economic context affects the level of violence. We run the simulations until the system reaches a stable equilibrium. We also vary the initial distributions of strategies to examine the possibility of hysteresis, the dependence of the outcome on the initial conditions of the system.

2.3.2 Individual strategies and fitness

At each time step, agents can choose between three strategies: ‘exploitation’, ‘violence’ and ‘submission’. Exploitation represents property crime. When exploiting, an agent tries to take resources from another agent. This strategy entails two potential costs. First, the exploiter might be caught and sanctioned with a probability , costing units of resources (see Table 2.1 for a summary of the parameters). This reflects exogenous social control, such as policing. We set the probabilities and magnitude of these costs (, and) such that the expected payoff of stealing is always negative, ensuring exploitation stays on average a bad decision. Second, the target agent may react violently: agents either fight (‘violence’ strategy) or not do so (‘submission’). ‘Exploiters’ are also assumed to react violently to exploitation, but henceforth we use ‘violent’ to describe an agent who plays the violent strategy but does not exploit. The fight’s winner, selected by a coin toss, obtains or keeps the disputed resources. The loser pays a proportionate fitness cost □ , described in the next subsection.We also assume that violent agents sometimes enter unnecessary fights: with probability m, they attack a non-exploiter agent by mistake. This triggers a fight if the other individual is also violent.

Table 2.1. Notation summary

Symbol	Meaning	Typical value or range
N	Population size	105
	Mean resource level	[5, 25]
	Variance of resource levels	[4, 10]
r	Resource levels autocorrelation	.99
n	Number of possible targets	[1, 50]
	Exploitation resource stake	10
	Resource cost of punishment	20
	Probability of punishment	1/3
m	Probability of violent mistake	[.01, .3]
ω	Fitness cost of being below threshold	[.01, .3]
	Lost fight fitness cost	[.01, .3]

The violent strategy also sends a ‘toughness signal’: it is observable and confers a ‘toughness reputation’, which reduces the probability of being the target of exploitation at this round. We assume that choosing the violent strategy suffices to confer this reputation, even for an agent who has never fought. This is a simplifying assumption, that also guarantees the coherence of the model (see Supplementary Materials). Exploiters choose their target out of a set of n randomly drawn agents, among which they prefer submissive targets over violent ones. Agents playing ‘violent’ at this round therefore have (if n>1) a non-zero but lower probability of being victimised than agents playing 'submissive' (see Supplementary Materials for details). The parameter n controls how much lower, and thus represents the toughness signal's efficiency: it has no effect if n=1, whereas if n , then violent agents are never victimised as long as there is at least one submissive agent in the population. The 'violent' strategy is designed to represent forms of violence involving either a material or a reputational stake, our model thus focuses on these forms.

Agents choose the strategy that yields the highest expected 'fitness', defined as the resource level attained after T periods reduced by (i) a fraction ω for every period spent below the desperation threshold and (ii) a fraction for every lost fight, representing the risk of an injury when fighting. In other words, agents try to maintain their head above water financially while fighting as rarely as possible. Since we use a Stochastic Dynamic Programming algorithm, the decision takes into account not only the possibility of being below the desperation threshold immediately, but also at any later point in the future.

2.3.3 Population simulations

We simulate populations of $N = 10^5$ agents whose level of resources are drawn from a Gaussian distribution. At every time step, we let 10% of the population, randomly chosen, update their strategies. This way, the distribution of strategies in the population can evolve smoothly to an equilibrium rather than oscillating. When updating their strategies, agents take into account their level of resource and the current frequency of 'exploitation' and 'violence' in the population. For simplicity, we assume agents have perfect knowledge of others' strategies. We iterate this process enough times for the distribution of strategies to stabilise.

We then compare the outcomes of the model for different values of the mean and the variance of the distribution of resources in the population, representing economic affluence and inequality, respectively. To investigate the possibility of hysteresis, we test if the outcome depends on the initial proportion of violent agents. In the Supplementary Materials, we explore how the model is affected by varying the other parameters.

2.4 Results

2.4.1 Individual decisions

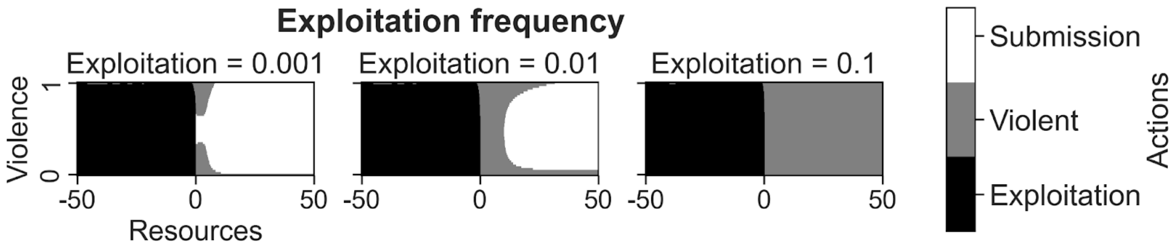

Figure 2.1: Optimal strategies depending on resource levels (x-axis), prevalence of violence (y-axis) and prevalence of stealing (panel). The central tick on the x-axis (0) represents the desperation threshold. Agents tend to exploit below the threshold and to be violent either when exploitation is frequent, when violence is very rare or when violence is frequent.

Figure 2.1 represents the optimal decisions depending on resource levels and the prevalence of exploitation and violence in the population. It is generally optimal to exploit when one is below the desperation threshold, confirming the previous finding that being under water makes risk-taking contextually appropriate (Courson & Nettle, 2021). The area where agents exploit is roughly a square. This decision is thus virtually independent of the level of violence, even though exploitation is greatly disincentivized by the presence of violent agents. In a fully violent population, an exploiter will always have to fight, which halves its probability of success and reduces its "fitness" in case of loss.

Above the threshold, agents should be violent in several cases. First, when exploitation is frequent (in figure 2.1, compare the right panel to the left). This is unsurprising: violence lowers the risk of being exploited, so the higher this risk is, the more agents should protect themselves. Second, when violence is very rare (in figure 2.1, at the bottom of the y axis). A lone violent agent will never be exploited (as the exploiters will always be able to choose a submissive target instead) and never fight, as it never meets other violent agents. Therefore, being violent in a fully non-violent environment has benefits but no costs, and is favoured.

Agents should also choose violence when violence is very frequent (in figure 2.1, at the top of the y-axis). The more violence there is, the more exploitation is concentrated on the rare submissive agents. This incentivizes them to be violent, and thus violence begets violence. Finally, agents are prone to violence when close to the threshold. This is due to risk preferences: being violent reduces the risk of being exploited. Just as agents are risk-prone below the threshold because they have 'nothing to lose', they are risk-averse just above the threshold as they have 'too much to lose', like a person on the edge of a cliff. Intuitively, close-to-the-edge individuals choose to risk their health in an attempt to hang on to their resources.

2.4.2 Population simulations

At the population level, outcomes depend chiefly on the proportion of agents below the desperation threshold, the 'desperation rate'. This rate determines the number of exploiters, which in turn determines the number of violent agents (see figure 2.1). Both poverty (low mean level of resources) and inequality (high variance) increase the desperation rate: the lower or the broader the distribution, the larger the left tail consisting of desperate agents (figure 2.2).

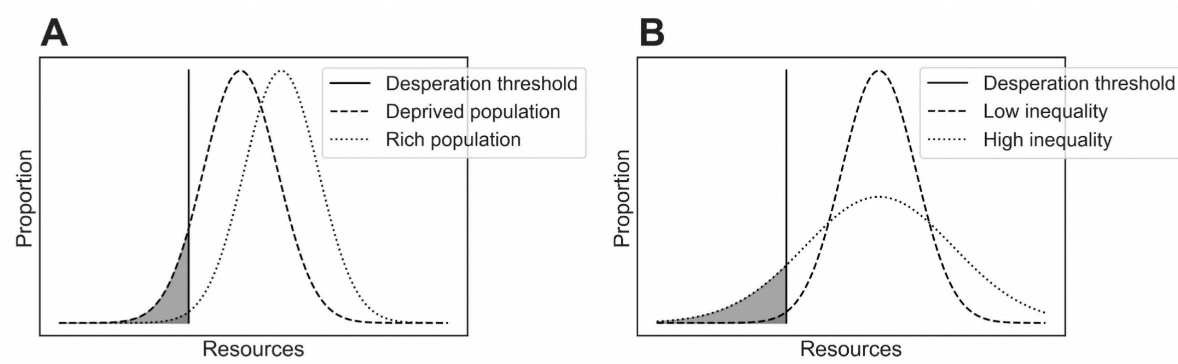

Figure 2.2: Effect of poverty (A) and inequality (B) on desperation rate. Either reducing the mean of the resource distribution or increasing its variance leads to a larger tail of individuals whose resources are below the desperation threshold.

The higher the proportion of desperate agents, the higher the prevalence of violence at equilibrium (figure 2.3). In our model, therefore, both poverty () and inequality () increase violence. However, the relationship of the desperation rate to the equilibrium frequency of violence depends on how we initialise the strategies. If we begin with no violent agents in the population, we reach the equilibrium frequencies shown with the crosses on figure 2.3. We observe an inverse s-shaped function. For low values of desperation rate, we have a concave relation: the violent strategy gets costlier as it spreads, dampening the increase. For high values, we observe a convex relation revealing a positive feedback effect: exploitation is deflected onto the submissive agents, and violence begets violence. In the Supplementary Materials, we show that this result is qualitatively robust to changes in the exogenous parameters values.

Here, it must be noted that inequality only plays a role by increasing the amount of desperate agents. In other words, inequality increases violence through absolute poverty, not relative poverty. Concretely, enriching the rich without impoverishing the poor would not increase violence. It must however be noted that we assumed the desperation threshold to be fixed and independent on the average level of resource , which, by construction, precludes the role of relative deprivation. We explore this limitation in the Discussion.

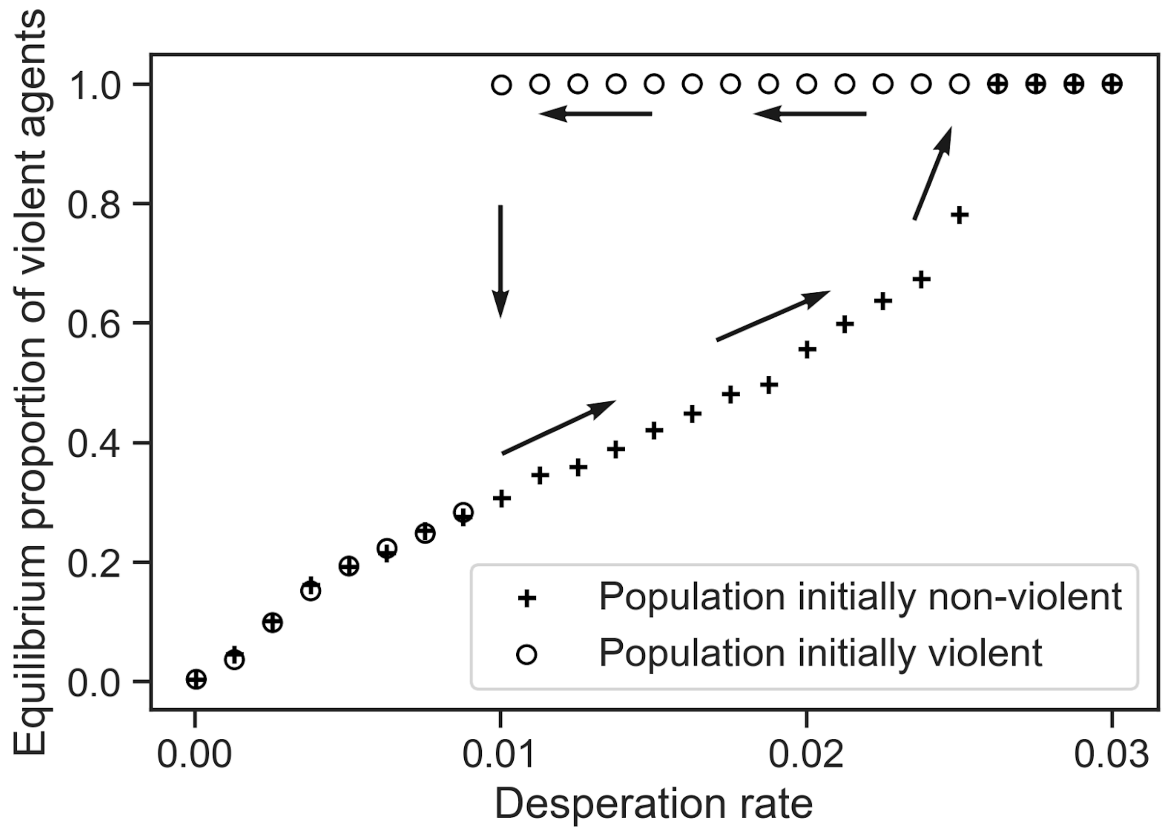

Figure 2.3: Proportion of agents playing 'violent' or 'exploiting' at equilibrium against the desperation rate. The crosses show the data for populations initialised with no violent strategies, and the circles populations initialised with all violent agents. We cut the x-axis when both curves reach 1 (beyond .03, crosses and circles stay at 1). The arrows illustrate the hysteresis loop: if a population's desperation rate increases from 0 to .04, it would follow the lower branch, but if it decreases from .04 to 0, it would follow the upper branch.

2.4.3 Multiple equilibria and hysteresis

If we initialise the simulation with only violent agents, the population moves to a completely violent configuration in a large range of the desperation rate range (figure 2.3, circles). Here, the system has two distinct stable equilibria. Which of these is reached depends on where the system comes from. We observe a hysteresis loop: if the desperation rate (here exogenous) increases from 0 to .03, the system follows the lower branch, but if it decreases from .03 to 0, it follows the upper branch and remains in a fully violent configuration for a long time. Thus, two equally deprived or unequal communities can have vastly different levels of violence for historical reasons, with high desperation in the past producing a persisting high violence. We can visualise this bistability using a vector field (figure 2.4A). The upper equilibria have small basins of attraction, and will therefore not be reached unless a very large share of the population is violent. However, figure 2.4B shows that the incentive to be violent soars as the prevalence of violence goes to 1, as rare non-violent agents concentrate exploitation costs. Thus, even though a few non-violent agents would suffice to reach the basin of attraction of the lower equilibrium, the model predicts these equilibria to be stable and robust to small changes in the parameters. In the Supplementary Materials, we show that the hysteresis effect holds if the parameters r and n are high enough, that is, if toughness signals are efficient enough and the experience of desperation sufficiently persistent.

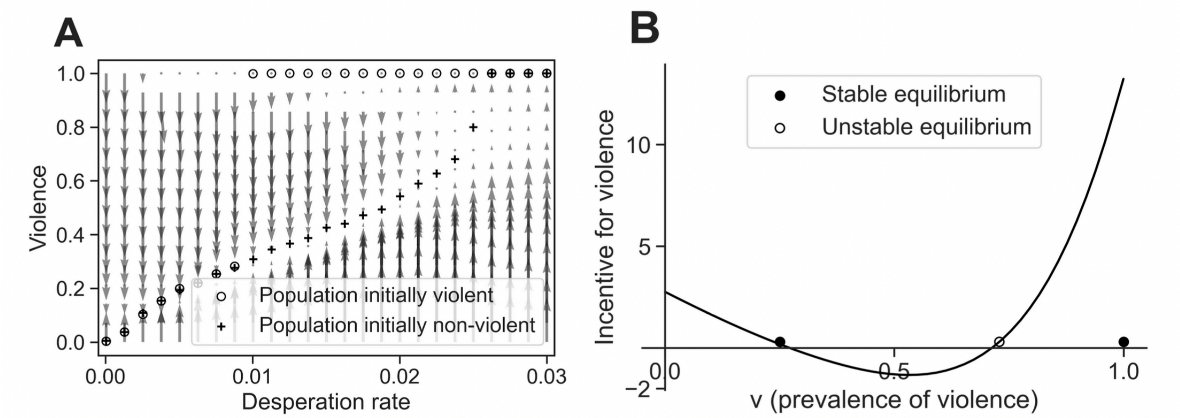

Figure 2.4: (Panel A) Vector field representation of the model results. We obtain the vector field numerically, by initialising the population with a certain proportion of violent agents and a certain desperation rate. We let agents update their strategies and the arrows represent how much the proportion of violent agents has changed. For intermediate desperation rates, the vector field reveals a bistable system, explained by figure 2.4B. (Panel B) Incentives for violence, defined as the mean difference in payoffs between the violent and submissive strategies, obtained with a fixed desperation rate, varying the prevalence of violence. The incentive for violence first decreases as the risk of actually fighting increases, then explodes as the costs of exploitation concentrate on the rare non-violent agents.

2.5 Discussion

Violence rates vary considerably throughout time and space, in association with economic deprivation and inequality, and can have a persistent character. We have shown that a single mechanism can account for these three empirical observations. We therefore offer a candidate explanation, proving that some conditions are sufficient to generate a particular phenomenon. The innovation in this work resides in demonstrating the consequences that flow from making two original assumptions, namely (i) that agents have a desperation threshold and (ii) that violence sends a 'toughness signal' that reduces the risk of being exploited. Assumption (i) has been explored in a previous model to explain property crime, but not in relation with violence. Assumption (ii) has been explored earlier in game theoretical models of conflict (Johnstone, 2001; Johnstone & Bshary, 2004; McElreath, 2003), but not yet in relation to deprivation and inequality.

2.5.1 Desperation triggers high violence

The assumption that agents have a desperation threshold has important consequences. First, it triggers risk-proneness below the threshold (Courson & Nettle, 2021). Intuitively, desperate individuals have 'little to lose': if their gamble succeeds, they lift their head above water, and if it fails, it makes little difference. As we assume that stealing entails the highest variance, 'desperate' agents are likely to exploit. This result holds as long as individuals possess such a threshold. The 'threshold' idea can have several interpretations, starvation being the most obvious, but perhaps not the most relevant for the inhabitants of industrialised countries.

Therefore, a larger proportion of desperate agents – as a consequence of either poverty or inequality (figure 2.2) – leads to more violence (figure 2.1), as non-desperate individuals try to reduce the risk of exploitation. The exploitation that stems from being below a desperation threshold is largely insensitive to the magnitude of punishment (Courson & Nettle, 2021), in line with empirical evidence (Nagin, 2013). As individuals scramble to get back above the threshold, desperate individuals care more about the maximum payoff than the expected payoff of their strategy. In our model, this means that desperate agents continue to steal even when facing a high risk of violence. As a consequence, violence acts as a 'deflector' rather than a deterrent: it will not prevent exploitation , but might make the offender shift to a different, non-violent target.

This 'deflector' property of violence fundamentally influences the results of the model. In conventional rational choice models (Becker, 1968), violence deters stealing by increasing its potential cost. In such models, violence acts as a 'thermostat', dampening variation in rates of property crime – a sort of homeostasis. This prediction is at odds with empirical evidence showing massive variation in rates of violence across space and time (Glaeser et al., 1995). Instead our model predicts, due to the desperation threshold, that high rates of property crime can persist despite high rates of violence, which is more consistent with the empirical record (Quick et al., 2018).

Despite the common intuition that 'violence begets violence', standard game theory models actually predict the reverse. For instance, the Hawk-Dove model (Maynard Smith & Parker, 1976) finds violence to be a negatively frequency-dependent strategy: as violence becomes more common, a violent individual is more likely to meet another violent individual and to get into a costly fight. Put differently, every increase in violence diminishes its appeal, which stifles its spread. For that reason, the Hawk-Dove model predicts that the population only reaches a pure equilibrium where all individuals adopt a violent strategy when the cost of losing a fight is smaller than the cost of the resource at play (Maynard Smith & Parker, 1976). Again, this suggests that violence should display little variation between communities: the costs and benefits might vary, but the negative frequency dependence should homogenise violence rates. This mechanism – violence becoming more costly as it spreads – also operates in our model. However, the assumption that violence confers a 'toughness reputation' counteracts this dynamic. As being violent deflects property crime on non-violent agents, the spread of violence also makes non-violence more costly. The frequency dependence reverses for high enough levels of violence and turns into a positive feedback, whereby violence actually begets violence. Which one of these dominates depends heavily on the prevalence of exploitation, which in turn depends on the proportion of desperate individuals. Thus, our model recovers the potential for rates of violence to vary sharply in a way that depends notably on socioeconomic deprivation.

In some regions of the parameter space, high- and low-violence configurations can simultaneously be stable equilibria in our model. Depending on the starting point, the population can end up in either of the two equilibria: if violence is low, then it stays low due to the negative frequency dependence; if violence is high, it stays high due to the positive feedback. If violence is rare, it is not worth sending a violent signal as the risk of victimisation is diluted in the population, whereas if the vast majority of individuals are violent, a rare non-violent agent will bear the brunt of victimisation and suffer untenable costs. To understand this result more intuitively, one can think of bike locks, which play a protective role analogous to violence in our model. When leaving your bike among dozens of unlocked bikes, it may not be necessary to lock it, as the risk of it being stolen is diluted among all the bikes. However, if all the bikes around are locked, a stealer passing by would likely steal the only unlocked bike. Similarly, the risk of being exploited might be low enough in the low-violence equilibrium for the cost of violence to be too high to incur. In the high-violence equilibrium, however, any submissive deviant will inevitably concentrate the risks of exploitation.

This situation is analogous to coordination games, where positive frequency dependence generates multiple equilibria – for instance left- and right-hand driving. But whereas collective wellbeing is roughly equal whether cars drive left- or right-wing, in our case, settling in a high- or low-violence equilibrium is very consequential. An earlier evolutionary game theory model of toughness signals also reports the possible coexistence of two equilibria with very different levels of aggression (Johnstone & Bshary, 2004). The authors conclude that a population is unlikely to persist in the high-violence equilibrium, as mean fitness is lower than in the low-violence one. Our model does not include an equilibrium selection process. But in the human case and for the relatively short timescales we are interested in, extending only to a few generations, it seems plausible that a community could be trapped in such a detrimental equilibrium, and that such an equilbrium can therefore be empirically relevant.

This bistability generates a hysteresis effect: violence rates do not only depend on the current economic conditions, but also on their history. Concretely, a neighbourhood can be more violent than an equally rich neighbourhood because it was poorer and more violent in the past. Thus, violence can persist despite some economic improvement. This result aligns with the 'enduring neighbourhood effect' (Sampson, 2012) of violence, and thus offers an alternative explanation for it – not necessarily incompatible with the prevailing approach, the social efficacy theory (Sampson, 1997).

2.5.2 Relative poverty or absolute poverty?

In our model, poverty and inequality only increase violence through the proportion of desperate agents. Thus, the effect is driven only by absolute poverty, and not by relative poverty. Concretely, our model predicts that making the richest individuals richer with no impact on the poorest does not increase violence. This might seem at odds with several empirical findings (Blau & Blau, 1982; Daly, 2017; Kelly, 2000; M. Wilson & Daly, 1997) and theories (Daly & Wilson, 2001; Krupp & Cook, 2018; Pickett & Wilkinson, 2015; R. Wilkinson, 2004). For instance, comparing the neighbourhoods of Chicago, Daly and Wilson report that when controlling for economic inequality, median household income did not predict homicide rate in Chicago neighbourhoods (M. Wilson & Daly, 1997). However, our model's prediction is a consequence of our assumption that the desperation threshold is exogenously fixed across communities. Instead, the threshold itself may increase with affluence and with inequality. For example, the existence of inequality has been found experimentally to increase individuals' "perceived needs" (Payne et al., 2017). In our model, if the threshold was assumed to be proportional to the median resource level (as the poverty line is defined in the European Union), then any change in poverty through the parameter would affect equally both agents' level of resources and the threshold, without consequence. In this setting, the level of violence would only depend on inequality (). One could also imagine that an exploited agent loses a proportion of his wealth instead of a fixed amount of resources. In this setting, the presence of very well-off individuals could act as an incentive for exploitation, which could in turn create a stronger need for protection among these individuals.

2.5.3 Future directions

Our model analyses violence as a binary decision, where choosing 'violence' essentially means being ready to fight when exploited, which yields a 'toughness reputation', known by all of the other agents. This assumption is restrictive in two respects that we could explore in the future. First, we could allow agents to fine-tune their level of violence. This would require specifying how the fitness costs of violence relate to the level of violence and how exploiters choose their targets in this new context. It would be interesting to test, for instance, whether the hysteresis effect holds in this case, and to observe if the insensitivity to deterrence induced by the desperation threshold triggers arms race dynamics through an 'inflation of toughness'.

Second, our assumptions implicitly entail that an agent simply needs to be ready to fight so that every other agent treats him as tough, even if she has never fought. In our simulations, the majority of violent agents reap the benefits of violence without actually paying the costs, as fights rarely occur. We chose here to directly specify how the signal changes the receiver's behaviour, in order to focus on the population dynamics. An alternative assumption would be to only attribute a toughness reputation to an agent after she actually fought. This would make the model more complex, but would enable it to study another question: under what conditions should an agent be violent without material necessity, for pure reputational reasons? This could shed light on Anderson's observation that, in the deprived communities he studies, "there are always people around looking for a fight", a situation he attributes to "campaigning for respect" (Anderson, 2000).

Finally, our model also generates novel testable predictions and can guide empirical data collection. For instance, we predict individuals to be violent when they live in a deprived neighbourhood, whether they are themselves materially deprived or not (figure 2.1). This suggests that an individual's attitude toward violence would be better predicted by the economic situation of their neighbourhood, rather than by their own personal socio-economic status, whereas the reverse would be true for property crime. It is reminiscent of Anderson's observation that in deprived neighbourhoods, relatively better-off "decent families" reluctantly teach the "code of the streets" to their children, as they consider a toughness reputation as necessary to navigate this social environment (Anderson, 2000). Cohen and Nisbett also found that geographical origin (North or South) determined whether individuals endorsed "culture of honor" values, regardless of their current circumstances (D. Cohen & Nisbett, 2016).

2.5.4 Implications for policy and intervention

We discuss implications of our model for public policy and intervention. First, our model predicts that helping the poorest individuals to get back above the threshold of economic deprivation can have a ripple effect. Not only would such help reduce the probability that desperate individuals choose to steal, violence would also diminish among the rest of the population, for whom there has been no change in resource levels. In our model, the dire poverty of some has an emergent effect on the population: in a world where some individuals are ready to do anything to get their head above water, everyone must take protective steps like violence. By eliminating desperation, one might then improve the welfare of all members of the group, even those who do not benefit from the policy.

The second implication is related to the hysteresis effect our model produces. For a community trapped in a high violence equilibrium (figure 2.3, upper branch), the effect of an economic intervention would be a step function (figure 2.3, top arrows). Minor interventions would have no effect, then at some point, a sufficiently large intervention would cause a phase transition to a low violence equilibrium, and have a massive impact (figure 2.3, vertical downward pointing arrow). Similarly, interventions on violence (i.e. lowering violence without changing the desperation rate) would need to be sufficiently large to have an effect. In figure 2.4B, it would be necessary to pass the unstable equilibrium to reach the basin of attraction of the low-violence equilibrium, otherwise violence goes back to maximum when the intervention ends. Therefore, our model suggests a non-linear relationship between intervention magnitude and resulting change. It also calls into question the use of linear models to test the efficiency of these interventions. An empirical researcher might for instance find a null effect of economic support on violence if she only looks at a limited intervention, whereas more of this same intervention could have a tremendous positive impact.

To conclude, we presented a simple model combining individual optimal decisions and population simulations. We make two original assumptions: agents have a desperation threshold, and violence serves as a 'toughness signal'. We show that their combination is able to explain three cornerstone empirical findings: the large variation of violence rates between neighbourhoods or communities; the effect of poverty and inequality on violence; and the persistence of violence across time.

Funding and acknowledgements

The authors report no conflict of interest. WEF's contributions have been supported by the Dutch Research Council (V1.Vidi.195.130) and the James S. McDonnell Foundation (https://www.jsmf.org/grants/20170007/). DN's contribution was supported by ANR grant ANR-21-CE28-0009. JLvG's contribution was supported by a Consolidator Grant from the European Research Council [Grant Number 772911– CRIMETIME]. The authors thank Julien Lie, Karthik Panchanathan, Daniel Nagin, Ulysse Klatzmann, Sebastian Kübel, Laura Pick, Daniel B. Krupp and two anonymous reviewers for their precious help.

Data transparency and reproducibility

The Python code of the model and of the figures can be found in this repository: https://github.com/regicid/model_deprivation_violence. An online notebook to manipulate the model online without installing Python is available here: https://colab.research.google.com/drive/1wf3KBd95YO_WTluGztaR-8l-1zOD-e0o?usp=sharing.

2.6 Appendix

2.6.1 The model

Notation used in the model

Symbol	Meaning	Typical values
s_t	State (i.e. resource level) at time t	

Symbol	Meaning	Typical values
r	Correlation between s_t and $s_t + 1$	0.99
σ	Inequality (standard deviation of states)	
μ	Affluence (average state)	
p	Prevalence of exploitation	
v	Prevalence of violence	
n	Number of possible targets	10
N	Population size	
ω	Fitness reduction imposed below the desperation threshold	.1
λ	Fitness reduction imposed when losing a fight	.1
β	Stake of exploitation	5
γ	Probability of being caught	1/3
π	Cost of being caught	10
m	Probability of violent misfire	.01
T	Number of SDP iterations	100

2.6.1.1 States

An agent is defined by a dynamic state variable $s_t \in [-50, 50]$, which represents his level of resources at time t. It fluctuates through time as the result of actions taken and random perturbations. As adding these random perturbations to resources levels increases inequality of state in the population by 'diffusion', we add a reversion to the mean set to precisely offset this effect. This gives a stationary AR(1) process, which maintains on average the mean state $\mu = \sum_i \frac{s^i}{N}$ and the variance $\sigma^2 = \sum_i \frac{(s^i-\mu)^2}{N}$ of the population (for a formal proof, see (Bateson & Nettle, 2017)) :

$$s_{t+1} = (1-r) \cdot s_t + r \cdot \epsilon$$
$$\epsilon \sim \mathcal{N}(\mu, \frac{1-r^2}{(1-r)^2} \cdot \sigma^2)$$

The term $r \in [0, 1]$ is the correlation between an agent's current and subsequent level of resources. This process is a shuffling of agents' state, but is not 'redistributive': population inequality is left unchanged. The state space ($[-50, 50]$) is discretized with 1001 steps of size 0.1.

2.6.1.2 Actions description

Agents choose among three strategies:

- 'Exploitation', i.e. trying to take β resources from another agent. An exploiter has an exogenous probability γ of being caught by the police, in which case he loses π resources. The exploiter chooses whom to exploit in a sample of n individuals, drawn randomly from the population. Among them, he picks uniformly among the least violent (see below).

- 'Violence', i.e. fighting when another agent tries to exploit you. The winner of the fight is chosen by a coin toss and gets or keeps the disputed β resources. Choosing this strategy also send a toughness signal to exploiters: when choosing among the n possible targets (see above), exploiters know which agents are violent and pick, if there are any, among submissive agents (defined below).

  Violent agents also have a small probability m of attacking when not exploited (a 'misfire'), which triggers a fight if the attacked agent is also violent.

- 'Submission': never fight.

2.6.1.3 Consequences of actions

Formally, decisions are defined by their probabilistic consequences on state. The expected consequences depend on the proportions of exploiters and of violent agents in the population. We denote these respectively p and v.

- An exploiter has a probability γ of getting caught, which costs π units of resources. If not caught (probability: $1-\gamma$), he gets β resources if there is a submissive individual in the sample, or if he wins the fight against the (necessarily) violent target. The probability is thus: $(1-\gamma)(1-\frac{v^n}{2})$. He loses a fight with probability $(1-\gamma)\frac{v^n}{2}$, which slashes the fitness by a proportion λ.

- Every exploiter draws a sample of n individuals, so a non-exploiter has a n/N chance of being in such a group. In a round (defined by a process in which every exploiter makes a move, successful or not), the number of such interactions is distributed as a binomial distribution $\mathcal{B}(Np, \frac{n}{N})$. p being typically very small, we neglect for simplicity the unlikely possibility ($\sim np^2$) of multiple encounters and model it as a binary event with probability pn, the expected number of encounter with an exploiter.

- If possible, the exploiter targets one of the submissive individuals. If there is none, then he targets a violent individual. So:

  (i) A violent individual will only be picked if every other agent in the sample is also violent (probability: v^{n-1}), and if he is picked among them (probability: $\frac{1}{n}$). So, for a violent individual,

  $$P(exploitation|encounter) = \frac{v^{n-1}}{n}$$

  (ii) When there are submissive agents among the n available targets, the exploiter picks uniformly among them. For a submissive agent, the probability of being exploited is thus $\frac{1}{K+1}$, K being the number of others submissive individuals in the sample, distributed as a binomial with v and $n-1$ as parameters. The law of total probability gives:

  $$P(exploitation|encounter) = \sum_{i=0}^{n-1} \frac{P(K=i)}{i+1}$$

$$= \sum_{i=0}^{n-1} \binom{n-1}{i} (1-v)^i v^{n-1-i} = \sum_{i=0}^{n-1} \frac{(n-1)!(1-v)^k v^{n-1-i}}{(i+1)i!(n-1-i)!}$$

$$= \sum_{k=1}^{n} \frac{(n-1)!}{k!(n-k)!} (1-v)^{v-1} v^{n-k}$$

$$= \frac{1}{n(1-v)} [\sum_{k=0}^{n} \binom{k}{n} v^k (1-v)^{n-k} - v^n]$$

$$= \frac{[(1+(1-v)]^n - v^n}{n(1-v)} = \frac{1-v^n}{n(1-v)}$$

- When not exploited (probability: $(1 - pv^{n-1})$), a violent individual attacks anyway with probability m. If the attacked agent is also violent (which happens with probability v), this escalates into a fight, which he loses with probability $\frac{1}{2}$. If the attacked agent is submissive, nothing happens. All in all, a violent individual has a probability $\frac{mv}{2}(1 - pv^{n-1})$ of losing a fight, which slashes his fitness by a proportion λ.

2.6.1.4 Fitness function and optimisation

Agents have an horizon of T time steps. Their fitness is defined by their terminal level of resources (s_T), reduced by penalties in two cases:

(i) Each round t where $s_t < 0$ (i.e. below the 'desperation threshold') reduces fitness by a proportion ω

(ii) Each lost fight reduces fitness by a proportion λ, to represent possible health sequelae.

The fitness is thus:

$$s_T \cdot (1-\omega)^{\#(i \;/\; s_i < 0)} \cdot (1-\lambda)^{\#(\text{lost fights})}$$

Agents compute the expected payoff of the three strategies by stochastic dynamic programming (SDP) ((Houston et al., 1999; Mangel & Clark, 1988)). We use dynamic rather than static optimisation so that agents take into account not only the probability of falling below the desperation threshold in the next time step, but also at any point in the future. As we increase T, the algorithm converges to an optimal long-term policy. We choose a value of T large enough (100) to obtain that convergence.

The model is not a full game theory model. There are strategic interactions (agents' payoff depend on others' strategies). Agents take into account the distribution of strategies in the population but not the consequences of their decision on others. As we simulate large and well-mixed populations, we can safely consider this effect as negligible. We also assume, for tractability, that agents optimise as if p and v stayed constant in the future - which is true at equilibrium.

2.6.1.5 Population simulations

We simulate populations of N agents. Initial states are drawn from a Gaussian distribution with mean μ and variance σ^2. To decide their strategies, agents need to measure the frequency of violence and exploitation in the population (p and v), which raises a chicken-and-egg problem. To circumvent it, we first initialise strategies by letting agents choose the optimal strategy for $p = v = 0$. We then exogenously fix v (the proportion of violent agents) in the population either to 0 or to 1 by assigning either the submissive or the violent strategy to non-exploiting agents. This allows us to test whether the end results change depending if we start from an initially violent of non-violent population (figure 2.3 & 2.4 in the paper).

We then let, at each time step, 10% of the population update their strategies. This gradual updating allows the equilibrium to be smoothly reached, and avoids large oscillations. When updating their strategies, agents measure p and v in the population and choose the optimal strategy for their state by the aforementioned SDP algorithm. We run the simulations for 100 time steps, so that the population can reach an equilibrium in the distribution of strategies. During the simulations, we let the resource levels of the agents fluctuate following the stochastic AR(1) process described in Section 2.6.1.1, but we neglect the consequences of agents' actions on the overall population affluence and inequality. In other words, we assume that individual behaviours have negligible consequences on the economic context. We make this choice to preserve the Gaussian distribution we started from. Including the effect of agents' actions on their state often prevents reaching an equilibrium. In particular, agents below the desperation threshold choose exploitation and have thus a negative expected payoff, which leads them to 'drown'. Hence an ever-increasing value of p, as more agents fall below the desperation threshold by stochasticity and are then stuck below. The choice to neglect actions' economic consequences in population simulations reduces their realism but not their interest: the model aims to explore how the economic context (the distribution of resource levels), treated exogenously, determines behaviour. Exploring potential feedback between behaviours and economic context, or tracking individual-level life course trajectories, is beyond our present scope.

2.6.2 Supplementary results

2.6.2.1 Fitness function

The SDP algorithm computes implicitly a "value function" comparing the expected fitness of all actions. As the backward induction advances, its shape tend to stabilise in what we can interpret as a long-term fitness function. The typical shape is shown in Fig. 2.5 and allows to visualise the risk-preferences of the agents. The desperation threshold produces a S-shape, with risk-proneness below and risk-aversion above. This explains why agents tend to exploit below the threshold as it is the strategy associated with the highest variance. It also explains why, in Fig. 2.1 of the main manuscript, agents are especially willing to fight when close to the threshold, where the curve is particularly concave, so where the agents are particularly risk averse. Counter-intuitively, our assumptions make the violent strategy the most risk-averse one: it reduces the risk of exploitation, and the risk of fighting has direct consequences on fitness (a measure where agents are by definition risk-neutral, as it is the maximand). This result might alter or reverse if we instead assumed that losing a fight had consequences on resource levels.

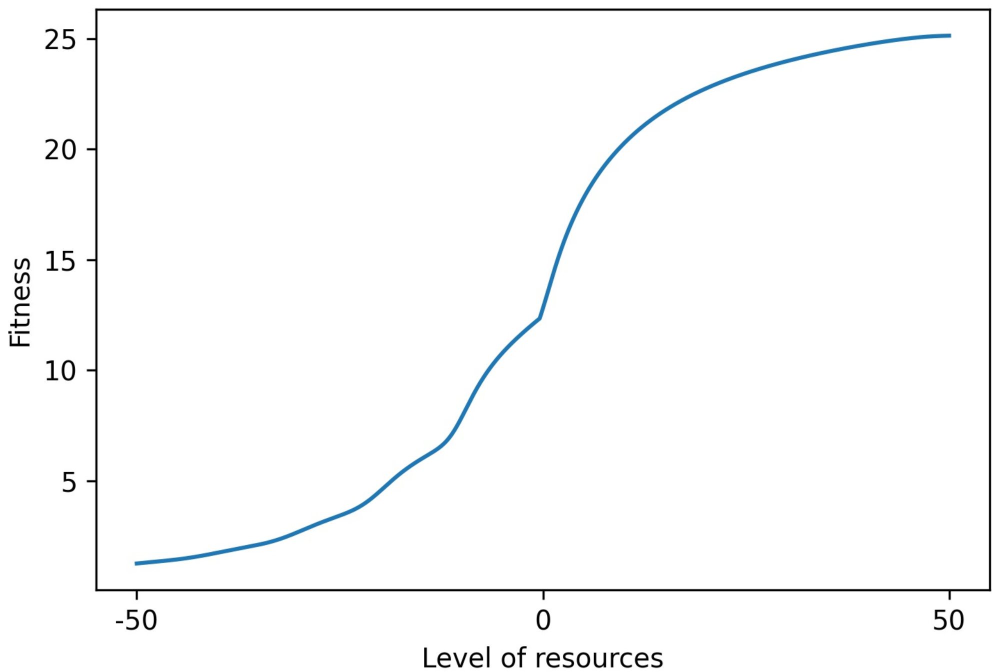

Figure 2.5: Long-term expected fitness depending on the level of resources

2.6.2.2 Sensitivity analysis

In the paper, we use fixed values for most of the parameters defining the rules of the game. In this section, we explore how the model reacts when we vary these parameters and we explore to what extent the pattern we report in the paper are robust to such changes.

2.6.2.3 Varying the costs of exploitation

When exploiting, an agent faces an exogenous risk of punishment, costing π units of resources with probability γ. In a previous model where the same hypothesis was used ((De Courson & Nettle, 2021)), we found that varying the the severity of punishment π was not deterring desperate agents from exploiting, as the fitness function (similar to Fig. 2.5) is very concave below the threshold and quite flat in the lower values). As violence is, in the current model, a response to the risk of exploitation, we would expect π to have no impact on violence. We indeed find no clear effect (Fig. 2.6).

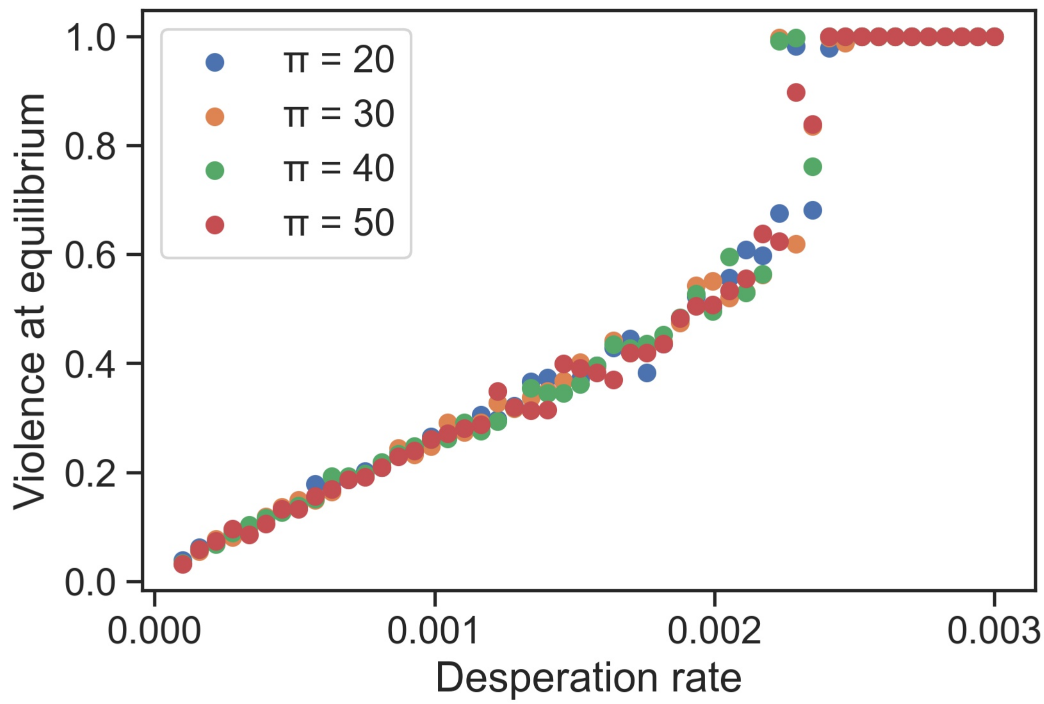

Figure 2.6: Effect of π on the mapping between desperation rate and the proportion of violent agents at equilibrium, starting from a non-violent population.

We can also vary the probability of punishment γ (Fig. 2.7). In (De Courson & Nettle, 2021), we found a small deterrent effect for this same parameter. Here, we reproduce this finding: the higher γ, the less violence, as some desperate agents (the closest to the threshold) choose not to exploit.

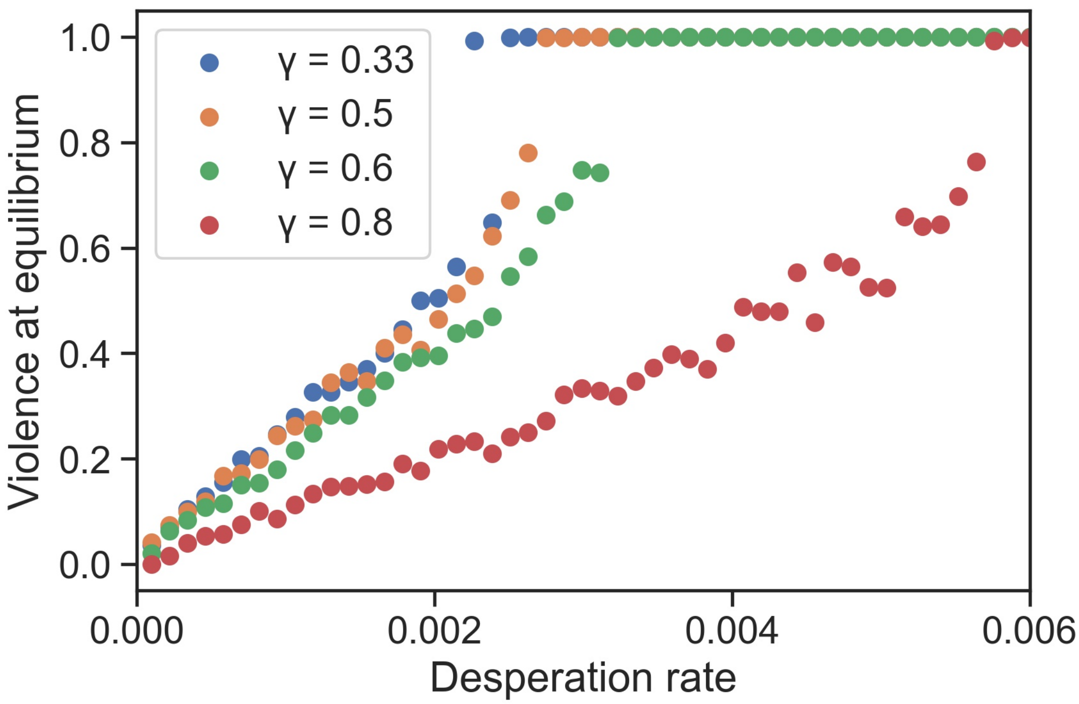

Figure 2.7: Effect of γ on the mapping between desperation rate and the proportion of violent agents at equilibrium, starting from a non-violent population.

2.6.2.4 Varying the costs of violence

When adopting the violent strategy, an agent fights when he is exploited, and also by "mistake" with probability m. When he loses a fight, his fitness is reduced by a proportion λ [1]. The parameters λ and m thus control the costs of violence. Increasing these two parameters strongly reduces violence (Fig. 2.8 & 2.9). Contrary to exploitation (and predictably, as it is not a consequence of desperation), the violent strategy is thus sensitive to its costs.

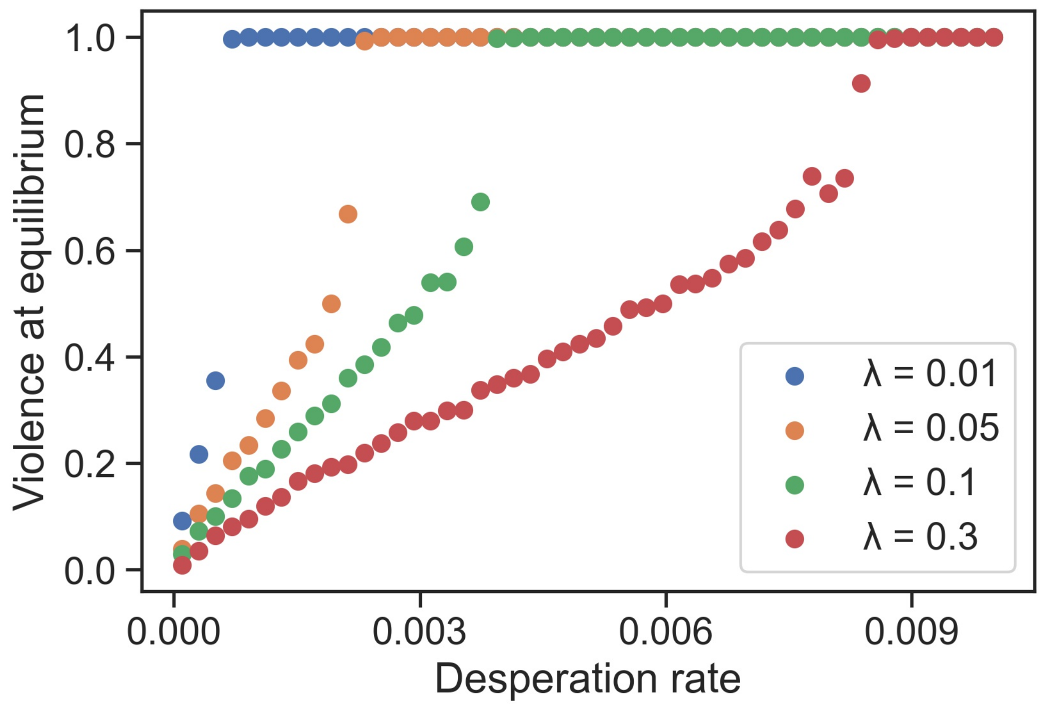

Figure 2.8: Effect of λ on the mapping between desperation rate and the proportion of violent agents at equilibrium, starting from a non-violent population.

2.6.2.5 Hysteresis effect depends on n and r

In the model, exploiters choose their target among n randomly drawn individuals, and choose if possible a submissive one. The parameter n thus controls the "toughness reputation" efficiency: if $n = 1$, a violent agent is as likely to be exploited as a submissive one, whereas if $n \to \infty$, an agent will never be exploited as long as there are submissive individuals in the population.

[1] Increasing ω would have the same effect as decreasing λ. The model's outcome depends on the relative importance of these two parameters, which determines whether it is more important for an agent to be below the threshold or to avoid losing fights. For that reason, we explore the consequences of varying λ but not ω.

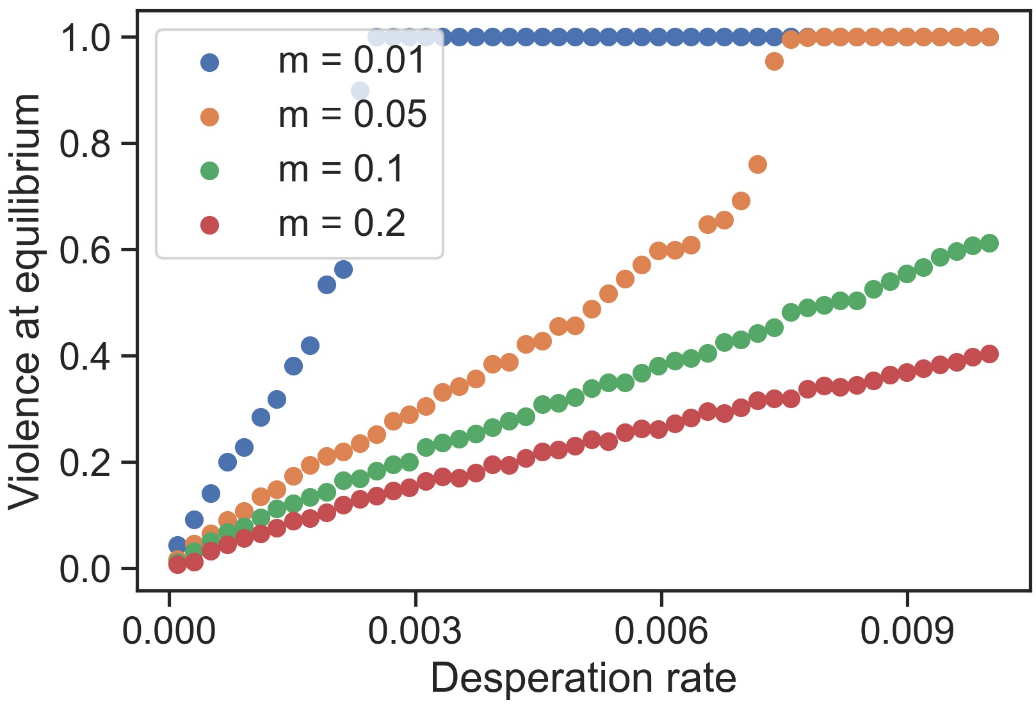

Figure 2.9: Effect of m on the mapping between desperation rate and the proportion of violent agents at equilibrium, starting from a non-violent population.

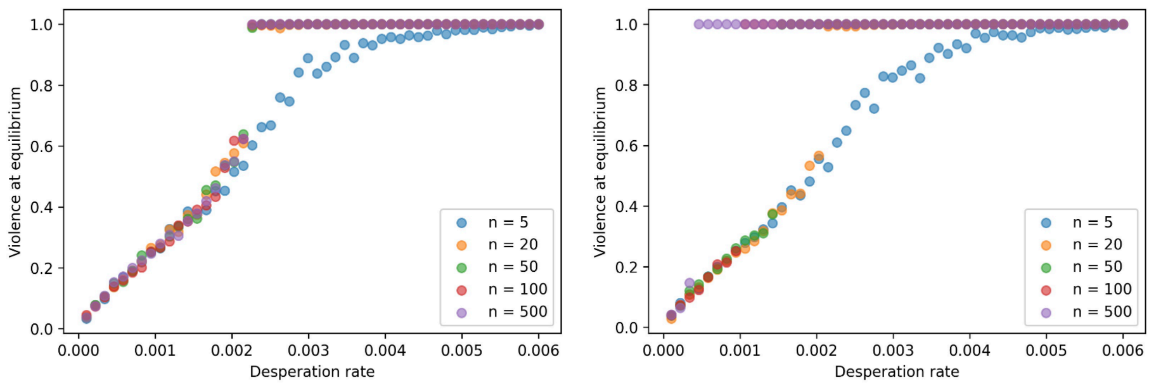

Figure 2.10: Effect of n on the mapping between desperation rate and the proportion of violent agents at equilibrium, starting from a non-violent (left) or violent (right) population.

Modifying the value of n has two effects on the model's dynamics.

First, the model typically produce a S-curve between desperation rate and the proportion of violent individuals, with a concave then a convex phase (Fig. 2.3 in the main manuscript). The value of n does not affect the concave phase, but makes the convex one steeper (Fig. 2.9). The S-shape can be interpreted in terms of frequency dependence of the violent strategy: violence is negatively frequency-dependent at low levels, as in the Hawk-Dove model, and positively frequency-dependent at high levels, because violence deflects exploitation on the rare submissive individuals (see Fig. 2.4b in the main manuscript). n controls this deflection effect: if $v \to 1$, then the risk of being exploited converges to p for a violent agent and to pn for a submissive one (see Sec. 2.6.1.3). It is thus logical to observe that n affects the convex phase. For low v (the concave phase) violent agents are almost sure not to be exploited, so the value of n makes little difference. This phase actually depends on the parameters m and λ, which control how frequently rare violent individuals will fight and how costly it is (see Fig. 2.8 and 2.9). Second, and also because it controls the deflection effect, n determines if we obtain one or two equilibrium, i.e. the hysteresis effect. In Fig. 2.11, we see that the initial level of violence has no impact on the end state for $n = 5$, and that the higher n, the lower the desperation rate needed to obtain two equilibria.

Finally, the results depend on the parameter r, the auto-correlation between an agent's present and future states defined in Sec. 2.6.1.1. The lower r, the more gently violence increases with the desperation rate. This effect comes from the fact that a lower r makes the decision to exploit sensitive to the level of violence: when $v \to 1$, desperate agents often choose not to exploit, and violence plays thus a regulating role. To understand this result, we can interpret r as a measure of how serious "desperation" is. A low r means that regression to the mean plays a strong role, so that being below the threshold is likely to be an episodic moment rather than a persistent situation. The correlation between s_t and s_{t+x} is r^x, which converges exponentially quickly to zero. In other words, a low value of r implies that a desperate agent can expect to be back above the threshold in the near future without taking any risk.

In this case, an agent may have a higher fitness by waiting for the tide than by taking a gamble which has more chances to fail than to succeed. Interestingly, this effect is offset by increasing the stakes of exploitation β and π (not shown). Desperate agents are still very risk prone, but the risks they are offered are too small to offer a better option as one needs several successful gambles in a row to succeed, which is very unlikely.

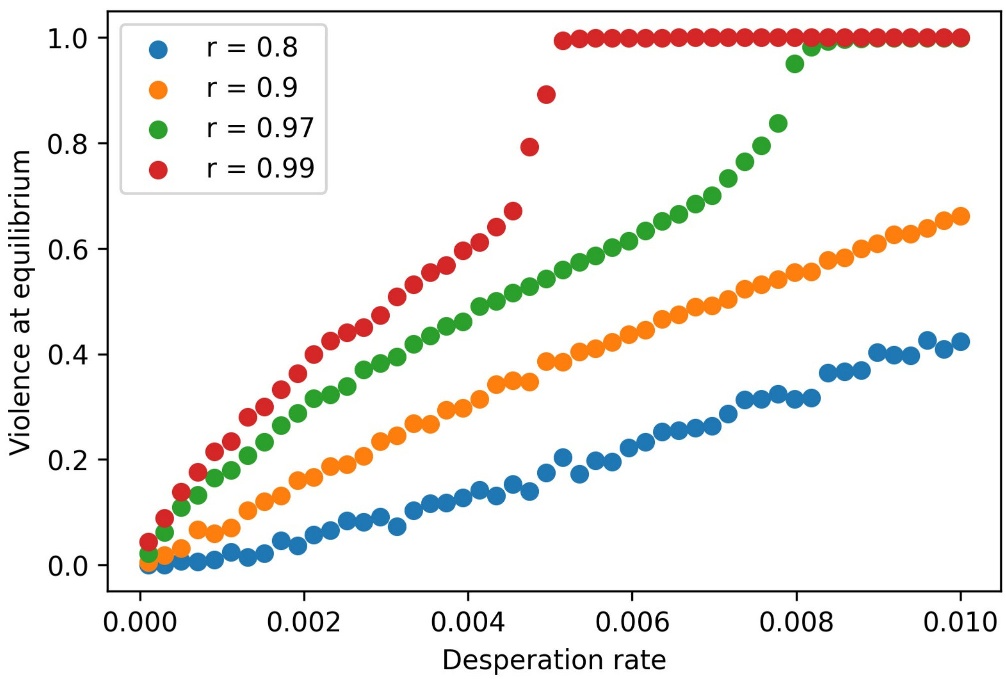

Figure 2.11: Effect of r on the mapping between desperation rate and the proportion of violent agents at equilibrium, starting from a non-violent population.

For that reason, a low value of r can suppress the hysteresis effect: in Fig. 2.10, $n = 100$ and $n = 500$ produce no hysteresis contrarily to Fig. 2.10. High-violence reduces exploitation, which destabilises the high-violence equilibrium. The hysteresis effect still occurs with a higher value of n (Fig. 2.12). Thus, the hysteresis result holds for a high enough value of r and n. In other words, it holds if toughness signals are efficient enough and desperation persistent enough.

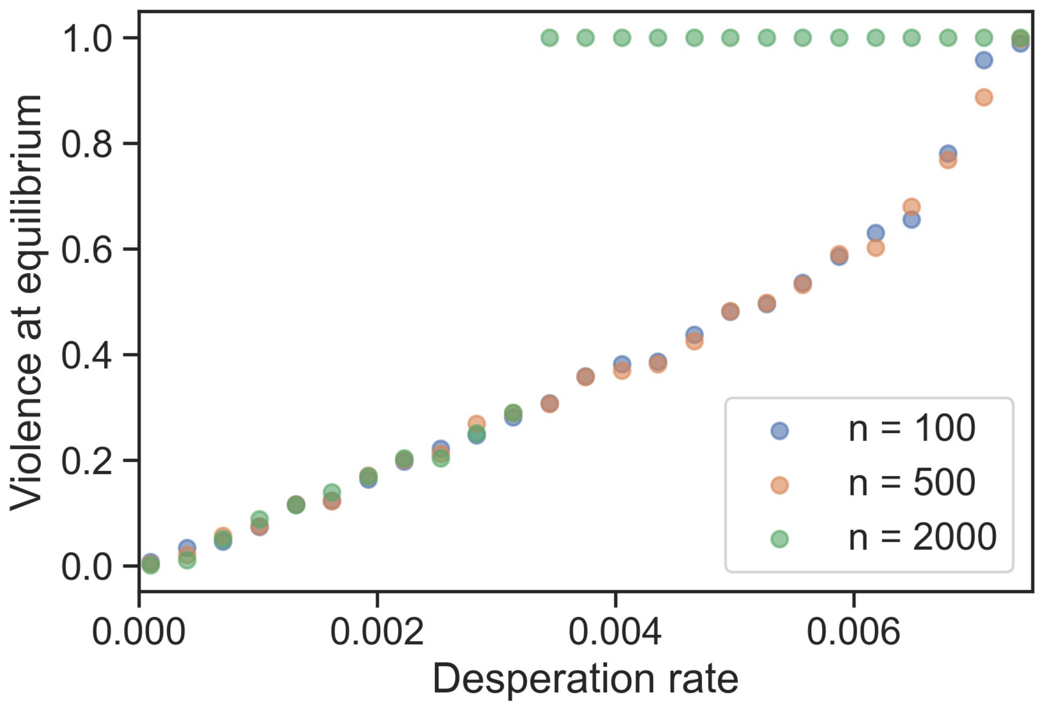

Figure 2.12: Model results with a lower value or r (.9), starting from a violent population.

3 Why does poverty increase time discounting? Present needs and uncertain future

3.1 Abstract

In situations of poverty, people are observed to heavily discount the future. Despite a clear empirical consensus, the theoretical literature lacks satisfying models explaining this social gradient. In particular, the urge of satisfying urgent needs is often invoked verbally as an explanation, but has never been properly modeled. Here, we show that the desperation threshold model can explain high discounting in situations of poverty. We present an analytical model with four different intertemporal scenarios of the desperation threshold, varying the consequences of the threshold on future utility. The model predicts high discounting around the threshold, and high patience at intermediate levels of resources. In contrast with the consequences of the desperation on risk taking, as the effect is predicted to occur on both sides of the threshold. We show that, unlike existing accounts, our explanation does not depend on assuming a future improvement, but predicts a U-shaped effect of future expectations. We discuss the relevance of our findings for social sciences and public policy.

3.2 Introduction

In situations of poverty, people are often observed to heavily discount the future (Carvalho, 2010; Green et al., 1996; Haushofer & Fehr, 2014; Lawrance, 1991; Reimers et al., 2009). A dramatic manifestation of this phenomenon is 'payday loans': each year, about ten million Americans with low incomes resort to short term borrowing, at an annual interest rate of the order of 400% (A. V. Banerjee & Duflo, 2007; Bertrand & Morse, 2011; Dobbie & Skiba, 2013). An association between poverty and time discounting has been observed repeatedly since Malthus (1798). Causality has been proven to be bidirectional (Doepke & Zilibotti, 2008): not only do short-term oriented individuals accumulate less wealth (Epper et al., 2020; Sunde et al., 2022), but low resources also increases time discounting (Carvalho et al., 2016; Handa et al., 2020; Haushofer et al., 2013) – the process we are here interested in. In a recent review, time discounting was found to be the only known causally robust effect of poverty on decision making (Haushofer & Salicath, 2023). This effect is of interest to several disciplines, including economics (Lawrance, 1991), sociology (Duvoux, 2023), psychology (Griskevicius et al., 2013; Haushofer & Fehr, 2014) and criminology (Gelder & Frankenhuis, 2025). It has profound implications: it has been proposed (i) as the common denominator of the 'behavioural constellation of poverty' - the set of behaviours typical of low-income populations (Pepper & Nettle, 2017), (ii) as a possible reason for poverty persistence (Haushofer & Fehr, 2014), and (iii) as a reason for the higher prevalence of crime - a behaviour that often brings short-term benefits and potential long-term legal troubles - in deprived populations (Brezina et al., 2009; Pepper & Nettle, 2017).

In stark contrast with the settled empirical case, it remains unclear why poverty increases time discounting. Two perspectives have been proposed. The first considers high discounting as a symptom that poverty degrades decision making. This can occur through stress (Haushofer & Fehr, 2014), ego-depletion (Spears, 2011) or, most famously, a 'tunneling effect': as Shah (Shah et al., 2012) put it, "While focusing on the groceries from week to week, we might neglect next month's rent" (p. 682). In a similar vein, A. V. Banerjee & Duflo (2007) suggest that not thinking about the future is "emotionally wise [...], to avoid confronting the sheer inadequacy of the standard of living" (p. 165).

A second perspective, which we adopt here, proposes that high discounting is not dysfunctional, but on the contrary an appropriate response to a context of poverty. A common argument concerns "collection risks": in poverty, people may be less likely to actually collect the future reward, for instance because of a higher mortality risk (Griskevicius et al., 2011). However, people with low incomes also exhibit high discount rates over very short periods of times (e.g. weeks in the case of payday loans), where mortality risks are negligible (Riis-Vestergaard & Haushofer, 2017). Furthermore, this class of explanations cannot account for the influence of 'states', like hunger (Allen & Nettle, 2021) or more generally financial need (Carvalho et al., 2016; Fitzpatrick & Coleman-Jensen, 2014; Sharma et al., 2023) on time discounting: collection risks are an environment-level parameter, presumably stable on short-term scales. In any case, collection risks are only one side of the problem: poverty also plausibly increases how much one needs resources right now, and can thereby generate 'waiting costs' (Mell et al., 2021). Many authors (Epper, 2015; Fisher, 1930; Frankenhuis & Nettle, 2020; Haushofer et al., 2013; Mell et al., 2021; Sharma et al., 2023) thus propose a simple verbal justification, well summarised by the character Earn in the TV series *Atlanta*: "poor people don't have time for investments, because poor people are too busy trying not to be poor! I need to eat today, not in September...".

However intuitive Earn's argument may be, we consider it underspecified and potentially misleading. The optimal level of time discounting depends not only on the value of present consumption, but also on the (expected) value of future consumption – which should also increase in situations of poverty, if low resources today tends to be correlated with low resources tomorrow. Simply put, Earn will also need to eat in September; his current level of need is therefore not a sufficient reason to discount the future. The reasoning only holds if survival is at stake (Chavas, 2013) or if Earn has reasons to expect his situation to improve in the meantime – that is, if his poverty is not a persistent condition, but a rough patch. We are aware of only two attempts to formalize this intuition, one in economics (Epper, 2015) and one in evolutionary psychology (Mell et al., 2021). Both rely on the assumption that individuals in poverty expect their situation to improve. If someone expects to be even worse off in the future, these models instead predict patience (Epper, 2015, p. 4). In reality, the "truly disadvantaged" populations (W. J. Wilson, 2012) tend to be stuck in poverty, and are often found by ethnographers to be rather pessimistic (Lewis, 1963; MacLeod, 2018). Among them, pessimism has been found to be associated with low saving (Gladstone & Pomerance, 2025), and in particular, offenders have been described in ethnographies as both extremely short term oriented and particularly pessimistic about the future (Anderson, 2000; Dickinson et al., 2025; W. J. Wilson, 2012). Thus, the literature lacks a model capable of explaining why people tend to discount the future when they struggle to meet basic needs, and their future is not expected to be brighter.

In this paper, we show that Earn's intuition is warranted under an alternative conceptualisation of needs', grounded in the desperation threshold model (DTM) (Courson, Frankenhuis, Gelder, et al., 2025). The DTM posits that individuals experience a critical resource level representing basic needs above which they strongly prefer to be. In contrast with the standard microeconomics model, the DTM does not assume a concave mapping between resources and utility, but a S-shape. The utility function features a very steep region – the desperation threshold – where basic needs hang in the balance. It is flatter both above and below the threshold, as basic needs are respectively securely satisfied and definitively unmet. Here, we extend the DTM from the study of risk taking to the study of intertemporal decisions, introducing four distinct scenarios, varying the consequences of the desperation threshold on utility. We demonstrate that, regardless of implementation, one should discount the future more when close to this threshold. This occurs because the long term is more uncertain than the present: individuals situation may improve or worsen, both resulting in lower subjective resource valuation. For the same reason, three out of the four scenarios predicts even more pronounced discounting when a desperate individual has *directional* expectations about the future: whether she expects to have more or less resources in the future, future rewards become further devalued. Thus, unlike previous approaches (Epper, 2015; Mell et al., 2021), our result is not contingent on assuming that individuals in poverty are optimistic about the future, but it integrates those models highlighting optimism's role with evidence of extreme discounting among fatalistic populations (Anderson, 2000; Dickinson et al., 2025; M. Wilson & Daly, 1985).

3.3 Model

We model an agent living for two periods (Fig. 3.1A), defined by a single state parameter: its level of resources, that changes stochastically over time. The agent begins with x_0 resources. The resource level is subject to random shocks before the first time period, and between the first and the second. These shocks are independent and identically distributed, following a normal distribution with mean zero and variance σ^2, with σ representing environmental volatility. Between periods, a constant drift parameter d is applied to the resource level. This parameter captures future expectations: $\mathbb{E}(x_2|x_1) = x_1 + d$, in other words one expects his state to improve over time if $d > 0$, and to deteriorate if $d < 0$. For simplicity, we do not distinguish between consumption, income and wealth: the variables x_i summarises the material standing of the agent at time i.

The agent's preferences are represented by a utility function that depends on resource states in both periods, x_1 and x_2. Here, we realized that the desperation threshold concept could be translated into an intertemporal utility function in multiple ways. The threshold is verbally defined as a strong disutility below some level of resources (Courson, Frankenhuis, Gelder, et al., 2025). Yet, it has been formalised in several, slightly different ways (Courson, Frankenhuis, & Nettle, 2025; Courson & Nettle, 2021; De Courson et al., 2023). While these implementations yield qualitatively similar predictions regarding risk taking — the primary dependent variable in previous studies — their implications on time discounting may differ substantially. We identified four subtly different scenarios of the DTM idea within our two-period setup. For the sake of exhaustiveness, we present all four scenarios, highlighting the places where the results diverge. We keep these functions as simple as possible, combining a linear dependence on states with thresholds effects. In other words, we neglect diminishing marginal utility at high resource levels, since our analysis focuses on decision making around the threshold.

In Fig. 3.1, we define the four utility functions, along with conceptual figures and their intuitive names. In the first one, falling below the threshold incurs a fixed utility penalty w. This penalty applies additively: being below the threshold in both periods generates twice the disutility of being below once. Importantly, utility continues to decrease linearly below the threshold without a lower bound, meaning that one is still sensitive to its level of resources even if can not meet the goal. The second function sets period utility to zero whenever resources fall below the threshold. Here and in the next functions, an agent becomes indifferent to its state when below the threshold: if one is below, it does not matter how far below one is. To create a discontinuous utility jump at the threshold, we introduce a constant also denoted w in this and subsequent functions. This function can represent 'hibernation': being below the threshold makes it impossible to accumulate utility in the present, but preserves the possibility to do so in the future. The third function represents a 'game-over' below the threshold: it cancels not only the utility of this time period, but also of possible future time periods. This captures irreversible consequences, such as eviction: even if resources become sufficient tomorrow, today's eviction cannot be undone. Our fourth function sets lifetime utility to zero if resources fall below the threshold in any period. Even if one has been above the threshold in the past, it has all been 'in vain'. This can for instance capture starvation during development: life terminates, and the previously accumulated physical capital is inconsequential.

These utility functions give rise to a time orientation, i.e. a preference for sooner, or later, resources. We capture the agent's level of time discounting through its marginal rate of intertemporal substitution (MRIS) – the amount one must receive to willingly surrender one resource unit today. Formally,

$$MRIS(x_0) = \frac{\frac{d\mathbb{E}(U)}{dx_1}}{\frac{d\mathbb{E}(U)}{dx_2}}$$

In other words, the agent decides whether to discount the future based on her initial level of resources, by comparing to what extent an extra resource in the first time period makes her happier than an extra resource in the second one. Note that economists often distinguish between genuine time discounting – an exogenous disregard for future consequences just because they happen in the future – from rational motives to prefer immediate rewards (Carvalho et al., 2016; Haushofer & Salicath, 2023). Here, we do not make such a distinction, as we aim to find rational explanations for observed behaviour. Note also that when computing the marginal utility in the first period, we assume that the extra resource is not present in the second period. This is simply a way to present the results in a more insightful way. Otherwise, $MRIS > 1$ by construction: one always prefers to have the resource in the short term, even if it is mainly useful in the long term. Note also that x_1 and x_2 are random variables. $MRIS$ thus depends on *expected* marginal utilities knowing only x_0. By differentiating with respect to x_1, we mean with respect to its expectation, while keeping $\mathbb{E}(x_2)$ constant. This specification is necessary to obtain a meaningful discount factor: as we study discontinuous – and therefore non-differentiable – utility functions, the random perturbations smoothes utility, ensuring marginal utility is well-defined.

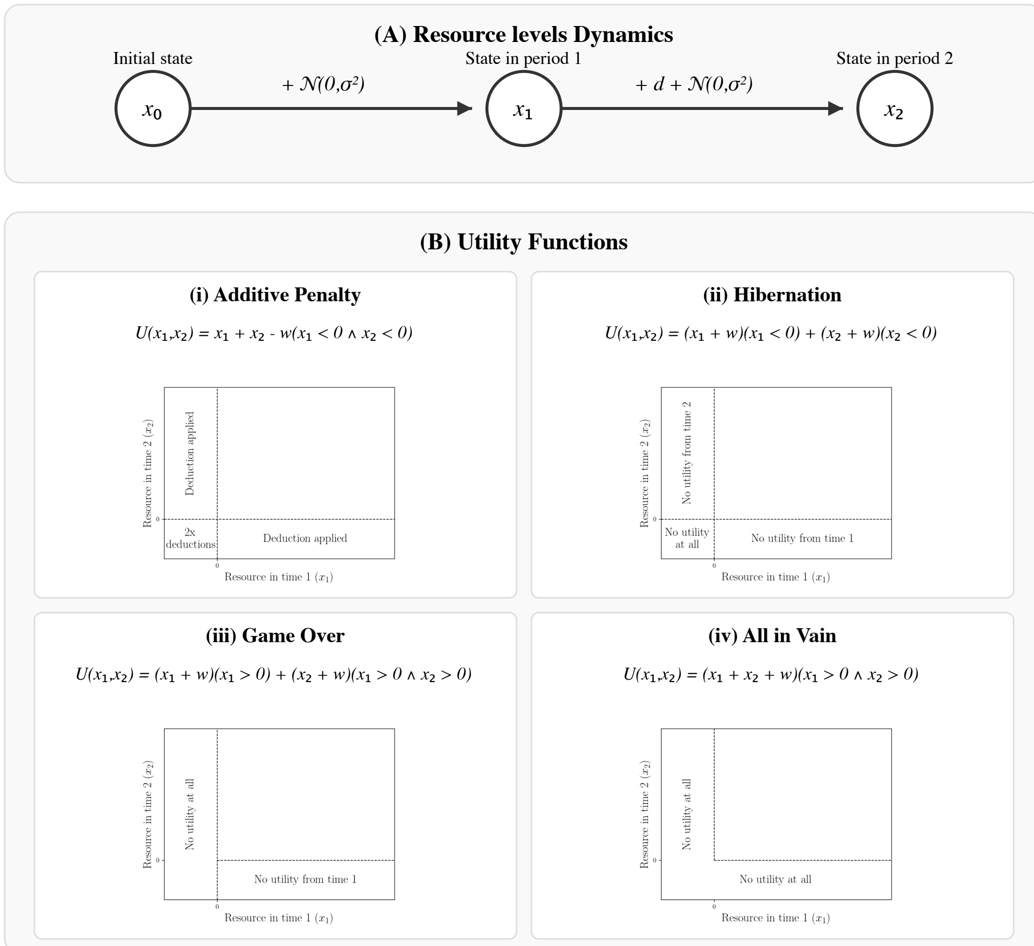

Figure 3.1: Summary of the model assumptions. Utility functions are visualized in heatmaps, where lighter tones indicate higher utility. Zero marks the desperation threshold, hatches mark areas where utility is zero.

3.4 Results

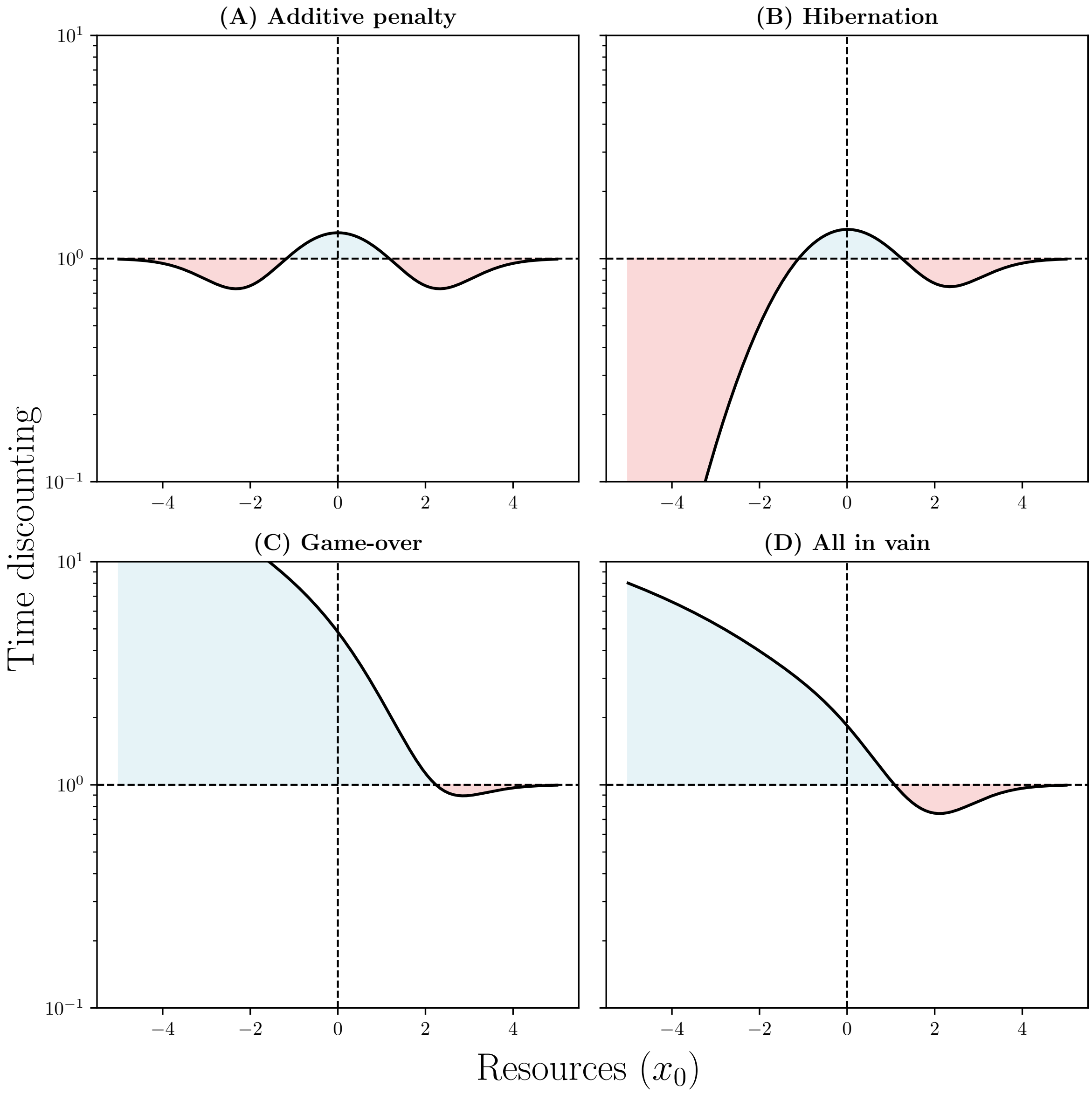

Figure 3.2: Time discounting depending on the initial level of resources x_0. Here, we assume neutral future expectations ($d = 0$), and $\sigma = 1$. The vertical dashed line marks the desperation threshold, the horizontal one marks time neutrality. The y-axis is truncated at .1 and 10 for legibility.

3.4.1 Analytical derivation

We analyse our model by describing how time discounting, as measured by the MRIS varies depending on the agent's state x_0, future expectations d and environment volatility σ. Here, we give an intuitive account of the results, and develop some mathematical details of only the simpler cases – the 'additive penalty' and the 'hibernation' scenario, that are time-separable. In the appendix, we present detailed analytical derivations for all four scenarios, asymptotic approximations and numerical sensitivity analysis.

To derive marginal utilities formulas, we note that an extra resource has two effects on the agent's utility. First, a 'level effect': it makes her richer on average. Second, the extra resource has a 'threshold effect': it may push one above the threshold, which brings a utility of w with a weight $\phi(x_0)$ – the normal probability density function. This component follows the bell-shaped Gaussian curve, with a peak at $x_0 = 0$. This captures the DTM intuition: one never needs resources more than on the threshold of desperation. The marginal utility decomposes naturally using the Leibniz rule: the 'level effect' comes from differentiating under the integral, while the 'threshold effect' arises from the change in probability mass at the threshold – a boundary term. In the second time period, the agent faces a similar dilemma, hence the same functional form, only with a doubled variance due to the longer time horizon, and a drift d. In the additive penalty case, the MRIS simplifies to:

$$MRIS = \frac{1 + w\phi_{\sigma^2}(x_0)}{\underbrace{1}_{\text{level effect}} + \underbrace{w\phi_{2\sigma^2}(x_0 + d)}_{\text{threshold effect}}}$$

3.4.2 The effect of resources

In Fig. 3.2, we plot discounting levels depending on x_0, assuming neutral future expectations ($d = 0$). Above the threshold, all four utility scenarios yield qualitatively similar patterns. Far above the threshold, the agent exhibits time neutrality ($MRIS \sim 1$). This occurs because the threshold becomes irrelevant ($\Phi(-x_0) = o(1)$), and by assumption, resources in both periods yield equal utility. Slightly above the threshold, the agent should be patient ($MRIS < 1$), out of precaution: immediate needs are almost certainly met, but future needs remain at stake.

The agent becomes impatient ($MRIS > 1$) when x_0 is very close to the threshold. In this region, meeting the threshold hangs in the balance both periods, but greater uncertainty about the future makes immediate gains more important. More precisely, one can thus be quite sure to need the resources in the short term, but in the long term, her situation is likely to have changed more. Whether her future condition improves or worsens, the probability of being near the threshold declines (Fig. 3.3), reducing the marginal value of future resources.

Fig. 3.3 illustrates these two results by comparing the probability that a marginal resource shifts the agent above the threshold in each period. Analytically, for $x_0 > 0$, $\phi_{2\sigma^2}(x_0) > \phi_{\sigma^2}(x_0) \iff x_0 < \sigma\sqrt{2\ln 2}$. This defines the region in which the agent prefers present resources in the 'additive penalty' case: $MRIS > 1 \Leftrightarrow x_0 < \sigma\sqrt{2\ln 2}$ (Fig. 3.3). In the 'hibernation' scenario, it is a sufficient condition for $MRIS > 1$ (see SI). This implies that size of this 'impatience' region is roughly proportional to the volatility σ: higher uncertainty requires a higher buffer to feel secure in the present. However, volatility does not affect overall time preference directionally. Instead, it acts like a scaling parameter, expanding both precautionary and impatient zones (Fig. 3.5). The pattern is also robust to changes in the parameter w (Fig. 3.6).

These results are related to the more general concept of 'prudence', defined in utility theory as the convexity of marginal utility – formally, the third derivative of the utility function, usually assumed to be positive. Under this assumption, uncertainty increases expected marginal utility: by Jensen's inequality, if U' is convex $\mathbb{E}(U'(x)) \geq U'(\mathbb{E}(x))$. This leads to 'precautionary savings': when future resources are on average equal to present ones but uncertain, one should save, as the risk of being worse off tomorrow outweighs the benefits of being better off. However, in our model, marginal utility is bell-shaped in all four scenarios, and thus convex for high values – hence patience at those level of resources – but concave around the desperation threshold, at the cusp of the bell. This point of view allows to recover the above result in the time-separable scenarios: in the 'additive penalty' scenario, $U'''(x) > 0 \iff |x| < \sigma$. Like in our model, this results in time discounting in a region centered around the threshold, and of width proportional to σ, but $\sqrt{2\ln 2}$ smaller – as this compares marginal utility in time 1 and $1+\epsilon$ rather than time 1 and time 2 as in the above model. A concave marginal utility reverts the Jensen inequality: $\mathbb{E}(U'(x)) \leq U'(\mathbb{E}(x))$, meaning that uncertainty makes resources less useful in the future, in expectation. This reasoning is analogous to the one-dimensional heat equation: in our framework, time has a 'diffusive' effect, it brings randomness, and therefore spreads marginal utility (Fig. 3.3). Like in the heat equation ($\frac{df}{dt} \propto \frac{d^2f}{d^2x}$), a resource is expected to be less useful in the future if and only if expected marginal utility is concave at that point.

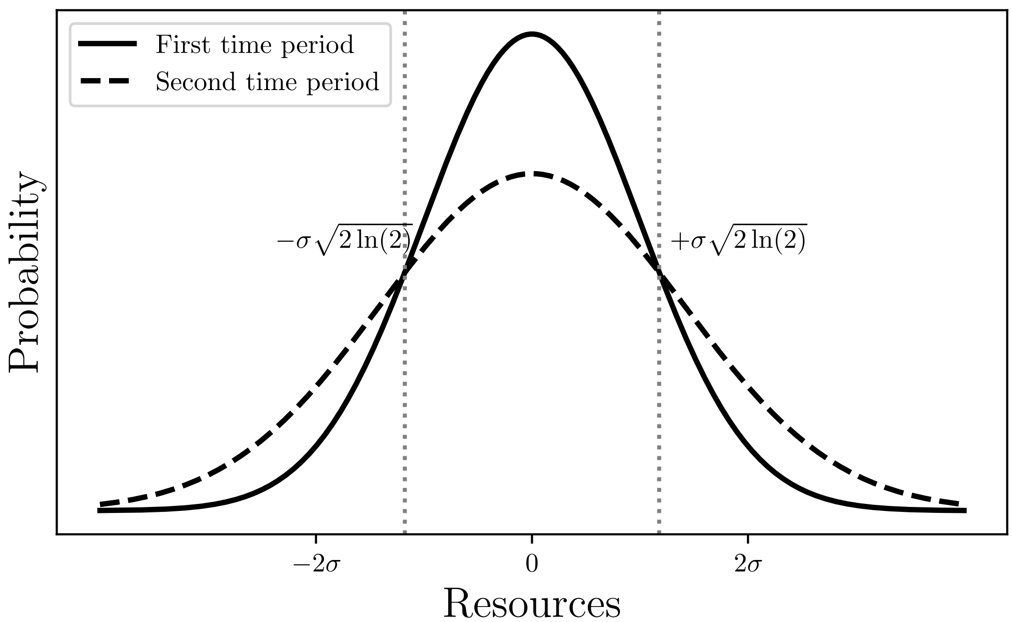

Figure 3.3: Normal probability density functions ϕ_{σ^2} and $\phi_{2\sigma^2}$. They represent the probability density function of x_1 and x_2, assuming $x_0 = 0$ and $d = 0$. Equivalently, due to the Gaussian density symmetry, they describe the likelihood that future resource levels x_1 and x_2 are exactly zero, given $x_0 = x$. This yields the 'threshold effect' (see Results) on marginal utility: the probability that an extra resource pushes one above the threshold. In the central region ($|x| < \sqrt{2ln(2)}$), an extra resource is more valuable to cross the threshold in the first period than in the second, and vice versa outside this region.

Far below the threshold, the four utility scenarios diverge in their predictions. The 'additive penalty' scenario predicts a symmetric pattern, in line with the symmetry of its utility function. When the threshold is out of reach, either because one is definitely above it, or definitely below it, utility becomes linear in this scenario (Fig. 3.1A), and the agent acts as if the threshold did not exist. In the 'hibernation' case, the agent becomes infinitely patient: she receives no utility today, but keeps some hope for recovery tomorrow. Formally, since uncertainty increases over time, the agent has a higher chance of surpassing the threshold in the second period than in the first: as $x_0 \to -\infty$, $\phi_{\sigma^2}(x_0) = o(\phi_{2\sigma^2}(x_0))$ (Fig. 3.3). The best strategy is to accept to be below the threshold in the short term and bet on the second period – hence the label 'hibernation'. Such a strategy is not viable in the 'game-over' and 'all in vain' scenarios – the game is over if $x_1 < 0$. This leads to extreme time discounting below the threshold: one needs to eat today in order for there to be a tomorrow.

3.4.3 The effect of future expectatoins

In all scenarios except 'all in vain', the effect of future expectations d on time preference is U-shaped (Fig. 3.4). The increasing discounting for large positive d is a known result: when tomorrow looks bright, one should prioritize present needs (Epper, 2015; Mell et al., 2021). By contrast, the increasing discounting for negative d is novel. It arises from the desperation threshold: if the threshold can still be reached today, but you strongly expect to fall below tomorrow, the best strategy is to enjoy the present. The effect is more pronounced in the 'hibernation' and the 'game-over' scenario: in these two cases, if below the threshold in the second period, it does not matter how much below. In this case, the agent tries to enjoy today, as tomorrow will be equally awful whatever she does. Of course, this strategy is impossible in the 'all in vain' scenario: if below the threshold in the second period, then the first period is also ruined, hence the monotonic effect of d in this setting (Fig. 3.4).

The U-shape of Fig. 3.4 is valid for any x_0 (see heatmaps in the SI), but the point of maximum patience shifts to $d \approx -x_0$, that is, when $\mathbb{E}(x_2) = 0$. In other words, patience peaks when the agent expects her basic needs to be in the balance in the long term, but not the short term. This result can be approached analytically in the 'additive penalty' and the 'hibernation' scenarios: for small $|x_0|$ and high w – that is, if the threshold is the main contribution on utility – we have the following approximation: $log(MRIS) \propto \frac{ln(2)}{2} + (d + x_0)^2 - 2x_0^2$, which is minimized when $d = -x_0$. This approximation also explains the parabolic shape of log(MRIS) around 0: downward-opening with respect to x_0 (Fig. 3.2) and upward-opening with respect to d (Fig. 3.4).

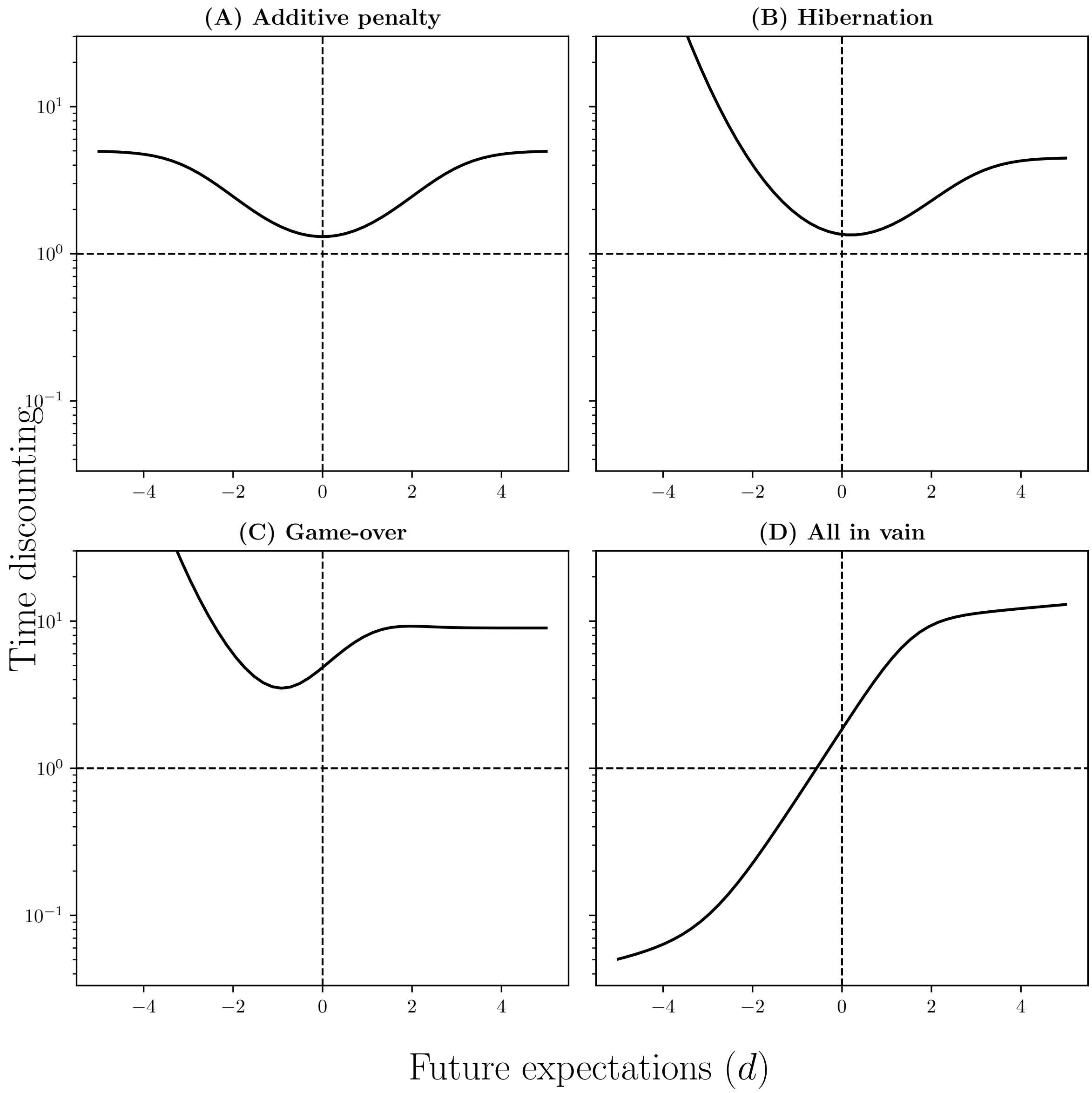

Figure 3.4: Time discounting depending on future expectations d, for $x_0 = 0$ and $\sigma = 1$. The vertical dashed line marks neutral future expectations, the horizontal one marks time neutrality. The y-axis is truncated at 1/30 and 30, for legibility.

3.5 Discussion

Time discounting in poverty is often justified on intuitive grounds (Epper, 2015; Fisher, 1930; Frankenhuis & Nettle, 2020; Haushofer et al., 2013; Mell et al., 2021; Sharma et al., 2023) by what we have called Earn's argument: in poverty, one 'needs to eat today', and thus prioritizes immediate needs. This paper began with a challenge to that idea: if one expects to also be in poverty tomorrow, then urgent needs today do not, by themselves, justify discounting the future. 'Need' is a folk psychological concept, and a clearer specification is needed. Based on the desperation threshold model, we propose that need corresponds to a steep region in the utility function – steeper than both above (where needs are met) and below (where they are not). We introduced four stylized scenarios of need, each producing distinct predictions. These divergences shows that Earn's argument is not trivial, and a formal model was needed. However, all four scenarios converge on one finding: near the desperation threshold, one should discount the future (Fig. 3.2). Counter-intuitively, this occurs not because the individual expects to need less resources in the future, but because she expects to be less likely to need them (Fig. 3.3). She definitely finds herself in need now, but is uncertain about whether she will find herself in need later; later, she may have either escaped poverty or fallen so far below that the additional resources then will be futile.

Two additional factors can amplify this effect. First, when agents hold directional expectations about their future – whether optimistic or pessimistic ($d \neq 0$), they expect to move further from the threshold in one direction or the other, and therefore discount the future more (Fig. 3.4). Second, when failing to meet the threshold carries irreversible consequences, as in the 'game over' and 'all in vain' scenarios, the agent focuses on short-term needs in order for there to be a tomorrow at all. This last result echoes previous models (Chavas, 2013), as well collection risk explanations, albeit in a state-dependent fashion. The two other effects (the effect of uncertainty and of $d \neq 0$) are however new, and direct consequences of the desperation threshold assumption.

When only the 'uncertainty' effect is present (Fig. 3.2A&B), our model predicts only a modest effect on time discounting: at best, $MRIS = \sqrt{2}$. This implies that one would trade 1€ in the first period for 1.41€ in the second. This result should not be interpreted literally: for technical and simplicity reasons (see Methods), our model compares two future time points rather than present versus future, with the second period being $\sqrt{2}$ times more uncertain than the first. In fact, maximum discounting is determined by the ratio of standard deviation of the resource levels at the two time periods. At the limit, if x_1 was known almost perfectly and we kept a discontinuous utility function, our model yields infinite discounting at the threshold in all four scenarios. This result also has an intriguing consequence if we vary the delay between time periods: in standard random walks or Brownian motion, variance increases linearly with time, which so the valuation of the reward is proportional to the square root of the delay. This is reminiscent of hyperbolic discounting, but with an even more extreme 'present bias': compared to exponential discounting, valuation drops heavily for short delays, and then very slowly. Thus, our model provides a possible rational explanation for non-exponential discounting and 'present-bias' which is commonly observed empirically, but often interpreted as 'time inconsistency' (Frederick et al., 2002).

Importantly, this effect occurs on both sides of the desperation threshold (Fig. 3.2). This contrasts with the implications of the desperation threshold on risk taking (Courson & Nettle, 2021; De Courson et al., 2023), that predict a shift from extreme risk taking to extreme risk avoidance at the threshold. In other words, the DTM predicts that while poverty has a polarizing effect on risk taking, it uniformly increases time discounting. This aligns with empirical findings: studies find that poverty can increase or decrease risk taking, but the effect on time discounting is consistently positive (Haushofer & Salicath, 2023).

What real-world behaviors might our model explain? We argue that it provides a new possible rational account of decisions that alleviate need in the short-term, even if they lead to possibly greater need later. It applies particularly well to behaviors like acquisitive crime in contexts of pressing need (Jacobs & Wright, 1999; Rossmo & Summers, 2022; Topalli et al., 2015), or to payday loans uptake (Bertrand & Morse, 2011; Dobbie &

Skiba, 2013). It does not, as presented here, account for, for example, high consumption of 'temptation goods' in deprived populations (A. Banerjee & Mullainathan, 2010). To extend the model to cover those goods, we would have to posit needs that those goods serve, such as reputational or signalling needs. Alternatively, the consumption of such goods may be a maladaptive byproduct of increased discounting whose proper domain is need goods.

A second common prediction across our four scenarios is that when above the threshold but still vulnerable in the long run, one should be particularly patient, out of caution (Fig. 3.2). This intuition echoes the concept of 'prudence' and 'precautionary savings' in microeconomics. However, standard utility theory predicts precautionary saving across the social ladder, and in particular among individuals with low resources. In contrast, our model predicts that patience should peak among the 'middle class', that Ravaillon (Ravallion & Ravallion, 2016) defines as those "who are not considered 'poor' in a specific society but face a non-negligible chance of falling into poverty" (p.270). We are not aware of cross-sectional data supporting this prediction that the middle class is more patient than the upper class: on the contrary, Epper et al. (2020) finds that the negative association between resources and time discounting "exists through the wealth distribution" (p. 1177). However, our prediction echoes multiple theories in social sciences and economic history, which claim that patience and saving belong to so-called 'middle class values' (Doepke & Zilibotti, 2008; McCloskey, 2007; Veblen, 1899; Weber, 1905). This view is famously expressed by Weber (Weber, 1905), who argued that the 'protestant ethic' — emphasizing thrift and self-discipline — emerged among the upper-middle class, not the aristocracy. Doepke & Zilibotti (2008), studying 18th-century Britain, draws a more direct link to discounting behavior: "the middle class developed a system of preferences and values centered around parsimony, the work ethic, and delay of gratification," whereas "members of the upper class displayed a low propensity to save and accumulated debt, which suggests low patience" (p. 749–750). Our model also resonates with Sharma's recent findings (Sharma et al., 2023), which find a "polarizing effect of scarcity" (p. 1040) in both surveys and experiments. Specifically: "Perceptions of scarcity that threatened needs with shorter time horizons predicted a significantly increased preference for smaller, sooner outcomes [...], while perceptions of scarcity that threatened needs with longer time horizons predicted a significantly increased preference for larger, later outcomes" (p. 1040). We hope our model encourages further empirical work to rigorously test this prediction in contemporary populations.

However, the four scenarios diverge sharply in their predictions far below the threshold (Fig. 3.2). If falling below the threshold has irreversible consequences (as in the 'game over' and 'all in vain' scenarios), the model predicts extreme impatience. In the 'hibernation' case, the agent becomes maximally patient. In the 'additive penalty' scenario, she remains time-neutral. We do not argue that one of the scenario best captures empirical reality. Rather, each scenario may correspond to different real-world situations, depending on which basic need is threatened. For example, threats to survival such as starvation may be best modeled as an irreversible threshold, whereas more symbolic or social needs — such as Adam Smith's 'linen shirt' — may align with the logic of the 'hibernation' scenario, and rental eviction may fall somewhere in between. In any case, the specific predictions below the threshold have limited implications for real-world population patterns. Such states are likely rare and transient, as it one would seek external help or engage in risk-taking in this situation (Courson, Frankenhuis, Gelder, et al., 2025). If these cases are indeed rare, all four scenarios converge on predicting a L-shaped association between resources and time discounting — high discounting in poverty, patience in the middle class, and time neutrality among the wealthy.

Our model also sheds light on how expectations about the future shape time preferences. In prior models of time discounting in poverty (Epper, 2015), and more generally in standard economic theory (Friedman, 1957), the effect of expectations is monotonic: the brighter one expects his future material situation to be, the more one prefers immediate resources. Yet in reality, extremely impatient behaviors such as acquisitive crime are often concentrated among populations with persistently pessimistic expectations (Anderson, 2000). In multiple large scale surveys, Gladstone & Pomerance (2025) actually finds an interaction effect: individuals with both low income and pessimistic beliefs save less than others (Fig. 3.4). Our model predicts a U-shaped effect of expectations. It can thus reconcile prior models — we also find that optimism can generate time discounting — with these empirical findings.

These findings have implications for public policy. Impatient behavior in poverty is frequently viewed as irrational and harmful both to individuals themselves and to society as a whole. Tt is often addressed as a unfortunate cognitive bias or failing, through interventions that aim to alter perceptions of the future (Rung & Madden, 2018). Our model suggests, instead, that high discounting is an appropriate response to material need, and therefore that directly addressing material need is the proper way of addressing discounting, while interventions on future orientation may be either ineffective or ethically questionable. Ensuring that everyone's basic needs are met would reduce impulsive behaviors and may yield positive externalities for society. It also makes a counterintuitive prediction: among middle-class individuals, anxiety about meeting future basic needs can lead to excessive saving — and, as a result, under-consumption or under-investment. An ambitious welfare state could therefore enable people with both adequate and inadequate incomes to better align consumption with their actual preferences, rather than having to adapt their behavior to the looming threat of falling below a desperation threshold.

3.6 Appendix

3.6.1 Mathematical derivations

Table 3.1: Parameters used in the model

Symbol	Interpretation	Type
x_0	Initial resource level	Parameter
x_1	Resource level in t_1	Random variable
x_2	Resource level in t_2	Random variable
σ	Resource noise between time periods	Parameter
d	Future resource expectations	Parameter
w	Utility jump at the threshold	Parameter
$U(.,.)$	Utility function	Function
$\mathbb{E}(U)$	Expected utility	Function
$\frac{d\mathbb{E}(U)}{d.}$	Marginal utility	Function
$MRIS$	Marginal rate of intertemporal substition	Outcome

3.6.1.1 Dynamics

The agent starts with a resource level x_0, and lives through two time periods. Between each time period, he is affected by a random perturbation, normally distributed with mean 0 and variance σ^2, with σ capturing the future uncertainty. In x_2, we also add a 'drift' parameter d, representing the agent expectation – if $d > 0$, she expects her situation to improve, while if $d < 0$, she expects it to degrade. We also add the possibility to add a small resource Δx_i in either of the time steps, to study the marginal effect of having more resources at some point in time. Note that these terms are only present in one time period: the term Δx_1 is absent in the second time period – we justify this choice in the Methods section of the main manuscript.

In other words,

$$x_1 = x_0 + \Delta x_1 + \epsilon_1$$

And,

$$x_2 = x_1 + \Delta x_2 + d + \epsilon_2 = x_0 + \Delta x_2 + d + \epsilon_1 + \epsilon_2,$$

with $\forall i \in \{1, 2\}, \epsilon_i \sim \mathcal{N}(0, \sigma^2)$

3.6.1.2 Additive penalty

In this scenario, the utility is the final state, minus a penalty for each period spent below the threshold 0.

$$U(x_1, x_2) = x_1 + x_2 - w * (x_1 < 0 + x_2 < 0)$$

Clearly, $x_1 \sim \mathcal{N}(x_0, \sigma^2)$ $x_2 \sim \mathcal{N}(x_0, 2\sigma^2)$

We have (denoting ϕ_σ the normal probability density of mean 0 and variance σ^2:

$$\begin{aligned}
\mathbb{E}(U) &= 2x_0 - w(p(x_1 < 0) + p(x_2 < 0)) \\
&= 2x_0 - w(p(\epsilon_1 < -x_0) + p(\epsilon_1 + \epsilon_2 < -x_0 - d)) \\
&= 2x_0 - w\left(\int_{-\infty}^{-x_0} \phi_\sigma(x)dx + \int_{-\infty}^{-x_0-d} \phi_{\sqrt{2}\sigma}(x)dx\right) \\
&= 2x_0 - w\left(\int_{-\infty}^{-x_0} \frac{1}{\sigma}\phi(\frac{x}{\sigma})dx + \int_{-\infty}^{-x_0-d} \frac{1}{\sqrt{2}\sigma}\phi\left(\frac{x}{\sqrt{2}\sigma}\right)dx\right)
\end{aligned}$$

To compute time discounting through the marginal rate of intertemporal substitution, we modify this formula by adding the option to add a small resource Δx_i in one of time steps. The formula becomes:

$$\mathbb{E}(U) = 2x_0 + \Delta x_1 + \Delta x_2 - w\left(\int_{-\infty}^{-x_0-\Delta x_1} \frac{1}{\sigma}\phi(\frac{x}{\sigma})dx + \int_{-\infty}^{-x_0-d-\Delta x_2} \frac{1}{\sqrt{2}\sigma}\phi\left(\frac{x}{\sqrt{2}\sigma}\right)dx\right)$$

Now, we compute the MRIS, which is defined as:

$$MRIS = \frac{\frac{dE(U)}{dx_1}}{\frac{dE(U)}{dx_2}}$$

By dx_i, we mean that we look at the marginal effect of the resource Δx_1 on utility.
In our case, differentiating under the integral and using the symmetry of the normal density, we get:

$$MRIS(x_0) = \frac{1 + \frac{w}{\sigma}\phi(\frac{x_0}{\sigma})}{1 + \frac{w}{\sqrt{2}\sigma}\phi(\frac{x_0+d}{\sqrt{2}\sigma})}$$

We can make a few observations: if $d = 0$, the MRIS is an even function ($\forall x_0 \in \mathbb{R}, MRIS(-x_0) = MRIS(x_0)$), symmetrical around the desperation threshold 0. It reaches a maximum at 0, that is, at the desperation threshold ($MRIS'(0) = 0, MRIS''(0) < 0$). This maximum is:

$$MRIS(0) = \frac{1 + \frac{w}{\sqrt{2\pi}\sigma}}{1 + \frac{w}{2\sqrt{\pi}\sigma}}$$

This maximum discounting value clearly increases with w (more generally one can prove that for all x_0 values $MRIS(x_0)$ increases with w). For very high values of w (a situation where utility approximates a step function around the threshold), we have:

$$MRIS(0) \to \sqrt{2}$$

For $d = 0$, we can derive analytically the condition for the agent to discount the future:

$$\begin{aligned}
MRIS > 1 &\iff \frac{dE(U)}{dx_1} > \frac{dE(U)}{dx_2} \\
&\iff 1 + \frac{w}{\sigma}\phi(\frac{x_0}{\sigma}) > 1 + \frac{w}{\sqrt{2}\sigma}\phi(\frac{x_0}{\sqrt{2}\sigma}) \\
&\iff e^{-x^2/2\sigma^2} > \frac{1}{\sqrt{2}}e^{-x^2/4\sigma^2} \\
&\iff e^{-x^2/4\sigma^2} > \frac{1}{\sqrt{2}} \\
&\iff \frac{-x^2}{4\sigma^2} > ln(\frac{1}{\sqrt{2}}) = \frac{-ln(2)}{2} \\
&\iff |x| < \sigma\sqrt{2ln(2)}
\end{aligned}$$

For extreme values of x_0, $\phi = o(1)$ whatever the variance, so $MRIS \to 1$ for $x \to \pm\infty$.

3.6.1.3 Hibernation

Now, utility is:

$$U(x_1, x_2) = (x_1 + w)(x_1 > 0) + (x_2 + w)(x_2 > 0)$$

Therefore,

$$\mathbb{E}(U) = \int_{-x_0-\Delta x_1}^{+\infty} (x_0+\Delta x_1+x+w)\phi(x)dx + \int_{-\infty}^{+\infty}\int_{-x_0-d-y-\Delta x_2}^{+\infty} (x_0+\Delta x_2+x+y+d+w)\phi(x)\phi(y)dxdy$$

Marginal utilities are computed in a similar way as in the previous scenario, using Leibniz rule:

$$\frac{d\mathbb{E}(U)}{dx_1} = \int_{-x_0}^{+\infty} \phi_\sigma(x)dx + w\phi_\sigma(-x_0) = \Phi_\sigma(x_0) + w\phi_\sigma(x_0) = \Phi(x_0/\sigma) + \frac{w}{\sigma}\phi(x_0/\sigma)$$

$$\frac{d\mathbb{E}(U)}{dx_2} = \int_{-x_0-d}^{+\infty} \frac{1}{\sigma\sqrt{2}}\phi(\frac{x}{\sigma\sqrt{2}})dxdy + \frac{w}{\sigma\sqrt{2}}\phi(\frac{x_0+d}{\sigma\sqrt{2}}) = \Phi(\frac{x_0+d}{\sigma\sqrt{2}}) + \frac{w}{\sigma\sqrt{2}}\phi(\frac{x_0+d}{\sigma\sqrt{2}})$$

Like in the first scenario, marginal utility in the second time period has the same shape as in the first, with only an increased variance. The formula has an intuitive interpretation. It is the probability to be above the threshold by that time (in which case you derive utility from extra resources), plus the density at the threshold, weighted by w (the utility at the threshold).

It is not possible to derive analytically a necessary and sufficient condition for $MRIS > 1$, but the one found in the first scenario can be shown to be a sufficient condition for positive x_0. Numerical results show that this actual region is slightly larger (see Fig. 3.2B in the main manuscript).

Indeed, if $x_0 > 0$, $\Phi_\sigma(x_0) > \Phi_{\sqrt{2}\sigma}(x_0)$, and as in the previous scenario, $\phi_\sigma(x_0) > \phi_{\sqrt{2}\sigma}(x_0) \iff |x_0| < \sigma\sqrt{2ln(2)}$.

Therefore, $0 < x_0 < \sigma\sqrt{2ln(2)} \implies \frac{d\mathbb{E}(U)}{dx_1} > \frac{d\mathbb{E}(U)}{dx_2} \implies MRIS > 1$.

For $x_0 \to +\infty$, in both cases $\Phi \to 1$ and $\phi \to 0$ (intuitively, one becomes sure to be above the threshold, and the density at the threshold vanishes). Clearly, $\frac{d\mathbb{E}(U)}{dx_1} \to 1$ and $\frac{d\mathbb{E}(U)}{dx_2} \to 1$, so $MRIS \to 1$.

For $x_0 \to -\infty$, in both cases Mills ratio implies that $\Phi = o(\phi)$: it becomes very unlikely to be above the threshold, so the dominant contribution to marginal utility comes form the possibility that the resources helps overcome the threshold. In this case, however, $\phi_\sigma = o(\phi_{\sqrt{2}\sigma})$: the normal distribution with a higher variance decays much slower. This implies that $\frac{d\mathbb{E}(U)}{dx_1} = o(\frac{d\mathbb{E}(U)}{dx_2})$, so $MRIS \to 0$.

For $x_0 \to +\infty$, clearly $P(x_1 > 0 \cap x_2 > 0) \to 1$ and the other terms become negligible, so $MRIS \to 1$.

3.6.1.4 All in vain

Now,

$$U(x_1, x_2) = (w + x_2)(x_1 > 0 \cap x_2 > 0)$$

Therefore,

$$\mathbb{E}(U) = \int_{-x_0-\Delta x_1}^{+\infty} \int_{-x_0-\Delta x_2-d-y}^{+\infty} (w + x_0 + \Delta x_1 + \Delta x_2 + x + y)\phi(x)\phi(y)dxdy$$

$$\begin{aligned}\frac{d\mathbb{E}(U)}{dx_1} &= 1 \cdot \int_{-x_0}^{+\infty} \int_{-x_0-d-y}^{+\infty} \phi(x)\phi(y)dxdy + \phi(x_0) \int_{-d}^{+\infty} (w + d + x)\phi(x)dx \\ &= P(x_1 > 0 \cap x_2 > 0) + \phi_\sigma(x_0)((w + d)\Phi_\sigma(d) + \sigma^2\phi_\sigma(x_0 + d))\end{aligned}$$

This formula is cumbersome, but can be interpreted. The first term is the probability to be able to derive utility from the resources. The second term is the density to be at the threshold in the first time period, weighted by several parameters. First, $w+d$, as $x_1 = 0$, $\mathbb{E}(x_2) = d$, so one expects to get a utility $w+d$. Second, $\Phi_\sigma(d)$, which is the probability to stay above the threshold in the second time period, given that $x_1 = 0$ (if one falls back below the threshold in the second period, having reached it in the first is useless). Last, one adds $\sigma^2\phi_\sigma(x_0+d))$, which is the partial expectation of x_2 conditional on x_2 > 0: there is a chance that one gets more resources in the second period, which brings utility that one would not have had if not above the threshold in the first.

The marginal utility in the second period is:

$$\frac{d\mathbb{E}(U)}{dx_2} = 1 \cdot \int_{-x_0}^{+\infty} \int_{-x_0-y}^{+\infty} \phi(x)\phi(y)dxdy + w \cdot \int_{-x_0}^{+\infty} \phi(y)\phi(-x_0-d-y)dy$$

The second member simplifies (after a change of variable):

$$\begin{aligned}\frac{d\mathbb{E}(U)}{dx_2} &= P(x_1 > 0 \cap x_2 > 0) + \frac{e^{\frac{-(x_0+d)^2}{4}}}{2\pi\sigma^2} \int_{-x_0}^{+\infty} e^{(\sqrt{2}y+(x_0+d)/\sqrt{2})^2/2}dy \\ &= P(x_1 > 0 \cap x_2 > 0) + w\phi_{\sqrt{2}\sigma}(x_0+d)\,\Phi_{\sqrt{2}\sigma}(x_0-d)\end{aligned}$$

This formula is simpler to interpret: the first term is still the probability to enjoy the extra resource because above the threshold in both periods, and the second is the density of x_2 in 0 (intuitively, the chance that the extra resource pushes one above the threshold), weighted by w (the utility at the threshold), and $\Phi_{\sqrt{2}\sigma}(x_0-d)$ gives, intuitively, the probability to have been above the threshold in the first period given that one is right at the threshold in the second.

For very low values of x_0, we can look for equivalents of the terms. First, we get the equivalent for the probability to be above in both time steps. The intuition here is that the normal density decays so fast that the majority of the probability mass allowing survival is concentrated just above 0. So, if $x_1 > 0$ in spite of $x_0 << 0$, most likely $x_1 \sim 0$, and then we need $\epsilon_2 > -d$ to stay above the threshold in t_2. Formally, we split the integral and show that the rest becomes negligible. Here goes:

$$\begin{aligned}\mathbb{P}(x_1 > 0, x_2 > 0) &= \int_{-x_0}^{+\infty} \int_{-x_0-y}^{+\infty} \phi(x)\phi(y)\,dx\,dy \\ &= \int_{-x_0}^{+\infty} \int_{0}^{+\infty} \phi(x)\phi(y)\,dx\,dy + \int_{-x_0}^{+\infty} \int_{-x_0-y-d}^{-d} \phi(x)\phi(y)\,dx\,dy \\ &= \Phi(x_0)\Phi(d) + R(x_0)\end{aligned}$$

Now, inside the rest integral, we remark that $\forall x \in [-x_0-y-d, -d], \phi(x) \leq \phi(-d) = \phi(d)$. We minimize the rest, and then we can make an explicit integration of the lower bound.

$$\begin{aligned}0 \leq R(x_0) &\leq \phi(d) \int_{-x_0}^{+\infty} \phi(y)(x_0+y)dy \\ &= \phi(d)\,[x_0\Phi(x_0) + \phi(x_0)]\end{aligned}$$

Now, we use the Mills ratio: for very negative x, we have:

$$x\Phi(x) \sim -\phi(x)\left(1 - \frac{1}{x^2} + o(\frac{1}{x^2})\right)$$

Therefore,

$$R(x_0) \sim \frac{\phi(x_0)}{x^2} = o(\Phi(x_0))$$

Since we have:

$\Phi(x_0)\Phi(d) \leq \mathbb{P}(x_1\ 0, x_2\ 0) \leq \Phi(x_0)\Phi(d) + R(x_0)$

And $R(x_0) = o(\Phi(x_0)\Phi(d))$, the upper bound is equivalent to the lower bound, and by a sandwich theorem, we have:

$$\mathbb{P}(x_1 > 0, x_2 > 0) \sim \Phi_\sigma(x_0)\Phi_\sigma(d) \sim -\sigma^2\Phi_\sigma(d)\frac{\phi_\sigma(x_0)}{x_0}$$

For $w > 0$, the other member of $\frac{d\mathbb{E}(U)}{dx_1}$ is clearly dominant, and we have:

$$\frac{d\mathbb{E}(U)}{dx_1} \sim w\frac{\phi(x_0/\sigma)}{\sigma}\Phi(d/\sigma)$$

As for $\frac{d\mathbb{E}(U)}{dx_2}$, we can compute an equivalent of the second member, using Mills ratio and simplifying:

$$\frac{w}{\sqrt{2}}\phi_{\sqrt{2}\sigma}(x_0 + d)\Phi_{\sqrt{2}\sigma}(x_0 - d) \sim -\frac{w}{\sqrt{2}}\phi(x_0/\sigma)\frac{\phi(d/\sigma)}{x_0}$$

Let us assume that w is large enough, so that this term dominates the other term – otherwise the terms are of the same order and we can combine them, leading to a similar behavior. In this case, we obtain:

$$\begin{aligned} MRIS = \frac{\frac{d\mathbb{E}(U)}{dx_1}}{\frac{d\mathbb{E}(U)}{dx_2}} &\sim \frac{w\frac{\phi(x_0/\sigma)}{\sigma}\Phi(d/\sigma)}{-\frac{w}{\sqrt{2}}\phi(x_0/\sigma)\frac{\phi(d/\sigma)}{x_0}} \\ &\sim -x_0\frac{\Phi(d/\sigma)}{\sqrt{2}\sigma\phi(d/\sigma)} \end{aligned}$$

For $x_0 \to +\infty$, clearly $P(x_1 > 0 \cap x_2 > 0) \to 1$ and the other terms become negligible, so $MRIS \to 1$.

3.6.1.5 Game-over

In this scenario, the utility function is:

$$U(x_1, x_2) = (x_1 + w)(x_1 > 0) + (x_2 + w)(x_1 > 0 \cap x_2 > 0)$$

Therefore,

$$\mathbb{E}(U) = \int_{-x_0-\Delta x_1}^{+\infty}(x_0+\Delta x_1+x+w)\phi(x)dx+\int_{-x_0}^{+\infty}\int_{-x_0-\Delta x_2-y}^{+\infty}(w+x_0+\Delta x_2+x+y+d)\phi(x)\phi(y)dxdy$$

Marginal utility in the first period is:

$$\frac{d\mathbb{E}(U)}{dx_1} = \Phi_\sigma(x_0) + w\phi_\sigma(x_0) + \phi_\sigma(x_0)((w + d)\Phi_\sigma(d) + \sigma^2\phi_\sigma(d))$$

The computation of marginal utility in t_2 is the same as the previous model:

$$\frac{d\mathbb{E}(U)}{dx_2} = P(x_1\ 0 \cap x_2\ 0) + w\phi_{\sqrt{2}\sigma}\,(x_0 + d)\,\Phi_{\sqrt{2}\sigma}(x_0 - d)$$

Using the same reasooning as in the previous scenario, we can show that the MRIS becomes approximately linear for $x_0 \to -\infty$, but with a steeper asymptotic slope. For high w, we have:

$$MRIS \sim -x_0 \frac{1 + \Phi(d/\sigma)}{\sqrt{2}\sigma\phi(d/\sigma)}$$

We note that for $d = 0$, the slope is precisely three time steeper than in the 'all in vain' scenario. For $d >> 0$, it is two times steeper. For $d << 0$, it is infinitely steeper.

3.6.2 Sensitivity analysis

The main text shows the effect of x_0 and d on time discounting. Here, we present the effect of the other parameters (σ and w).

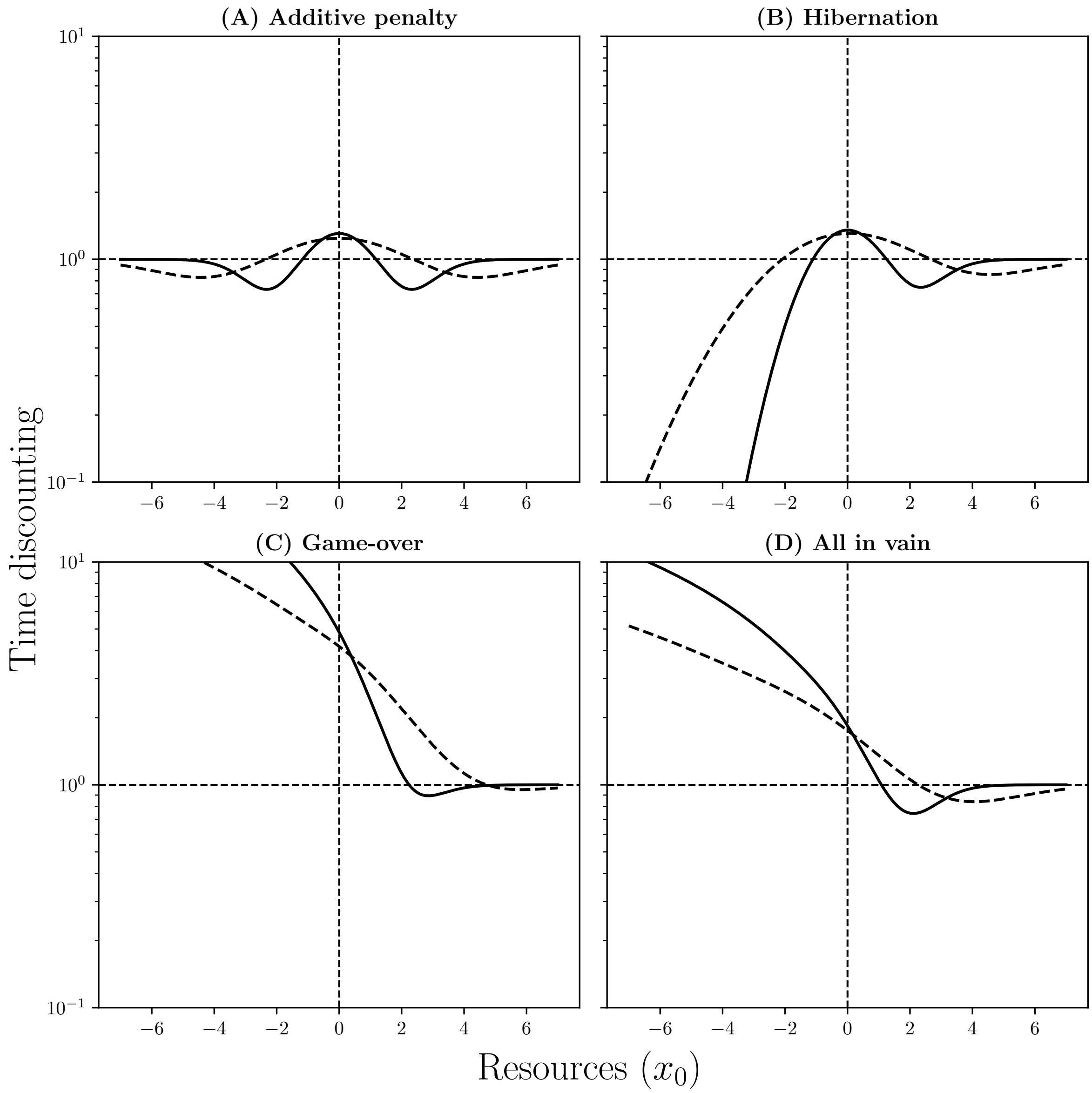

Figure 3.5: Time discounting depending on resources, for high and low resource noise between periods. The solid line denotes $\sigma = 1$, the dashed line denotes $\sigma = 2$. The y-axis is truncated at .1 and 10 for legibility.

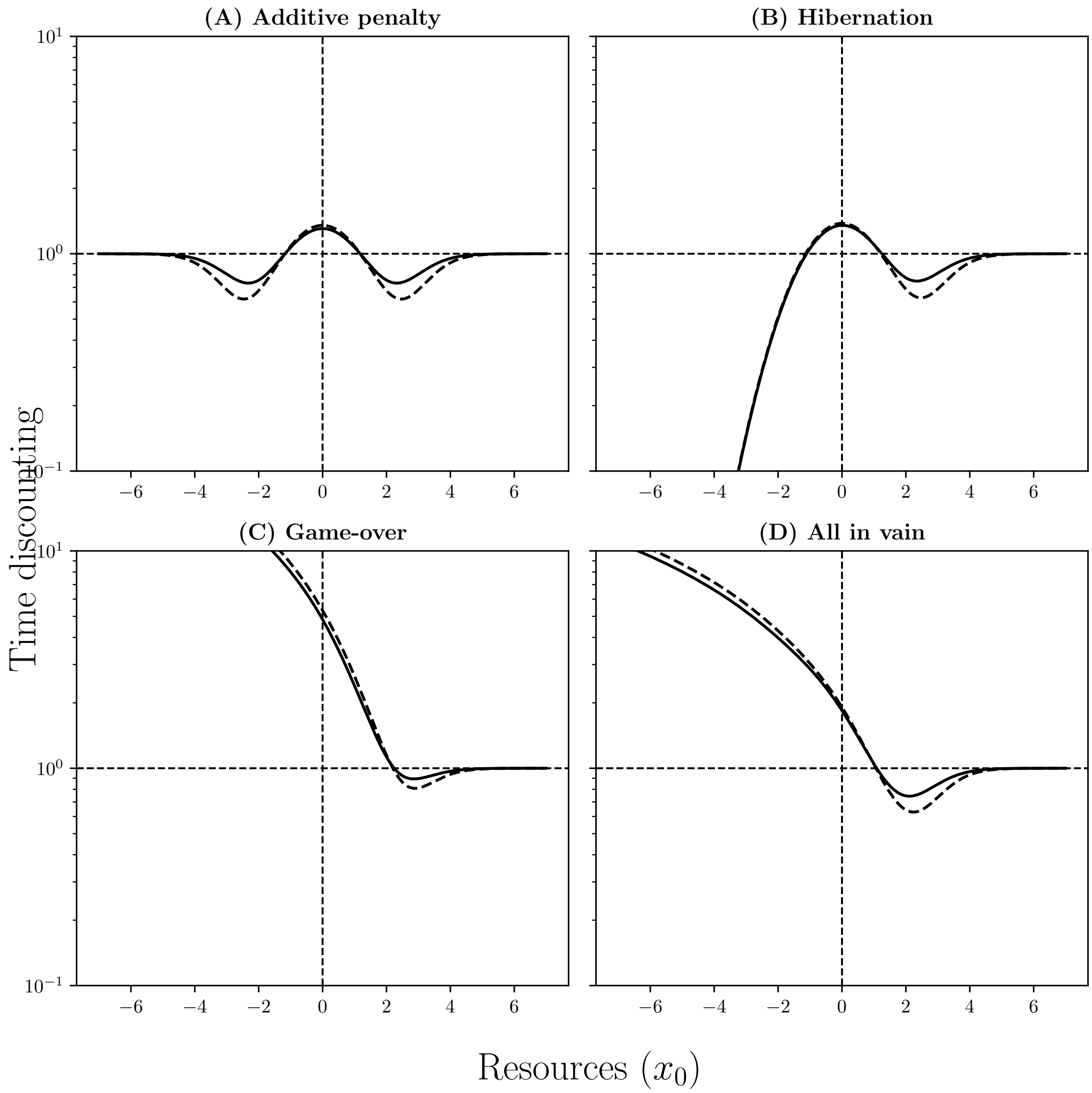

Figure 3.6: Time discounting depending on resources, for high and low utility jump at the desperation threshold. The solid line denotes low jump ($w = 10$), the dashed line denotes high jump ($w = 20$). The y-axis is truncated at .1 and 10 for legibility.

4 Poverty is associated with both risk avoidance and risk taking: empirical evidence for the desperation threshold model from the UK and France

This chapter is based on: de Courson, B., Frankenhuis, W. E., & Nettle, D. (2025). Poverty is associated with both risk avoidance and risk taking: empirical evidence for the desperation threshold model from the UK and France. Proceedings B, 292(2040), 20242071.

4.1 Abstract

In situations of poverty, do people take more or less risk? Some theories state that poverty makes people 'vulnerable': they cannot buffer against losses, and therefore avoid risk. Yet, other theories state the opposite: poverty makes people 'desperate': they have little to lose, and therefore take risks. Each theory has some support: most studies find a negative association between resources and risk taking, but risky behaviors such as crime and gambling are more common in deprived populations. Here, we test the 'desperation threshold' model, which integrates both hypotheses. We assume that people attempt to stay above a critical level of resources, representing their 'basic needs'. Just above this threshold, people have too much to lose, and should avoid risk. Below, they have little to lose, and should take risks. We conducted preregistered tests of this prediction using data of 472 adults over the age of 25 in France and the UK, who completed a survey once a month for 12 months. We found that risk taking followed a V-shape against subjective resources, but not objective resources. Next, we tested whether risk taking varies more among people with fewer resources, as our model predicts, and found strong evidence for this prediction.

4.2 Introduction

In situations of poverty, do individuals tend to take more or fewer risks? On this question, there are, as Banerjee puts it, "at least two distinct and, prima facie, inconsistent views" (A. Banerjee, 2004). The first is that poverty makes individuals 'vulnerable': they have barely enough to make ends meet and would suffer too much from a resource loss. Therefore, they avoid risk. The second is that poverty makes individuals 'desperate': they have little to lose, and are ready to gamble to have a chance to get out of poverty, since their situation cannot get much worse. Therefore, they take more risks. Even though these two views predict opposite associations between levels of resources and risk taking, both can be found in theories across the social sciences (A. V. Banerjee & Newman, 1994; Daly & Wilson, 2001; for examples of the view that poverty increases risk taking, see Ellis et al., 2012; Griskevicius et al., 2011; Hill et al., 1997; A. V. Banerjee & Duflo, 2007; Baumard, 2019; Gollier, 2002; for examples of the view that poverty decreases risk taking, see Haushofer & Fehr, 2014). Both views have also been used to make sense of empirical findings. The idea that people in poverty avoid risk has been invoked to explain the lack of professional specialization (A. V. Banerjee & Duflo, 2007), a reluctance to adopt new technologies or to invest in education (Haushofer & Fehr, 2014), and even the persistence of poverty (Haushofer & Fehr, 2014; Yesuf & Bluffstone, 2009). On the other hand, the idea that people in poverty have 'little to lose', and therefore seek risk, has been invoked (Brezina et al., 2009; Daly & Wilson, 2001; Griskevicius et al., 2011) to explain higher prevalence of crime (Hsieh & Pugh, 1993) and gambling (Wardle et al., 2014) in deprived populations.

The empirical record is also mixed (Haushofer & Salicath, 2023; Kish-Gephart, 2017; Tanaka et al., 2010; Vieider et al., 2012). In high-income countries, most cross-sectional studies have found that individuals with a lower income or wealth take fewer risks in experimental gambling tasks (Dohmen et al., 2011; Eckel et al., 2012; e.g., Guiso & Paiella, 2008; for a review, see Sheehy-Skeffington & Rea, 2017). In low-income countries, some studies have also reported less risk taking (Yesuf & Bluffstone, 2009), but others found no association (Binswanger, 1980; Cardenas & Carpenter, 2013; Mosley & Verschoor, 2005), or even more risk taking. For instance, the poorest Indian farmers were found to be extremely willing to take risks (Maertens et al., 2014). Among poor Madagascar farmers, food insecurity was the best positive predictor of risk taking in hypothetical gambles (Tucker, 2012). Another study used the choice between drought-resistant camels and more productive but riskier small livestock, as a proxy of risk taking among four herder groups (Mace, 1990). In three of the four groups, the poorest households kept mostly riskier small livestock. To sum up, there is a crucial inconsistency: two bodies of work propose and document exactly opposite associations between poverty and risk taking. Both views are intuitively appealing, and both have support in the empirical record. Both are relevant to explaining key social phenomena, such as occupational choices and crime.

Optimal foraging theory, and risk-sensitive foraging in particular, can resolve this conundrum (Courson & Nettle, 2021; De Courson et al., 2023). In a scenario first modeled by Stephens (1981), a 'small bird in winter' aims to acquire enough calories to get through the night. Just above the 'starvation threshold' – where the bird is likely to survive, but only just – it should avoid risks, so as to not fall below it. However, below this threshold, it should take risks, to have a chance to keep its head above water. Thus, low compared to high energetic resources will be associated with either greater risk avoidance or greater risk taking, depending on how low they are. Analogous applications of this idea to humans in situations of resource scarcity have emerged independently in disparate fields of research, including psychology (Barclay et al., 2018; Mishra & Lalumière, 2010), agricultural economics (Kunreuther & Wright, 1974; Roumasset, 1971), development economics (Lybbert & Barrett, 2011), anthropology (Winterhalder et al., 1999) and political science (Scott, 1977). In our papers, we (Courson & Nettle, 2021; De Courson et al., 2023) applied this same logic to criminal behaviour in situations of poverty. We assumed that individuals have a 'desperation threshold' representing 'basic needs' that they try to always meet. We elaborate the desperation threshold model and its predictions in section 4.2.

The desperation threshold model has been tested in lab experiments (Deditius-Island et al., 2007; Mishra & Lalumière, 2010; Pietras et al., 2006, 2008; Pietras & Hackenberg, 2001; Radkani et al., 2023; Rode et al., 1999). Participants – students or online participants from North America or the United Kindgom – typically play a game that includes an artificial threshold, such as a minimum number of points needed to obtain a monetary payoff at the end of the game. Participants tend to behave in accordance with the theoretical prediction, taking fewer risks when their resource level is above the threshold, and more below. These findings suggest that people are able to adjust their behavior when confronted with a threshold. But they tell us little about behavior in natural environments. Do such thresholds exist outside the lab? Do they affect the behavior of a sizeable fraction of the population?

Evidence for the predictions of the desperation threshold in real-world settings is scarce, in part because cross-sectional studies are often ill-suited to testing threshold effects. Such studies tend to model risk taking as a linear function of resources, whereas the desperation threshold predicts a non-linear mapping (a U- or V-shape): poverty should reduce risk taking up to some point, and then increase it. Nevertheless, several studies are informative. For instance, (Barsky et al., 1997) estimated risk taking by quintiles of income and wealth in the Health and Retirement Study, a representative panel of Americans over age 50. Consistent with the desperation threshold, people in the poorest and the richest quintiles, whether measured in income or in wealth, were ready to take the most risks. Recently, Akesaka et al. (Akesaka et al., 2023) documented in the same dataset that those who strongly depended on social security – those with fewer resources – were ready to take significantly more risks the day before receiving welfare checks, when they are most likely to be below the threshold, than at other times.

In anthropology, Kuznar (Kuznar, 2001) presented evidence of a U-shape between herd value and risk taking – but the small size of the sample (23 Andean farmers) limits statistical inference. Caballero (Caballero, 2010) estimated a subsistence threshold in extremely deprived neighbourhoods of Bogota, and found preliminary evidence of a jump in risk taking at that point. But again, the sample size was not sufficient to draw firm conclusions. In principle, though, any dataset that includes measures of resources and risk taking could be used to test the hypothesis, as long as there are enough people above and below the desperation threshold. In sum, there is some evidence from diverse populations of U- or V-shaped relationships between material resources and risk tolerance, but the number of studies is limited and many of them are based on small samples.

In this paper, we first offer a succinct formalization of the desperation threshold model, from which we derive the predicted non-linear relation between resources and risk taking. Then we test those predictions using the *Changing Cost of Living* dataset (Nettle, Chevallier, et al., 2025), a survey of British and French adults that includes questions about participants' levels of resources across time, as well as a measure of risk taking. Moreover, these questions concerned not only income, but also unavoidable costs and subjective feelings of poverty. Thus, we can test the prediction using an objective measure of resources, and a subjective one, the feeling of resource adequacy.

4.3 Theory

The desperation threshold idea can be summarised as follows: humans have a strong preference for having at least some amount of resources that represent their 'basic needs'. Above this level, they continue to derive utility from resources, but this is less important than keeping their basic needs secured. We can formalise this threshold with a utility function. The initial set of models captured this idea with a jump in the utility function (Masson, 1974), or even a step function, representing life and death (Stephens, 1981). Here, we assume a more general sigmoid shape. The utility function features a steep region, representing that at some point resources are particularly valuable because they secure basic needs. Below the threshold, the utility function is relatively flat, representing the intuition that one has 'little more to lose' once basic needs are not reached. Above the threshold, we assume that utility increases linearly with resources.

Our utility function is therefore:

$$U(x) = \frac{1}{1+e^{-x}} + \frac{x}{50}\mathbb{1}_{x>0},$$

where x represents resources and the threshold is placed at 0 $\mathbb{1}_{x>0}$ being an indicator function, whose value is 1 when $x > 0$ and 0 otherwise. Figure 4.1A represents this utility function, and highlights the central result of the model. Below the threshold, the function is convex: one has more to win than to lose, and should therefore take risks. Above the threshold, the function is concave: one has more to lose than to win, and should therefore avoid risks. It should be noted that the desperation threshold does not predict a change in 'risk preference' strictly speaking from an economics point of view: the taste for risky outcomes is unchanged. Rather, Lybbert Lybbert et al. (2013) has coined the term of 'risk response' to threshold effects, which applies here. Thus, we use the terms 'risk taking' and 'risk avoidance', rather than 'risk proneness' and 'risk aversion'.

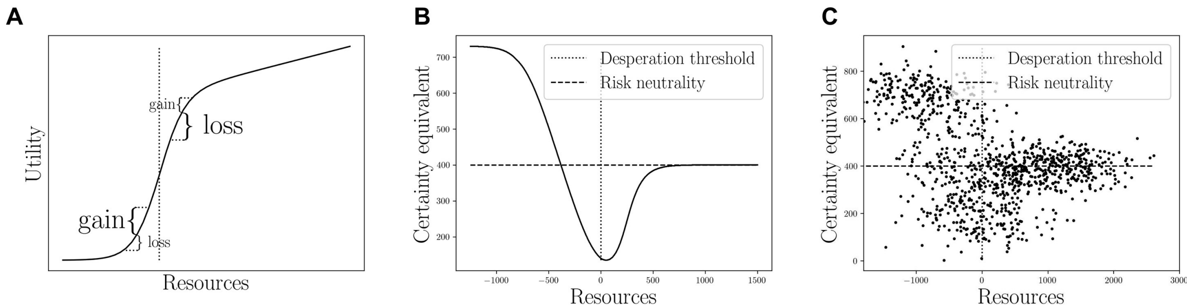

Figure 4.1: Summary of the model and predictions. (A) is the utility function we assume to represent the desperation threshold. (B) is the resulting certainty equivalent of the risky decision - the minimum guaranteed amount of money one would accept instead of taking a 50% chance to win €800 - depending on resources. Certainty equivalent being a measure of risk taking, this is the association we predict between risk taking and resources. (C) represents the same as panel B when resources are observed with a large noise (sd=€500) and certainty equivalents with a smaller noise (sd=€50). This is the basis of our second prediction, that risk taking should vary more among individuals with low resources.

In figure 4.1B, we plot the 'certainty equivalent' depending on resources. Concretely, we assume that an individual has the utility function shown in figure 4.1A and we let her decide between €x for sure and a 50% chance of getting €800. We vary x from 0 to 800 and we plot in figure 4.1B the minimum value of x she would take. This represents the value she attributes to the risky choice, and can therefore be used as a measure of risk taking. If the certainty equivalent is more than 400, the person is taking risk; if it is less than 400, they are avoiding risk, and if it is exactly 400, they are risk neutral. In the task used in the Changing Cost of Living survey (see next section), the certainty equivalent represents the point where participants would switch to the safe option. The resulting prediction (figure 4.1B) is that below the threshold, people should take risks even when the expected value of the certain option is higher than that of the risky options, whereas just above the threshold they should avoid risks even when the certain payoff has a worse expected value than the risky option. Note that the switch to risk taking occurs below the threshold here, since participants can only gain resources in the task. The switch from risk avoidance to risk taking is reached around $x = -400$, where €400 with certainty means ending up precisely at the desperation threshold. Thus, our first prediction is that risk taking should be a V-shape function of resources (figure 4.1B).

Now, what if resources are only imperfectly observed? As risk taking varies abruptly with resources around the desperation threshold, it is crucual to tell apart individuals just above the threshold from those just below. In practice, this might not be realistic: resource levels are not perfectly measured, and the threshold may vary from individual to individual. In figure 4.1C, we present our prediction if resources are observed with a high noise (sd = €500) and certainty equivalents with a low noise (sd = €50). The V-shape is not visible to the naked eye anymore, but we obtain a triangle-shaped scatter plot. This is the basis of our second prediction: risk taking should be more variable in the lower part of the resource distribution than the higher part. This is because the lower part comprises some individuals just above and some individuals just below the threshold, with opposite levels of risk taking.

To sum up, the desperation threshold model makes two predictions. First, that risk taking should follow a V-shape of resource levels, with both the poorest and the richest participants taking more risks than average

(P1). Second, that risk taking should vary more between individuals at low resource levels (P2), since one should find both 'vulnerable' participants avoiding risks, and 'desperate' ones taking risks. In the Analysis strategy subsection, we explain how we tested P1 and P2 using the *Changing Cost of Living* Dataset.

4.4 Methods

4.4.1 Panel

We used the data collected for the project *The Changing Cost of Living* study (for a complete description of this data collection, see (Nettle, Chevallier, et al., 2025); protocols available at https://osf.io/e8g3p). The authors recruited in September 2022 a panel of 232 French and 240 British adults over the age of 25. Participants were invited to complete a survey once a month for 12 months. On average, participants completed 10.05 of the 12 surveys each (sd 2.98). In August 2023, when the study ended, 157 (67.7%) and 216 (90%) of the original participants responded. Table 4.2 shows participant demographics. The panels were not nationally representative, and were skewed towards the low end of their respective national income distributions, especially in France (see (Nettle, Chevallier, et al., 2025) for details).

4.4.2 Measures

The full set of measures is described in the preregistered initial (https://osf.io/x26mf) and supplementary (https://osf.io/rj683) protocols of the study. The data were collected for multiple studies (in particular, Nettle, Chevallier, et al., 2025), and we only use some of its measures.

Objective resources. Participants reported the amount of income received into their household in the reference month (i.e., net of taxes and including benefits). UK figures were converted to euros at a purchasing-power parity rate. The mean income of participants was 3437€ and the median 3000€ (sd=2117.1). For costs, participants reported the amounts paid out for rent/mortgage, water, residence-based taxes, and energy (electricity, gas, oil) in the previous month. We summed these amounts to obtain an estimate of unavoidable living costs. We logged income and cost variables with a base 2 (adding €1 because of zeroes), to reduce positive skew and represent the fact that resources have diminishing returns. Our objective resources variable is the difference between the log-transformed income and log-transformed unavoidable costs. Since the difference in logs is the log of the ratio, this variable measures the proportional relationship of household income to unavoidable costs. Thus, a value of zero means that income just covered unavoidable costs; a value of 1 that income was twice unavoidable costs; and and a value of 2 means that income was four times unavoidable costs. Negative values (1.6% of cases) indicate failure of income to even cover unavoidable costs.

Subjective resources. Participants were asked three questions about their subjective risk of losing resources: their subjective risk of destitution, their subjective risk of losing "a suitable place to live", and their subjective risk of losing "a suitable employment". Participants answered these three questions on a 0-100 scale, which we summed and reverse coded to compute our subjective resources measure. The three variables had a Cronbach's alpha of 0.87. To avoid right-skew (a large number of participants reported almost zero on those three measures), we applied a square root transformation. Subjective resources were moderately correlated with objective resources ($r = 0.27$, p < .001).

Risk taking. Participants were asked whether they preferred a 50% chance of getting €800, or €x for sure, with x being increased by €100 from €100 to €700. We used the number of risky bets (choosing 50%

chance of getting €800) that participants preferred as our measure of risk taking. If participants were perfectly consistent, this measure would be proportional to the minimum certainty equivalent that we presented in Figure 4.1B. But it is more robust to a 'trembling hand' of the participants: if a participant mistakenly refuses the least risky bet, but is actually risk neutral, then our measure will almost be correct (3 instead of 4), while the minimum certainty equivalent would have yielded 1.

On average, participants accepted 2.31 of the 7 bets (sd= 1.6). Participants were weakly-to-moderately stable over time in their risk taking: the intra-class correlation coefficient (ICC) was 0.48.

Time-discounting Participants were asked whether they preferred €100 now or €x 90 days from now, with x ranging from 110 to 170. We used the number of immediate choices as our time discounting measure. We use this variable in our exploratory analysis (see below), for contrast with the results we obtained with risk taking.

4.4.3 Analysis strategy

We first investigated descriptively the relationship between resources and risk taking. We then ran five confirmatory tests of our predictions relating risk taking to resource levels. These analyses were preregistered here: https://osf.io/g4x8t/. In the results section, we present each test twice, using respectively objective and subjective resources. We corrected p-values using the Holm-Bonferroni method to control the error rate. These tests are divided in two distinct groups, differing in their level of severity to test our hypothesis (see below). The two groups relate respectively to P1 and P2 (see Theory).

In our first group of analyses (analysis 1), we predicted that risk taking would follow a V-shape against resources. First, we fitted mixed effects polynomial models, to test for evidence of a non-linear relationship between resources and risk taking. Second, we fitted segmented linear models, to estimate the association below and after a 'changepoint', fitted with maximum likelihood. This approach is less standard in psychology, and has been judged problematic in exploratory analyses (Breit et al., 2023). However, our analysis is confirmatory, and our model prediction is closer to a broken-stick relationship (Figure 4.1B) than a smooth polynomial. We constrained the model to have the two regression lines connected, by fitting the following formula: $risk\_taking = \beta_0 + \beta_1(r - cp)(r \leq cp) + \beta_2(r - cp)(r > cp) +$ controls, where cp is the changepoint and r stands for the resources. The polynomial and the segmented models are two different ways to represent the predicted V-shape. We see them as two different tests of the same prediction.

In these analyses, we included random effects of participants and fixed effects of age and gender, two variables known to influence risk taking (Daly & Wilson, 2001; Dohmen et al., 2011).

Our second group of analyses (analysis 2) tested the less specific prediction, that risk taking should be more variable in individuals with fewer resources. Our reasoning here was as follows: our resource measures may be too noisy for discriminating when individuals are just below the threshold and when they are just above, especially since the threshold might vary between individuals. In this case, we might not be able to identify a single switch point between risk avoidance and risk taking, but we should still expect a mixture of risk takers and risk avoiders at the bottom of the resource distribution, whereas risk preference should be more homogenous higher in the distribution (Figure 4.1C). We therefore tested in three ways whether variance in risk taking was higher among individuals with fewer resources. Specifically, we tested:

(i) whether variance in risk taking was higher among individuals reporting that "managing financially is very difficult";

(ii) whether squared residuals of a linear model were higher at the bottom of the resource distribution; and

(iii) whether participants with lower resources were less stable over time in their risk taking.

This second group of analyses represents a less severe test of the model than the third one, in the sense that the predicted result could be obtained under less stringent conditions, and, as a result, more alternative explanations could be proposed (see Discussion section).

Finally, we ran an exploratory analysis that was not preregistered. There, we used all the available resource variables to isolate the most deprived individuals, according to different criteria. We computed descriptive statistics of risk taking in these categories: the mean, variance, and frequency of extreme values, and compared them to the full sample population. We also contrasted the results with the ones obtained with richest individuals, and using time discounting instead of risk taking.

4.5 Results

4.5.1 Descriptive analysis

To visualize of how risk taking and resources were related, we plotted the average level of risk taking depending on the answer to the question "How are you managing financially?". We obtained (figure 4.5) an approximately linear, increasing trend: the easier to manage, the more risks, on average. This could however hide the fact that, as we suggested, those who report that managing financially is 'very difficult' include a minority of risk takers, hidden behind a majority of risk avoiders.

To investigate this possibility, we examined the average values on our two resource measures of people choosing each of the possible numbers of risky options (0-7). Figure 4.2 shows the results. An inverted V-shape is clear in both cases: both the participants who were ready to take *the least* and *the most* risks had on average fewer objective and subjective resources.

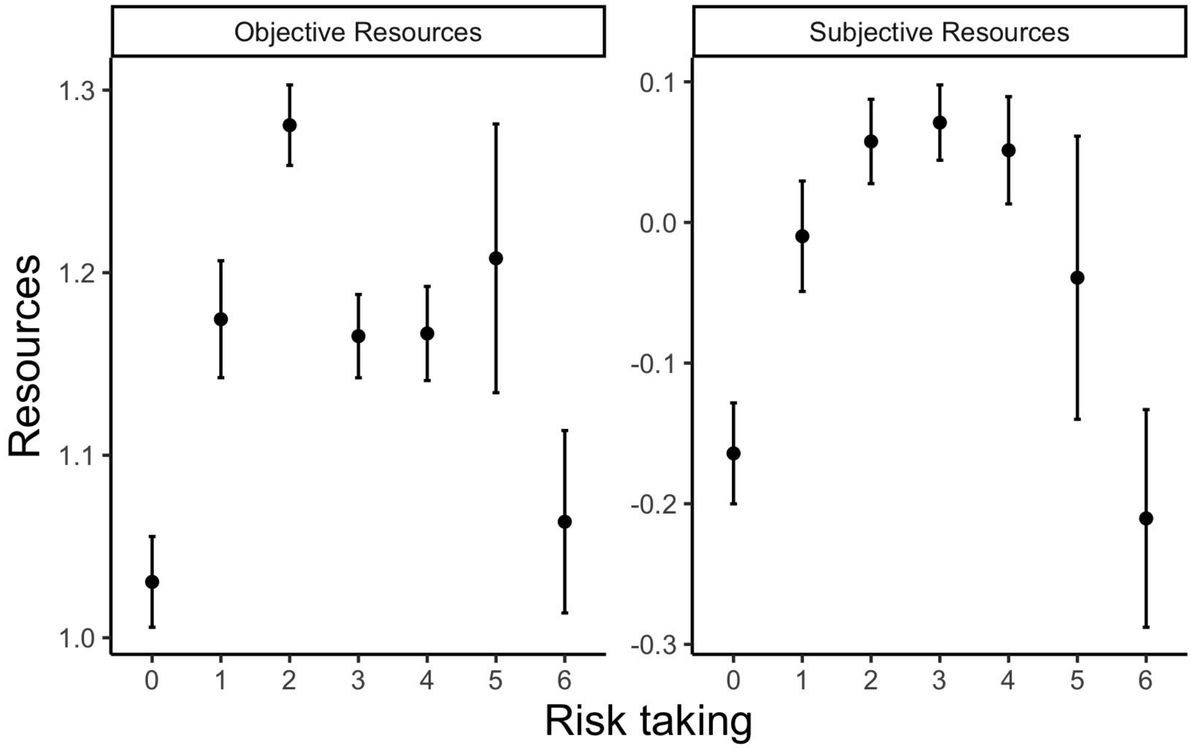

Figure 4.2: Objective and subjective resources summarized by risk taking answer. In these plots, we have pooled together the participants who accepted six and seven risky bets, to have a large enough group. The error bars represent 1 standard error of the mean.

Table 4.1: Extreme risk taking prevalence among participants low on resources. Asterisks denote the p-values of tests comparing the category with the rest of the sample, using chi-squared tests. Asterisks represent significance levels: *p < 0.05; **p < 0.01; ***p < 0.001.

Categories	% of risk takers	% of risk avoiders	n
Full sample	6	17.4	4882
Bottom 5% in objective resources	8.4	34.7 ***	242
Bottom 5% in subjective resources	12 ***	23.7 *	243

Finally, we looked at the prevalence of extreme risk taking among the 5% with the lowest levels of objective and subjective resources (Table 4.1). We defined participants as 'risk avoiders' when they accepted no bets, and as 'risk takers' when they accepted more than four bets. We use this term because a participant accepting more than four bets necessarily preferred a risky bet to a safe one that had a higher expected payoff (for instance, a 50% chance of getting 800€, rather than 500€ for sure). In Table 4.4, we expand this table, adding more descriptive statistics of risk taking.

Risk avoiders were more common in the bottom 5% than in the full sample. This was true whether resources were defined objectively or subjectively. Risk takers were also more common in the bottom 5% than the full sample. Again this was true whether objective or subjective resources were used, but it was particularly marked for subjective resources. The difference in prevalence of risk takers was only significant with subjective resources, but since risk takers were about three times rarer than risk avoiders, the power of these tests was much lower. Also, risk taking was on average lower (significantly for objective resources), but the variance in risk taking was respectively 37% and 44% higher than in the full sample ($p < .001$ in both cases) (see Table 4.3).

4.5.2 Analysis 1

4.5.2.1 Polynomial regressions

We fitted a cubic polynomial of resources on risk taking, with a random effect for participant and fixed effects for age and gender. Here and in all the following regression models, we found the usual association for age and gender, with women and older individuals taking fewer risks (for the linear model, we obtained $\beta =$ -0.19, $p =$ 0.005 for woman, $\beta =$ -0.085, $p =$ 0.01 for standardised age).

We predicted that the fitted polynomial would have an inflection point in the lower half of the resource distribution. This prediction was supported with subjective resources, but not with objective resources, which showed an almost linear relationship (Figure 4.3A & B). We predicted that a quadratic or cubic model would fit the association of resources to risk taking better than a linear one. For objective resources, this was not the case: both the quadratic and the cubic model had a higher AIC (11587.7 and 11588.5 respectively) than the linear one (11585.7). Neither can reject the linear model in a likelihood ratio test (χ^2= 0.032, $p =$ 0.859 for the quadratic model, χ^2= 0.032, $p =$ 0.537 for the cubic one). As a preregistered follow up analysis, we fitted higher degree polynomials, looking for the model with the least AIC. No model had a lower AIC than the linear one.

With subjective resources, a cubic model had a lower AIC (11603.1) than the linear one (11603.4), the quadratic one (11604.3) and any higher degree model. However, the superior fit of the cubic model over the linear one was not significant in a likelihood ratio test (4.31, $p = 0.232$).

4.5.2.2 Segmented mixed models

We fitted segmented mixed models between resource variables and risk taking. The changepoint was fitted by maximum likelihood, testing all possible values to identify the breakpoint giving the smallest deviance, which is a smaller-is-better measure of model fit. In Figure 4.6, we plot the deviance of the model, depending on the changepoint location.

Tables 4.2 and 4.3 show the scaled coefficients and the associated significance two-sided t-tests, for objective and subjective resources respectively. Figures 4.3C and 4.3D show the patterns between resources and risk taking predicted by the fitted models. With objective resources, we obtained the predicted V-shape (see Figure 4.3C). The slope of the association was significantly different from zero above the changepoint, but not below. The changepoint was found at the extreme bottom of the distribution (99% of the observations are above).

With subjective resources, all our predictions were supported. We obtained a V-shape, with resources having a significantly negative effect below and significantly positive above the threshold. After correction for multiple comparison with objective resources, both tests remained significant ($p = 0.029$ and $p = 0.034$). As predicted, the changepoint was found at the lower end of the resource distribution (3.9% of the data points are below it). The effect below the threshold was 19 times stronger than the effect above the threshold. We had not predicted a stronger effect below the changepoint in our preregistration, but this is clearly an implication of the desperation threshold model (Figure 4.1A). Figure 4.6 revealed that one could account almost as well for the data with a slightly higher changepoint (11% of the data points were below it). As a robustness check, we checked that our predictions were also supported with this alternative changepoint. Table 4.3 presents the scaled coefficients of this model. A V-shape was also found, with a significant effect on both sides of the changepoint.

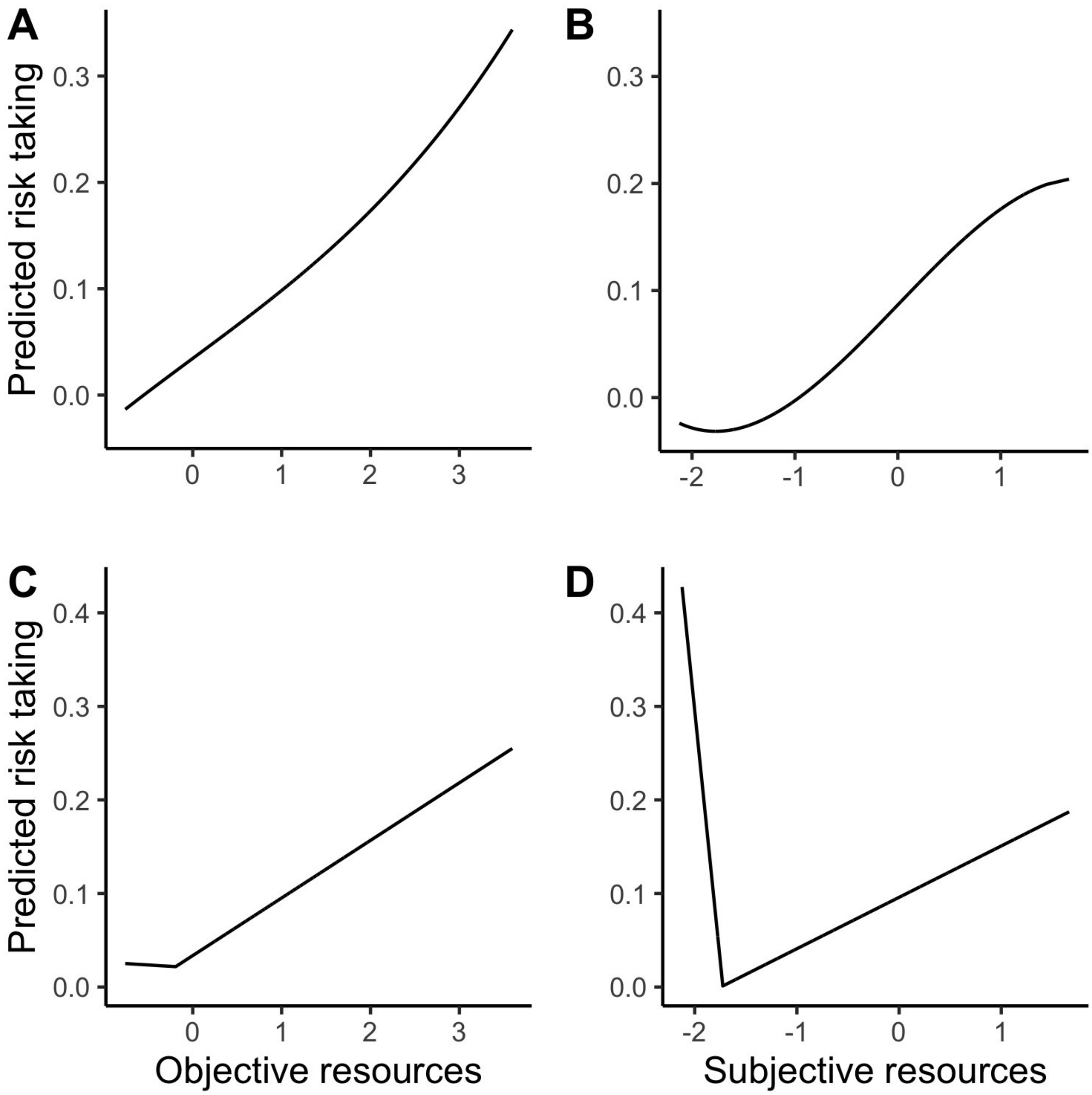

Figure 4.3: Risk taking predictions by the nonlinear statistical models, with polynomial (first line) and segmented regressions (second lines).

4.5.3 Analysis 2: do individuals with low resources vary more in risk taking?

4.5.3.1 Is there more variance in risk taking among close-to-the-edge participants?

In our second analysis, we predicted that there would be more variance in risk taking at the bottom of the resources distribution. We tested this prediction using the financial strain question, the objective and the subjective resources variables. As predicted, individuals who report that managing financially is "very difficult" had a 35% higher variance in their risk taking answers (F(4590,250)= 0.74, p < 0.001). This also applied, to a lesser extent, for people who reported that it was "quite difficult" to manage financially (Figure 4.5B).

To test the same question with our (continuous) resource variables, we fitted linear regressions between resources and risk taking, keeping age and gender as controls, but without a changepoint and without random effects, so as not to neutralise the between-individual variance. Then, we predicted that squared residuals would decrease with resources in a new linear regression, that is, that the absolute deviation from the line of best fit would be larger at the bottom of the resource distribution. Since this analysis tests for the same prediction as the one above using the financial strain question, we apply a Holm-Bonferroni correction to the three p-values. The prediction was clearly met for both objective and subjective resources (β =-0.09 and β = -0.06 respectively, p< 0.001 and p< 0.001).

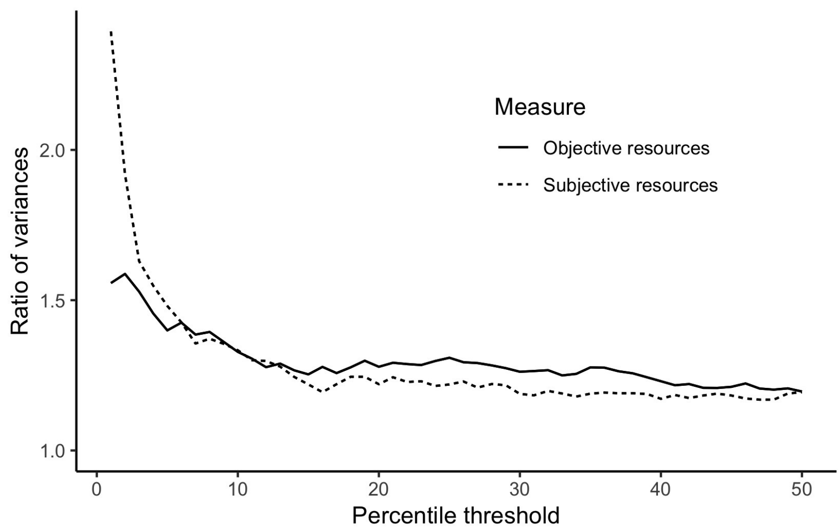

Figure 4.4: Ratio of variances in risk taking below and above resource thresholds set at different levels, from the first percentile to the median. For any threshold, the difference in variance is significant ($p <$ .05).

We visualised this effect by comparing variance in risk taking below and above some resource threshold, varying this threshold from the first percentile of the resource distribution to the median value (Figure 4.4). For any threshold below the median, the variance was at least 17% higher in the bottom part of the distribution. This variance soars as the threshold goes toward zero, in particular using subjective resources.

4.5.3.2 Are participants with low resources less stable over time in their risk taking?

Finally, we tested a slightly different prediction: participants with fewer resources should sometimes hover around the threshold, and should then alternate between taking and avoiding risks. We would thus expect that an individual with fewer resources will vary more in risk taking over time. We computed the intra-personal variance in risk taking over all time periods for every individual, and fitted a linear model between this variance over time and the average resource value.

For objective and subjective resources, the association was in the predicted direction. It was significant with objective resources (standardised $\beta =$ -0.14, $p = 0.004$), but not with subjective resources (standardised $\beta =$ -0.058, $p = 0.22$). We must note that the statistical power of these two tests was much lower than the previous ones: since they aggregated all the responses from the same individual, they are based on only 485 data points, against 4817 before.

4.5.4 Ruling out alternative explanations

We were interested in knowing whether our finding was specific to participants with fewer resources and to risk taking. Therefore, we replicated Table 4.1 on the top 5% answers in terms of objective and subjective resources (Table 4.4, line 2 and 3), and using the time discounting variable of the dataset, instead of risk taking (Table 4.5). We preregistered this analysis as a follow up (https://osf.io/54hfq).

With time discounting, we predicted (i) that there would be more individuals with high time discounting (defined as choosing only immediate rewards), but (ii) not more individuals with low time discounting (defined as never choosing immediate rewards) in the deprived categories than in the full sample, and (iii) that similarly, variance would not be more than 30% higher (30% being the lowest difference we found in risk taking). In both categories, high time discounting was more than twice as frequent in the deprived categories. In the bottom 5% of objective resources, our two other predictions were not supported: variance in time discounting was 44% higher than in the full sample, and low time discounting was slightly more frequent (22.4%) than in the full sample (18%). With subjective resources, all predictions were supported: variance was 27% higher than in the full sample, and low time discounting was less frequent (15%) than in the full sample (18%). Thus, it seems that our observation that low resources was associated with extreme risk taking was specific to risk taking, and did not reveal a tendency to make extreme decisions in other domains.

Finally, as another test of comprehension, we examined whether individuals with fewer resources were more likely to produce inconsistent answers in the risk questions. Among the full sample, we categorized 6.5% of the answers as inconsistent, in the sense that the participant refused a bet that was more profitable than another bet they accepted. However, neither objective nor subjective resources were correlated with consistency ($r = 0$ and $r = 0.05$, respectively), providing no evidence for differences in comprehension.

4.6 Discussion

4.6.1 Summary of results

In a panel of adults from France and the UK, we investigated the association between (lack of) resources and risk taking. We found clear evidence that having low resources is associated with a higher variance in risk taking (Figure 4.4), and with a large increase in both extreme risk avoidance and extreme risk taking (Table 4.2). This result is so clear in our data that it seems surprising that it is not an established finding in the social sciences. This might be due to most social science research focusing on linear relations, and undersampling of individuals who are below the threshold. We look forward to future studies of the desperation threshold in other datasets on risk taking and future discounting as well as other domains of cognition and behavior.

Our finding that poverty is associated with both risk avoidance and risk taking is important for several reasons. First, as noted, it reconciles two opposing perspectives on poverty and risk taking, which (A. Banerjee, 2004) named 'vulnerability' and 'desperation'. In our sample, a larger proportion of individuals living in situations of poverty avoid risk, suggesting that they have 'too much to lose'. At the same time, a larger proportion declare themselves ready to take risks that are on average detrimental, suggesting they have 'little to lose'. We also proposed an explanation for why poverty could lead to either vulnerability or desperation: the 'desperation threshold', an hypothesis that is analogous to other social sciences theories (Barclay et al., 2018; Kunreuther & Wright, 1974; Lybbert & Barrett, 2007; Mishra & Lalumière, 2010; Roumasset, 1971; Scott, 1977; Winterhalder et al., 1999). Our study provides a new source of evidence for the desperation threshold model. Until now, tests of the model have mainly been conducted either (i) in a lab, where poverty (or more precisely, 'need') is artificially induced (Deditius-Island et al., 2007; Mishra & Lalumière, 2010; Pietras et al., 2006, 2008; Pietras & Hackenberg, 2001; Radkani et al., 2023; Rode et al., 1999), or (ii) in populations where starvation is a realistic possibility (Caballero, 2010; Kuznar, 2001; Mace, 1990; Maertens et al., 2014; Tucker, 2012). Our study suggests that a formally equivalent mechanism can apply in the real world to more affluent populations, and that 'desperate' risk taking can happen when starvation is unlikely.

The desperation threshold model makes a more precise prediction (P1): individuals should avoid risk just above a 'desperation threshold' yet seek risk below it (Figure 4.1B). Most previous real-world studies only searched for an increase in risk taking when poverty increased (Caballero, 2010; Kohler & West, 1996; Mace, 1990; Tucker, 2012). In our study, we aimed to simultaneously test the increase and the decrease. Our findings clearly show that both risk taking and risk avoidance were more common among participants with the fewest resources (Table 4.2). Yet, the evidence for a V-shape was less clear: we obtained the predicted V-shape when using our subjective resources measure and a segmented regression model, but not when using our objective resources measure or a polynomial model. In our preregistration, we stated the expectation that we would be less likely obtain evidence for P1: it requires (i) our resource measure to be precise enough to tell apart individuals just-above the threshold from the ones just-below, and (ii) that the threshold itself does not vary too much between individuals. Still, our Analysis 1 produced conflicting results: we only obtained the predicted V-shape when using subjective resources and a segmented model. Even though we did not anticipate it, we can propose *post-hoc* explanations for this finding. The segmented model might be better suited to test our hypothesis: it fits one relation on only the very bottom part of the resource distribution, while a polynomial regression fits the whole sample at once. Polynomial regressions can also be unreliable for making predictions for extreme values of the independent variable (Simonsohn, 2018), the case we are interested in here.

As for the measure, subjective resources produced more clear-cut results than objective resources in all analyses (Figure 4.2, Figure 4.4, Table 4.4, and – on time discounting – Table 4.5). This could mean that the subjective measure is simply a better measure of poverty, and that people are better than researchers at estimating their own situation. In particular, their self-assessment could take into account savings and anticipations of the future, whereas our objective measure did not. This echoes the recurrent finding that subjective socio-economic status is more predictive of health outcomes than objective socio-economic status (Adler et al., 2000; S. Cohen et al., 2008; Pepper & Nettle, 2014). This result is also reminiscent of a recent finding (Blasco, 2023), that in multiple European countries, "deprivation ceases to be correlated with income below a certain threshold (p. 1). Importantly, the desperation threshold might differ between individuals, as some individuals have higher needs. We tried to capture this in our objective measure, by dividing income by unavoidable costs. Yet, there are likely other 'needs' that were not measured. Our subjective measure might better incorporate those needs, since participants estimated for themselves their risk of lacking resources in the near future. Furthermore, our objective resources variable measures flows of resources over a month (income and unavoidable costs), but not stocks (capital). It could thus measure variations in resources, rather than the total amount of resources available, which determines whether an individual can make ends meet. In our sample, 1.6% of the answers have higher unavoidable costs than income over a month. Our objective measure places those answers at the very bottom of the resources distribution. Those points likely reflect an exceptional expense or an unusually low income over one month, which massively influences our objective measure – probably more so than our subjective measure, which should also capture savings and anticipations of the future. Actually, it might be impossible for an extremely poor individual to spend more than she earns, if she has no savings and no options to borrow money. That being said, subjective measures of resources risk are influenced by psychological states, which brings a danger of circularity. It is possible, for instance, that some individuals are panicking because of some unmeasured factor, and therefore report both a higher readiness to take risks and a worse subjective financial situation. In this case, our results still suggest that high financial worries can produce both risk taking and risk avoidance, which is also a new finding.

4.6.2 Alternative explanations

The desperation threshold model proposes that poverty causes variations in risk taking, but our data only provide evidence for associations. Yet, our finding that populations in poverty are 'polarized' in terms of risk taking, with a mixture of risk avoiders and risk takers, enriches the picture of the link between poverty and risk taking.

This result could be produced by different mechanisms. First, causality could be reversed. If risk taking was an entirely stable personality trait, one would expect extreme risk taking or risk aversion to produce a higher chance of poverty. Indeed, some of the most risk-prone individuals would end up very poor as the risks they took have not paid off, while the risk-averse individuals would refuse profitable opportunities, and end up poorer than average. However, risk taking is only weakly-to-moderately stable over time in our data (ICC = .48), in line with other findings (Mata et al., 2018; Schildberg-Hörisch, 2018). Moreover, there is evidence that short-term variations in resources can modify risk taking. Using the same data and measures, (Nettle, Chevallier, et al., 2025) found evidence that within-person reduction in the objective resources variable were associated with within-person reduction in risk taking. Recently, (Akesaka et al., 2023) also found that individuals most dependent on social security were ready to take more risks the week before welfare checks arrived.

Poverty could also produce our results through a different mechanism. For instance, a lower education or a lower cognitive capacity due to financial stress (Mani et al., 2013) could lead individuals with fewer resources to not understand the risk questions as well. Though, we did not find any evidence of an association between resources and consistency in risk answers (section 4.4). This class of explanation would also predict that individuals in poverty misunderstand other questions as well, and display extreme scores in other domains than risk taking. In our data, the "time discounting" questions were similar in terms of language, and allow for comparison. To test for this alternative explanation, we replicated our exploratory analysis using time discounting. Our results (section 4.4) suggest that among the most deprived participants, steep time discounting was more frequent, but flat time discounting less frequent, whereas the alternative explanation (i.e. more errors amongst participants with low resources) would predict both to be more frequent.

Our results could also be driven by measurement error: some participants may fill the survey less seriously, and report extreme levels of both resources and risk taking, in either direction. But if so, we would find the same phenomenon not only on time discounting, but also among the individuals with high objective resources. This was not the case: the top 5% in objective and subjective resources showed a lower variance in risk taking, and provided fewer extreme answers (Table 4.4).

4.6.3 Limitations

The Changing Cost of Living sample was not representative of UK or French populations. There were no participants below the age of 25, and few over 45. Also, the recruitment via online participation platforms produced an oversampling of individuals with low incomes (for details, see Nettle, Chevallier, et al. (2025)). This could have been an advantage to test our hypothesis, which requires a sufficient number of low income individuals to detect the pattern. To evaluate how generalisable our results are, future research should test our predictions in other populations, ideally from different regions with different levels of standard of living.

Our risk taking measure also has limitations. Hypothetical lotteries measures may have suboptimal external validity. They predict behaviors like portfolio choice, occupational choice, smoking, and migration Dohmen et al. (2011), but less well than "general risk questions", like "Are you generally a risk taking person or do you try to avoid risks?" (Dohmen et al., 2011; Frey et al., 2017). This second measure also tends to be more stable over time, and have a higher 'convergent validity' - that is, better generalizes across domains of risk taking Dohmen et al. (2011). However, the 'desperation threshold' only applies to risks related to resources. It can make a clear prediction on hypothetical lotteries (figure 4.1B), but not on the general risk questions. Moreover, because our goal was to capture risk taking as a response to current material conditions rather than a lasting personality trait, the lower temporal stability is thus not an issue for our research question. The hypothetical gambles thus seemed appropriate for our study, even if imperfect, for example because they were not actually incentivized.

4.6.4 Implications

Our study has important societal implications, both to explain and to remedy problems associated with poverty. In our data, people in poverty were more likely to (i) avoid risk even when it would, on average, benefit them, and to (ii) take risks even when it will, on average, be detrimental. In both cases, such individuals are further from 'expected payoff' decision-making, which is, by definition, optimal if one wants to maximize resources in the long term. In a way, the desperation threshold makes it optimal to make decisions that are long-term sub-optimal from a poverty-reduction perspective.

Concretely, Banerjee (A. Banerjee, 2004) points out that both 'poverty as vulnerability' and 'poverty as desperation' can lock people in poverty: if people in poverty have too much to lose, they refrain from investing; if they have little to lose, they have "no obvious reason to want to repay" (p.62) a loan, and therefore no one would lend them resources. In both cases, it is harder for them to escape poverty. In previous research in economics, risk aversion has often been deemed as the cause of suboptimal decisions – in particular in agricultural economics, where it was proposed as the cause of field scattering (e.g, McCloskey (1976)) or refusal to adopt new, more profitable, technologies (Morduch, 1995).

'Desperate risk taking' likely imposes major costs on individuals, communities, and society at large. When below the desperation threshold, our model predicts that people will take risks even when they have a negative expected payoff (Figure 4.1B). In our data, the proportion of participants ready to take such 'bad risks' was twice as high in the lowest 5% in subjective resources (Table 4.2). In reality, risks that people in poverty have access to are likely to fall into this category: they lack the money to invest in risky but profitable assets, and can only borrow with astronomically high interest rates (A. V. Banerjee, 2003). Also, a desperate individual needs resources urgently, to fulfill a basic need. One way to obtain resources quickly without investing might be to engage in property crime. It is a particularly risky activity: it implies the fundamental uncertainty of being caught and punished.

In some cases, it is thus plausible that desperate risk taking takes the form of crime. Empirically, risk taking (measured by hypothetical lotteries) has indeed been found to strongly predict property crime (Epper et al., 2022). Crime (and in particular property crime) is more frequent in deprived (Hsieh & Pugh, 1993) or unequal (Daly, 2017; Kelly, 2000) populations, a phenomenon that some attribute to a 'little to lose' feeling (Brezina et al., 2009; Daly & Wilson, 1997), or to "a mind-set in which offenders are seeking less to maximize their gains than to deal with a present crisis" (p. 167, Jacobs & Wright, 1999).

However, if we equate willingness to take risks and willingness to engage in property crime, our model and our data have a counter-intuitive prediction. It is possible that people in poverty are, on average, more law-abiding (risk taking is on average lower), and yet, most crime occurs there, since people ready to take extreme risks are mostly found among them (Figure 4.2). This could, in turn, create discrimination: people in poverty could be suspected and mistrusted more, even though the majority of them are on the contrary especially unlikely to engage in crime. In other words, the fact that a minority of people in poverty are in a situation where they have to take risks might create a stigma affecting other people also in poverty. This could generate the fact that poorer people are, empirically, trusted less Boon-Falleur et al. (2024), even though they might be less likely to engage in unethical behavior (Piff et al., 2010; Piff et al., 2012).

Finally, the desperation threshold has implications for the welfare system. By helping to meet basic needs under any conditions, social security measures – for instance, unemployment benefits or health insurance – should alleviate the desperation thresholds, and therefore 'smoothen' individuals' utility function. This should reduce both extreme risk aversion (one has less to lose if there is a strong safety net) and extreme risk taking (desperation would become rarer, or non-existent). Empirically, both risk aversion (Schroyen & Aarbu, 2018) and crime rates (Rudolph & Starke, 2020) tend to be lower in countries that have a stronger welfare state, which may indicate that such smoothing indeed takes place.

4.7 Funding and acknowledgements

The authors report no conflict of interest. BdC's contributions have been supported by the Agence Nationale de la Recherche (ANR-23-CE28-0005-01). WEF's contributions have been supported by the Dutch Research Council (V1.Vidi.195.130) and the James S. McDonnell Foundation (https://doi.org/10.37717/220020502). The Changing Cost of Living Study was funded by the French Agence Nationale de la Recherche (ANR-21-CE28-0009); the NIHR (Application Development Award: Universal Basic Income. Grant number: NIHR154451. Research Registry number: researchregistry8567); the University of York Cost of Living Research Group; and the UK Prevention Research Partnership (MR/S037527/1) collaboration, ActEarly. UK Prevention Research Partnership is funded by the British Heart Foundation, Cancer Research UK, Chief Scientist Office of the Scottish Government Health and Social Care Directorates, Engineering and Physical Sciences Research Council, Economic and Social Research Council, Health and Social Care Research and Development Division (Welsh Government), Medical Research Council, National Institute for Health Research, Natural Environment Research Council, Public Health Agency (Northern Ireland), The Health Foundation and Wellcome. The authors thank Ulysse Klatzmann, Camille Boissel and Aurélien Allard for their precious help.

4.8 Data transparency and reproducibility

The data are available here: https://osf.io/e8g3p/. This article was written in R markdown, which makes the analyses and the plots reproducible inside the document. The code, and the python code used to produce Figure 4.1, can be found in this repository: https://github.com/regicid/changing_cost_of_living_desperation.

4.9 Appendix

Table 4.2: Demographic characteristics of the samples. Ns in this table represent numbers of participants. Variables are as reported in the first month of the study (September 2022). Financial strain is a self-report variable of how the participant is managing financially.

	France	UK	Overall
	(N=232)	(N=240)	(N=472)
Gender			
Woman	119 (51.3%)	122 (50.8%)	241 (51.1%)
Man	108 (46.6%)	116 (48.3%)	224 (47.5%)
Prefers not to say	0 (0%)	0 (0%)	0 (0%)
Missing	5 (2.2%)	2 (0.8%)	7 (1.5%)
Age			
Mean (SD)	41.2 (8.45)	42.2 (12.3)	41.7 (10.6)
Median [Min, Max]	41.0 [25.0, 59.0]	40.0 [24.0, 76.0]	41.0 [24.0, 76.0]
Missing	3 (1.3%)	0 (0%)	3 (0.6%)
Financial strain			
Finding it very difficult	12 (5.2%)	10 (4.2%)	22 (4.7%)
Finding it quite difficult	26 (11.2%)	22 (9.2%)	48 (10.2%)
Just about getting by	75 (32.3%)	51 (21.3%)	126 (26.7%)
Doing alright	97 (41.8%)	112 (46.7%)	209 (44.3%)
Living comfortably	22 (9.5%)	40 (16.7%)	62 (13.1%)
Missing	0 (0%)	5 (2.1%)	5 (1.1%)

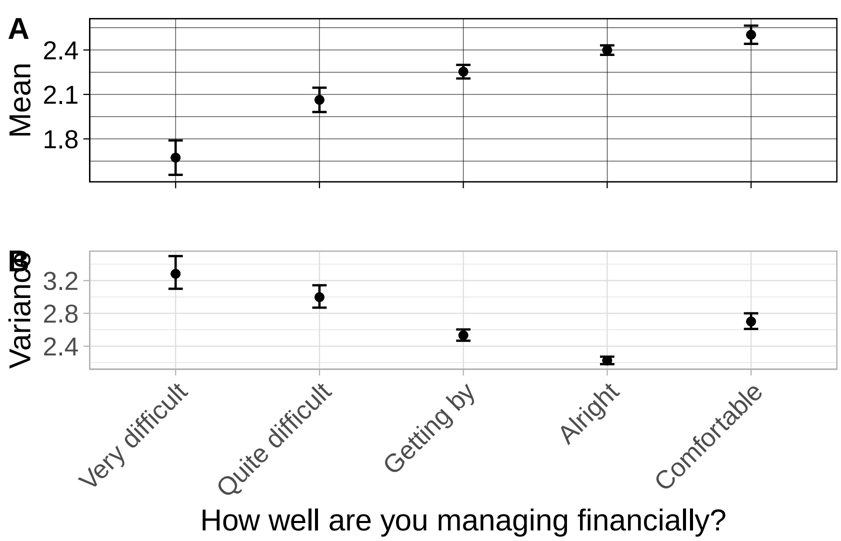

Figure 4.5: Mean and variance in risk taking for participants, grouped by their answer in the 'managing financially' question

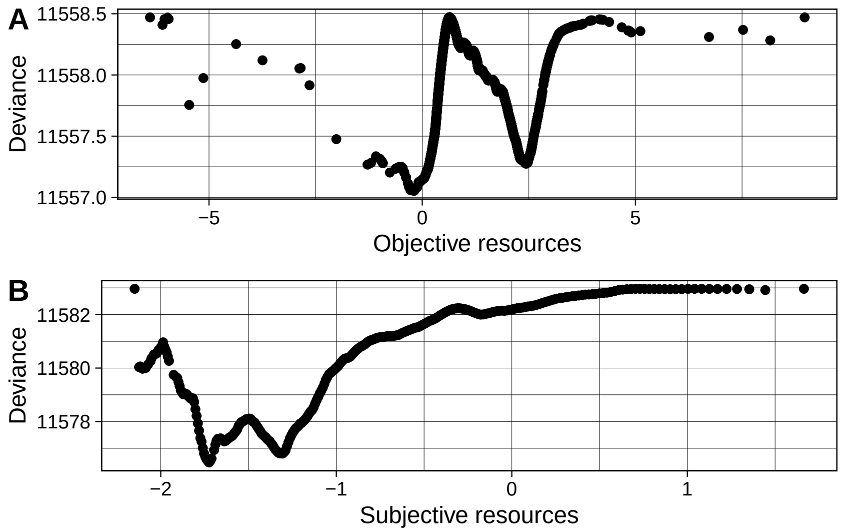

Figure 4.6: Deviance of the statistical models depending on the changepoint location, using objective (A) and subjective (B) resources

Table 4.3: Standardised coefficients of the segmented regression using objective resources as independent variable.

Variable	Estimate	Std. Error	df	t value	p-value
Intercept	0.022	0.059	939	0.368	0.713
Objective Resources (before changepoint)	-0.006	0.046	4781	-0.127	0.899
Objective Resources (after changepoint)	0.062	0.026	4612	2.391	0.017 *
Age	-0.084	0.033	552	-2.563	0.011 *
Gender: prefers not to say or self-describe	-0.418	0.368	643	-1.135	0.257
Gender: woman	-0.196	0.067	475	-2.934	0.004 **

Table 4.4: Standardised coefficients of the segmented regression using subjective resources as independent variable.

Variable	Estimate	Std. Error	df	t value	p-value
Intercept	0.001	0.064	907	0.018	0.986
Objective Resources (before changepoint)	-1.07	0.437	3800	-2.449	0.014 *
Objective Resources (after changepoint)	0.055	0.023	2704	2.357	0.018 *
Age	-0.085	0.033	554	-2.58	0.01 **

Variable	Estimate	Std. Error	df	t value	p-value
Gender: prefers not to say or self-describe	-0.39	0.37	639	-1.054	0.292
Gender: woman	-0.186	0.067	476	-2.766	0.006 **

Table 4.5: Standardised coefficients of the model using subjective resources as independent variable, and the alternative changepoint.

Variable	Estimate	Std. Error	df	t value	p-value
Intercept	0.004	0.06	826	0.067	0.947
Subjective Resources (before changepoint)	-0.335	0.154	3918	-2.181	0.029 *
Subjective Resources (after changepoint)	0.067	0.025	2962	2.697	0.007 **
Age	-0.087	0.033	554	-2.637	0.009 **
Gender: prefers not to say or self-describe	-0.392	0.37	639	-1.06	0.29
Gender: woman	-0.191	0.067	475	-2.846	0.005 **

Table 4.6: Risk taking statistics by resources categories. Asterisks denote the p-values of tests comparing the category with the rest of the sample, using t-tests to compare means, F-tests to compare variances and Chi-squared tests to compare prevalences. In each column, the set of p-values was corrected for multiple comparisons, using Holm-Bonferroni method. Asterisks represent significance levels: * $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$.

Categories	Mean risk taking	Variance in risk taking	% of risk takers	% of risk avoiders	n
Full sample	2.31	2.57	6	17.4	4882
Top 5% in objective resources	2.47	2.11 *	6.2	10.4 *	242
Top 5% in subjective resources	2.32	2.09 **	4.7	15.5	429
Bottom 5% in objective resources	1.94 **	3.51 ***	8.4	34.7 ***	242
Bottom 5% in subjective resources	2.29	3.72 ***	12 ***	23.7 *	243

Table 4.7: Time discounting statistics in extreme resources categories. Asterisks denote the p-values of tests comparing the category with the rest of the sample, using t-tests to compare means, F-tests to compare variances and Chi-squared tests to compare prevalences. In each column, the set of p-values was corrected for multiple comparisons, using Holm-Bonferroni method. Asterisks represent significance levels: * p < 0.05; ** p < 0.01; *** p < 0.001.

Categories	Mean time discounting	Variance in time discounting	% of high discount	% of low discount	n
Full sample	3.17	4.98	13.5	18	4882
Top 5% in objective resources	2.36 ***	3.87 *	5.8 **	21.7	242
Top 5% in subjective resources	2.71 ***	4.35	8 **	23.2 *	429
Bottom 5% in objective resources	3.65	7.19 ***	30 ***	22.4	242
Bottom 5% in subjective resources	4.1	6.35 **	31.2 ***	15	243

5 Explaining the paradoxical effects of poverty on decision making: The Desperation Threshold Model

This paper has been published as a preprint: de Courson, B., Frankenhuis, W., van Gelder, J., & Nettle, D. (2025). Explaining the paradoxical effects of poverty on decision making: The Desperation Threshold Model. https://doi.org/10.31234/osf.io/bdvpa_v1. Daniel Nettle and I have contributed equally.

5.1 Abstract

The impacts of poverty and material scarcity on human decision making appear paradoxical. One set of findings associates poverty with risk aversion, whilst another set associates it with risk taking. We present an idealized general model, the 'desperation threshold model' (DTM), that explains how both these accounts can be correct. The DTM posits utility functions with a threshold or 'cliff', a point where utility declines steeply with a small loss of resources because basic needs cannot be met; and a 'rock bottom', a point where utility is not made any worse by further loss of resources, because basic needs are not being met anyway. Above the threshold, people's main concern is not falling below, and they are predicted to avoid risk. Below the threshold, they have little left to lose, their most important concern is jumping above, and they are predicted to take risks that would otherwise be avoided. Versions of this model have been proposed under various names across biology, anthropology, economics and psychology. We review a broad range of relevant empirical evidence from a variety of societal contexts. Though the model primarily concerns individual decision making, it connects to a range of population-scale and societal issues such as: the consequences of economic inequality; the deterrence of crime; and the behavioural consequences and optimal design of the welfare state. We discuss a number of interpretative issues and offer an agenda for future DTM research that bridges disciplines.

5.2 Poverty and risk taking: A paradoxical relationship

In a sample of 17,000 Swedes, those with fewer financial resources are less likely to invest in risky assets like stocks and shares. The relationship holds even after controlling for how much money they invest in total. It's not just that poorer individuals save less (which is unsurprisingly the case), it's that they are less likely to choose risky assets for what they do save. Since risky assets generally have higher long-run financial returns, poorer individuals, by avoiding risk, may be missing out on long-term gains. Taking less risk when having fewer resources seems perfectly intuitive: one has less of a buffer in the event of a bad outcome; one's first priority should be to avoid the financial situation getting any worse.

Yet consider U.S. state lotteries. These are highly risky: for every dollar handed over, the average return is only 70c; but that 70c on average is distributed as a large chance of getting nothing and a small chance of getting a big payout. Income is a strong predictor of buying lottery tickets: the lower people's incomes, the more they buy. In the 1% poorest zip codes in states with lotteries, the average adult spends $600 a year on lottery tickets, compared to $150 a year in the richest 1%; four times as much in absolute terms, and thirty times as much as a share of income (Economist, 2024). This seems intuitive too: when people have so little that they can't make ends meet, they will grasp at any chance of getting a lump more resources, even a highly risky one.

These two examples illustrate two plausible accounts of what poverty does to decision making: the first, that people in poverty cannot afford to take risk; the second, that they are especially prone to do so. Both accounts have been discussed and supported in the literature over decades (Kish-Gephart, 2017). As a consequence, the literature is confusing, containing "at least two distinct and, prima facie, inconsistent views" (A. Banerjee, 2004, p. 60): that people in poverty have too much to lose, and hence have a safety-first attitude (Donkers et al., 2001; Guiso & Paiella, 2008; Haushofer & Fehr, 2014; M. Lipton, 1968); and that they have little left to lose, and hence throw prudence out the window (A. V. Banerjee & Newman, 1994; Haisley et al., 2008; Hsieh & Pugh, 1993; Patterson, 1991; Pratt & Cullen, 2005).

This paper presents and discusses an idealised model of decision making, the desperation threshold model (DTM). The DTM does not just accommodate, but actually predicts, that poverty would sometimes increase and sometimes decrease risk taking. The DTM assumes that the relationship between material resources and utility, rather than being a wholly concave function, contains a cliff edge and a 'rock bottom'. This is because people have some bundle of basic needs that they seek to satisfy as a first and most important priority. If they feel they are just succeeding in doing so, they are on top of the cliff. Once they fail to do so, or seem likely to fail, they fall to rock bottom. The implication of poverty for decision making thus depends on whether poverty puts a person just below or just above the cliff edge. Just below, it matters little whether one has missed by a little or a lot: one is in dire straits and has 'little more to lose'. Just above, though, one has a great deal to lose: usually more, in fact, than to gain by taking risks for further acquisition.

The basic idea of the DTM has been proposed or implied in several disciplines at several times. It has generated multiple research programs, which often make little reference to one another. In this paper, we aim to: bring together the diverse versions of the DTM under one name; clarify assumptions, implications and conceptual issues; and review the relevant empirical evidence. The DTM also provides a bridge between individual-level (micro) and population-level (macro) processes. As such, it can be a parsimonious lens for understanding population-scale phenomena, such as the effects of inequality and different kinds of institutions on behaviour. We will review some of these societal applications, discuss interpretative issues, and make some suggestions for how DTM research could be extended and refined later. First, though, we present the DTM itself.

5.3 The desperation threshold model

5.3.1 The core of the model

To introduce the DTM, we employ the language of rational choice theory and utility functions. This should not be seen as a commitment to the idea that humans are always rational and deliberate, or maximise a single currency. Rather, it is a useful though simplified idealisation to make explicit the pattern of valuation that we propose.

The DTM posits that the mapping between material resources and utility is non-linear with a particular shape. Namely, as one moves in the direction from more to less resources, there must be a point where utility declines with increasing steepness, like dropping off a cliff. At a lower resource point still, this steep decline must level out at rock bottom. Two examples of such mappings are shown in figure 5.1A. The dotted line shows the 'starvation threshold' of Stephens (1981) version, whilst the dashed line is a sigmoid curve, another utility function often discussed in instantiations of the DTM (e.g. Kuznar, 2001). We consider these both instances of DTMs.

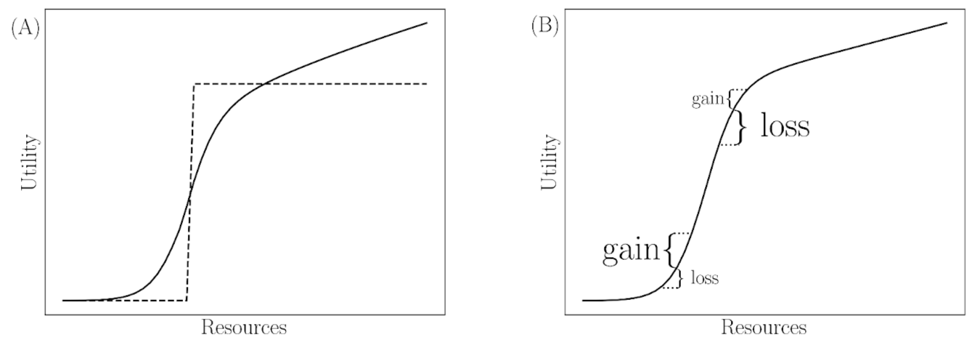

Figure 5.1: (A) Utility functions that count as instances of the DTM. The dotted line represents Stephens' (1981) classic biological model, where the step is starvation. The dashed line represents a sigmoid function, a more general formulation that also qualifies as a DTM. (B) Graphical illustration of why the curvature of the utility function determines optimal risk taking. In the convex segment, a resource gain brings more utility than an equal loss takes away. In the concave segment, the reverse is true.

The central insight found in all versions of the DTM concerns risky decisions, where risk is defined as variance in outcomes. For example, a lottery that might result in a £10 win, or might result in the loss of the £2 stake, is risky. Accepting £1 for sure is not. The utility impact of a risky decision depends on where on the resource curve one currently stands (figure 5.1B). If one's current resources put one at the top of the steep section, then a loss would be much worse than a gain would be good. Even a small loss of resources would make one markedly worse off in utility. This makes the (smaller) potential upside gain much less interesting than avoiding the possible loss. If one is currently at the bottom of the cliff, things can barely be any worse, so the downside risk of a risky decision is not so consequential. By contrast, a small gain in resources could mean a huge utility gain. Thus, an agent should be averse to risk when resources are above the threshold level, and choose risk when resources are below. The principle surfaces in many contexts. In the last minutes of a knockout game of football (soccer), the leading team typically plays safe and tries to use up time, avoiding risk. The trailing team, on the contrary, takes desperate actions, such as the goalkeeper leaving their net empty to try to score a goal. What is usually a terrible idea becomes reasonable due to a threshold: losing 1-0 is not much worse than losing 2-0; but drawing 1-1 is dramatically better.

5.3.2 Grounding the basic assumptions

The DTM is constituted by the twin elements of: a cliff in the utility function, and a rock bottom. Why might this be a reasonable pattern to assume?

We begin by the cliff, i.e. a steep, or vertical, section around the basic needs level. This assumption is not radically new. Economists routinely assume 'diminishing marginal utility': as consumption increases, the extra pleasure derived from every dollar spent decreases. This assumption is reasonable. People will use their first available resources to satisfy the desires that boost utility the most, and then turn to progressively less impactful ones. To put this the other way around, the poorer one gets, the more painful it is to lose any further money, as this requires cuts to increasingly impactful or 'basic' goods. The assumption of diminishing marginal returns is also validated empirically. When we replace the theoretical notion of utility with measured life satisfaction, the overall relationship we observe with income is one whose gradient flattens out as resources increase (see e.g. Nettle & Dickins, 2022).

For some fundamental goods, one cannot get any of the benefit for any less than all of the expenditure. For example, a person can be evicted for paying 90% of their rent; only if they pay 100% do they get the right to a home. This produces a near-verticality in the utility function around the point where the home is secured. Utility functions can thus have extremely steep or even vertical regions, where resources are making the difference between securing or losing goods that satisfy basic needs.

We see basic needs as encompassing material safety and bodily integrity (food, shelter, warmth), but also what has been termed 'the social basis of respect' (REF). This is whatever one needs to have in order to be considered a recognised and adequate member of society; to be, as Sen (1983) puts it: 'free from public shame from failure to satisfy convention' (p. 167). Smith (1776) similarly stated that 'by necessities, I understand not only the commodities which are indispensably necessary for the support of life, but whatever the customs of the country renders it indecent for creditable people...to be without. [...] a creditable day labourer would be ashamed to appear in public without a linen shirt.' (p. 869-870). The British sociologist Townsend argued that the poverty line was a point where, descending the income scale, a large number of families dropped out or were excluded from their community's style of living (Townsend, 1979). These various formulations all capture the idea that there are levels of income below which not just somatic but also basic social integrity is endangered.

As well as a cliff, the DTM assumes a rock bottom. There are several ways to justify this assumption. The first is a reductio ad absurdum: what would it mean for utility to go down endlessly? There must be a level of resources x so inadequate that the individual cannot satisfy any needs at all. Having 90% of x or 50% of x is not actually any worse than having x: the number of needs that can be satisfied is the same. Resources and needs satisfaction must then become decoupled at some point. Note that this decoupling, as well as occurring at the point where no needs can be met, also occurs if there is a 'safety net' and the individual has reached it. By a safety net we mean any mechanism that guarantees minimal well being, such as social assistance or the welfare state, or 'outside options' like fleeing or defaulting (Kohler & West, 1996). Once one has reached the safety net level, a further loss of personal financial resources does not necessarily entail a further loss of utility.

A related justification of the rock bottom assumption comes from evolutionary reasoning. Natural selection favours behaviour that maximizes individuals' reproductive value. Reproductive value is bounded at zero. Along these lines, Rubin & Paul (1979) argue that below the 'minimum income needed in order to support a mate and offspring' (p. 593), reproductive value is as good as zero, and hence natural selection would favour mechanisms that led to risk taking under these circumstances. when the individual received cues that their reproductive value was close to zero).

5.3.3 The predictions of the DTM

Having introduced the DTM, we turn to its predictions. We have mentioned two:

- Caution prediction. Individuals whose resources are only just adequate to meet their needs will show greater avoidance of risk, compared to those whose resources are abundant;

- Desperation prediction. Individuals who are unable to meet their basic needs will take greater risk, compared to individuals who can meet their basic needs.

Though these predictions do follow from the assumptions, they are vague as stated. For example, the DTM does not predict that people just above the threshold will never take any risk. Some risks are very attractive, like a $1 ticket with a 95% chance of winning $1000. We would expect pretty much anyone to take this risk.

It is helpful to classify risky options on the basis of the average return if they were taken many times. This is the sum of the possible resource outcomes multiplied by their respective probabilities (statistically, the expected value). An 'positive-average-return' risk is one where this number is positive; if you took it many times, you would gain more than you lost. For a 'negative-average-return' risk, your long-run losses would be larger than your gains. If the mapping of monetary resources to utility were linear, it would be simple: one would take positive-average-return risks and avoid negative-average-return ones.

This helps us make the DTM predictions more specific. We define the risk premium as the amount by which the average return of a risky option has to exceed zero in order for a rational person to take it. The refined version of the caution prediction then becomes that a person whose resources are just above the threshold requires a large risk premium. The model predicts that there are some positive-average-return risks they will not take. The refined version of the desperation prediction is that a person whose resources are at rock bottom will accept a negative risk premium. The model predicts them to take all positive-average-return risks with a potential payoff large enough to move them up the cliff; but also, many negative-average-return risks, as long as these too offer some chance of jumping up.

Figure 5.2 illustrates this principle. The figure assumes a sigmoid utility function, and depicts a scenario where an individual is offered an option that will, with equal probability, yield either -100 resource units, or 100 + x resource units. We denote the risk premium with x: The risk premium converges to zero as resources pull away above the threshold. With resources just above the threshold, she needs a large positive risk premium to offset the chance of plunging below the threshold on the downside. Equivalently, she would readily pay for a safer option even if it had a lower average return. With resources just below the threshold, by contrast, she has to take risks with a negative premium, just because of the chance of returning above the threshold. She would thus be ready to pay for a riskier option, even one that will, on average, make her poorer.

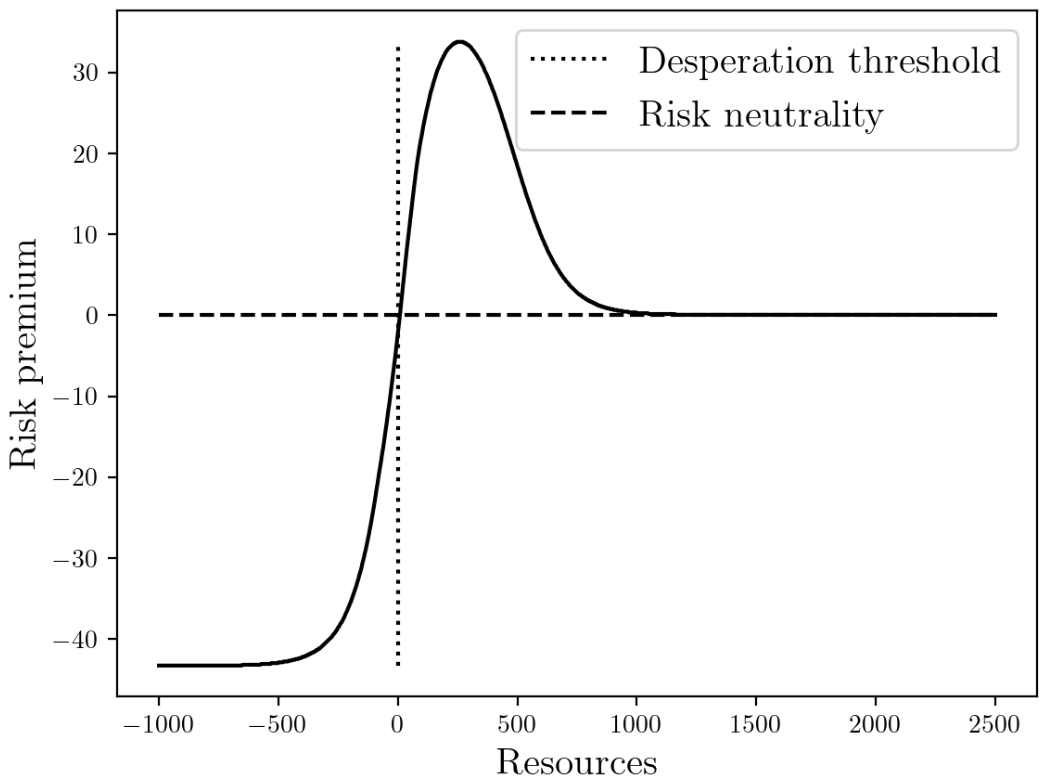

Figure 5.2: The 'risk premium', the minimum amount x that is required to make an option leading with equal probability to a payoff of -100 or 100 + x resource units worth taking, assuming a utility function combining a sigmoid function and a linear one: $U(x) = 1/(1 + exp(-x) + (x\ 0) * x/50$.

The DTM also makes a testable prediction about variation in risk taking. Let us assume the utility function underlying figure 5.2 and imagine that people's resources vary over time, at random, by up to a few hundred units. For an individual with a baseline of 2000 units of resources, these fluctuations would make absolutely no difference to which risks they were or were not prepared to take. For an individual with a baseline of 0 resource units, they would make a vast difference: with a small disturbance to their resource levels, they would go from fairly extreme risk avoidance to fairly extreme risk seeking. Thus, the model predicts that individuals whose resources are scarce should show greater intra-person temporal variability in their risk taking behaviour than individuals whose resources are abundant.

We can also state this prediction with regard to variation at the population level. Imagine that individuals vary a little in the exact position of their thresholds on the resource axis. For one person, +50 might be just above the threshold, but for another, +50 might be slightly below, because their needs and commitments are slightly different. If we are observing an affluent population all of whose resources are above 2000 units, this variation in threshold position has no consequences; such a population would be uniform in their risk behaviour. By contrast, a deprived population all of whose resources were +50 units would constitute a mixture of some people just above their thresholds and some people just below theirs. In such a population there would be a marked heterogeneity in risk taking. This leads to the variation prediction:

- Variation prediction. Populations in conditions of resource scarcity should show greater variation in risk taking than those in conditions of resource abundance, whether variation is defined within individuals over time, or between individuals.

5.3.4 Antecedents of the DTM

As noted, the DTM has arisen independently in several literatures, but these have remained extremely siloed. Our presentation here aims to bring the different versions together in a common format. We see four literatures as flowing directly into the DTM (though see 5.6.1 and 5.6.4 for links to further literatures that explore similar constructs, such as basic needs, thresholds, and sigmoid functions).

One literature, from microeconomics, focuses on the fact that people sometimes seek and sometimes avoid risk: they simultaneously gamble and purchase insurance. The classic works literature introduced non-monotonic utility functions and 'aspiration levels' (thresholds) to explain this (Diecidue & Van De Ven, 2008; Friedman & Savage, 1948; Robson, 1992; Roy, 1952; Simon, 1955).

A second, from agricultural economics, is concerned with why subsistence farmers are risk averse and conservative in their farming choices, assuming that they aim to avoid falling below a 'disaster level' (i.e. the caution prediction) (Chayanov, 1926; Kunreuther, 1971; Masson, 1974; Roumasset, 1971). This literature has also explored the idea that when things get really bad, a 'reswitching' to risky strategies should occur (desperation prediction).

The third literature comes from development economics. It focuses on the situation of poverty, covering both the idea that when things are at rock bottom they cannot get any worse (A. Banerjee, 2004; A. V. Banerjee & Newman, 1994), and the idea that a small extra resource can have an outsized effect, by making escape from poverty possible (Lybbert & Barrett, 2007, 2011).

Finally, an influential tradition of 'risk-sensitive foraging theory' began in animal behavioural ecology (Caraco et al., 1980; Stephens, 1981). The idea here is that starvation constitutes the ultimate threshold. When it is imminent, animals should take any level of risk to gain food (desperation prediction), whereas once it has been averted for the time being, they should avoid too much risk (caution prediction). This idea diffused from animal behavioural ecology into evolutionary anthropology and evolutionary psychology (Kuznar, 2001; Mace & Houston, 1989; Mishra & Lalumière, 2010; Pietras & Hackenberg, 2001; Rode et al., 1999; Winterhalder et al., 1999).

Whilst we acknowledge that DTM ideas are widespread, we are keen to stress that the DTM is different from the status quo in models of human decision making. Most work in microeconomics assumes that utility functions are concave across all the ranges that matter for decision making, generating mild risk aversion. This is known as Gossen's first law. The DTM is compatible with Gossen's first law across most of the resource spectrum; it merely adds that there is a convex segment brought about by the presence of a rock bottom, and that people find themselves in this segment often enough for it to matter. Non-monotonic utility functions that depart from Gossen's first law have been proposed multiple times, as mentioned above. But they have not been widely adopted in practice.

This may be in part for reasons of analytic convenience. Assuming concavity of the whole utility function is necessary to produce unique equilibria in models of agents interacting in markets. For example, it is a condition of the Arrow-Debreu model, which guarantees the existence and uniqueness of a 'general equilibrium' in a perfectly competitive economy. Assuming concave utility functions preferences may be what Cherrier (2023) called a 'tractability trap', i.e. a modelling choice made for tractability purposes that is so convenient that it becomes entrenched in the field.

5.3.5 The DTM and Prospect Theory

Readers may well be familiar with an existing model that features a non-monotonic value function, and which predicts a combination of risk taking and risk aversion: Prospect Theory (Kahneman & Tversky, 1979). The DTM is not, however, reducible to Prospect Theory. Indeed the two approaches do not generally tackle the same questions or make the same predictions.

Prospect Theory is a descriptive psychological theory concerning how people evaluate risky options. It was developed to capture the ways in which people appear to depart from models of perfect rationality, notably expected utility theory. It has two main components: a probability weighting function, and a value function. The probability weighting function captures cognitive biases related to probabilities: people have been observed to overweight very unlikely outcomes, and underweight very likely ones (at least when scenarios are presented by description as opposed to by experience; (Hertwig & Erev, 2009)). The value function captures the fact that valuation of outcomes is asymmetric around a reference point. That reference point is usually taken to be the status quo. Thus, people evaluate the same material change differently if it represents a loss, as opposed to a gain, relative to what they already have. They are predicted to be more risk averse for gains than for equivalent losses.

The DTM does not assume constraints on rationality, nor that people depart from maximising expected utility. Rather, it models which decisions would maximise expected utility given a utility function with the particular shape shown in figure 5.1. It does not incorporate any biases in estimating probabilities or any difference between losses and gains relative to the status quo. Under the DTM, what should drive decisions under risk is whereabouts in the resources-utility space the various possible outcomes would leave the person. Whether these outcomes represent a loss or a gain relative to the status quo is not considered. Prospect Theory-type departures from perfect rationality could also occur, but they would be deviations from the rational pattern predicted by the DTM.

Mishra et al. (2012) designed experiments in which the predictions of the DTM and those of Prospect Theory could be tested simultaneously. Participants chose between risky and riskless options to gain resources. There were two cross-factored independent variables: participants currently had (or did not have) a minimum level of resources that they needed; and the options were framed in terms of losses (or gains). The results showed both DTM and Prospect Theory effects. People chose risk more often when they were going to fall short of what they needed (the DTM's desperation prediction). They were also, collapsing across positions relative to need, more likely to choose risk when the framing was in terms of losses than gains (the Prospect Theory prediction). The need-based effect size was however considerably larger (see their figures 1 and 3). (See also Zeisberger (2022) for other evidence that people are often concerned about the probability of meeting some aspiration level in ways that are not captured by Prospect Theory).

5.4 Empirical evidence to date

In this section, we review the empirical evidence relevant to the DTM's predictions. We can classify the sources of evidence into four major groups, which vary on the two dimensions of causal identification and external validity (figure 5.3). Laboratory experiments are high in causal identification and low in external validity (section 5.3.1); observational studies of artificial lottery choices are low in both (section 5.3.2); observational studies of real-world decisions are low in causal identification but high in external validity (section 5.3.3); and finally natural experiments are (fairly) high in both causal identification and external validity (section 5.3.4). This typology over-simplifies. For example, some of the natural experiment studies (3.4) use artificial lottery choices, but we place them in their own quadrant because of their stronger causal design.

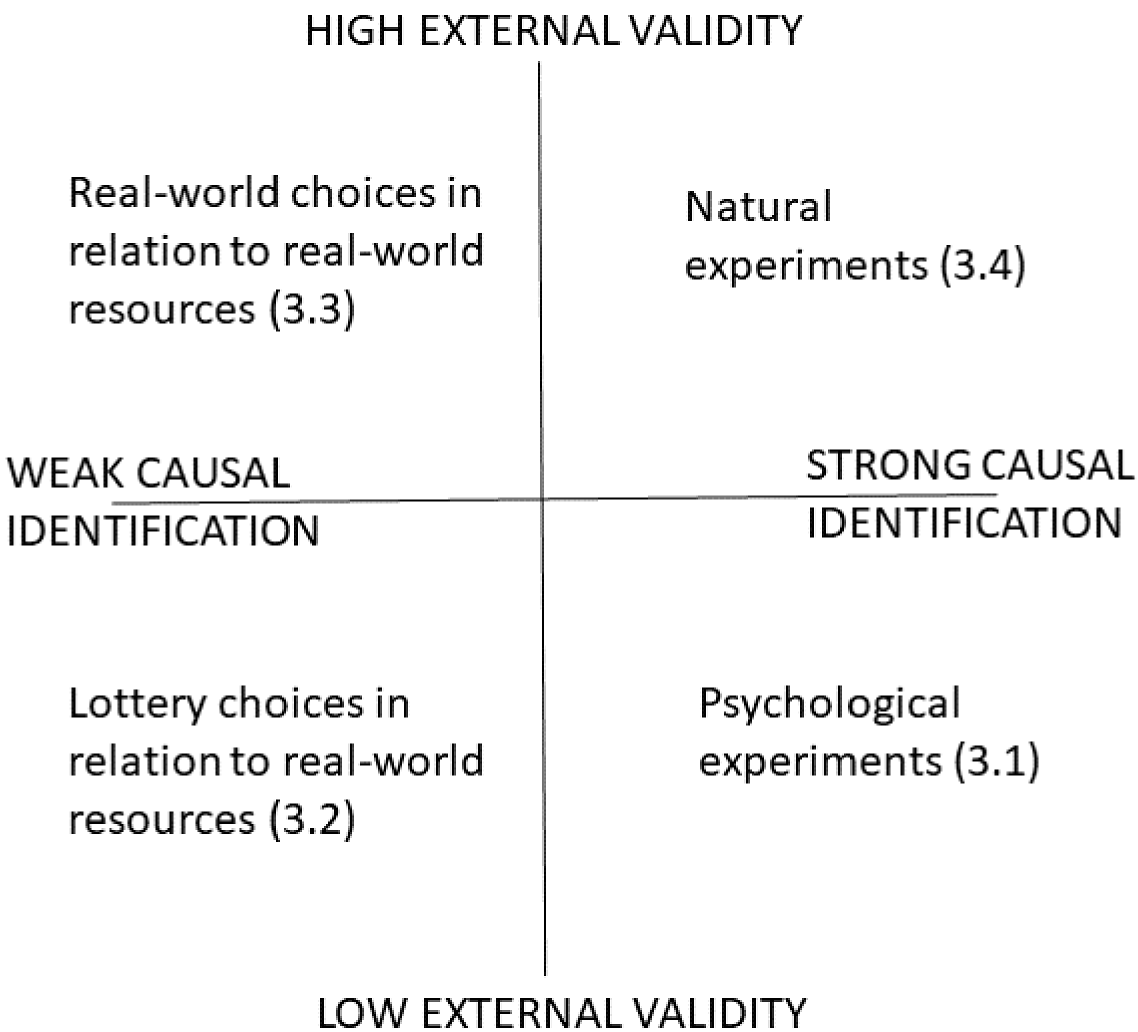

Figure 5.3: Organising classification for the sources of evidence reviewed in section 5.3. Parenthetical numbers refer to the subsections.

Our review is non-systematic, as the relevant literature is so varied as to preclude systematic review and meta-analysis. Although we have included non-supportive findings where we have encountered them, our informal search strategy will tend to bias us towards including instances that fit the narrative. Thus, the reader should consider this section as providing a guide to the diversity of evidence that can be interpreted within the framework of the DTM, not a strong falsification test. We have counted evidence as relevant where there is some test of: the desperation prediction; the desperation prediction and caution prediction jointly; or the variation prediction. A test of the caution prediction alone would not feature the DTM's hallmark feature, namely switching to risk taking at very low levels of resources.

The rest of section 5.3 only covers evidence from humans. There are also literatures that test versions of the DTM in birds (see Kacelnik & Bateson, 1996; Kacelnik & El Mouden, 2013 for reviews), bees (Cartar, 1991), and even plants (Dener et al., 2016). We refer readers to those papers for further information.

5.4.1 Psychological experiments

Experimental tests of DTM predictions began when researchers wondered whether ideas about risk-sensitive foraging in animals were relevant to humans (Pietras & Hackenberg, 2001; Rode et al., 1999). The varied paradigms that have been used (table 5.1) share some core features. The researcher creates an experimental currency (e.g. points or cents). An exogenous threshold level of this currency is defined, below which a negative consequence occurs (e.g. a cash payment at the end of the experiment is lost). The participant chooses between options that produce payoffs in the experimental currency and differ in their level of risk. The general finding is that participants are more likely to choose the risky option when they are not currently on target to meet the threshold requirement. Most experiments show a switch point from risk avoidance to risk taking within subjects, thus ruling out explanations in terms of stable dispositions or personality traits. The consistency of the findings is extremely high, and the effect sizes are substantial.

Most of the studies involve impersonal 'games against nature', but a subset introduces a social element. In Pietras et al. (2006), the less risky option was to share resources with another participant. In Radkani et al. (2023), the riskiest option was to steal points from other participants, with the possibility of being caught and fined. Thus, the results were a test of the DTM's ability to explain desperation-driven breakdown of cooperation, or crime.

In creating table 5.1, we excluded a number of adjacent papers that appeal to the DTM but differ methodologically from studies shown. We only included experiments in which participants made choices that could increase their (at least hypothetical) resource levels. This ruled out studies using DTM logic to investigate completely abstract or non-self-interested decision making (Mishra & Fiddick, 2012; Wang, 2002). The choices on offer had to differ in risk for amount of payoff. This meant excluding Pietras et al. (2003), where the options differed in their risk for temporal delay, rather than resource amount. It is also meant excluding several experiments such as Rode et al. (1999), where the critical choice is between options whose riskiness is known and options whose riskiness is unknown. They found that people will accept options with unknown risk more readily when their resources are below a desperation threshold. Assuming that an unknown risk feels, from a psychological point of view, like a large risk, this finding is closely related to the desperation prediction. However, it is not not identical and we have not included these studies. Finally, we excluded studies where the manipulation is purely status relative to another individual, rather than level of resources in some currency (Mishra, 2014). The DTM can be extended to explain effects of relative social status on risk-taking by assuming that 'doing as well as competitors' constitutes a basic need. However, this is an extension of the DTM rather than a test of the basic version (Deditius-Island et al., 2007) is marginal under this criterion, but we opted to include it).

Whilst the results of the experimental studies are virtually unanimous, the obvious limitations concern external validity. The experiments demonstrate that people are able to adjust their decisions as predicted when they are given, in a contrived scenario, an explicit threshold, a reason for meeting it, and a set of well-defined choices differing in risk. This is not the same as showing that their decisions outside the lab, in non-contrived scenarios, are driven by those same principles. Nonetheless, it is impressive how clearly, consistently and accurately the participants adjust their risk taking to their probability of meeting the threshold.

Table 5.1. Summary of psychological experiments testing predictions of the DTM. Ps: participants.

Study	**Sample**	**Task**	**Implementation of threshold**	**Outcome variable**	**Key manipulation/comparison**	**Result**
Pietras & Hackenberg (2001)	3 US adults	Pressing buttons to accumulate points	Minimum number of points required in each block of trials in order to earn money	Choice between a button with fixed yield and one with risky yield	Points requirement either small enough to meet with fixed button, or too large; within subjects	Ps favoured the fixed button when this would meet the block's requirement, and switched to the risky button when the fixed one would not
Pietras et al. (2006)	4 (exp 1) + 4 (exp 2) US adults	Pressing buttons to accumulate points	Minimum number of points required in each block of trials in order to earn money	Choice between working alone, which is risky, and sharing points with another participant, which reduces risk by pooling	Points requirement either small enough to meet by sharing, or too large; within subjects	Ps favoured sharing when this led to a higher probability of meeting the points requirement, and working alone when it did not

Deditius-Island et al. (2007)	235 US undergraduate students	Computer choice task	Position relative to a fictive competitor	Choice between a fixed and a variable option	Ps assigned to be always ahead of or always behind the fictive competitor; between subjects	Ps favoured the fixed option when ahead (both sexes) and the variable option when behind (men only)
Pietras et al. (2008)	8 US adults	Computer choice task	Minimum number of points required in each block of trials in order to earn money	Choice between a fixed and a variable option	Ps assigned reserves and rate of gain sufficient for the fixed option to reach threshold, or not; within subjects	Ps favoured the fixed button when this would meet the block's requirement, and switched to the risky button when the fixed one would not
Mishra & Lalumière (2010)	115 Canadian undergraduate students	Computer foraging task (plus another task not discussed here)	Minimum of apples to be gathered to 'survive the week' and earn $2	Choice between trees with same mean but different variances in apple number	Ps either close or far from meeting requirement; within subjects	The greater the probability of failing to meet requirement with low-variance tree, the greater the probability of choosing the high-variance tree.

Searcy & Pietras (2011)	10 (exp 1) + 5 (exp 2) US adults	Pressing buttons to accumulate points	Minimum number of points required in each block of trials in order to earn money	Choice between a high variance and a high variance option (fixed option in some conditions of exp. 2)	Points requirement either small enough to meet with low-variance button, or too large; within subjects	Participants favoured the high variance option when the low variance option had a low probability of meeting requirement
Mishra et al. (2012)	50 (exp 1) + 84 (exp 2) Canadian undergraduate students	Exp 1B: Computer foraging task (plus another task not discussed here). Exp 2: Hypothetical investment task	Exp 1B: Minimum number of apples/points to be paid for experiment. Exp 2: Imaginary debt that needs to be paid off.	Exp 1B: Choice between trees with same mean but different variances in apple number. Exp 2: Choice between a higher risk and low risk hypothetical investment option	Exp 1B: Ps either close or far from meeting requirement; within subjects. Exp 2: Hypothetical debt either small enough or too large to be paid off with less risky investment option; within-subjects.	Exp 1B: More choice of high-variance tree when far from meeting requirement. Exp 3: More choice of risky option when debt too large to be paid off with safe option.

Bennett & Pietras (2021)	5 (exp 1) + 8 (exp 2) US adults	Pressing buttons to accumulate points	Minimum number of points required in each block of trials in order to earn money	Choice between fixed and risk option (exp 1) or lower and higher risk option (exp 2)	Per trial 'energy cost' in points that either made it either possible or impossible to meet the minimum requirement using the fixed/lower-risk option; within-subjects	Fewer choices of fixed option (exp 1) or low-risk option (exp 2) when energy cost was high

Radkani et al. (2023)	Computer cooperation task	Minimum number of points required in order to access a cash bonus	Choice between working alone (no risk but unprofitable); cooperation (slightly profitable and slightly risk); or stealing from other players (highly profitable but highly risky)	Exps 1-3: Whether current points level was above minimum requirement; within subjects. Exp 4: Whether initial points level was above minimum requirement; between subjects.	Stealing more common when points level below the minimum requirement (all exps). Control conditions rule out alternative explanations (exps 2 and 3). High inequality in group produces more stealing if it entails that some players are below minimum requirement (exp 4).

5.4.2 Choice tasks in relation to real-world resources

This section concerns observational studies that use participants' real-world resources (for example, their income or wealth) to predict their choices on artificial dilemmas involving risk (table 5.2). The dilemmas are typically expressed as choices between gambles, such as 'Would you prefer $100 for certain, or a 50% chance of getting zero and a 50% chance of getting $200?'. The currency of the payoffs and the size of the stakes varies across studies. In some studies, the gambles are paid out; in others, hypothetical.

We excluded studies that aim to establish whether people in a certain population are risk averse on average, and those that test only for monotonic relationships between resources and risk taking. Such studies are numerous, both of large datasets from mostly high-income countries (Dohmen et al., 2011; Donkers et al., 2001; Eckel et al., 2012; Guiso & Paiella, 2008) and smaller samples from rural subsistence contexts (Miyata, 2003; Wik et al., 2004). The typical finding is that risk taking increases with income and wealth, supporting the caution prediction. However, since the distinctive prediction of the DTM is the desperation prediction, the minimum criterion for inclusion in table 5.2 was either a comparison of individuals who could not meet their basic needs with individuals who could, or some kind of test for non-monotonicity.

The studies in table 5.2 all find some evidence for the desperation prediction. One study, Courson, Frankenhuis, & Nettle (2025), also tested the variation prediction. Populations studied range from farmers and herders for whom starvation is a serious possibility, through to people in contemporary France, the UK and USA, where this is presumably not the case. Some of the studies defined what the threshold point should be a priori. For example, Caballero (2010) calculated what income would be needed in Bogota to avoid malnourishment. Others used the data to identify an inflection point, for example by using curvilinear or broken-stick regression. Some studies used subjective rather than objective resources variables (Courson, Frankenhuis, & Nettle, 2025; e.g. Tucker, 2012). That is, rather than measuring material assets, they used the participants' appraisals of whether they had enough to meet their basic needs as the predictor.

Though the predictor variable in these studies is ecologically valid, the outcome variable is not spontaneous decision-making. Where the dilemmas are incentivized, the stakes are necessarily small or moderate (up to a few days' wages). The studies that have deliberately made the stakes large enough to have life-changing consequences have, perhaps necessarily, used hypothetical incentives. Kahneman & Tversky (1979) defend the use of hypothetical dilemmas for such problems, given the ethical and practical impossibility of making such stakes real, and on the basis that it is reasonable to assume that people know how they would behave, and have no special reason to disguise their inclinations (p. 265). Holt & Laury (2002) show that choices in incentivized and hypothetical risk dilemmas follow a similar pattern, although as the stakes increase, people become more risk averse for the incentivized case than the hypothetical one.

Table 5.2. Summary of choice-task studies relevant to the DTM.

Study	**Sample**	**Resource measure**	**Risk measure**	**Result**
Dillon & Scandizzo (1978)	130 Brazilian small farmers	Tenure (farm owner vs. sharecropper); risky prospect (worst case outcome yields enough for subsistence or not)	Hypothetical gambles over different farm yields	Sharecroppers (poorer) took more risks than owners (more affluent); within groups, people with higher income took more risks; less risk taking when subsistence at risk than when not

Barsky et al. (1997)	11,000 US adults	Income and wealth	Hypothetical gambles with large stakes (up to doubling lifetime income)	U-shaped relationship with more risk taking by people in the lowest and the highest quintiles of income and wealth than the middle
Caballero (2010)	87 adults from Colombia	Having sufficient income to avoid malnourishment, or not	Incentivised gambles with moderate stakes (up to 23% of participants' monthly wage)	More risk taking/less risk aversion for participants just below the nutritional threshold
Kuznar (2001)	23 adult Andean herders	Wealth in terms of livestock herd value	Hypothetical gambles with large stakes (in the currency of livestock)	Curvilinear relationship between wealth and risk taking, with high risk taking among the poorest and richest herders
Tucker (2012)	340 rural Madagascan adults	Food security (being able to consistently access adequate food)	Incentivised gambles worth up to a day's labour equivalent	More risk taking by food insecure participants, taking into account large number of other ethnic, village and economic predictors
Maertens et al. (2014)	206 Indian farmers	Total household wealth	Hypothetical gambles with large stakes (in the currency of cotton yield)	U-shaped relationship with more risk taking by members of poorest and richest households

Courson, Frankenhuis, & Nettle (2025)	232 French and 240 UK adults, repeatedly assessed over one year	Subjective perception of adequacy of resources, plus objective ratio of monthly income to monthly essential costs, plus ancillary measures of resource adequacy.	Hypothetical gambles with medium stakes (payoffs of up to 800 euro)	The most extreme risk takers and the most extreme risk avoiders had lower resources than the intermediate risk takers; people with lower resources showed more variability in their risk taking; evidence for a broken-stick relationship between subjective resources and risk taking (negative relationship to a certain point, then positive relationship)

5.4.3 Real-world choices in relation to real-world resources

This section reviews observational studies of real-world decisions between alternatives that differ in risk, in relation to real-world resource levels (income or wealth). We opt for a narrative approach rather than a table, and concentrate on two sets of studies: of subsistence strategies (3.3.1), and of acquisitive crime (section 5.3.3.2). The strength of these studies is the external validity of the outcome measure: they measure what people actually do to try to make their living. On the other hand, as for the studies in 3.2, the causal identification is weak.

5.4.3.1 Subsistence strategies

Subsistence strategies are a suitable domain in which to test the DTM's predictions. Resource levels can be well quantified, for example using acreage or herd size. Producers constantly have to decide between different options, for instance between consumption crops and cash crops (Kunreuther, 1971), or between drought-resistant camels and drought-susceptible goats (Mace, 1990). These options vary in risk in ways that can be estimated empirically from available data.

Kunreuther & Wright (1974) examined the behaviour of farmers in 20th century Bangladesh and the 19th century US South. In both cases, the farmers had to choose between a consumption crop (rice/corn) and a crop for cash sale (jute/cotton). Those choosing the cash crop would mostly use the cash to buy the consumption crop at market. Producing the cash crop is riskier due to the vagaries of market prices: the year-to-year standard deviation in the amount of food a farmer could end up with was 2-3 times higher (Bangladesh) or 4-5 times higher (US South) if they chose to plant the cash crop. On the other hand, the mean amount was also often higher. In both locations, those with large farms planted a greater proportion of their fields with cash crops than those with moderate-sized farms (caution prediction). However, among the very smallest farms, the trend reversed, and the farmers went for a high proportion of cash crops (desperation prediction). Kunreuther and Wright commented 'one possible explanation would be that the farmer has a utility function which decreases sharply at some critical income level, so that he prefers to gamble to avoid poverty' (p. 3).

Mace (Mace, 1990; Mace & Houston, 1989) studied the choice by African herders to keep sheep and goats versus camels. Camels can better tolerate drought conditions, and hence are less risky, but less profitable. In a theoretical model, Mace & Houston (1989) showed that very poor households should keep only sheep and goats, to get their herds to a critical size. Above this size, they should buy safer camels, which should then be the bulk of their herds. This prediction was clearly supported in three groups studied, and ambiguous in a fourth (Mace, 1990). Households with a small herd kept exclusively sheep and goats (desperation prediction), whilst households with large herds kept mostly camels (caution prediction).

5.4.3.2 Property crime

Property crime as a high-risk way of gaining resources compared to legitimate economic activity. It necessarily involves the risk of being caught and punished, not to mention the payoffs being highly variable for other reasons. Making risky choices in artificial risk dilemmas predicts criminal behaviour in young men, even after controlling for other factors (Epper et al., 2022). The DTM thus predicts an increased probability of turning to acquisitive crime when resources are extremely low (desperation prediction). There is some criminological evidence compatible with this prediction (which was tested experimentally in Radkani et al. (2023), see section 5.3.1).

McCarthy & Hagan (1992) found that the best predictor of theft among homeless Canadian youth was hunger. More generally, property crime rates are higher in poor neighbourhoods (Patterson, 1991) and in periods of high unemployment (Levitt, 2001). Extremely disadvantaged neighbourhoods, where desperation is presumably more frequent, display 'unusually high rates of crimes' (Krivo & Peterson, 1996; W. J. Wilson, 2012), even though most individuals there avoid crime. In a study of bank robbers, Camp (1968) explicitly explained the robberies by a "nothing to lose" feeling. Shover (1996), in a study of individuals who committed theft that, 'all their lives most have been poor or just a financial crisis and a few paychecks away from it' (p. 30). Jacobs & Wright (1999) reported that 'with few exceptions, the decision to commit a robbery arises in the face of.....a pressing need for fast cash' (p. 153), often linked to their ability to secure basic necessities. Rossmo & Summers (2022) found that many respondents distinguished offending based on 'wants' from offending based on 'needs'. The authors coined the concept of 'quantum jumps' in subjective utility, which can trigger offending. The quantum jump captures our notion of a threshold. A quantum jump exists when someone 'needs a specific amount of money such that anything less has limited value; for example, a person who has a debt with an impending payment due or must come up with the rent in order to avoid eviction. For these individuals, it is a matter of all or nothing' (p.7).

5.4.4 Natural experiments

This section deals with cases with studies where there is some shock to, or exogenous driver of, resource levels. This allows researchers to measure subsequent variation in risk taking with moderate confidence that changes in resource levels are the causal factor. The strength of these studies is that many third-variable and reverse causality explanations can be ruled out. There are two kinds of relevant study: resource shock studies, and resource cycle studies.

Resource shock studies examine the consequences of exposure to natural disasters or civil upheaval for risk taking, usually measured with artificial risk dilemmas. These studies find sometimes that exposure increases risk taking (Eckel et al., 2009; Hanaoka et al., 2018; Kettlewell et al., 2024; Page et al., 2014), and sometimes that it decreases it (Callen et al., 2014; Cassar et al., 2017). Many of these studies are difficult to relate directly to the DTM. Their independent variable is some measure of exposure to the shock. The researchers are mostly interested in identifying the psychological impact of exposure, but it is not clear whether or how the respondents' objective resource levels were altered, or whether they have been restored by the time of study. An exception is the study by Page et al. (2014), who studied an unexpected Australian flood. They examined risk taking by homeowners with large property losses compared to neighbours whose houses happened to be a little way above the waterline. The homeowners with losses took more risk in a gambling task, and the worse the losses, the more likely they were to choose the risky options.

Resource cycle studies use exogenous temporal variation in resource levels to identify their causal impact. The classic example is the welfare check cycle: in jurisdictions where welfare payments are made around the 1st of the month, the day of the calendar month serves as an instrumental variable for people's current resource levels. Foley (2011) found that in US cities where welfare payments are concentrated at the beginning of the month, acquisitive crimes follow 'welfare payment cycles', with an increase in the rates over the course of the month as welfare payments run out. Akesaka et al. (2023) studied artificial risk dilemmas in American and Japanese samples who depended on a monthly payout. In both cases, risk taking increased in the period leading to the pay day. An oddity of these results is that the gambles had lifetime consequences and extremely large stakes. If the actual resource shortfall is a minor one that will only last a few days, it is unclear why, under strict rationality, preferences for long-term decisions ought to change. The best interpretation here is that falling short of a need level induces a risk taking mindset, which then gets applied generally, both to decisions that are strategically appropriate to solving the problem, and to decisions that are not. We note also that Carvalho et al. (2016) did not find any difference in weakly-incentivized gamble risk taking before versus after payday in two panels of relatively low-income US adults.

In the context of the DTM, many of these studies suffer from a problem of prediction specificity: what does the model actually predict in these cases? The DTM predicts a non-monotonic mapping of risk taking to resources. A negative shock could thus either increase or decrease risk taking, depending on where in relation to the threshold the person started out, and the magnitude of the shock. At least one of these is usually unknown. The fact that resource shock studies sometimes find increases in risk taking and sometimes decreases makes sense in the context of the DTM, but it causes an epistemological problem. If both an increase or a decrease in risk taking could be counted as support for the DTM, then how could the DTM ever be falsified? We return to this question in section 5.5.3.

5.5 Population consequences of the DTM

The DTM is a model of individual decision making, but it can be used to predict and interpret patterns at the levels of populations and societies. Thus, it has potential to contribute to solving the 'micro-macro' problem in social science. This is the challenge of linking individual-level actions and decisions to broader societal patterns (Coleman, 1990; Elster, 2007; J. M. Epstein, 2012). Inference between the DTM and population-level patterns is potentially bidirectional. On the one hand, one can assume the DTM is true at the individual level in order to make predictions about regularities at the societal level [Courson & Nettle (2021), see 4.1). On the other hand, patterns observed at the societal level can provide evidence that the DTM is a realistic model of how the individuals in those societies are making decisions (see 4.2). This seems rather circular: we assume that the DTM is true in order to understand macro-patterns, and use macro-patterns as evidence that the DTM is true. In fact, this is just an example of 'inference to the best explanation' (P. Lipton, 2017). The more varied the phenomena that turn out to be concordant with the DTM, the stronger the case that it is a useful idealization.

5.5.1 Explaining associations between inequality and aggregate outcomes

Many studies have detected correlations, across cities, countries or states, between the inequality of the income or wealth distribution (as measured with the Gini index), and aggregate outcome variables such as average life satisfaction, average health, crime rate, or average social trust (Barone & Mocetti, 2016; Kelly, 2000; Rufrancos et al., 2013; R. G. Wilkinson & Pickett, 2009). This has led to considerable debate about causality (Lynch et al., 2004; Nettle & Dickins, 2022; Sommet et al., 2018; Truesdale & Jencks, 2016; Vilalta et al., 2024). The Gini index is an abstract population statistic. It is unclear by what causal pathway it could affect the health, emotions or decisions of individual people.

One simple way that greater inequality in the resource distribution can affect aggregate outcomes is if the mapping between resources and outcomes at the individual level is non-linear. For example, imagine that the probability of committing an acquisitive crime rises sharply when individuals have less than $1000, and is a flat line for all incomes greater than that. If the income distribution is made more unequal (keeping its mean in the same place), then more people than before will have less than $1000, and their probability of committing crimes will go up. There will also be people who have got richer by a corresponding amount, but their probability of committing crimes won't go down, because the resources-crime function is flat at the higher end. So, the people who are made worse off will commit more crimes, and the people who are made better off will not commit any fewer. The total amount of crime goes up. This is known as a concavity effect (Gravelle, 1998). Due to the non-linear mapping at the individual level, the aggregate outcome is affected by changes in not just the mean, but also the variance, of the resource distribution.

Because the DTM predicts a non-linear mapping between individual resources and decisions, it implies that concavity effects will be widespread, and thus that inequality will often matter (statistically) for aggregate outcomes. Concavity effects follow by mathematical necessity. They do not rely on the people in the population having any particular reaction to inequality per se, or even perceiving it. Much of the debate in the inequality literature concerns whether concavity effects are sufficient to explain associations between inequality and aggregate outcomes, or whether other processes must also be at work (Daly, 2023; Kelley & Evans, 2017; Nettle & Dickins, 2022; Sommet & Elliot, 2023).

It may be helpful in this context to distinguish between primary effects of concavity, and secondary effects, which are due to people responding to the primary effects. De Courson et al. (2023) argued that greater acquisitive crime may be a primary effect of increased desperation as inequality becomes larger; it is committed largely by individuals who find themselves below the desperation threshold. Decreased social trust and increased violent crime may be secondary effects. People find themselves in a population in which others may try to steal from them. Hence, they trust less; and they may also need to use violence as a toughness signal, to avoid being the target of stealing. Secondary effects need not be restricted to individuals who are below the desperation threshold. In a population in which more people are desperate, the lower trust could become general through interaction.

If associations between inequality and aggregate outcomes are driven by concavity effects and their secondary consequences, then there is a sense in which inequality is not the real causal variable. The real causal variable is the fraction of people who are below the threshold (Courson & Nettle, 2021). Across many scenarios, the Gini and the fraction of people who are below the threshold are perfectly correlated. However, there are thought experiments in which the two are decoupled. For example, the DTM predicts that in a society so rich or so well institutionally protected that every individual's basic needs were guaranteed always to be met, the Gini coefficient should cease to predict aggregate outcomes. A second thought experiment is that in a society where almost everyone's resources were below the threshold, the DTM predicts that increasing inequality could improve aggregate outcomes. This would be because broadening the dispersion would put some individuals into above-threshold positions, whilst the bulk of people, already being below the threshold, cannot be made much worse off than they already are.

5.5.2 Impact of welfare states on risky behaviours

Economically advanced countries have welfare states that function to boost low incomes, and prevent them ever becoming critically low. In principle, in a perfectly effective welfare state, there would be no fear of falling below the threshold, and zero incidence of actually doing so. This means we should not observe either the extreme caution characteristic of people just above, nor the desperate risk taking of people below, in a society with such a system.

A few cross-national studies have examined the effect of welfare provision on risk taking. Bird (2001) showed that where there is a more generous welfare provision, people take on economic activities with more variable income streams such as entrepreneurship. Likewise, Iversen & Soskice (2001) found that in countries where people take on more training for highly specialised trades, there is higher public support for welfare provision. The researchers argue that trade specialisation is a risky investment, so where it is common, people want insurance against the downsides. The direction of causality cannot be unambiguously identified in these studies: it could be that where people's incomes are more variable, they vote for welfare expansion; or where there is good welfare, they take on risky jobs. Schroyen & Aarbu (2018) compared risky choices, measured using artificial risk dilemmas, across six countries. People in countries with more extensive welfare provision chose more risky options. In DTM terms, this can be interpreted as a reduction in above-threshold caution that comes from knowledge that there is an effective safety net.

If the welfare state effectively prevents people from falling below the threshold, then better welfare prediction should reduce crime. The hypothesis that welfare provision suppresses crime is over 125 years old, with Franz von Liszt describing social policy as 'the best and most effective crime policy' in 1898 (cited in Rudolph & Starke (2020)). Rudolph & Starke (2020) reviewed 41 cross-national studies testing the hypothesis that more generous welfare provision is associated with lower crime rates. Thirty-two studies, plus the original study they present, found support for the hypothesis. In their own data, the strongest welfare-provision predictor of a lower crime rate (operationalised as homicide rate) was the generosity of unemployment insurance. They argue that unemployment insurance insulates people from the extreme strain of loss of livelihood. Relatedly, Calnitsky & Gonalons-Pons (2021) found that, in an experimental trial of a guaranteed basic income scheme (the Manitoba Basic Annual Income Experiment), the intervention reduced both property crime and violent crime.

In summary, correlates of more generous welfare provision appear to include both increased risk taking (for socially benign risks such as choice of profession), and decreased extreme risk taking (such as property and violent crime). The DTM provides micro-foundations through which these two seemingly contrary effects could both occur. The positive effects of better welfare institutions on risk judgments has been used as a central argument for investing in more generous and universal welfare systems (Johnson et al., 2025).

5.5.3 Deterrence of crime

Since Beccaria (1764) and Bentham (1789), one of the main justifications for the penal system punishing people has been that fear of punishment should deter crime. Implicitly, this argument is based on expected utility: if individuals balance costs and benefits, authorities could prevent crime by imposing sanctions harsh enough to make the payoff negative on average (Becker 1968). Making the punishment more severe may be easier and cheaper than increasing the probability of punishment, and should be as effective if individuals were indifferent to risk (since expected utility is the product of the probability of the sanction and its size). However, in empirical studies, there is little evidence that increasing punishment severity has a negative effect on crime rates, while the effect of the probability of sanction is clear (Dölling et al., 2009; Nagin, 2013; Barnum & Nagin 2023).

The DTM can potentially explain why increasing severity is apparently not deterrent (whilst improving welfare provision is, see section 5.4.2). Assuming that much crime is committed by individuals with below-threshold resources, the perpetrators are typically at or close to rock bottom. A larger punishment then has no greater effect on them than a smaller one. What matters is that the deviant act gives them some probability of moving back above the threshold. A formal model by de Courson and Nettle (2021), based on the DTM, predicted that increasing punishment severity beyond a minimal level would not reduce property crime, since this was only ever committed (under the assumptions of their model) by people already at rock bottom anyway. The model even predicted some circumstances in which more severe punishment could make property crime more prevalent: very severe punishments push temporarily desperate individuals further into desperation, hence in the direction of subsequent crime. This prediction - of increasing punishment severity sometimes being not just ineffective but counterproductive - was made independently in a theoretical paper using similar assumptions to the DTM (MacLeod, 2023).

5.6 Critical issues

In our presentation thus far, we have left some important conceptual and epistemological issues unaddressed. Resolving these is important for identifying more precisely the predictions of the model and ascertaining its scientific value.

5.6.1 Is the threshold a subjective or objective construct?

The first question is whether the input variable to the DTM - the level of resources - should be interpreted in objective material terms (e.g. a number of dollars or calories) or subjective psychological ones (a feeling of basic needs being met). Our answer to this question is both. The subjective feeling that needs are, or are not, being met should be a strong proximal determinant of either taking or avoiding risks. However, we would expect objective resource availability, in turn, to influence these subjective feelings. Hence the DTM is relevant to people who want to study the consequences of changes in objective economic resources and their distribution.

The effect of changing material resources should be mediated by changes in subjective feelings. In a straightforward comparison, the subjective variables should often be the stronger predictors, as they are closer in the causal chain. Different people need different levels of objective resources to achieve the same level of security, so dollar or euro incomes are noisy measures of desperation. However, people are presumably good at taking a 'read' of their situation, and so subjective measures may be less noisy. In many domains, subjective appraisal variables turn out to be good predictors of future outcomes, outperforming more objective indicators (REFS). In a recent study, de Courson et al. (2024) used both a subjective resource adequacy measure and an objective measure of household income to predict risky choice. The hallmark DTM pattern of risk avoidance at low resource levels, and risk taking at very low resource levels, was more clearly supported with the subjective appraisal measure.

5.6.2 Is the threshold level absolute or relative?

Another question is whether the threshold level is absolute or relative, that is, to what extent its position depends on others' levels of resources. Both perspectives are defensible. Hunger does not intrinsically depend on what other people have to eat. On the other hand, what is considered a basic need clearly varies over time and space, depending on what it is normal to have in a society: as Marx (1847:16) observed, "let there arise next to the little house a palace, and the little house shrinks to a hut".

We leave this question somewhat open, but we are unattracted by either extreme position. A purely absolute conception of threshold level is clearly problematic. The threshold of desperation is a level of material resources that allows people to satisfy the basic needs constituted both by their physiology (which are largely absolute), and by the expectations and social roles available in the broader society (which must have a relative component). It surely differs between a hunter-gatherer society and an industrial market society. We have already mentioned (section 5.2.2) Adam Smith's observation that necessities include whatever it is "indecent for creditable people to be without". This is necessarily society-relative.

On the other hand, if the position of the threshold were purely relative, then uniform increase in society's wealth (affecting all percentiles of the distribution in the same way) would have no impact on the prevalence of desperation. Yet there have been directional historical reductions in many important risk-related behaviours, such as violence, as societies have become more affluent (Baumard 2018; Thome 2007; Pinker better angels of our nature). We are interested in using the DTM to understand these changes. It seems unreasonable not to acknowledge that the overall growth in society's wealth has decreased the amount of desperation.

We favour a hybrid position. We know that as people's individual incomes increase, their idea of the level of income necessary to meet basic needs also increases. But it only increases about half as fast as their incomes. Thus, as they get richer, their individual subjective threshold rises, but they also perceive themselves to be further from it. We suspect something similar can happen at the societal level. As the people around us obtain more, our notion of what is indecent to be without does change, but not necessarily at the same rate. Thus, there is scope for societies to differ sharply in the prevalence of desperation.

5.6.3 Is the DTM falsifiable?

In many datasets, it is hard to know a priori where on the resource scale the cliff and the rock bottom are located. This makes the DTM able to accommodate a variety of patterns without its predictions being clearly falsified. If the observed association between resources and risk taking is linear and negative, we could conclude that the DTM is supported, but there are no desperate individuals in the sample. If the association is U-shaped, we would definitely conclude that the DTM is supported. There can also be an apparent circularity: we identify those individuals who are below the threshold because they take risks, and also explain that risk taking by the fact they are below the threshold. Thus, the model could be accused of being so permissive and hermetic that it is essentially unfalsifiable.

We defend the DTM against this charge. The above criticisms apply mainly to observational studies relating some measure of objective resources to some measure of risk taking. Even for these studies, there are many patterns that would falsify DTM predictions, for example no association, or an inverted U-shape with the highest risk taking in the middle of the resource distribution. More importantly, studies of this type form only one part of the evidence supporting the DTM (section 5.3). Studies that use subjective appraisals of whether people feel their needs to be met make stronger predictions: a switch to risk taking around the point where the participants feel unable to to meet their basic needs. The experimental studies are also important, despite the ecological validity concerns, because the predictions are unambiguous and the causality clear.

The DTM is a middle-range theory. A middle range theory is not usually falsified by any individual data set or experiment (Ketelaar & Ellis, 2000). Applying a middle range theory to any particular empirical setting always requires additional contextual understanding. Middle-range theories prove their value by generating useful understanding over many different local contexts, and their ability to unify diverse observations. This is why we have stressed the diversity of relevant evidence in section 5.3, and the DTM's ability to illuminate population-level phenomena in section 5.4. A middle-range theory like the DTM should be discarded if it fails to give rise to a generative research programme, where generativity is assessed by: connection of diverse phenomena; production of avenues for enquiry; and capacity for progressive refinement by data whilst retaining a core set of assumptions (REF Lakatos). Our contention is that the DTM could lie at the core of a generative research programme in this sense; though of course, only time will tell.

5.7 An agenda for DTM research

In this final, non-exhaustive section, we outline possible areas for the growth of future research inspired by the DTM.

5.7.1 Proximal representations: thresholds in the mind

The DTM posits that people's utility functions have a particular shape (see figure 5.1A). This could be taken in an 'as if' sense: people behave 'as if' their decisions were driven by maximisation of a function of this shape. But there must be underlying cognitive computations or heuristics that deliver the predicted pattern of choices. Two literatures we are aware of have attempted to directly measure the shape of utility functions in the mind. Interestingly, they both posit sigmoid functions resembling figure 5.1A.

The first, the individual welfare function literature of the 1970s and 1980s, used survey data in which respondents stated what levels of income they would consider 'very bad', 'bad'...'good', or 'excellent' (Van Praag 1971, Kapteyn & Wansbeek, 1985). The 'very bad' income level was assumed to carry a utility of zero, and the 'excellent' a utility of one; the income values given for the other descriptors were used to estimate the shape of the function across the interval in between. Though the resulting function was sigmoid, this was largely due to the assumptions made. Moreover, a logarithmic function, which would satisfy Gossen's first law but not the DTM, fitted the data almost as well (van Herwaarden & Kapteyn, 1981). In short, this paradigm was hampered by a number of assumptions (such as that a 'very bad' income is the worst possible income someone could imagine) and limitations (such as fitting non-linear functions to just nine points per respondent). We do however feel that the objective was important and that the limitations could be addressed in future research.

The second literature comes from neuroscience, where researchers have estimated the shape of utility functions for sweet juice in monkeys (Genest et al., 2016; Stauffer et al., 2014). The functions are sigmoid, and the magnitude of response to reward cues in midbrain dopamine neurons also reflects the sigmoid shape. The paradigm uses choices under risk to infer the shape of the function. In other words, the researchers used the fact that the monkeys are risk prone for small rewards and risk averse for large ones to back out the sigmoid shape, rather than observing the sigmoid shape first and then predicting risky choices from it. Nonetheless, we would like to see this approach extended to humans and the reward domain of income or wealth.

5.7.2 The connection to wellbeing and poverty research

There is considerable epidemiological research associating measures of subjective wellbeing and mental health to levels of actual financial resources (Nettle, Chevallier, et al., 2025; Nettle & Dickins, 2022). Whether we should expect these associations to be sigmoid (indeed, whether the DTM predicts that they should be) depends on the extent to which we see subjective wellbeing (or mental health) measures as capturing the same thing as utility.

All accounts of the resources-wellbeing mapping feature the cliff, because they all include diminishing marginal returns, usually by assuming a logarithmic relationship. However, wellbeing research has not, to our knowledge, demonstrated the existence of rock bottom. This may in part be due to methodological choices: fitting a monotonic function, such as a logarithmic one, precludes the detection of non-monotonic mappings. Alternatives such as 'broken-stick' regression (as used in Courson, Frankenhuis, & Nettle, 2025) allows the investigation of non-monotonicity.

Another relevant literature links financial resources to material deprivation. A material deprivation is the inability, for financial reasons, to achieve a key objective. Examples are: keeping one's home warm; having adequate and substantial meals; replacing worn-out furniture; buying new clothes; and being able to meet friends and family at least once a month. These objectives are chosen so as to represent 'the goods and services necessary to lead a decent life' (Blasco, 2023, p. 7). As such they correspond closely to the notion of basic needs we developed in section 5.2.2.

Empirical research across multiple European countries shows that the relationship between income and the number of material deprivations is non-linear, with three regimes (Blasco, 2023). Between incomes of

0 and around half the median income, the relationship between income and the number of deprivations is a flat line. Between around 0.5 and 1.5 times the median income, there is a steep negative relationship; each increment of extra income reduces the number of deprivations. Above 1.5 times median income, there is again a flat line, because the number of deprivations is typically zero.

This looks very like what the DTM requires: at rock bottom, small increments in income are insufficient to make any difference to deprivations. Around the cliff level, extra resources rapidly reduce deprivations, and this flattens off once all deprivations are gone. However, the interpretation of the pattern by Blasco (2023) is more methodological than substantive. He argues that the flat relationship between income and deprivations below 0.5 times the median income is that people with incomes this low are very heterogeneous. Some may be living off capital or support from family. Thus, the incomes people report in this bottom part of the distribution are simply a poor guide to their actual resources, rather than any deeper discovery about rock bottom. Nonetheless, we view the research on material deprivations as highly relevant to the DTM and an area for future DTM-inspired research.

5.7.3 Moral and ethical thought

There is a cluster of moral and ethical questions, some of them empirical, some normative, concerning basic needs and distributive justice. We believe these connect to the DTM, and in some cases tacitly assume the DTM utility function pattern, but we would like to see the connections explored explicitly.

Empirically, participants sometimes find distribution on the basis of effort or merit to be morally just (even if this leads to inequality), and sometimes find unconditional distribution of resources to all group members to be morally required (Nettle & Saxe, 2020; Starmans et al., 2017). The difference-maker between these two cases may be whether the putative recipients are perceived as being above or below the basic needs cliff. The psychology of sharing is highly sensitive to cues of need (Lightner et al., 2023). Relatedly, participants tend to have 'quasi-maximin' preferences for social distributions (Kameda et al., 2016; Nettle, Chrisp, et al., 2025). That is, they place great weight on how good or bad the distribution is for the worst-off participants. This implies, in effect, that there are representations of others' need functions, and of a threshold, available during moral computation.

Notions of cliffs and thresholds also crop up in normative reasoning. The philosophical position of sufficientarianism holds that justice requires that everyone has 'enough'. This requires a definition of 'enough', and a threshold where 'enough' has been reached. Many political philosophers have argued that society should protect people from being unable to meet their basic needs through no fault of their own. The grounds for this requirement are varied: the utilitarian (being below the threshold is disproportionately unpleasant, and so eliminating this possibility is an efficient way of increasing aggregate wellbeing (Singer, 2009)); the contractarian (if people decided on a social order under a veil of ignorance about what position in society they would occupy, they would prefer one in which there was no chance they would find themselves below the threshold (Rawls, 1971)); and the liberal (people below the threshold are vulnerable to arbitrary domination by other people, so ensuring no-one is in the position maximises freedom; (Pettit, 2014)). All versions tacitly require that something like the DTM pattern exists: that there is a level of resources it is disastrous to be without, so that attaining and maintaining this level has a moral priority over other kinds of claim (see Wiggins, 1998).

In modern states, the welfare system is the set of institutions that addresses the moral claims of need. Although normative justifications for welfare systems vary, it is often said that they should 'put a floor under people's feet' or 'protect people from the worst outcomes'. In more explicitly DTM terms, we could see welfare systems as (ideally) insulating people from any danger of falling down the cliff, and hence removing any need for them to ever be excessively risk averse, or irresponsibly risk prone (see 4.2).

5.7.4 Sociopolitical implications

Societies generate 'moral orders', sets of stable expectations about what resources people will be entitled to. A long-standing puzzle in social science is the fact that people who are relatively disadvantaged by these moral orders often nonetheless comply with them, and even justify them (ref. Jost). On the other hand, moral orders can collapse quite rapidly in episodes of social flux and rebellion. Predicting these episodes is difficult, and is the topic of longstanding enquiry (Gurr, 2015; e.g. Turchin et al., 2017).

The DTM may shed some light on the combination of frequent compliance and occasional rebellion. If an order provides people a very high probability of meeting basic needs, the DTM predicts risk aversion. People who are currently above the threshold will prefer a fairly bad status quo to the huge risk involved in a rebellion. However, once the moral order fails to satisfy the basic needs of enough people (or seems likely to do so in the near future) then the DTM predicts a widespread turn to risk taking (for relevant evidence, see Humphreys & Weinstein, 2008). It is then that rapid social flux becomes more probable.

Political elites can predict that the populace will remain more or less compliant as long as their basic needs are met. Indeed, elites have an incentive to maintain the populace just above the threshold, where they are maximally risk averse. We should expect elites to put in place institutions just generous enough to allow most people to guarantee basic needs, but not more generous (Juvenal's famous 'bread and circuses'). This implies that societies may exhibit 'self-organised criticality' (Bak et al., 1988): they will spend most of their time close to a tipping point, where a relatively small subsistence shock could lead to sociopolitical upheaval.

A case study comes from the work of Scott (1977) on peasants in Southeast Asia, who considered their ability to secure their subsistence as their central "moral claim" (p.32). Their criterion of justice was thus not whether the share of profit taken by the ruling class was reasonable, but rather, "does this institution...provide me with a living regardless of what the land may yield this season?" (p.44). They therefore preferred their rent to be proportional to yearly production, rather than a fixed amount, as this eliminates the risk of a rent liability greater than available resources. Landlords were also pragmatic, postponing taxes in bad years. Colonial powers failed to appreciate the delicate balance of the moral order, imposing uniform and unyielding taxes that put people at risk of falling below the threshold. For Scott, this explained the unforeseen explosion of political violence in Vietnam and Burma in 1930-1931. Thus, the DTM may provide a useful vocabulary for work in comparative anthropology and political economy that examines moral orders, stability, and rebellion.

5.8 Conclusion

We have introduced the DTM, an idealised model of resource-dependent decision making that assumes individuals have a rock bottom in their utility functions, and a steep cliff around the point where they can satisfy their basic needs. The DTM makes predictions about what types of risk people will take, and when. It provides a principled understanding of why poverty, compared to affluence, would be associated both with more risk aversion, and more risk taking.

The DTM has potential to connect individual-level decision making to population-level and societal questions. These questions encompass the effects of increasing inequality on aggregate outcomes, and the behavioural effects and optimal design of the welfare state. For us, the DTM's potential role as a micro-macro linking theory is one of its main appeals, giving it the potential to lie at the heart of a generative research programme spanning cognitive and social sciences.

That said, the evidence for the DTM at the individual level needs to be strong for it to be considered credible. We do view the evidence we reviewed in section 5.3 as strong. It is particularly striking how diverse the contexts are, from subsistence communities to post-industrial ones, in which this mid-level idealisation has proved to be predictive and illuminating. However, like any mid-level theory of human behaviour, the DTM raises many further detailed questions about the interpretation of its key constructs, their cognitive representation, and how they apply to different societal contexts. We hope to have stimulated research on these issues by writing this article.

6 General discussion

6.1 Summary of the findings

In the chapters that precede, I have presented the desperation threshold model (DTM), investigated its predictions in multiple domains, and assessed its empirical plausibility. I have used multiple methodologies: numerical optimisation and agent-based modeling (Chapter 2), analytical mathematics (Chapter 3), data analysis (Chapter 4) and literature review (Chapter 5). These results are part of a broader research program that now includes many more persons. Thus, this dissertation is an interim report of a continuing and expanding project.

The origin of the project is outside this dissertation, as it was published before I was a PhD student. In this paper, Daniel Nettle and I showed that the desperation threshold (DT) can account, through risk taking, for the higher property crime and lower trust found in deprived populations. The second chapter extends the DTM to violent crime, which is by definition not directly economically motivated. My model shows that the DT, combined with the assumption that violence sends a toughness signal, can explain why violent crime is also high in deprived or unequal populations. Interestingly, the model predicts that everyone should be violent in a deprived population, but that only desperate agents should commit property crime. The model can also account for the persistence of violence in neighbourhoods, even after economic conditions have improved.

The third chapter extends the scope of the DTM from risk taking to time discounting. I present four different scenarios that capture different versions of the DT in an intertemporal context, varying the consequences of desperation on future utility. In all scenarios, the model predicts a higher time discounting when the agent is close to the DT. It also predicts higher patience when she is safe from the DT in the short term but not the long term, which echoes the idea of 'middle class values' in social sciences.

The fourth chapter is the only empirical analysis strictly speaking. I use secondary data that Daniel Nettle had collected to study the effect of poverty on mental health, that includes measures of resources and measures of risk taking through hypothetical gambles. I translate the DTM into clear-cut empirical predictions. First, risk taking should follow a U-shape of resources. Second, a fuzzier prediction: risk taking should vary more in deprived populations, both between people and within-person over time. I find partial support for the first prediction: I obtain the U-shape with subjective resources and a broken-stick model, but not with objective resources or a polynomial model. The support for the second prediction is unequivocal, and the effect is very large. Risk taking is clearly polarized among the participants with low income: both extreme risk taking and extreme risk avoidance are more frequent.

The fifth chapter is the less technical, but the most ambitious one. It presents a sort of manifesto for the DTM. I start from the paradoxical relationship between poverty and risk taking: theories and empirical results in social sciences predict both an increase and a decrease of risk taking in situations of poverty. I present the DTM as an answer to this paradox. I present it in its purest form. I highlight and justify its core assumptions: there is a utility 'cliff', and a 'rock bottom'. I derive its main predictions and replace it within the broader social sciences, showing that the DTM has many antecedents in diverse disciplines. Then, I review empirical evidence relevant to assess the DTM, using results from diverse disciplines and methodologies. Finally, I expose the population-level implications of the DTM, the remaining issues and an agenda for DTM research.

The last chapter already discusses at length the state and the future of the DTM research agenda. I will not repeat those conclusions here, but simply close with just a few reflections to situate this thesis within the broader social sciences.

6.2 Concluding remarks

6.2.1 Social life and poverty

In his introduction of The code of the street, that has been so useful for this dissertation, Anderson (2000) starts by giving the reader a walk "Down Germantown Avenue", which "provides an excellent cross section of the social ecology of a major American city" (p. 26). As he exits the rich Chestnut Hill and progresses further south, Anderson observes not just a change of landscape, but also of behaviour: "There are businesses that cater mostly to the criminal class, such as pawnshops and beeper stores. Pawnshops are, in a sense, banks for thieves; they are places where stolen goods can be traded for cash, few questions asked. Check-cashing exchanges, which continue to be a common sight, also ask few questions, but they charge exorbitant fees for cashing a check. As in Chestnut Hill, merchandise is often displayed on the sidewalk, but here it is under the watchful eye of unsmiling security guards. The noise level here is also much louder. Cars drive by with their stereo systems blaring. Farther down, young people walk down the street or gather on someone's stoop with their boom boxes vibrating, the bass turned way up. On adjacent streets, open-air drug deals occur, prostitutes ply their trade, and boys shoot craps, while small children play in trash-strewn abandoned lots." (p.45).

Most readers will recognize what Anderson describes. Social life is spectacularly different in deprived populations, which tend, among other things, to have low trust, low cooperation, high crime and high violence (Nettle, 2015). Social scientists, however, tend to favor holistic explanations – such as the idea that poverty provokes a social dislocation (W. J. Wilson, 2012), or disrupts 'collective efficacy' (Sampson, 2012) – rather than attributing those social outcomes to individual decisions. Put otherwise, social scientists tend to resist opening the black box of poverty. This would risk, they fear, blaming people in poverty, and essentialising them as intrinsically and irretrievably different. Social scientists often prefer to believe, as A. Banerjee (2004) ironically puts it, that "the poor [are] just like you and me except in that they have less money" (p. 129).

My dissertation aims at showing that, on the contrary, a reductionist and rational choice approach is possible, desirable and non-stigmatizing. While methodological individualism might not be relevant to explain the existence of poverty (Brady, 2023), it is essential to understand the behavioral consequences of poverty: people do not choose to be in poverty, but they decide whether to trust their neighbours, or to take a payday loan. Viewing these decisions as state-dependent rational choices allows us to explain them at the individual level, without portraying people in poverty as fundamentally different. They simply face different constraints, which call for different actions. Actually, people commonly explain these decisions by saying that people 'have no choice', that their 'back is against a wall'. What people actually mean, I think, is that the alternative choice (not taking a payday loan, not committing a crime) produces an awful situation. This is precisely the focus of the desperation threshold (DT): understanding decisions under extreme constraint. This is not a simple change framing: the DTM shows that the predictions are actually not so simple.

6.2.2 The desperation threshold: an obvious, but disturbing idea

Thus, my dissertation shows that many social outcomes typical of deprived populations can be attributed to rational individual decisions, and in particular to the struggle to make ends meet. As I argued in the introduction, this idea is intuitive, and we spontaneously invoke it when we observe the decisions of people in poverty. What this verbal model misses, and what the formal modeling reveals, is that the effect of the threshold is rarely trivial. In most cases, the threshold does not produce monotonic relationships between economic resources and behavior. People should take risks when below the threshold, but avoid risk when just above. People should discount the future around the threshold, but on the contrary save resources when they are safe in the short term but not in the longer term.

More broadly, my dissertation reveals that the DT has disturbing effects on social life. It paints a much messier world than the traditionally used concave utility functions. It is, I believe, especially clear when viewed from a population-level perspective. It can account for clichés – crime is more frequent in deprived populations – but it also shows what is simplistic about them: some people take extreme risks like crime, while most of them avoid risk, and are especially unlikely to commit crime. Our model and our empirical findings in Chapter 4 suggest that a deprived neighbourhood brings together people with much to lose and others with very little.. Furthermore, since levels of resources are not public and a minor change in resources can trigger a massive change in behavior, people in deprived populations probably know less well what to expect from others. This can have intriguing emerging effects, like the runaway of violence we study in Chapter 2.

6.2.3 What next?

I believe that we are only starting to perceive the full consequences of the DT. In the future, I hope to build models to study the effect of the DT decision to spend time in work or in leisure, for instance, or its possible effects on voting. I am also interested in elaborating the idea that we float in Chapter 5: if a greedy landlord or company manager is aware of the DT, she should set the rent or the wages just above the threshold, in order to maximise profit while avoiding the risk of a catastrophe. More broadly, I think the field should build more formal models to justify or invalidate the profusion of verbal theories we have about behaviours in situations of poverty. For too long, the field has relied on verbal theories like the "fast-slow continuum" or the "I need to eat today" intuition (see Chapter 3). It is becoming increasingly clear that these theories are shaky, and the field is, fortunately, I hope, moving toward more formalisation.

However, I fear that there is a risk of overusing the desperation threshold concept. In the Introduction, I have pledged to use the threshold in an abductive manner – to explain empirical regularities – rather than a deductive one. Recently, I have found myself and my colleagues increasingly eager to use it deductively – after spending half a decade on this idea, it starts to feel like the DT actually exists. Perhaps this is justified, given that we now have strong reasons to believe the DT offers a compelling account of decision-making under poverty. But the risk of taking the DTM too seriously and forgetting that it is a toy model worries me. Its abstractness and generalizability makes it possible to apply it to most aspects of social life, but when you only have a hammer, everything looks like a nail. The precise scope of the DTM remains unclear to me, but it must have clearer limits.

The proper next steps should probably be empirical. My Chapter 4 is just a start, and the clear findings that we report – a polarization of risk taking among low-income participants – could easily be replicated in other datasets. Another question remains. The DTM is not a psychological model but a behavioural one. It only predicts that some behaviours are more frequent in some situations, but is agnostic about psychological states. Nevertheless, the opposite behaviors the DTM predicts on either side of the threshold must stem from different psychological processes and emotional states.

My colleague Arnaud Wolff has recently run qualitative interviews to understand the experiences of people in poverty, and to analyse them in the light of the DTM. In his sample, he finds that most people find ways to make ends meet, in general by budgeting or asking help from others in their social network. The world is, of course, more complex than the DTM represents it, and decisions are embedded in social networks. This is something I had entirely missed when elaborating the models. I think it might have been for the best, as this helped phrasing the DTM in its purest and most detached way. But the DTM may now be ripe for adaptation to better fit social realities. This makes me wonder more generally about my position, as a social scientist born far from poverty, who has spent his whole life in rich neighbourhoods. This has led me to ignore obvious facts, like the key role of social support in making ends meet. But I believe my inexperience of poverty and my emotional distance with it has also led me to always be surprised by empirical findings, and to approach them as puzzles rather than self evident. This has probably helped me to propose a formalisation of commonsensical intuitions, and to see their previously unseen consequences. I am also grateful to my supervisors, in particular Willem Frankenhuis, for having kept me on a tight leash on my writing and pushed me toward writing in a non-stigmatizing and non-essentializing way. I doubt I have entirely succeeded in that regard, but I would undoubtedly have failed without their guidance.

References

Adler, N. E., Epel, E. S., Castellazzo, G., & Ickovics, J. R. (2000). Relationship of subjective and objective social status with psychological and physiological functioning: preliminary data in healthy white women. *Health Psychology*, *19*(6), 586–592. https://doi.org/10.1037//0278-6133.19.6.586

Agnew, R. (1992). Foundation for a general strain theory of crime and delinquency. *Criminology : An Interdisciplinary Journal*, *30*(1), 47–88.

Akesaka, M., Eibich, P., Hanaoka, C., & Shigeoka, H. (2023). Temporal Instability of Risk Preference among the Poor: Evidence from Payday Cycles. *American Economic Journal: Applied Economics*, *15*(4), 68–99. https://doi.org/10.1257/app.20220073

Allen, C., & Nettle, D. (2021). Hunger and socioeconomic background additively predict impulsivity in humans. *Current Psychology*, *40*(5), 2275–2289. https://doi.org/10.1007/s12144-019-0141-7

Anderson, E. (2000). *Code of the street: Decency, violence, and the moral life of the inner city* (Reprint edition). W. W. Norton & Company.

Backhouse, R. E., & Cherrier, B. (2017). The age of the applied economist: The transformation of economics since the 1970s. *History of Political Economy*, *49*(Supplement), 1–33.

Bak, P., Tang, C., & Wiesenfeld, K. (1988). Self-organized criticality. *Physical Review A*, *38*(1), 364.

Banerjee, A. (2004). *The two poverties* (S. Dercon, Ed.; p. 0). Oxford University Press. https://doi.org/10.1093/0199276838.003.0004

Banerjee, A. V. (2003). Contracting constraints, credit markets, and economic development. In M. Dewatripont, L. P. Hansen, & S. J. E. Turnovsky (Eds.), *Advances in economics and econometrics: Theory and applications, eighth world congress* (pp. 1–46). Cambridge University Press.

Banerjee, A. V., & Duflo, E. (2007). The economic lives of the poor. *The Journal of Economic Perspectives*, *21*(1), 141–168. https://doi.org/10.1257/jep.21.1.141

Banerjee, A. V., & Newman, A. F. (1994). Poverty, incentives, and development. *The American Economic Review*, *84*(2), 211–215. https://www.jstor.org/stable/2117831

Banerjee, A., & Mullainathan, S. (2010). *The shape of temptation: Implications for the economic lives of the poor* (Working Paper NBER Working Paper No. 15973). National Bureau of Economic Research. https://doi.org/10.3386/w15973

Barclay, P., Mishra, S., & Sparks, A. M. (2018). State-dependent risk-taking. *Proceedings of the Royal Society B: Biological Sciences*, *285*(1881). https://doi.org/10.1098/rspb.2018.0180

Barone, G., & Mocetti, S. (2016). Inequality and trust: New evidence from panel data. *Economic Inquiry*, *54*(2), 794–809.

Barsky, R. B., Juster, F. T., Kimball, M. S., & Shapiro, M. D. (1997). Preference parameters and behavioral heterogeneity: An experimental approach in the health and retirement study. *The Quarterly Journal of Economics*, *112*(2), 537–579. https://doi.org/10.1162/003355397555280

Bateson, M., & Nettle, D. (2017). The telomere lengthening conundrum – it could be biology. *Aging Cell*, *16*(2), 312–319. https://doi.org/10.1111/acel.12555

Baumard, N. (2019). Psychological origins of the Industrial Revolution. *Behavioral and Brain Sciences*, *42*, e189. https://doi.org/10.1017/S0140525X1800211X

Becker, G. S. (1968). Crime and punishment: An economic approach. *Journal of Political Economy*, *76*(2), 169–217.

Bennett, J. A., & Pietras, C. J. (2021). Human choices respond to added costs according to the energy budget rule. *Learning and Motivation*, *75*, 101745. https://doi.org/10.1016/j.lmot.2021.101745

Bertrand, M., & Morse, A. (2011). Information Disclosure, Cognitive Biases, and Payday Borrowing. *The Journal of Finance*, *66*(6), 1865–1893. https://doi.org/10.1111/j.1540-6261.2011.01698.x

Binswanger, H. P. (1980). Attitudes toward risk: Experimental measurement in rural india. *American Journal of Agricultural Economics*, *62*(3), 395–407.

Bird, E. J. (2001). Does the welfare state induce risk-taking? *Journal of Public Economics*, *80*(3), 357–383. https://doi.org/10.1016/S0047-2727(00)00117-1

Blasco, J. (2023). Measuring deep poverty in developed countries. A cumulative indicator of income and material deprivation. *LIEPP Working Paper*, *155*. https://doi.org/hal-04342540

Blau, J. R., & Blau, P. M. (1982). The cost of inequality: Metropolitan structure and violent crime. *American Sociological Review*, *47*(1), 114–129. https://doi.org/10.2307/2095046

Bolte, G., Tamburlini, G., & Kohlhuber, M. (2010). Environmental inequalities among children in europe—evaluation of scientific evidence and policy implications. *European Journal of Public Health*, *20*(1), 14–20. https://doi.org/10.1093/eurpub/ckp213

Boon-Falleur, M., André, J.-B., Baumard, N., & Nettle, D. (2024). Household wealth is associated with perceived trustworthiness in a diverse set of countries. *Social Psychological and Personality Science*, 1–11. https://doi.org/10.1177/19485506241289461

Bouchaud, J.-P. (2009). The (unfortunate) complexity of the economy. *Physics World*, *22*(04), 28. https://doi.org/10.1088/2058-7058/22/04/39

Boudon, R. (2003). Beyond Rational Choice Theory. *Annual Review of Sociology*, *29*, 1–21. https://doi.org/10.1146/annurev.soc.29.010202.100213

Box-Steffensmeier, J. M., Burgess, J., Corbetta, M., Crawford, K., Duflo, E., Fogarty, L., Gopnik, A., Hanafi, S., Herrero, M., Hong, Y., Kameyama, Y., Lee, T. M. C., Leung, G. M., Nagin, D. S., Nobre, A. C., Nordentoft, M., Okbay, A., Perfors, A., Rival, L. M., … Wagner, C. (2022). The future of human behaviour research. *Nature Human Behaviour*, *6*(1), 15–24. https://doi.org/10.1038/s41562-021-01275-6

Brady, D. (2023). Poverty, not the poor. *Science Advances*, *9*(34), eadg1469. https://doi.org/10.1126/sciadv.adg1469

Breit, M., Preuß, J., Scherrer, V., & Preckel, F. (2023). Why the use of segmented regression analysis to explore change in relations between variables is problematic: A simulation study. *Psychological Methods*, 1–47. https://doi.org/10.1037/met0000576

Brezina, T., Agnew, R., Cullen, F. T., & Wright, J. P. (2016). The Code of the Street: A Quantitative Assessment of Elijah Anderson's Subculture of Violence Thesis and Its Contribution to Youth Violence Research. *Youth Violence and Juvenile Justice*, *2*(4), 303–328. https://doi.org/10.1177/1541204004267780

Brezina, T., Tekin, E., & Topalli, V. (2009). "Might not be a tomorrow": A multimethods approach to anticipated early death and youth crime. *Criminology*, *47*(4), 1091–1129.

Caballero, G. A. (2010). *Risk preferences under extreme poverty: a field experiment*. https://doi.org/10.2139/ssrn.1720983

Callen, M., Isaqzadeh, M., Long, J. D., & Sprenger, C. (2014). Violence and Risk Preference: Experimental

Evidence from Afghanistan. *American Economic Review*, *104*(1), 123–148. https://doi.org/10.1257/aer.104.1.123
Calnitsky, D., & Gonalons-Pons, P. (2021). The impact of an experimental guaranteed income on crime and violence. *Social Problems*, *68*(3), 778–798. https://doi.org/10.1093/socpro/spaa001
Camp, G. M. (1968). *Nothing to lose: A study of bank robbery in america* [Ph.D. dissertation]. Yale University.
Caraco, T., Martindale, S., & Whittam, T. S. (1980). An empirical demonstration of risk-sensitive foraging preferences. *Animal Behaviour*, *28*(3), 820–830. https://doi.org/10.1016/S0003-3472(80)80142-4
Cardenas, J. C., & Carpenter, J. (2013). Risk attitudes and economic well-being in Latin America. *Journal of Development Economics*, *103*, 52–61. https://doi.org/10.1016/j.jdeveco.2013.01.008
Cartar, R. V. (1991). A test of risk-sensitive foraging in wild bumble bees. *Ecology*, *72*(3), 888–895.
Carvalho, L. S. (2010). *Poverty and Time Preference* (SSRN Working Paper 1625524). Social Science Research Network. https://doi.org/10.2139/ssrn.1625524
Carvalho, L. S., Meier, S., & Wang, S. W. (2016). Poverty and Economic Decision-Making: Evidence from Changes in Financial Resources at Payday. *American Economic Review*, *106*(2), 260–284. https://doi.org/10.1257/aer.20140481
Cassar, A., Healy, A., & Kessler, C. von. (2017). Trust, risk, and time preferences after a natural disaster: Experimental evidence from thailand. *World Development*, *94*, 90–105. https://doi.org/10.1016/j.worlddev.2016.12.042
Chavas, J.-P. (2013). On the microeconomics of food and malnutrition under endogenous discounting. *European Economic Review*, *59*, 80–96. https://doi.org/10.1016/j.euroecorev.2013.01.002
Chayanov, A. V. (1926). *The theory of peasant economy*. University of Wisconsin Press.
Cherrier, B. (2023). The Price of Virtue: Some Hypotheses on How Tractability Has Shaped Economic Models. *Œconomia. History, Methodology, Philosophy*, *13-1*, 23–48. https://doi.org/10.4000/oeconomia.14116
Cohen, D., & Nisbett, R. E. (2016). Self-Protection and the Culture of Honor: Explaining Southern Violence: *Personality and Social Psychology Bulletin*. https://doi.org/10.1177/0146167294205012
Cohen, S., Alper, C. M., Doyle, W. J., Adler, N., Treanor, J. J., & Turner, R. B. (2008). Objective and subjective socioeconomic status and susceptibility to the common cold. *Health Psychology*, *27*(2), 268–274. https://doi.org/10.1037/0278-6133.27.2.268
Coleman, J. S. (1990). *Foundations of social theory*. Harvard university press.
Collins, D., Morduch, J., Rutherford, S., & Ruthven, O. (2009). *Portfolios of the poor: How the world's poor live on $2 a day*. Princeton University Press.
Courson, B. de, Frankenhuis, W. E., & Nettle, D. (2025). Poverty is associated with both risk avoidance and risk taking: Empirical evidence for the desperation threshold model from the UK and france. *Proceedings of the Royal Society B: Biological Sciences*, *292*(2040), 20242071. https://doi.org/10.1098/rspb.2024.2071
Courson, B. de, Frankenhuis, W., Gelder, J.-L. van, & Nettle, D. (2025). *Explaining the paradoxical effects of poverty on decision making: The desperation threshold model*. https://doi.org/10.31234/osf.io/bdvpa_v1
Courson, B. de, & Nettle, D. (2021). Why do inequality and deprivation produce high crime and low trust? *Scientific Reports*, *11*(1), 1937. https://doi.org/10.1038/s41598-020-80897-8
D'Orsogna, M. R., & Perc, M. (2015). Statistical physics of crime: A review. *Physics of Life Reviews*, *12*, 1–21. https://doi.org/10.1016/j.plrev.2014.11.001
Daly, M. (2017). *Killing the Competition : Economic Inequality and Homicide*. Routledge. https://doi.org/10.4324/9780203787748

Daly, M. (2023). Inequality, grievances, and the variability in homicide rates. *Evolution and Human Behavior*, *44*(3), 296–304.

Daly, M., & Wilson, M. (1997). Crime and conflict: Homicide in evolutionary psychological perspective. *Crime and Justice*, *22*, 51–100. https://doi.org/10.1086/449260

Daly, M., & Wilson, M. (2001). Risk-taking, intrasexual competition, and homicide. *Nebraska Symposium on Motivation*, *47*, 1–36.

De Courson, B., Frankenhuis, W. E., Nettle, D., & Van Gelder, J.-L. (2023). Why is violence high and persistent in deprived communities? A formal model. *Proceedings of the Royal Society B*, *290*(1993), 20222095.

De Courson, B., & Nettle, D. (2021). Why do inequality and deprivation produce high crime and low trust? *Scientific Reports*, *11*(1), 1–11.

Deditius-Island, H. K., Szalda-Petree, A. D., & Kucera, S. C. (2007). Sex differences in risk sensitivity under positive and negative budgets and predictors of choice. *The Journal of General Psychology*, *134*(4), 435452. https://doi.org/10.3200/GENP.134.4.435-452

Dener, E., Kacelnik, A., & Shemesh, H. (2016). Pea plants show risk sensitivity. *Current Biology*, *26*(13), 1763–1767.

Dickinson, T., Topalli, V., & Wright, R. (2025). A criminology of time. *The British Journal of Criminology*, azaf027.

Diecidue, E., & Van De Ven, J. (2008). Aspiration Level, Probability of Success and Failure, and Expected Utility. *International Economic Review*, *49*(2), 683–700. https://doi.org/10.1111/j.1468-2354.2008.00494.x

Dillon, J. L., & Scandizzo, P. L. (1978). Risk attitudes of subsistence farmers in northeast brazil: A sampling approach. *American Journal of Agricultural Economics*, *60*(3), 425–435.

Dobbie, W., & Skiba, P. M. (2013). Information Asymmetries in Consumer Credit Markets: Evidence from Payday Lending. *American Economic Journal: Applied Economics*, *5*(4), 256–282. https://doi.org/10.1257/app.5.4.256

Doepke, M., & Zilibotti, F. (2008). Occupational choice and the spirit of capitalism*. *The Quarterly Journal of Economics*, *123*(2), 747–793. https://doi.org/10.1162/qjec.2008.123.2.747

Dohmen, T., Falk, A., Huffman, D., Sunde, U., Schupp, J., & Wagner, G. G. (2011). Individual risk attitudes: Measurement, determinants, and behavioral consequences. *Journal of the European Economic Association*, *9*(3), 522–550. https://doi.org/10.1111/j.1542-4774.2011.01015.x

Donkers, B., Melenberg, B., & Van Soest, A. (2001). Estimating risk attitudes using lotteries: A large sample approach. *Journal of Risk and Uncertainty*, *22*(2), 165–195. https://www.jstor.org/stable/41761025

Du Bois, W. E. B. (2010). *The Philadelphia Negro: A Social Study*. University of Pennsylvania Press. https://doi.org/10.9783/9780812201802

Ducate, C. S., Bostrom, S. R., Proctor, K. R., & Niemeyer, R. E. (2024). *The theory crisis in criminology: Causes, consequences, and solutions*. CrimRxiv. https://doi.org/10.21428/cb6ab371.7c56d280

Duvoux, N. (2023). *L'avenir confisqué: Inégalités de temps vécu, classes sociales et patrimoine*. PUF.

Eckel, C. C., El-Gamal, M. A., & Wilson, R. K. (2009). Risk loving after the storm: A bayesian-network study of hurricane katrina evacuees. *Journal of Economic Behavior & Organization*, *69*(2), 110–124. https://doi.org/10.1016/j.jebo.2007.08.012

Eckel, C. C., Grossman, P. J., Johnson, C. A., Oliveira, A. C. M. de, Rojas, C., & Wilson, R. K. (2012). School environment and risk preferences: Experimental evidence. *Journal of Risk and Uncertainty*, *45*(3), 265–292. https://doi.org/10.1007/s11166-012-9156-2

Eisner, M. (2003). Long-term historical trends in violent crime. *Crime and Justice*, *30*, 83–142. https://doi.org/10.1086/652229

Ellis, B. J., Del Giudice, M., Dishion, T. J., Figueredo, A. J., Gray, P., Griskevicius, V., Hawley, P. H., Jacobs, W. J., James, J., Volk, A. A., & Wilson, D. S. (2012). The evolutionary basis of risky adolescent behavior: implications for science, policy, and practice. *Developmental Psychology*, *48*(3), 598–623. https://doi.org/10.1037/a0026220

Elster, J. (2007). *Explaining social behavior: More nuts and bolts for the social sciences* (2nd ed.). Cambridge University Press. https://doi.org/10.1017/CBO9781107763111

Epper, T. (2015). Income expectations, limited liquidity, and anomalies in intertemporal choice. *University of St. Gallen, School of Economics and Political Science Discussion Paper No*, *19*.

Epper, T., Fehr, E., Fehr-Duda, H., Kreiner, C. T., Lassen, D. D., Leth-Petersen, S., & Rasmussen, G. N. (2020). Time Discounting and Wealth Inequality. *American Economic Review*, *110*(4), 1177–1205. https://doi.org/10.1257/aer.20181096

Epper, T., Fehr, E., Hvidberg, K. B., Kreiner, C. T., Leth-Petersen, S., & Nytoft Rasmussen, G. (2022). Preferences predict who commits crime among young men. *Proceedings of the National Academy of Sciences*, *119*(6), e2112645119.

Epstein, J. (2008). Why model? *Journal of Artificial Societies and Social Simulation*, *11*(4), 12.

Epstein, J. M. (2012). *Generative social science: Studies in agent-based computational modeling*. Princeton University Press.

Eronen, M., & Bringmann, L. F. (2021). The Theory Crisis in Psychology: How to Move Forward. *Perspectives on Psychological Science*, *16*(4), 779–788. https://doi.org/10.1177/1745691620970586

Fajnzylber, P., Lederman, D., & Loayza, N. (2002). Inequality and violent crime. *The Journal of Law and Economics*, *45*(1), 1–39. https://doi.org/10.1086/338347

Fessler, D. M. T., Tiokhin, L. B., Holbrook, C., Gervais, M. M., & Snyder, J. K. (2014). Foundations of the Crazy Bastard Hypothesis: Nonviolent physical risk-taking enhances conceptualized formidability. *Evolution and Human Behavior*, *35*(1), 26–33. https://doi.org/10.1016/j.evolhumbehav.2013.09.003

Fisher, I. (1930). *The theory of interest*. Macmillan.

Fitzpatrick, K., & Coleman-Jensen, A. (2014). Food on the fringe: Food insecurity and the use of payday loans. *Social Service Review*, *88*(4), 553–593. https://doi.org/10.1086/679388

Foley, C. F. (2011). Welfare payments and crime. *The Review of Economics and Statistics*, *93*(1), 97–112. https://doi.org/10.1162/REST_a_00068

Frankenhuis, W. E., & Nettle, D. (2020). The Strengths of People in Poverty. *Current Directions in Psychological Science*, *29*(1), 16–21. https://doi.org/10.1177/0963721419881154

Frankenhuis, W. E., Panchanathan, K., & Smaldino, P. E. (2023). Strategic Ambiguity in the Social Sciences. *Social Psychological Bulletin*, *18*, 1–25. https://doi.org/10.32872/spb.9923

Frederick, S., Loewenstein, G., & O'donoghue, T. (2002). Time discounting and time preference: A critical review. *Journal of Economic Literature*, *40*(2), 351–401.

Frey, R., Pedroni, A., Mata, R., Rieskamp, J., & Hertwig, R. (2017). Risk preference shares the psychometric structure of major psychological traits. *Science Advances*, *3*(10), e1701381. https://doi.org/10.1126/sciadv.1701381

Friedman, M. (1957). *The permanent income hypothesis* (pp. 20–37). Princeton University Press.

Friedman, M., & Savage, L. J. (1948). The utility analysis of choices involving risk. *Journal of Political Economy*, *56*(4), 279–304. https://www.jstor.org/stable/1826045

Gambetta, D. (2009). *Codes of the underworld: How criminals communicate*. Princeton University Press. https://www.jstor.org/stable/j.ctt7tbn3

Gelder, J.-L. van, & Frankenhuis, W. E. (2025). Short-Term Mindsets and Crime. *Annual Review of Criminology*, *8*(Volume 8, 2025), 333–358. https://doi.org/10.1146/annurev-criminol-022422-124536

Genest, W., Stauffer, W. R., & Schultz, W. (2016). Utility functions predict variance and skewness risk preferences in monkeys. *Proceedings of the National Academy of Sciences*, *113*(30), 8402–8407.

Gladstone, J. J., & Pomerance, J. (2025). A glass half full of money: Dispositional optimism and wealth accumulation across the income spectrum. *Journal of Personality and Social Psychology*, *128*(1), 147–195. https://doi.org/10.1037/pspp0000530

Glaeser, E. L., Sacerdote, B., & Scheinkman, J. A. (1995). *Crime and social interactions*. https://www.nber.org/papers/w5026

Gollier, C. (2002). What does the classical theory have to say about household portfolios? In *Household portfolios* (pp. 27–54). MIT Press.

Gravelle, H. (1998). How much of the relation between population mortality and unequal distribution of income is a statistical artefact? *BMJ*, *316*(7128), 382–385. https://doi.org/10.1136/bmj.316.7128.382

Green, L., Myerson, J., Lichtman, D., Rosen, S., & Fry, A. (1996). Temporal discounting in choice between delayed rewards: The role of age and income. *Psychology and Aging*, *11*(1), 79–84. https://doi.org/10.1037/0882-7974.11.1.79

Griskevicius, V., Ackerman, J. M., Cantú, S. M., Delton, A. W., Robertson, T. E., Simpson, J. A., Thompson, M. E., & Tybur, J. M. (2013). When the economy falters, do people spend or save? Responses to resource scarcity depend on childhood environments. *Psychological Science*, *24*(2), 197–205.

Griskevicius, V., Tybur, J. M., Delton, A. W., & Robertson, T. E. (2011). The influence of mortality and socioeconomic status on risk and delayed rewards: A life history theory approach. *Journal of Personality and Social Psychology*, *100*(6), 1015–1026. https://doi.org/10.1037/a0022403

Guiso, L., & Paiella, M. (2008). Risk aversion, wealth, and background risk. *Journal of the European Economic Association*, *6*(6), 11091150. https://doi.org/10.1162/JEEA.2008.6.6.1109

Gurr, T. R. (2015). *Why men rebel*. Routledge. https://doi.org/10.4324/9781315631073

Haisley, E., Mostafa, R., & Loewenstein, G. (2008). Myopic risk-seeking: The impact of narrow decision bracketing on lottery play. *Journal of Risk and Uncertainty*, *37*(1), 57–75. https://www.jstor.org/stable/41761444

Hanaoka, C., Shigeoka, H., & Watanabe, Y. (2018). Do Risk Preferences Change? Evidence from the Great East Japan Earthquake. *American Economic Journal: Applied Economics*, *10*(2), 298–330. https://doi.org/10.1257/app.20170048

Handa, S., Seidenfeld, D., & Tembo, G. (2020). The impact of a large-scale poverty-targeted cash transfer program on intertemporal choice. *Economic Development and Cultural Change*, *69*(1), 485–512. https://doi.org/10.1086/702997

Hardin, G. (1968). The tragedy of the commons. *Science*, *162*(3859), 1243–1248. https://doi.org/10.1126/science.162.3859.1243

Harford, T. (2015). *The undercover economist strikes back: How to run–or ruin–an economy*. Penguin.

Haushofer, J., & Fehr, E. (2014). On the psychology of poverty. *Science*, *344*(6186), 862867. https://doi.org/10.1126/science.1232491

Haushofer, J., & Salicath, D. (2023). The psychology of poverty: Where do we stand? *Social Philosophy and Policy*, *40*(1), 150–184.

Haushofer, J., Schunk, D., & Fehr, E. (2013). *Negative Income Shocks Increase Discount Rates* (Working Paper 163). University of Zurich. https://ideas.repec.org/p/iso/educat/0132.html

Heeks, M., Reed, S., Tafsiri, M., & Prince, S. (2018). The economic and social costs of crime second edition. *Home Office Research Report99*.

Hertwig, R., & Erev, I. (2009). The description–experience gap in risky choice. *Trends in Cognitive Sciences*, *13*(12), 517–523. https://doi.org/10.1016/j.tics.2009.09.004

Hill, E. M., Ross, L. T., & Low, B. S. (1997). The role of future unpredictability in human risk-taking. *Human Nature (Hawthorne, N.Y.)*, *8*(4), 287–325. https://doi.org/10.1007/BF02913037

Holdsworth, L., Tiyce, M., & Hing, N. (2020). Exploring the relationship between problem gambling and homelessness: Becoming and being homeless. *Gambling Research: Journal of the National Association for Gambling Studies (Australia)*, *23*(2), 39–54. https://doi.org/10.3316/informit.659354563147675

Holt, C. A., & Laury, S. K. (2002). Risk Aversion and Incentive Effects. *American Economic Review*, *92*(5), 1644–1655. https://doi.org/10.1257/000282802762024700

Houston, A. I., McNamara, J. M., & I, H. A. (1999). *Models of Adaptive Behaviour: An Approach Based on State*. Cambridge University Press.

Hsieh, C.-C., & Pugh, M. D. (1993). Poverty, income inequality, and violent crime: a meta-analysis of recent aggregate data studies. *Criminal Justice Review*, *18*(2), 182202. https://doi.org/10.1177/073401689301800203

Humphreys, M., & Weinstein, J. M. (2008). Who Fights? The Determinants of Participation in Civil War. *American Journal of Political Science*, *52*(2), 436–455. https://doi.org/10.1111/j.1540-5907.2008.00322.x

Iversen, T., & Soskice, D. (2001). An asset theory of social policy preferences. *American Political Science Review*, *95*(4), 875–893.

Jacobs, B. A., & Wright, R. (1999). Stick-up, Street Culture, and Offender Motivation. *Criminology*, *37*(1), 149–174. https://doi.org/10.1111/j.1745-9125.1999.tb00482.x

Johnson, E. A., Webster, H., Morrison, J., Thorold, R., Mathers, A., Nettle, D., Pickett, K. E., & Johnson, M. T. (2025). What role do young people believe universal basic income can play in supporting their mental health? *Journal of Youth Studies*, *28*(1), 175–194. https://doi.org/10.1080/13676261.2023.2256236

Johnstone, R. A. (2001). Eavesdropping and animal conflict. *Proceedings of the National Academy of Sciences*, *98*(16), 9177–9180. https://doi.org/10.1073/pnas.161058798

Johnstone, R. A., & Bshary, R. (2004). Evolution of spite through indirect reciprocity. *Proceedings of the Royal Society of London. Series B: Biological Sciences*, *271*(1551), 1917–1922. https://doi.org/10.1098/rspb.2003.2581

Kacelnik, A., & Bateson, M. (1996). Risky theories—the effects of variance on foraging decisions. *American Zoologist*, *36*(4), 402–434. https://doi.org/10.1093/icb/36.4.402

Kacelnik, A., & El Mouden, C. (2013). Triumphs and trials of the risk paradigm. *Animal Behaviour*, *86*(6), 1117–1129. https://doi.org/10.1016/j.anbehav.2013.09.034

Kahneman, D. (2011). *Thinking, fast and slow*. Farrar, Straus; Giroux.

Kahneman, D., & Tversky, A. (1979). Prospect theory: An analysis of decision under risk. *Econometrica*, *47*(2), 363–391.

Kameda, T., Inukai, K., Higuchi, S., Ogawa, A., Kim, H., Matsuda, T., & Sakagami, M. (2016). Rawlsian maximin rule operates as a common cognitive anchor in distributive justice and risky decisions. *Proceedings of the National Academy of Sciences*, *113*(42), 11817–11822.

Kelley, J., & Evans, M. D. R. (2017). Societal inequality and individual subjective well-being: Results from 68 societies and over 200,000 individuals, 1981–2008. *Social Science Research*, *62*, 1–23. https://doi.org/10.1016/j.ssresearch.2016.04.020

Kelly, M. (2000). Inequality and crime. *The Review of Economics and Statistics*, *82*(4), 530–539. https://doi.org/10.1162/003465300559028

Kettlewell, N., Rijsdijk, F., Siribaddana, S., Sumathipala, A., Tymula, A., Zavos, H., & Glozier, N. (2024). Natural disaster and risk preferences: Evidence from sri lankan twins. *Applied Economics*, *56*(5), 558–581.

Kish-Gephart, J. J. (2017). Social class & risk preferences and behavior. *Current Opinion in Psychology*, *18*, 89–92. https://doi.org/10.1016/j.copsyc.2017.07.034

Kohler, T. A., & West, C. R. V. (1996). *The calculus of self-interest in the development of cooperation: Sociopolitical development and risk among the northern anasazi*. CRC Press.

Kokko, H. (2007). *Modelling for field biologists and other interesting people*. Cambridge University Press. https://doi.org/10.1017/CBO9780511811388

Krivo, L. J., & Peterson, R. D. (1996). Extremely disadvantaged neighborhoods and urban crime. *Social Forces*, *75*(2), 619–648. https://doi.org/10.2307/2580416

Kropotkin, P. (1902). *Mutual aid: A factor of evolution*. McClure Phillips & Co. https://www.gutenberg.org/ebooks/4341

Krupp, D. B., & Cook, T. R. (2018). Local Competition Amplifies the Corrosive Effects of Inequality. *Psychological Science*, *29*(5), 824–833. https://doi.org/10.1177/0956797617748419

Kunreuther, H. (1971). *Risk taking and farmers' crop growing decisions* (Center Discussion Paper 115). Economic Growth Center, Yale University.

Kunreuther, H., & Wright, G. (1974). Safety-First, Gambling, and the Subsistence Farmer. *Miscellaneous Series*, *59*. https://ideas.repec.org//p/ags/psumis/257756.html

Kuznar, Lawrence A. (2001). Risk sensitivity and value among andean pastoralists: Measures, models, and empirical tests. *Current Anthropology*, *42*(3), 432–440. https://doi.org/10.1086/320483

Lantz, P. M., House, J. S., Lepkowski, J. M., Williams, D. R., Mero, R. P., & Chen, J. (1998). Socioeconomic factors, health behaviors, and MortalityResults from a nationally representative prospective study of US adults. *JAMA*, *279*(21), 1703–1708. https://doi.org/10.1001/jama.279.21.1703

Lawrance, E. C. (1991). Poverty and the rate of time preference: Evidence from panel data. *Journal of Political Economy*, *99*(1), 54–77.

Levitt, S. D. (2001). Alternative strategies for identifying the link between unemployment and crime. *Journal of Quantitative Criminology*, *17*, 377–390.

Lewis, O. (1963). The culture of poverty. *Trans-Action*, *1*(1), 17–19.

Lightner, A. D., Pisor, A. C., & Hagen, E. H. (2023). In need-based sharing, sharing is more important than need. *Evolution and Human Behavior*, *44*(5), 474–484.

Lipton, M. (1968). The theory of the optimizing peasant. *The Journal of Development Studies*, *4*.

Lipton, M. (1977). Rice and risk. Decision making among low-income farmers. *The Economic Journal*, *87*(348), 825–828. https://doi.org/10.2307/2231398

Lipton, P. (2017). Inference to the Best Explanation. In *A Companion to the Philosophy of Science* (pp. 184–193). John Wiley & Sons, Ltd. https://doi.org/10.1002/9781405164481.ch29

Lucas, R. E. Jr. (1976). Econometric policy evaluation: A critique. In K. Brunner & A. H. Meltzer (Eds.), *The phillips curve and labor markets* (Vol. 1, pp. 19–46). North-Holland.

Lundahl, M. (1977). Review of rice and risk, decision making among low-income farmers. *The Scandinavian Journal of Economics*, *79*(3), 390–393. https://doi.org/10.2307/3439727

Lybbert, T. J., & Barrett, C. B. (2007). Risk responses to dynamic asset thresholds. *Review of Agricultural Economics*, *29*(3), 412418. https://www.jstor.org/stable/4624849

Lybbert, T. J., & Barrett, C. B. (2011). Risk-Taking Behavior in the Presence of Nonconvex Asset Dynamics. *Economic Inquiry*, *49*(4), 982–988. https://doi.org/10.1111/j.1465-7295.2009.00198.x

Lybbert, T. J., Just, D. R., & Barrett, C. B. (2013). Estimating risk preferences in the presence of bifurcated wealth dynamics: Can we identify static risk aversion amidst dynamic risk responses? *European Review of Agricultural Economics*, *40*(2), 361–377. https://doi.org/10.1093/erae/jbs027

Lynch, J., Smith, G. D., Harper, S., Hillemeier, M., Ross, N., Kaplan, G. A., & Wolfson, M. (2004). Is Income Inequality a Determinant of Population Health? Part 1. A Systematic Review. *The Milbank Quarterly*, *82*(1), 5–99. https://doi.org/10.1111/j.0887-378X.2004.00302.x

Mace, R. (1990). Pastoralist herd compositions in unpredictable environments: A comparison of model predictions and data from camel-keeping groups. *Agricultural Systems*, *33*(1), 111. https://doi.org/10.1016/0308-521X(90)90067-Z

Mace, R., & Houston, A. (1989). Pastoralist strategies for survival in unpredictable environments: A model of herd composition that maximises household viability. *Agricultural Systems*, *31*(2), 185–204. https://doi.org/10.1016/0308-521X(89)90020-6

MacLeod, J. (2018). *Ain't no makin' it: Aspirations and attainment in a low-income neighborhood, third edition* (3rd ed.). Routledge. https://doi.org/10.1201/9780429495458

Maertens, A., Chari, A. V., & Just, D. R. (2014). Why farmers sometimes love risks: Evidence from india. *Economic Development and Cultural Change*, *62*(2), 239–274. https://doi.org/10.1086/674028

Malthus, T. R. (1798). *An essay on the principle of population*. J. Johnson. https://oll.libertyfund.org/title/malthus-an-essay-on-the-principle-of-population-1798

Mangel, M., & Clark, C. W. (1988). *Dynamic Modeling in Behavioral Ecology*. Princeton University Press.

Mani, A., Mullainathan, S., Shafir, E., & Zhao, J. (2013). Poverty impedes cognitive function. *Science*, *341*(6149), 976–980. https://doi.org/10.1126/science.1238041

Masson, R. T. (1974). Utility Functions with Jump Discontinuities: Some Evidence and Implications from Peasant Agriculture. *Economic Inquiry*, *12*(4), 559–566. https://doi.org/10.1111/j.1465-7295.1974.tb00422.x

Mata, R., Frey, R., Richter, D., Schupp, J., & Hertwig, R. (2018). Risk Preference: A View from Psychology. *Journal of Economic Perspectives*, *32*(2), 155–172. https://doi.org/10.1257/jep.32.2.155

Matsueda, R. L. (2017). Toward an Analytical Criminology: The Micro–Macro Problem, Causal Mechanisms, and Public Policy. *Criminology*, *55*(3), 493–519. https://doi.org/10.1111/1745-9125.12149

Maynard Smith, J. (1982). *Evolution and the theory of games*. Cambridge University Press. https://doi.org/10.1017/CBO9780511806292

Maynard Smith, J., & Parker, G. A. (1976). The logic of asymmetric contests. *Animal Behaviour*, *24*(1), 159–175. https://doi.org/10.1016/S0003-3472(76)80110-8

McCarthy, B., & Hagan, J. (1992). Mean streets: The theoretical significance of situational delinquency among homeless youths. *American Journal of Sociology*, *98*(3), 597–627. https://www.jstor.org/stable/2781459

McCloskey, D. N. (1976). English open fields as behavior towards risk. *Research in Economic History*, *1*, 124–170. https://www.semanticscholar.org/paper/English-Open-Fields-as-Behavior-Towards-Risk-McCloskey/6fb21407bbd92cf671d735f14aa78d979d92749a

McCloskey, D. N. (2007). *The Bourgeois Virtues: Ethics for an Age of Commerce*. University of Chicago Press.

https://press.uchicago.edu/ucp/books/book/chicago/B/bo3750637.html
McElreath, R. (2003). Reputation and the evolution of conflict. *Journal of Theoretical Biology*, *220*, 345–357. https://doi.org/10.1006/jtbi.2003.3166
Mell, H., Baumard, N., & André, J.-B. (2021). Time is money. Waiting costs explain why selection favors steeper time discounting in deprived environments. *Evolution and Human Behavior*, *42*(4), 379–387. https://doi.org/10.1016/j.evolhumbehav.2021.02.003
Merton, R. K. (1938). Social structure and anomie. *American Sociological Review*, *3*(5), 672–682. https://doi.org/10.2307/2084686
Messner, S. F., & Rosenfeld, R. (1994). *Crime and the American Dream*. Wadsworth.
Mishra, S. (2014). Decision-making under risk: Integrating perspectives from biology, economics, and psychology. *Personality and Social Psychology Review*, *18*(3), 280–307. https://doi.org/10.1177/1088868314530517
Mishra, S., & Fiddick, L. (2012). Beyond Gains and Losses: The Effect of Need on Risky Choice in Framed Decisions. *Journal of Personality and Social Psychology*, *102*, 1136–1147. https://doi.org/10.1037/a0027855
Mishra, S., Gregson, M., & Lalumière, M. L. (2012). Framing effects and risk-sensitive decision making. *British Journal of Psychology*, *103*(1), 83–97. https://doi.org/10.1111/j.2044-8295.2011.02047.x
Mishra, S., & Lalumière, M. L. (2010). You can't always get what you want: The motivational effect of need on risk-sensitive decision-making. *Journal of Experimental Social Psychology*, *46*(4), 605–611. https://doi.org/10.1016/j.jesp.2009.12.009
Miyata, S. (2003). Household's risk attitudes in indonesian villages. *Applied Economics*, *35*(5), 573–583. https://doi.org/10.1080/0003684022000020823
Monroe, J. (2005). Women in street prostitution: The result of poverty and the brunt of inequity. *Journal of Poverty*, *9*(3), 69–88.
Morduch, J. (1995). Income smoothing and consumption smoothing. *Journal of Economic Perspectives*, *9*(3), 103–114.
Mosley, P., & Verschoor, A. (2005). Risk attitudes and the 'vicious circle of poverty'. *The European Journal of Development Research*, *17*(1), 59–88. https://doi.org/10.1080/09578810500066548
Muthukrishna, M., & Henrich, J. (2019). A problem in theory. *Nature Human Behaviour*, *3*(3), 221–229. https://doi.org/10.1038/s41562-018-0522-1
Nagin, D. S. (2013). Deterrence: A review of the evidence by a criminologist for economists. *Annual Review of Economics*, *5*(1), 83–105. https://doi.org/10.1146/annurev-economics-072412-131310
Nettle, D. (2009). An evolutionary model of low mood states. *Journal of Theoretical Biology*, *257*(1), 100–103. https://doi.org/10.1016/j.jtbi.2008.10.033
Nettle, D. (2015). *Tyneside neighbourhoods: Deprivation, social life and social behaviour in one british city*. Open Book Publishers. https://doi.org/10.11647/OBP.0084
Nettle, D., Chevallier, C., Courson, B. de, Johnson, E. A., Johnson, M. T., & Pickett, K. E. (2025). Short-term changes in financial situation have immediate mental health consequences: Implications for social policy. *Social Policy & Administration*, *59*(2), 293–308. https://doi.org/10.1111/spol.13065
Nettle, D., Chrisp, J., Johnson, E. A., & Johnson, M. T. (2025). What do people want from a welfare system? Conjoint survey evidence from UK adults. *Poverty & Public Policy*, *17*(2), e70018.
Nettle, D., & Dickins, T. E. (2022). Why is greater income inequality associated with lower life satisfaction and poorer health? Evidence from the european quality of life survey, 2012. *The Social Science Journal*, 1–12.

Nettle, D., & Saxe, R. (2020). Preferences for redistribution are sensitive to perceived luck, social homogeneity, war and scarcity. *Cognition*, *198*, 104234.

O'Donnell, M., Dev, A. S., Antonoplis, S., Baum, S. M., Benedetti, A. H., Brown, N. D., Carrillo, B., Choi, A. L., Connor, P., & Donnelly, K. (2021). Empirical audit and review and an assessment of evidentiary value in research on the psychological consequences of scarcity. *Proceedings of the National Academy of Sciences*, *118*(44), e2103313118.

Page, L., Savage, D. A., & Torgler, B. (2014). Variation in risk seeking behaviour following large losses: A natural experiment. *European Economic Review*, *71*, 121–131. https://doi.org/10.1016/j.euroecorev.2014.04.009

Patterson, E. B. (1991). Poverty, Income Inequality, and Community Crime Rates. *Criminology*, *29*(4), 755–776. https://doi.org/10.1111/j.1745-9125.1991.tb01087.x

Payne, B. K., Brown-Iannuzzi, J. L., & Hannay, J. W. (2017). Economic inequality increases risk taking. *Proceedings of the National Academy of Sciences of the United States of America*, *114*(18), 4643–4648. https://doi.org/10.1073/pnas.1616453114

Pepper, G. V., & Nettle, D. (2014). Perceived extrinsic mortality risk and reported effort in looking after health. *Human Nature*, *25*(3), 378–392. https://doi.org/10.1007/s12110-014-9204-5

Pepper, G. V., & Nettle, D. (2017). The behavioural constellation of deprivation: Causes and consequences. *Behavioral and Brain Sciences*, *40*. https://doi.org/10.1017/S0140525X1600234X

Pettit, P. (2014). *Just freedom: A moral compass for a complex world*. W. W. Norton & Company.

Pickett, K. E., & Wilkinson, R. G. (2015). Income inequality and health: A causal review. *Social Science & Medicine*, *128*, 316–326.

Pietras, C. J., Cherek, D. R., Lane, S. D., & Tcheremissine, O. (2006). Risk reduction and resource pooling on a cooperation task. *The Psychological Record*, *56*(3), 387401. https://doi.org/10.1007/BF03395557

Pietras, C. J., & Hackenberg, T. D. (2001). Risk-sensitive choice in humans as a function of an earnings budget. *Journal of the Experimental Analysis of Behavior*, *76*(1), 119. https://doi.org/10.1901/jeab.2001.76-1

Pietras, C. J., Locey, M. L., & Hackenberg, T. D. (2003). Human Risky Choice Under Temporal Constraints: Tests of an Energy-Budget Model. *Journal of the Experimental Analysis of Behavior*, *80*(1), 59–75. https://doi.org/10.1901/jeab.2003.80-59

Pietras, C. J., Searcy, G. D., Huitema, B. E., & Brandt, A. E. (2008). Effects of monetary reserves and rate of gain on human risky choice under budget constraints. *Behavioural Processes*, *78*(3), 358–373. https://doi.org/10.1016/j.beproc.2008.01.016

Piff, P. K., Kraus, M. W., Côté, S., Cheng, B. H., & Keltner, D. (2010). Having less, giving more: The influence of social class on prosocial behavior. *Journal of Personality and Social Psychology*, *99*(5), 771–784. https://doi.org/10.1037/a0020092

Piff, P. K., Stancato, D. M., Cote, S., Mendoza-Denton, R., & Keltner, D. (2012). Higher social class predicts increased unethical behavior. *Proceedings of the National Academy of Sciences*, *109*(11), 4086–4091. https://doi.org/10.1073/pnas.1118373109

Pratt, T. C., & Cullen, F. T. (2005). Assessing macro-level predictors and theories of crime: A meta-analysis. *Crime and Justice*, *32*, 373–450. https://doi.org/10.1086/655357

Quick, M., Li, G., & Brunton-Smith, I. (2018). Crime-general and crime-specific spatial patterns: A multivariate spatial analysis of four crime types at the small-area scale. *Journal of Criminal Justice*, *58*, 22–32. https://doi.org/10.1016/j.jcrimjus.2018.06.003

Radkani, S., Holton, E., De Courson, B., Saxe, R., & Nettle, D. (2023). Desperation and inequality increase

stealing: Evidence from experimental microsocieties. *Royal Society Open Science*, *10*(7), 221385.
Ravallion, M., & Ravallion, M. (2016). *The economics of poverty: History, measurement, and policy*. Oxford University Press.
Rawls, J. (1971). *A theory of justice: Original edition*. Harvard University Press. https://doi.org/10.2307/j.ctvjf9z6v
Reimers, S., Maylor, E. A., Stewart, N., & Chater, N. (2009). Associations between a one-shot delay discounting measure and age, income, education and real-world impulsive behavior. *Personality and Individual Differences*, *47*(8), 973–978.
Riis-Vestergaard, M. I., & Haushofer, J. (2017). Stuff goes wrong, so act now. *Behavioral and Brain Sciences*, *40*, e340. https://doi.org/10.1017/S0140525X17001091
Robson, A. J. (1992). Status, the distribution of wealth, private and social attitudes to risk. *Econometrica: Journal of the Econometric Society*, 837–857.
Rode, C., Cosmides, L., Hell, W., & Tooby, J. (1999). When and why do people avoid unknown probabilities in decisions under uncertainty? Testing some predictions from optimal foraging theory. *Cognition*, *72*(3), 269304. https://doi.org/10.1016/S0010-0277(99)00041-4
Rossmo, D. K., & Summers, L. (2022). Uncertainty and heuristics in offender decision-making: Deviations from rational choice. *Journal of Criminal Justice*, *81*, 101923. https://doi.org/10.1016/j.jcrimjus.2022.101923
Roumasset, J. A. (1971). *Risk and Choice of Technique for Peasant Agriculture: Safety First and Rice Production in the Philippines* (Workshop Series 1). Social Systems Research Institute, University of Wisconsin.
Roy, A. D. (1952). Safety first and the holding of assets. *Econometrica*, *20*(3), 431–449. https://doi.org/10.2307/1907413
Rubin, P. H., & Paul, C. W. (1979). An Evolutionary Model of Taste for Risk. *Economic Inquiry*, *17*(4), 585–596. https://doi.org/10.1111/j.1465-7295.1979.tb00549.x
Rudolph, M., & Starke, P. (2020). How does the welfare state reduce crime? The effect of program characteristics and decommodification across 18 OECD-countries. *Journal of Criminal Justice*, *68*, 101684. https://doi.org/10.1016/j.jcrimjus.2020.101684
Rufrancos, H., Power, M., Pickett, K. E., & Wilkinson, R. (2013). Income inequality and crime: A review and explanation of the time series evidence. *Sociology and Criminology-Open Access*, *1*.
Rung, J. M., & Madden, G. J. (2018). Experimental reductions of delay discounting and impulsive choice: A systematic review and meta-analysis. *Journal of Experimental Psychology: General*, *147*(9), 1349.
Sampson, R. J. (1997). Neighborhoods and Violent Crime: A Multilevel Study of Collective Efficacy. *Science*, *277*(5328), 918–924. https://doi.org/10.1126/science.277.5328.918
Sampson, R. J. (2012). *Great American City: Chicago and the Enduring Neighborhood Effect* (W. J. Wilson, Ed.). University of Chicago Press. https://press.uchicago.edu/ucp/books/book/chicago/G/bo5514383.html
Scheel, A. M., Tiokhin, L., Isager, P. M., & Lakens, D. (2021). Why Hypothesis Testers Should Spend Less Time Testing Hypotheses. *Perspectives on Psychological Science*, *16*(4), 744–755. https://doi.org/10.1177/1745691620966795
Schelling, T. C. (1971). Dynamic models of segregation. *The Journal of Mathematical Sociology*, *1*(2), 143–186. https://doi.org/10.1080/0022250X.1971.9989794
Schildberg-Hörisch, H. (2018). Are risk preferences stable? *Journal of Economic Perspectives*, *32*(2), 135–154. https://doi.org/10.1257/jep.32.2.135

Schroyen, F., & Aarbu, K. O. (2018). Attitudes Towards Large Income Risk in Welfare States: An International Comparison. *Economica*, *85*(340), 846–872. https://doi.org/10.1111/ecca.12267

Schultz, T. W. (1964). *Transforming traditional agriculture.* (Yale University Press).

Scott, J. C. (1977). *The moral economy of the peasant: Rebellion and subsistence in southeast asia*. Yale University Press. https://doi.org/10.12987/9780300185553

Searcy, G. D., & Pietras, C. J. (2011). Optimal risky choice in humans: Effects of amount of variability. *Behavioural Processes*, *87*(1), 88–99.

Sen, A. (1983). Poor, relatively speaking. *Oxford Economic Papers*, *35*(2), 153–169. https://www.jstor.org/stable/2662642

Shah, A. K., Mullainathan, S., & Shafir, E. (2012). Some consequences of having too little. *Science*, *338*(6107), 682–685. https://doi.org/10.1126/science.1222426

Sharma, E., Tully, S. M., & Wang, X. (2023). Scarcity and intertemporal choice. *Journal of Personality and Social Psychology*, *125*(5), 1036.

Shaw, C. R., & McKay, H. D. (1942). *Juvenile delinquency and urban areas*. University of Chicago Press.

Sheehy-Skeffington, J., & Rea, J. (2017). *How poverty affects people's decision-making processes* [Research Report]. Joseph Rowntree Foundation. https://www.jrf.org.uk/report/how-poverty-affects-peoples-decision-making-processes

Shover, N. (1996). *Great pretenders: Pursuits and careers of persistent thieves*. Routledge. https://doi.org/10.4324/9780429493751

Simon, H. A. (1955). A behavioral model of rational choice. *The Quarterly Journal of Economics*, *69*(1), 99–118. https://doi.org/10.2307/1884852

Simonsohn, U. (2018). Two Lines: A Valid Alternative to the Invalid Testing of U-Shaped Relationships With Quadratic Regressions. *Advances in Methods and Practices in Psychological Science*, *1*(4), 538–555. https://doi.org/10.1177/2515245918805755

Singer, P. (2009). *The Life You Can Save: Acting Now to End World Poverty*. Random House Inc.

Smaldino, P. E. (2017). Models are stupid, and we need more of them. *Computational Social Psychology*, 311331.

Smaldino, P. E. (2020). How to translate a verbal theory into a formal model. *Social Psychology*, *51*(4), 207–218. https://doi.org/10.1027/1864-9335/a000425

Smith, A. (1776). *The wealth of nations*. W. Strahan; T. Cadell.

Sommet, N., & Elliot, A. J. (2023). A competitiveness-based theoretical framework on the psychology of income inequality. *Current Directions in Psychological Science*, *32*(4), 318–327.

Sommet, N., Morselli, D., & Spini, D. (2018). Income inequality affects the psychological health of only the people facing scarcity. *Psychological Science*, *29*(12), 1911–1921.

Spears, D. (2011). Economic decision-making in poverty depletes behavioral control. *The BE Journal of Economic Analysis & Policy*, *11*(1).

Starmans, C., Sheskin, M., & Bloom, P. (2017). Why people prefer unequal societies. *Nature Human Behaviour*, *1*(4), 1–7.

Stauffer, W. R., Lak, A., & Schultz, W. (2014). Dopamine reward prediction error responses reflect marginal utility. *Current Biology*, *24*(21), 2491–2500.

Stephens, D. W. (1981). The logic of risk-sensitive foraging preferences. *Animal Behaviour*, *29*(2), 628629. https://doi.org/10.1016/S0003-3472(81)80128-5

Sunde, U., Dohmen, T., Enke, B., Falk, A., Huffman, D., & Meyerheim, G. (2022). Patience and comparative development. *The Review of Economic Studies*, *89*(5), 2806–2840.

Tanaka, T., Camerer, C. F., & Nguyen, Q. (2010). Risk and time preferences: Linking experimental and household survey data from vietnam. *American Economic Review*, *100*(1), 557–571. https://doi.org/10.1257/aer.100.1.557

Tiokhin, L. (2021). *5 modeling misconceptions*. https://doi.org/10.13140/RG.2.2.19688.39688

Topalli, V., Wright, R., & Fornango, R. (2015). Drug dealers, robbery and retaliation. Vulnerability, deterrence and the contagion of violence. *British Journal of Criminology*, *42*, 337–351. https://doi.org/10.1093/bjc/42.2.337

Townsend, P. (1979). *Poverty in the united kingdom: A survey of household resources and standards of living*. University of California Press.

Truesdale, B. C., & Jencks, C. (2016). The health effects of income inequality: Averages and disparities. *Annual Review of Public Health*, *37*(1), 413–430.

Tucker, B. (2012). Do risk and time experimental choices represent individual strategies for coping with poverty or conformity to social norms? Evidence from rural southwestern madagascar. *Current Anthropology*, *53*(2), 149–180. https://doi.org/10.1086/664569

Turchin, P., Gavrilets, S., & Goldstone, J. A. (2017). Linking "micro" to "macro" models of state breakdown to improve methods for political forecasting. *Cliodynamics*, *8*(2).

Veblen, T. (1899). *The theory of the leisure class: An economic study of institutions*. Macmillan.

Vieider, F. M., Chmura, T., & Martinsson, P. (2012). Risk attitudes, development, and growth: Macroeconomic evidence from experiments in 30 countries. *Discussion Papers, WZB Junior Research Group Risk and Development*. https://ideas.repec.org//p/zbw/wzbrad/spii2012401.html

Vilalta, C., Cadena, E., Garrocho, C., & Fondevila, G. (2024). Beyond the immediate effects of income inequality on homicide rates: A reply to daly's critique. *Evolution and Human Behavior*, *45*(4), 106597.

Vohs, K. D. (2013). The poor's poor mental power. *Science*, *341*(6149), 969–970. https://doi.org/10.1126/science.1244172

Walters, G. D., & Mandracchia, J. T. (2017). Testing criminological theory through causal mediation analysis: Current status and future directions. *Journal of Criminal Justice*, *49*, 53–64. https://doi.org/10.1016/j.jcrimjus.2017.02.002

Wang, X. T. (2002). Risk as reproductive variance. *Evolution and Human Behavior*, *23*(1), 35–57.

Wardle, H., Keily, R., Astbury, G., & Reith, G. (2014). 'Risky Places?': Mapping Gambling Machine Density and Socio-Economic Deprivation. *Journal of Gambling Studies*, *30*(1), 201–212. https://doi.org/10.1007/s10899-012-9349-2

Weber, M. (1905). Die protestantische ethik und der geist des kapitalismus. *Archiv Für Sozialwissenschaft Und Sozialpolitik*, *21*, 1110.

Weisburd, D., Bushway, S., Lum, C., & Yang, S.-M. (2004). Trajectories of Crime at Places: A Longitudinal Study of Street Segments in the City of Seattle*. *Criminology*, *42*(2), 283–322. https://doi.org/10.1111/j.1745-9125.2004.tb00521.x

Wiggins, D. (1998). *Needs, values, truth: Essays in the philosophy of value* (Vol. 6). Oxford University Press.

Wik, M., Aragie Kebede, T., Bergland, O., & Holden, S. T. (2004). On the measurement of risk aversion from experimental data. *Applied Economics*, *36*(21), 2443–2451. https://doi.org/10.1080/0003684042000280580

Wilkinson, R. (2004). Why is Violence More Common Where Inequality is Greater? *Annals of the New York Academy of Sciences*, *1036*(1), 1–12. https://doi.org/https://doi.org/10.1196/annals.1330.001

Wilkinson, R. G., Kawachi, I., & Kennedy, B. P. (1998). Mortality, the Social Environment, Crime and Vio-

lence. *Sociology of Health & Illness*, *20*(5), 578–597. https://doi.org/10.1111/1467-9566.00120
Wilkinson, R. G., & Pickett, K. E. (2009). Income inequality and social dysfunction. *Annual Review of Sociology*, *35*(1), 493–511.
Wilkinson, R., & Pickett, K. (2010). *The Spirit Level: Why Greater Equality Makes Societies Stronger*. Bloomsbury Publishing.
Wilson, M., & Daly, M. (1985). Competitiveness, risk taking, and violence: The young male syndrome. *Ethology and Sociobiology*, *6*(1), 59–73.
Wilson, M., & Daly, M. (1997). Life expectancy, economic inequality, homicide, and reproductive timing in Chicago neighbourhoods. *BMJ*, *314*(7089), 1271. https://doi.org/10.1136/bmj.314.7089.1271
Wilson, W. J. (2012). *The Truly Disadvantaged: The Inner City, the Underclass, and Public Policy*. University of Chicago Press.
Winterhalder, B., Lu, F., & Tucker, B. (1999). Risk-senstive adaptive tactics: Models and evidence from subsistence studies in biology and anthropology. *Journal of Archaeological Research*, *7*(4), 301–348. https://doi.org/10.1007/BF02446047
Yesuf, M., & Bluffstone, R. A. (2009). Poverty, Risk Aversion, and Path Dependence in Low-Income Countries: Experimental Evidence from Ethiopia. *American Journal of Agricultural Economics*, *91*(4), 1022–1037. https://doi.org/10.1111/j.1467-8276.2009.01307.x
Zeisberger, S. (2022). Do people care about loss probabilities? *Journal of Risk and Uncertainty*, *65*(2), 185–213.