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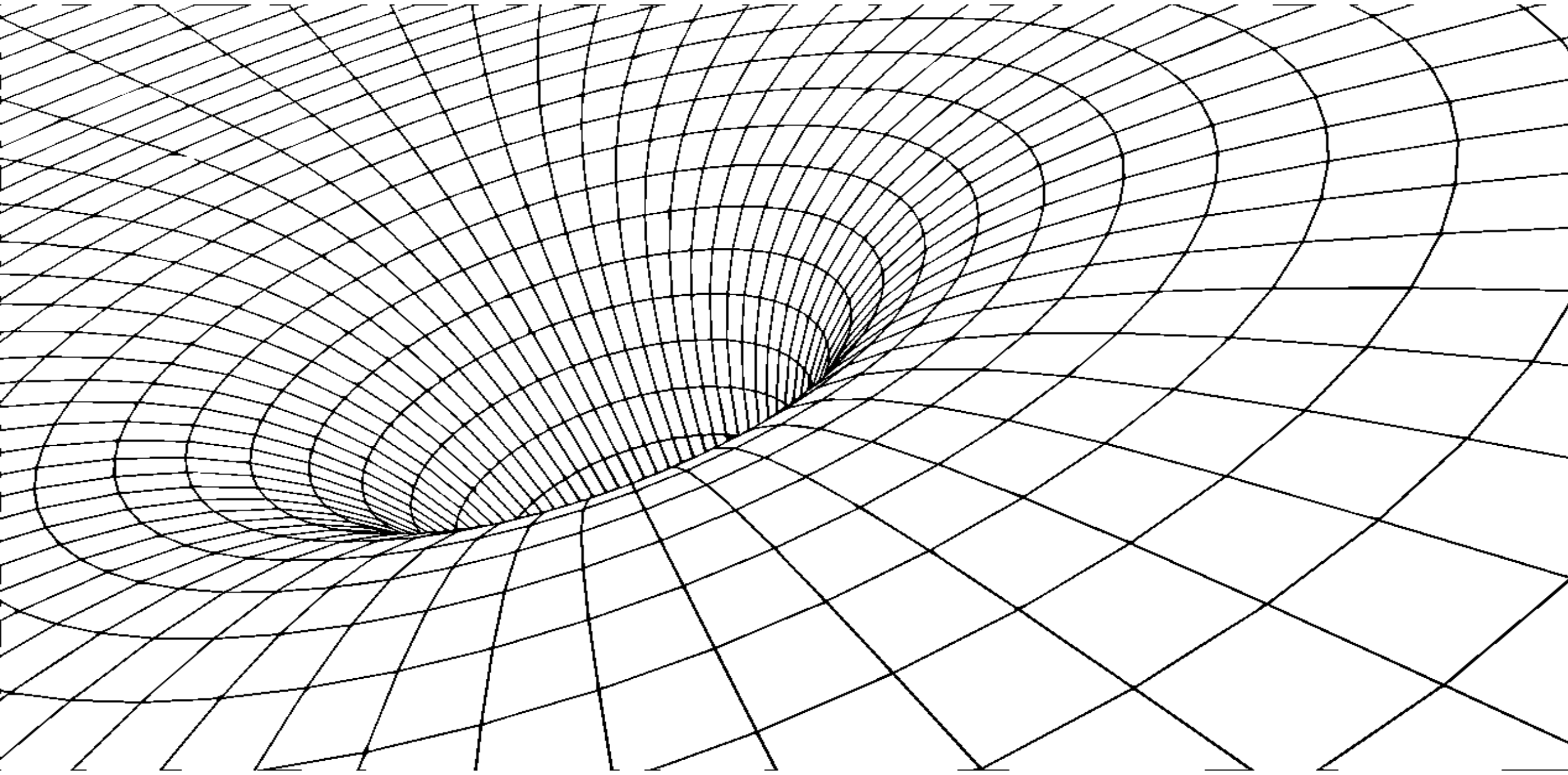

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On the Social Cost of Orbital Debris*

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Abstract

Orbital debris represents a global environmental externality in outer space, akin to terrestrial environmental externalities, imposing a social cost on humanity. Accurately quantifying this social cost is crucial for designing and implementing effective debris mitigation policies. This paper estimates the social cost of orbital debris (SCOD) using a methodology inspired by climate-change economics, particularly the approach used to calculate the social cost of carbon (SCC) through projections derived from integrated assessment models (IAMs). We introduce an IAM that links economic activity with space activity, modeling orbital debris emissions as a function of launches and collisions. The model generates optimal trajectories for orbital debris emissions and consumption, which are then used to estimate the SCOD. Our results indicate that the SCOD is approximately $84,200 per piece of debris larger than 1 cm for the year 2023 (in international US dollars), based on a 1.5% social discount rate and an intertemporal marginal consumption rate of 1.5.

Keywords: Orbital debris; Integrated assessment model; Social cost of orbital debris.

JEL Classification: D62; E21; E22; Q53; Q58.

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1. Introduction

With humanity's access to outer space, pollution is no longer confined to Earth. Human exploration and exploitation of space have profoundly altered the near-Earth environment, generating millions of human-made objects collectively referred to as orbital debris or space junk. Orbital debris constitutes a form of space pollution that is distinct from terrestrial pollution in several key ways and poses significant risks to both commercial and other activities in outer space (Liou and Johnson, 2006). Satellite launches and orbital operations produce debris that can collide with operational satellites, potentially causing catastrophic damage. Even tiny fragments with minimal mass can inflict severe damage due to their extremely high velocities. Orbital debris originates from various sources, including launch vehicle components, fragments from the breakup of spent rocket stages, intentional and unintentional satellite explosions, inactive satellites abandoned in orbit, and other sources. The National Aeronautics and Space Administration (NASA) and the European Space Agency (ESA) estimate that Earth's orbit currently contains approximately 35,000 pieces of debris larger than 10 cm, 1,000,000 objects between 1 cm and 10 cm, and over 130 million fragments ranging from 1 mm to 1 cm. Debris smaller than 1 cm poses a relatively low risk of causing fatal damage in the event of collision with a satellite. However, fragments larger than 1 cm can have catastrophic consequences due to their high velocities (Krisko, 2007; Lafleur, 2011; and Mains et al., 2024). A distinctive characteristic of orbital debris is its self-perpetuating nature: collisions between objects create additional debris, triggering a cascade effect. This phenomenon, known as the "Kessler syndrome," describes a scenario in which collisions exponentially increase the amount of debris (Kessler and Cour-Palais, 1978; Kessler, 1991). In this context, quantifying the social cost of orbital debris generation is a critical step toward formulating effective mitigation strategies and ensuring the long-term sustainability of the space environment.

Environmental economics has a long tradition of quantifying the social cost of environmental externalities. In the context of climate-change economics, a central concept is the social cost of carbon (SCC), which represents the net present value of damages caused by a marginal increase in carbon emissions in a specific year. This monetary estimate captures the societal impacts of global climate change and serves as a key tool for policy analysis (Anthoff et al., 2009; Foley et al., 2013; Metcalf and Stock, 2017; Rose et al., 2017; Pindyck, 2019; Tol, 2023; and Braun et al., 2024). The SCC is typically calculated using climate-economy models known as integrated assessment models (IAMs), which integrate an economic framework, often based on growth theory, with a climate change model. Prominent IAMs include the ETA-MACRO (Model of Energy-Economy Interactions) by Manne (1977), DICE (Dynamic Integrated Climate-Economy) model by Nordhaus (1992, 1993, 2008, 2017), the GLOBAL-2100 model of Manne and Richels (1992), the CETA (Carbon Emissions Trajectory Assessment) model by Peck and Teisberg (1992), and the MERGE (Model for Evaluating Regional and Global Effects) model by Manne et al., (1995). These models have been instrumental for the U.S. Interagency Working Group in estimating the SCC. As Pizer et al. (2014) emphasize, regular updates and transparency in the SCC estimation process are critical for ensuring credible economic analyses of climate policies.

The standard methodology for estimating the SCC involves projecting key variables into the future (namely consumption and emissions), applying a hypothetical shock to carbon emissions at a specific time, recalculating the projections, and measuring the resulting change in discounted welfare. This process enables policymakers to assess the societal costs of emissions and formulate effective mitigation strategies. The SCC is defined as the reduction in aggregate consumption required to produce the same welfare effect as a one-unit increase in carbon emissions. Its calculation depends on several factors, including the economic model, the environmental model, and the damage function that links environmental changes to economic outcomes. While consensus exists on the broad structure of IAMs, uncertainty remains regarding the damage function, which significantly influences SCC estimates. Additionally, key parameters, such as the discount rate and the intertemporal marginal consumption rate, play a crucial role in the estimate of the social cost of environmental externalities.

Leaving the Earth and returning to space, the humanity faces several challenges related to the internationally shared nature of Earth's orbit, its overuse, and the creation of negative externalities such as the proliferation of orbital debris. The growing human activity in space, fueled by the rise of the so-called New Space Economy, has raised concerns about the accumulation of orbital debris in Earth's orbit. Research has projected future trajectories for objects in orbit, using various models and policy scenarios. Examples include Adilov et al. (2020), Nozawa et al. (2023), Bongers et al. (2024), and Rao and Rondina (2025). These authors use IAMs to assess the economic and environmental implications of debris emissions and the likelihood of the Kessler syndrome. A natural step ahead would consist in the computation of the SCOD as key information for the design and implementation of orbital debris mitigation policies.

Colvin, Karcz, and Wusk (2023) conduct a cost-benefit analysis for active debris remediation in two scenarios. For large debris (derelict satellites and rocket bodies) remediation, they estimate the benefits of removing the 50 statistically most concerning derelict objects in LEO (Low Earth Orbit), as identified by McKnight et al. (2021). They estimate a benefit of \$3.5 million in the first year after removal and an accumulated benefit of \$1,100 million over 25 years. The cost of removal is approximately \$800 million for uncontrolled reentry and over \$1 billion for controlled reentry. For small debris remediation, they estimate the benefit of removing 100,000 pieces of 1–10 cm debris from altitudes of 450–850 km. The expected reduction in risk is valued at \$23 million, with an accumulated benefit of around \$7.5 billion over 25 years, at an estimated cost between \$30 and \$600 million using ground-based lasers. This implies that the cost of removing a single piece of debris ranges from \$300 to \$6,000. This cost-benefit analysis has been extended in Locke et al. (2024) to include post-mission disposal (PMD), shielding, debris tracking, warnings, and collision-avoidance maneuvers. Lee (2024) and Lee et al. (2024) define the cost of orbital debris as the sum of costs associated with satellites (including damages, collision avoidance, and service disruptions), impacts on space stations, and effects on Earth. Using a contingent valuation approach, Lee (2024) estimates the loss of satellite value due to orbital debris in South Korea, calculating households' willingness to pay at \$16.4, resulting in a total value of \$388.8 million when multiplied by the number of households. As a percentage of GDP, the economy's willingness to pay represents 33.9% for the potential losses of the country's Earth observation satellites over 10 years (the GDP of South Korea is \$1,713 billion US dollars).

This paper represents a first attempt to estimate the global social cost of orbital debris (SCOD), defined as the net present value of damages resulting from an increase in orbital debris emissions. Our approach draws inspiration from the methods used in climate-change economics. We develop an integrated assessment model (IAM) that combines an optimal growth model with a simplified orbital debris evolutionary model. To compute the SCOD, we introduce an IAM called ISEM (Integrated Space-Economy Model), where the economic module is based on the Ramsey (1928) neoclassical growth model, and the space module is a simplified version of the debris model in Bongers and Torres (2023). The space environment module accounts for two sources of debris: launches, which serve as the primary source of emissions, and collisions between debris and satellites, which act as an endogenous in-orbit secondary source. The IAM is used to compute optimal trajectories for emissions and consumption, enabling the calculation of the SCOD.

In short, the SCOD is derived by analyzing the reduction in future consumption resulting from an increase in debris emissions. This concept mirrors the social cost of negative externalities in climate-change economics. Specifically, the SCOD is estimated using the shadow prices associated with the emissions and consumption constraints within the discounted utility maximization framework. In essence, the SCOD for a given year represents the monetary value of economic damages caused by the release of an additional piece of orbital debris. It is measured in U.S. dollars per piece of orbital debris larger than 1 cm.[1] An alternative interpretation of the SCOD is that it represents a monetization of the economic benefits achieved by avoiding the emission of one additional piece of debris.

The infinite-horizon space-economy model is simulated over a finite horizon of 200 years, using terminal conditions following Barr and Manne (1967) and Lau et al. (2002). Baseline estimates indicate that the SCOD is approximately $84,200 for the year 2023 (in US international dollars) for a social discount rate of 1.5% and an intertemporal marginal consumption rate of 1.5. This estimate of SCOD is well above the range of the estimated cost of removing one piece of debris larger than 1 cm estimated by Colvin et al. (2023). We investigate how the estimated SCOD varies depending on the discount rate, the intertemporal marginal consumption rate, and alternative scenarios related to debris-free launch systems and collision avoidance. As expected and similarly to the SCC estimates, the SCOD is very sensitive to the calibration of those parameters, ranging from a value of $646,000 for a social discount rate of 1%, to $14,400 for a social discount rate of 3%.

The remainder of the paper is organized as follows. Section 2 describes the Integrated Assessment Model (IAM) for the space economy. Section 3 presents the parameterization and calibration of the model's parameters. Section 4 introduces the concept of the social cost of orbital debris (SCOD). Section 5 presents the results of the estimated SCOD. Section 6 conducts a sensitivity analysis and discusses the results from alternative scenarios. Finally, Section 7 provides concluding remarks.

2. The integrated space-economy model

This section introduces the structure of an Integrated Assessment Model (IAM), called the Integrated Space-Economy Model (ISEM), designed to estimate the social cost of orbital debris (SCOD). Similar to IAMs in climate-change economics, ISEM consists of two components: an economic submodel and an environmental submodel. The economic submodel is based on an optimal neoclassical growth model (Ramsey, 1928) for the global economy, encompassing both Earth-based and space-based economic activity. It considers two types

[1] The analysis only considers orbital debris larger than 1 cm. Pieces of debris smaller than 1 cm can cause some damage to spacecraft but are generally not fatal (Mains et al., 2024).

of capital assets: Earth capital and space capital (i.e., satellites). Economic output is allocated among consumption, investment in physical capital on Earth, and investment in satellites. Unlike traditional environmental economic models, pollution does not directly reduce productivity in this framework. Instead, the cost of orbital debris arises from the increased risk of collisions, which can critically damage or destroy functional satellites. The risk of collision could reduce the stock of operational in-orbit equipment and, consequently, final production if the damaged equipment is not replaced. The environmental submodel is a simplified orbital debris evolutionary model that accounts for two sources of debris: launches and collisions. Establishing the ISEM requires mapping economic variables to physical variables, such as the number of launches, satellites, and pieces of orbital debris. In the model, physical variables are represented by capital letters, while economic variables are represented by lowercase letters.

2.1. The economy model

The economy component of the model is based on the optimal neoclassical growth model, extended to incorporate human activity in space. Time is discrete and extends to an infinite horizon. The economy is inhabited by a large number of identical households. There is a representative household with instantaneous utility $U(\hat{c}_t, N_t)$, defined over per capita consumption $\hat{c}_t$, and where N_t represents population. The aggregate consumption, c_t, is defined as $c_t = \hat{c}_t N_t$. The function $U(\hat{c}_t, N_t)$ is the flow of utility which is assumed to reflect social well-being. The function $U(\cdot)$ is assumed to be concave and twice continuously differentiable.

The problem to be solved by the stand-in household involves maximizing the sum of discounted utility,

$$max_{\{\hat{c}_t\}_{t=0}^{\infty}} \sum_{t=0}^{\infty} \left(\frac{1}{1+\rho}\right)^t U(\hat{c}_t, N_t) \tag{1}$$

where $\rho > 0$ is the subjective intertemporal preference parameter, also known as the pure rate of social time preference. The discount factor, $0 < \beta < 1$, is defined as $\beta = 1/(1+\rho)$. The household faces the following budget constraint, which aligns with the feasibility constraint of the economy:

$$c_t + i_t + h_t = y_t \tag{2}$$

where i_t is investment in physical capital other than satellites, h_t is investment in satellites, which includes all costs to launch satellites into orbit, and y_t is final output. All prices are defined in output units and normalized to one.

Output is assumed to be a function of aggregate productivity, the stock of physical capital on Earth, k_t, the stock of satellites, s_t, and labor, which is assumed equal to the population, N_t.

$$y_t = a_t f(k_t, s_t, N_t) \tag{3}$$

where a_t is the aggregate productivity factor, which is assumed to follow an exogenous growth process. The Earth capital accumulation process follows the standard inventory equation:

$$k_{t+1} = (1 - \delta_k)k_t + i_t \tag{4}$$

where $0 < \delta_k < 1$ is the capital depreciation rate. The law of motion of operational satellites in orbit is not only a positive function of investment, but also depends negatively on the damage provoked by orbital debris. The stock of satellites, measured in final output units as an equipment asset, is given by the following accumulation process,

$$s_{t+1} = (1 - \delta_s)s_t + q_t h_t - x_t \tag{5}$$

where $0 < \delta_s < 1$ is the depreciation rate for satellites, and x_t is the loss of satellite assets by collisions (damage from pollution to be defined later), and q_t represents investment specific technological change (ISTC), as defined by Greenwood, Hercowitz and Krusell (2000). ISTC indicates a decreasing trend in satellite asset prices, particularly the declining cost of launches. Damage results in the destruction of satellites, reducing the stock used in production, and lowering final output if assets are not replaced.

2.2. Exogenous growth sources

The model incorporates three exogenous sources of growth: aggregate Hicks-neutral technological change, investment-specific technological change (ISTC) for satellites, and labor (population) growth. Growth rates of technical change and population are not constant, but similarly to climate change AIMs it is assumed that the growth rate declines over time. Aggregate productivity technological progress is characterized as,

$$a_{t+1} = exp(g_{a,t})a_t \tag{6}$$

where $g_{a,t}$ is the growth rate of TFP defined as,

$$g_{a,t} = g_{a,0} exp(-\delta_a t) \tag{7}$$

where δ_a is the decay rate in the TFP growth rate. We assume a similar specification for the satellite investment-specific technological progress,

$$q_{t+1} = exp(g_{q,t})q_t \tag{8}$$

where $g_{q,t}$ is the growth rate of TFP defined as,

$$g_{q,t} = g_{q,0} exp(-\delta_q t) \tag{9}$$

where δ_q is the decay rate in ISTC for satellites.

The last source of economic growth is population growth, as it is assumed that labor equals population. Following the specification by Hassell (1975), population dynamics are defined as,

$$N_{t+1} = N_t \left(\frac{N^*}{N_t} \right)^{\varsigma} \tag{10}$$

where N^* is the asymptotic population at the end of the simulation period and ς is a parameter driving population growth rate.

2.3. Mapping between economic and physical variables

The model includes both economic variables (measured in terms of final output) and physical variables (measured in units). We introduce a mapping parameter that converts economic variables into physical variables (i.e., number of satellites). The first mapping step links the stock of satellites as a capital asset, denoted by output units, s_t, with the number of satellites, S_t, as follows,

$$S_t = \mu s_t \tag{11}$$

where μ is the conversion parameter that transforms "economic" values into "physical" values. ISTC is considered a form of technological progress embodied in physical capital assets. This can be interpreted as a reduction in the cost of satellites. Similarly, the number of satellites destroyed by collisions, X_t, is defined as,

$$X_t = \mu x_t \tag{12}$$

On the other hand, the mapping between investment in satellites and the number of new satellites launched into orbit, H_t,

$$H_t = \mu q_t h_t \tag{13}$$

By substituting the above mappings into the restriction (5), we derive the accumulation process for the number of satellites in orbit, expressed as,

$$S_{t+1} = (1 - \delta_s) S_t + H_t - X_t \tag{14}$$

where $0 < \delta_s < 1$ is the depreciation rate of satellites.

2.4. Launches

The primary source of orbital debris emissions is the launch of satellites and other spacecraft. Therefore, it is essential to include the number of launches as an additional variable in our model. Traditional launch systems use multi-stage rockets (typically with two to four stages). After successfully deploying the payload into orbit, debris such as connection parts, fairings, and spent rocket bodies—including fuel tanks and engines—remains in space. It is important to note that orbital debris is not solely released at the moment of launch. Over time, debris can be generated as rocket bodies break up, producing additional fragments, or through collisions with operational satellites.

The number of new satellites inserted into orbit, H_t, is assumed to be a proportion η of the number of launches, L_t:

$$H_t = \eta L_t \tag{15}$$

where η represents the number of satellites per launch rocket, as a single rocket can carry more than one satellite. From this expression, we derive the relationship between the number of launches and investment in satellites as:

$$L_t = \frac{\mu q_t h_t}{\eta} \tag{16}$$

2.5. The space model

The space environment is vastly different from that on Earth. Space pollution can be either natural or man-made. It primarily consists of objects moving at extremely high speeds, which have the potential to collide with and destroy other objects. Any human-made object that is non-functional and orbiting Earth is classified as space debris. In this paper, we focus exclusively on man-made space debris, as natural space pollution is rare and poses minimal risk to humans, except in cases where a relatively large object is on a collision course with Earth. The lifetime of orbital debris is highly dependent on the orbit. Over time, the altitude of orbital debris decreases, primarily due to atmospheric drag and solar activity. The Earth's atmosphere acts as a protective shield, mitigating the impact of smaller objects, including orbital debris, that collide with our planet. However, debris can collide with operational satellites, destroying this type of capital assets and producing more debris from fragmentation.

2.5.1. Emissions of orbital debris

We use a highly stylized model to describe the law of motion of orbital debris. Debris originates from various sources, including objects related to launches, discarded rocket stages and fuel tank bodies, derelict satellites that are not removed from orbit, accidental explosions and breakups, in-orbit collisions, and intentional debris creation through military activities, such as the destruction of a satellite using anti-satellite missiles. For modeling the population of debris, we employ a simplified version of Bongers and Torres (2023). Formally, we consider two sources of debris emissions: launches and collisions with operational satellites. The production of debris is modeled as follows:

$$Z_t = \omega L_t + \gamma X_t \tag{17}$$

where ω represents the amount of debris produced per launch, and γ denotes the amount of debris generated by collisions and the destruction of operational satellites. The parameter representing the number of debris produced by launches accounts for the fact that debris is generated not only at the time of launch but also in subsequent periods. Some debris, such as rocket bodies, rocket engines, and abandoned derelict satellites, can produce additional debris over time due to breakups and explosions caused by residual fuel, and collisions with each other and with fragments.

2.5.2. The stock of pollution

Before the first launch in 1957, the stock of orbital debris was zero. Since then, the primary source of space debris has been the launch of spacefaring equipment. It is measured in terms of the number of objects rather than in units of output. The law of motion for orbital debris, D_t, is given by:

$$D_{t+1} = (1 - \delta_d)D_t + Z_t \tag{18}$$

where $0 < \delta_d < 1$ is the natural decay rate of debris due to atmospheric drag and solar conditions, and Z_t are emissions.

2.5.3. Damage

Orbital debris travels at extremely high speeds (averaging 36,000 km/h, or ten kilometers per second in LEO). Such debris can collide with operational satellites and other spacecraft, potentially resulting in the loss of space equipment. While it is true that some uncontrolled large-mass debris in low orbit may re-enter the Earth's atmosphere and cause damage to life or property, such events are highly unlikely. In this analysis, we focus exclusively on damage caused by collisions that remain confined to space.

The damage function establishes the link between the economy and the space environment. Following Farinella and Cordelli (1991), the number of satellites destroyed per period due to collisions with space debris is assumed to be a function of the quantity of space debris and the number of operational satellites,

$$X_t = \theta D_t S_t \tag{19}$$

where $\theta > 0$ is a parameter representing the probability or risk of collision. Based on the above expression, the value of satellite assets destroyed by collisions, x_t, is defined as,

$$x_t = \theta D_t s_t \tag{20}$$

2.6. Finite-horizon conditions

The optimal growth model assumes that the economy is populated by forward-looking agents with rational expectations, who make economic decisions over an infinite horizon. However, numerical solutions can only be obtained for a finite number of periods. In practice, we solve a non-linear infinite-horizon economic growth model by approximating it within a finite-horizon framework. For transforming the original infinite-horizon optimal control problem into an equivalent finite-horizon optimal control problem, we need some terminal conditions that account for the post-terminal behavior of the economy. A key challenge in approximating an infinite-horizon equilibrium for a neoclassical growth model is determining terminal capital stock in such a way that the solution of the model over the period of interest remains unaffected by the choice of horizon or the terminal condition (Mercenier and Michel, 1994).

The literature has dealt with this issue by proposing alternative terminal conditions to be incorporated into the model to determine investment in the last computational period (T) but using some adjustment to approximate choices over the period $T + 1$ to infinity. Blake and Westaway (1995) argue that any distortionary effects of a terminal condition can be minimized by setting a terminal condition consistent with the steady state of the model and sufficiently distant so that it does not affect model properties over the horizon of interest, so that a change in either in the horizon period or in the terminal condition does not alter the solution over the period of interest. The simplest approach is to assume that the world ends at period T. This can be a valid method when the value of T is large and the discount rate is high, to minimize the effects of the terminal values on the optimal path. Because $\beta^t \to 0$ as $t \to \infty$, we can truncate the infinite horizon at a large finite period T. An alternative frequently used in climate-change economics is to use a fixed saving rate for the last periods of the simulation together with the use of large time intervals. This is the strategy followed by, for instance, Nordhaus (1992, 1993) in solving the DICE model.

For instance, in DICE2016 (Nordhaus, 2017), a constant saving rate equal to the long-run saving rate for the last 10 periods (50 years). In DICE2023 (Nordhaus, 2024) it is used a saving rate of 0.28 for periods larger than 37 (last 185 years).

The general infinity-horizon problem can be defined as an utility maximization problem which is divided into two parts,

$$\max_{c_t} W = \sum_{t=0}^{T} \left(\frac{1}{1+\rho}\right)^t U(c_t) + \sum_{t=T+1}^{\infty} \left(\frac{1}{1+\rho}\right)^t U(c_t) \tag{21}$$

where the first part is the finite-horizon already solved from $t = 0$ to T and the second part represents the economy behavior from period $T + 1$ to infinity, and where the two sub-problems are linked through the capital stock at period $T + 1$.

Barr and Manne (1967) assume that at the terminal period T, the economy is at the steady state where the growth rate is g_c. Under these assumptions, expression (21) can be written as,

$$\max_{c_t} W = \sum_{t=0}^{T-1} \left(\frac{1}{1+\rho}\right)^t U(c_t) + \sum_{t=T}^{\infty} \left(\frac{1}{1+\rho}\right)^t U(c_t(1+g_c^{t-T})) \tag{22}$$

where the second r.h.s. term is a constant. Abstracting from the constant term, the maximization problem can be written as,

$$\max_{c_t} W \quad = \quad \sum_{t=0}^{T} \hat{\beta}^t U(c_t) \tag{23}$$

where the discount factor would be,

$$\hat{\beta}^t = \begin{cases} \left(\frac{1}{1+\rho}\right)^t & \text{for} \quad t < T \\ \\ \frac{(1+\rho)^{1-T}}{\rho} & \text{for} \quad T \end{cases} \tag{24}$$

Following Lau et al. (2002), this condition is combined with a constraint for the final period that requires a minimal level of investment. This is the strategy we follow for the baseline solution of the model, by combining the discount factor given by expression (24), with the following two investment constraints for Earth and space capital, respectively,

$$i_T \geq (g_y + \delta_k) k_T \tag{25}$$

and

$$h_T \geq \frac{(g_y + \delta_s) s_T}{q_T} \tag{26}$$

3. Parameterization and calibration

This section presents initial values for the key variables for the base period, the parameterization of the household's utility function, the aggregate production function, and data sources for the calibration of the economic and physical parameters of the model. For the economic parameters, we use data from the BEA, OECD, World Bank, and United Nations. For the physical parameters we use primarily data from NASA and ESA.

3.1. Initial values

The base year from which the simulation starts is 2023. Initial output is world GDP estimated by the World Bank at 184.65 trillion international dollars. Initial capital stock is assumed to be 3 times world GDP (553.95 trillion dollars). This figure is split between Earth capital and space capital according to their respective steady state values. The initial space capital stock is 1.72 trillion dollars, whereas Earth capital stock is 552.23 trillion dollars. Initial population is taken from the United Nations Population Division with a value of 8,056 million.

Initial values for physical variables are taken from databases from NASA and ESA. According to the ESA, the initial number of satellites in orbit is 8,500 (December 2023). The number of launches in 2023 was a total of 217, inserting into orbit a total of 2,950 satellites. The ESA estimates a total of 36,500 objects larger than 10 cm. The number of tracked objects by NASA is 28,228, including operational satellites. The number of orbital debris between 1 cm and 10 cm estimated by the ESA is 1 million, and 130 million for debris between 1 mm and 1 cm. As only orbital debris larger than 1 cm are considered potentially deadly, the initial stock of debris is 1,036,500 units.

3.2. Parameterization

We assume perfect foresight and an additively separable utility function. There is a continuum of identical households, each of whom has preferences that are characterized by the following constant relative risk-aversion (CRRA-type) utility function,

$$U(\hat{c}_t) = \frac{\hat{c}_t^{1-\sigma} - 1}{1 - \sigma} \tag{27}$$

where $\sigma \geq 0$ is the risk aversion parameter. The parameter σ can also be interpreted as a measure of social aversion to changes in consumption (Nordhaus, 1993).

It is assumed that the production function is of Cobb-Douglas type with constant returns to scale, where labor equals population,

$$y_t = a_t k_t^{\alpha_1} s_t^{\alpha_2} N_t^{1-\alpha_1-\alpha_2} \tag{28}$$

where $0 < \alpha_1, \alpha_2 < 1$.

3.3. Calibration

For the calibration of economic parameters it is necessary to take into account that we are modelling the global economy. The US is the absolute leading spacefaring country and private spacefaring firms are also dominated by US companies, as SpaceX. However, an increasing number of countries are also developing space industries and gaining spacecraft launch capabilities. Therefore, the model is calibrated to an artificial world economy, as also the space is global. The economic parameters to be calibrated are the social discount rate, the intertemporal marginal utility of consumption, the technological parameters of the production function, and the physical capital and satellites depreciation rates. For that set of parameters, we use standard values from the literature. Additionally, the model includes two technological growth processes: total factor productivity and investment-specific technological change in satellites, and the labor growth rate.

The pure social discount rate is fixed to be 1.5% per year, following Nordhaus (2008). The intertemporal marginal utility of consumption is set to 1.5, a standard value used in the literature. Given the Ramsey equation, the combination of the pure social discount rate (ρ) and the intertemporal marginal utility of consumption (σ), and assuming an average consumption per capita growth of 2% ($g_c = 0.02$), these values correspond to an interest rate, r, of 4.5% ($r = \rho + \sigma g_c = 0.015 + 1.5 \times 0.02 = 0.045$).

Corrado et al. (2023) calibrate the space sector share of the whole economy to be 0.0056. The Bureau of Economic Analysis (BEA, 2023) estimates that the space industry contributed to 129.9 billion dollars to the US economy in 2021 (0.6% of GDP), with a total of 360,00 full- and part-time jobs in the private space industry. The Space Foundation (2023) estimates that the global space economy had an impact of $546 billion for the year 2022. The Satellite Industry Association (SIA, 2023) estimates that the global space economy represents $384 billion dollars for the year 2022. We use this information to calibrate the technological parameters. First, we fixed the labor share to 0.65. This means that, given the assumption of constant scale returns, the sum of the technological parameters for Earth capital and space capital is 0.35 (i.e., $\alpha_1 + \alpha_2 = 0.35$). Using the previous information, we split the capital share between Earth capital and space capital. The elasticity of the output with respect to the satellite equipment is calculated as $\alpha_2 = 0.35 \times 0.006 = 0.0021$. Hence, the elasticity of the output with respect to Earth's capital is $\alpha_1 = 0.35 - 0.0021 = 0.3479$. Nozawa et al. (2023) calibrated a Cobb-Douglas production function with labor, capital and satellites, and they used a value of 0.002 for the elasticity of output to the stock of satellites.

The depreciation rate of capital other than satellites, δ_k, is fixed to a standard value of 0.07. For calibrating the depreciation rate of satellites, we use data from NASA. The life span depends on the type of satellite, and varies from 6 months for CubSats (miniaturized satellites) to 15 years for GEO satellites. For LEO satellites the life-span varies from 3 to 8 years. Bongers and Torres (2023) assume an average lifetime of 8 years, so the annual depreciation rate for satellites is fixed at 0.1733, whereas Nozawa et al. (2023) fixed a value of 0.216. Here, we calibrated this parameter by simulating the satellites accumulation equation for the period 1957-2023, to match the estimated number of operational satellites in 2023 by the ESA (of around 3,500). The resulting value for δ_s is of 0.15.

Parameters driving the evolution of exogenous sources of growth. Values used in DICE 2016 are a TFP growth rate of 0.076 (per 5 years) and a decline rate of TFP of 0.005. Values used in DICE2023 are a TFP growth of 0.066 (per 5 years), with a decline rate of 0.0015. In the model we consider an additional technological progress specific to satellites, following Greenwood, Hercowitz and Krusell (1997). Greenwood et al. (1997) introduce ISTC in a growth model with two capital assets: structures and equipment. ISTC determines the amount of satellites that can be purchased by one unit of output, and represents the state of the technology for producing space capital. This reflects the observed decline path of space capital costs. Population is taken from World Population Prospects 2024 (UN, 2024) which includes projections to the year 2100. The base year (2023) world population is 8,056,505 thousand. The parameter governing the population growth rate towards the asymptotic population (10,200 millions) is fixed to $\varsigma = 0.5$.

	Parameter	Definition	Value	Source
Economy	β	Social intertemporal preferences	0.0150	Nordhaus (2008)
	σ	Relative risk aversion parameter	1.50	Weitzman (2007)
	α_1	Capital share	0.3479	BEA
	α_2	Satellite share	0.0021	BEA
	δ_k	Capital depreciation rate	0.0700	Standard
	δ_s	Satellite depreciation rate	0.1766	NASA
	g_a	TFP growth rate	0.012	Assumption
	g_q	Satellite ISTC growth rate	0.03	Assumption
	δ_a	TFP growth decay rate	0.005	Assumption
	δ_q	ISTC growth decay rate	0.005	Assumption
	ς	Population growth parameter	0.5	United Nations
	μ	Conversion parameter	4,941.86	Internal
Space	η	Satellites per launch	13.6	NASA
	θ	Collision risk parameter	1.25×10^{-10}	ESA/NASA
	δ_d	Debris depreciation rate	0.01	ESA/NASA
	ω	Number of fragments per launch	70	Lafleur (2011)
	γ	Number of fragments per collision	10,000	Lafleur (2011)

Table 1: Baseline calibration of the parameters of ISEM

3.4. Calibration of physical parameters

First, the number of satellites is calculated by dividing the number of spacecraft inserted into orbit by the number of launches, resulting in a value of 13.6 for 2023. Second, the debris decay rate (δ_s) is calibrated by assuming an average value that takes into account the distribution of objects in orbit. The decay rate of debris depends on several factors, including altitude, mass, area, solar radioflux, and geomagnetic index. The most important factor is altitude due to atmospheric drag. The Australian Space Weather Agency (1999) estimated that the lifetime of space objects varies as follows: 1 day at 200 km, 1 month at 300 km, 1 year at 400 km, 10 years at 500 km, 100 years at 700 km, and 1000 years at 900 km (King-Hele, 1987). On the other hand, the distribution of debris as a function of altitude is not homogeneous. The spatial density of debris shows that it is concentrated in the range 700-900 km (NASA, 2020). To calibrate this parameter we use data from the NASA's breakups database in Anz-Meador et al. (2022). We use a value of 1% per year.

The risk of collision (θ) is taken from the literature. Farinella and Cordelli (1991) estimated a value of $\theta = 3 \times 10^{-10}$, for an estimated debris quantity of 50,000. This means the number of satellites destroyed per year is 0.2, given a collision probability ($\theta \times 50,000$) of 1.5×10^{-5}. The total probability of collision for objects larger than 10 cm is approximately 0.1 for orbits between 800-900 km, 0.05 for 900-1,000 km orbits, and 0.025 for 600-700 km orbits. Following Farinella and Cordelli (1991) we take an estimated total probability of collision of 0.2 (i.e., one fatal collision every 5 years) as the reference, given the number of incidents observed in recent years (four collisions occurred between 1991 and 2009), resulting in a collision probability of $\theta \times D = 6.6 \times 10^{-5}$. Given a total number of potentially hazardous debris pieces of 1,036,500, this results in a risk of collision parameter value of $\theta = 1.25 \times 10^{-10}$.

The number of pieces of debris per launch (ω) determines the primary source of debris generation. In our simplified debris emission model, this parameter includes not only expended rocket and other components discarded in the process of inserting a satellite into its target orbit but also debris generated by launch vehicles explosions. Johnson et al. (2001) use the NASA Breakup model EVOLVE 4.0 to estimate the number of new fragments from an explosion of 238 larger than 10 cm, and 9,509 fragments larger than 1 cm. Lewis et al. (2009) estimated that explosions generate 50 fragments larger than 10 cm and that, on average, 2.75 intact objects are added to the orbital environment per launch. Farinella and Cordelli (1991) estimated this parameter by assuming an average of two unintentional explosions per year, each generating several thousand fragments with a mass greater than

1 gram, resulting in 70 new pieces of debris larger than 1 cm. We adopt this value and set $\omega = 70$. Finally, the number of pieces of debris per collision (γ), is taken from Farinella and Cordelli (1991) and Lafleur (2011), who estimate that each collision produces 10,000 fragments larger than 1 cm.

4. The social cost of orbital debris (SCOD)

The social cost of an environmental externality includes not only the private cost of emissions, but also their external costs. This concept is therefore the principal variable in the design and implementation of optimal mitigation policies. For instance, the social cost of carbon (SCC) has become a central concept in the economic evaluation of climate-change policies. Similarly, evaluating the social cost of orbital debris (SCOD) is also crucial for the design of efficient debris mitigation policies and the quantitative measure of their benefits. The costs of emission abatement must be justified by the benefits of avoiding impacts in the future, and hence, the social cost of the externality is a crucial element of any cost-benefit analysis. If evaluated along an optimal emission trajectory, the social cost of an externality would be equivalent to a Pigouvian tax on orbital debris.

Estimates of the SCOD can be obtained by solving a social welfare maximization problem whiting an IAM, where the economy is represented by an optimal growth model where the objective is the maximization of the discounted utility of households. The IAM is used to determine the optimal trajectories of economic and environmental variables, where space activity is driven by economic growth. From this model, we obtain future projections of orbital debris emission, the accumulation of orbital debris, and the probability of collision. The trajectory of orbital debris has an economic impact by reducing the stock of space capital assets, which alters optimal investment decisions and, hence, affects capital accumulation and output growth.

The SCOD is a monetized measured of the economic damages caused by orbital debris in an ideal first-best world where social welfare is maximized. It is measured in U.S. dollars per piece of orbital debris larger than 1 cm. An alternative interpretation of the SCOD is that it represents a monetization of the economic benefits of avoiding the emission of a single piece of debris. The SCOD can be computed from the pathway of emissions and consumption. From the IAM, it simulates the time path of orbital debris accumulation, the loss of satellites, and the resulting reduction in output and consumption. Defining W_0 as the aggregate discounted utility from consumption along a given pathway of consumption, c_t and debris emissions Z_t, the SCOD can be obtained from the total derivative of the expected value of the social welfare function,

$$dW_0 = \frac{\partial W_0}{\partial Z_t} dZ_t + \frac{\partial W_0}{\partial c_t} dc_t = 0 \tag{29}$$

Solving for dc_t/dZ_t, we obtain

$$SCOD_t \equiv \frac{dc_t}{dZ_t} = -\frac{\partial W}{\partial Z_t} / \frac{\partial W}{\partial c_t} \tag{30}$$

where the numerator quantifies the marginal impact of debris emissions on welfare and the denominator quantifies the marginal welfare value of a unit of aggregate consumption. Since the marginal impacts on welfare can change from period to period, the SCOD can also vary over time.

One method to estimate the SCOD is using the Lagrange multipliers from the optimal maximization problem. Lagrange multipliers represent shadow prices, which are, the prices associated with a constraints. If the constraint is relaxed by one unit, the change in the optimal objective function value is equal to the Lagrange multiplier. The SCOD is defined as the ratio of the marginal (negative) impact of releasing orbital debris at time t on aggregate social welfare to the marginal impact of one unit of consumption at time t on aggregate welfare. The SCOD represents the damage stream produced by an additional unit of debris emitted in a given period, it is time-dependent. Formally, the SCOD can be defined as the ratio of the shadow price of orbital debris emissions and consumption. Thus, the SCOD can also be defined as the ratio of the Lagrange multipliers of the constraint for debris emissions ($\lambda_{z,t}$) and the constraint for consumption ($\lambda_{c,t}$), as follows,

$$SCOD_t = -\frac{\lambda_{z,t}}{\lambda_{c,t}} \tag{31}$$

The expression we use defines the SCOD in US dollars per piece of orbital debris, defined as,

$$SCOD_t = -10^{12} \frac{dc_t}{dZ_t} \tag{32}$$

In the model, consumption is measured in trillions of dollars whereas debris is measured in units. Therefore, to convert the estimate of SCOD to dollars per piece of debris, the resulting expressions must be multiplied by 1×10^{12}.

5. Estimate results

This section presents an estimate of the SCOD for pieces of debris larger than 1 cm. The model is simulated over 200-year horizon, where a social planner maximizes social welfare. From the optimal solution of the model, we obtain the socially efficient trajectories of the economic, and environmental variables, which represent the impacts of the economic externality produced by orbital debris.

The main results of the paper are presented in Figure 1, where the optimal trajectories of debris, emissions, satellites, and SCOD are shown in the baseline scenario of a social planner who maximizes social welfare. The model indicates that the amount of debris larger than 1 cm would increase by a factor of 2,000 over a 200-year horizon. The trajectory for orbital debris shows a dramatic acceleration from the year 2150, due to the increasing number of collisions. This provokes a cascade effect on the population of debris as predicted by Kessler and Cour-Palais (1978). Emissions increase following an exponential path, due to economic growth, the increasing number of launches, and the increasing number of collisions. Initially, the primary source of debris emission is launches. However, as the number of objects in orbit grows, the contribution of collisions to the emission of debris becomes more significant. At first, the debris population expands at a low rate. However, as collisions become more frequent, emissions and debris growth rates accelerates.

Figure 1 also plots the optimal number of satellites in orbit for the baseline calibration. We observe the existence of a tipping point during the simulation horizon. This hump-shaped trajectory results from accumulation of debris and the increasing number of collisions. As output expand, also capital is accumulated both in the Earth and in the space. Initially, the ratio of space capital over Earth capital increases, due to ISCT specific to satellites. However, as the risk of collision increases with the accumulation of debris, the rate of accumulation of space capital declines. The tipping point reflects a situation in which the cost of damage exceeds than the welfare gains from satellites. The baseline simulation of the model starts with 8,500 satellites in 2023. The number of satellites reaches a maximum of around 50,000 by the year 2150.

The estimation of the social cost of orbital debris is presented in the botton-right of Figure 1 for the baseline calibration. The value corresponding to the first year of the simulation (2023) is of 84,200 international US dollar per piece of debris larger than 1 cm. This value reflects the social marginal damages from one additional piece of debris and can be interpreted as a measure of the price on debris emissions that should be set to equal to the produced social damage, using a Pigouvian tax. This is an average number, as the size and mass of debris can vary significantly, and arguably, the social cost of a small piece of debris would be different to the social cost of an intact object which potentially can produce thousands of piece of debris in case of breakup or collision. On the other hand, the potential

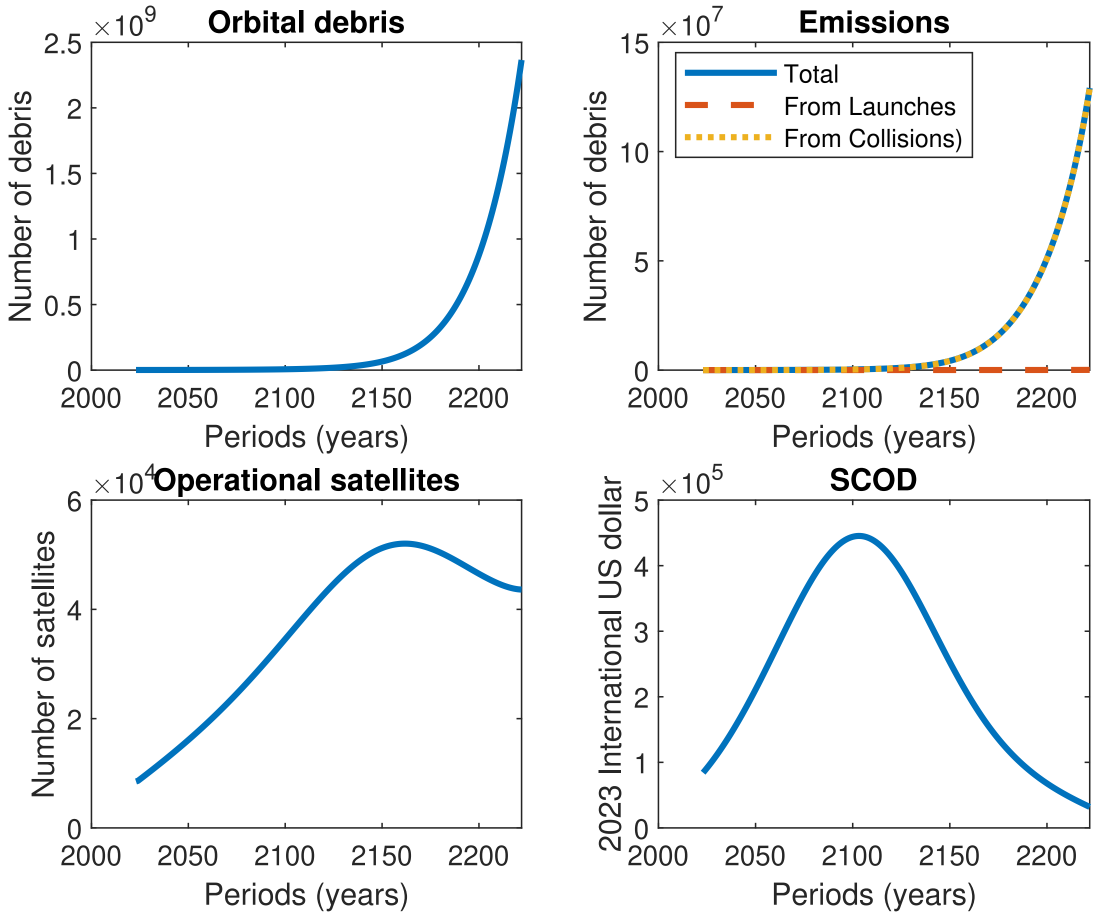

Figure 1: Optimal trajectories for satellites, orbital debris and the social cost of orbital debris

damage of debris depends on its spatial distribution across orbits. We observe how, over time, the SCOD escalates to a value close to half million dollars around the year 2110, and then starts to decrease.[2]

Next, we carry out a sensitivity analysis of the SCOD for key parameters. In particular, we study how estimates of SCOD vary depending on the discount rate and on the intertemporal marginal consumption rate.

5.1. The discount rate

The climate change literature has shown that the pure intertemporal rate is critical for the estimation of the SCC (Anthoff et al., 2009; Weitzman, 2007, 2014). The discount

[2]The SCOD has also been calculated using the CasADi algorithm in Matlab with a terminal condition for the investment rates. The estimation is of 85,183 international US dollars for the year 2023.

rate reflects the marginal rate of substitution between consumption in different time periods for an individual or for society. In macroeconomic dynamic general equilibrium models, the standard value for the annual discount rate is between 3 and 5 percent. Cost-benefit analysis uses higher values of about 7 percent. However, the choice of the discount rate is problematic for very long periods and no agreement exists in the literature. The Ramsey (1928) discounting formula is based on three elements: the pure intertemporal preference (ρ), the elasticity of marginal utility of consumption (σ), and the consumption growth rate ($g_{c,t}$). Formally, the social discount rate from the CRRA utility function, (r_t), is defined as,

$$r_t = \rho + \sigma g_{c,t} \tag{33}$$

In the climate-change literature there is a severe debate about the implications of the discount rate in the estimation of the SCC. Weitzman (1998) indicates that the far-distant future should be discounted at the lowest possible rate. This is the approach used by Stern (2008) who use a value for the pure intertemporal rate of 0.1%. IAMs in climate change use values for the discount rate ranging from 0.1% to 3%, which result in a wide range of estimated values for the SCC.

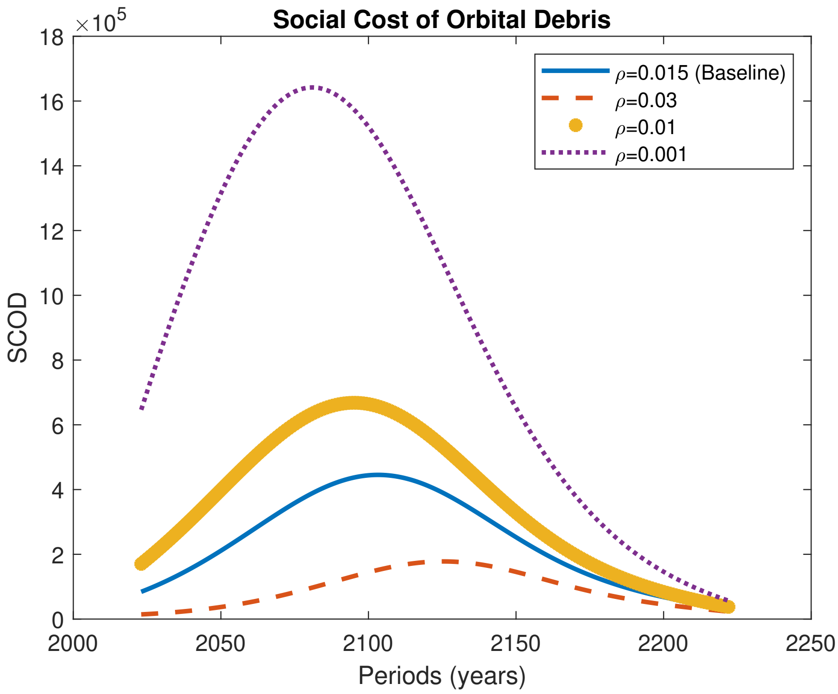

Figure 2: The social cost of orbital debris

Figure 2 plots the SCOD as a function of the discount rate. In the baseline model the pure discount rate is 1.5%. We simulate the model for different values of the discount rate. For a pure social discount rate of 0.1%, the SCOD is of around \$646,000. For a pure social discount rate of 3%, the SCOD declines to only \$14,400. This large difference is because orbital debris is basically a long-run problem, and hence very sensitive to how the future is discounted. Rao and Rondina (2025) argue that the role of the discount rate in orbit use is unique and, unlike in typical climate-change economics, the higher the discount rate, the lower the optimal use of the space resources (lower number of satellites in orbit). Here we find the opposite, where orbital debris has similar effects as other types of environmental negative externalities in the Earth. As the social discount rate increases, also increase space activity, as the main negative effects of orbital debris emerges in the long-run.

5.2. Intertemporal marginal consumption rate

The intertemporal marginal consumption rate of the household's CRRA utility function is a key parameter in the estimation of the SCOD. In a CRRA utility function, this parameter reflects the curvature of the utility function and the relative risk aversion. The central planner maximizes the social welfare,

$$\max_{c_t, i_t, h_t} \sum_{t=0}^{\infty} \beta^t N_t U(c_t) \tag{34}$$

subject to (2), (3), (4), (5), (16), (17) and (18). The Lagrange multiplier for constraint (2), the shadow price of consumption, is $\lambda_{c,t} = \beta N_t U'(c_t) = \beta N_t c_t^{-\sigma}$. This shows that the way changes in consumption affect social welfare is driven by the value of σ.

Figure 3 plots the SCOD for different values of the intertemporal marginal consumption rate. A value of $\sigma = 1$ implies that the utility function is the logarithm of consumption. For this value, we find that the SCOD is 241,200 international US dollars for the year 2023. As the intertemporal marginal consumption rate declines, also the SCOD reduces. For $\sigma = 2$, the social cost reduces to \$32,190, and for a $\sigma = 3$, the SCOD is around \$8,460.

6. Alternative scenarios

Previous estimates of the SCOD assume a scenario with no intervention to mitigate space pollution. However, international and national agencies are awarded of the dangers posed by orbital debris for a safety space environment. Both international organizations and national space agencies have elaborated a number of debris mitigation guidelines to reduce debris emissions. On the other hand, the satellite operators are implementing debris tracking and

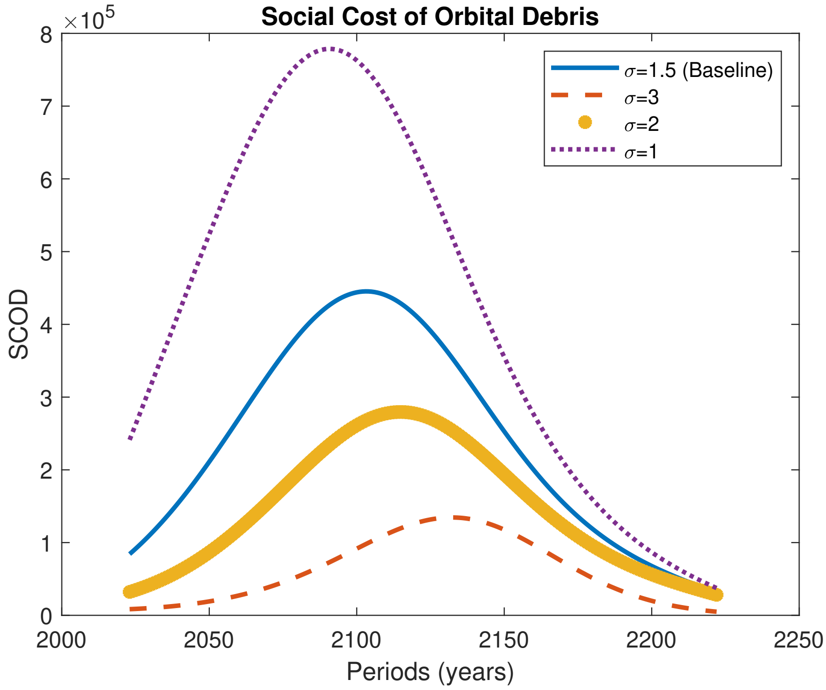

Figure 3: The social cost of orbital debris for alternative values of σ

collision avoidance technologies to reduce the risk of collision, or use shield in spacecraft for protection of impacts from small piece of debris (up to 2 cm).

In this section, we reestimate the SCOD under two scenarios: One in which the launch vehicles systems do not produce debris, and a second one in which the risk of collision is reduced through the implementation of collision avoidance strategies. Additionally, we estimate the SCOD for a range of values of the number of debris produced by launches and collisions.

6.1. Debris free launch vehicles

First, we study the scenario in which spacefaring agents are forced to use debris-free launch systems, which implies that no mission related objects are released and no upper stages remain into orbit. For simulating this scenario, we simply set $\omega = 0$, and hence, the only source of debris emissions is fragments resulting from collisions.

Figure 4 compares the SCOD in the baseline scenario with a scenario in which launch vehicles are debris-free. Unexpectedly, we find that the social cost of orbital debris increases with the elimination of launches as a source of debris. This counterintuitive results is explained by two factors. First, whereas this measure limits the growth of debris in the short-run, does not prevent the endogenous growth of debris in the long-run. Initially, the

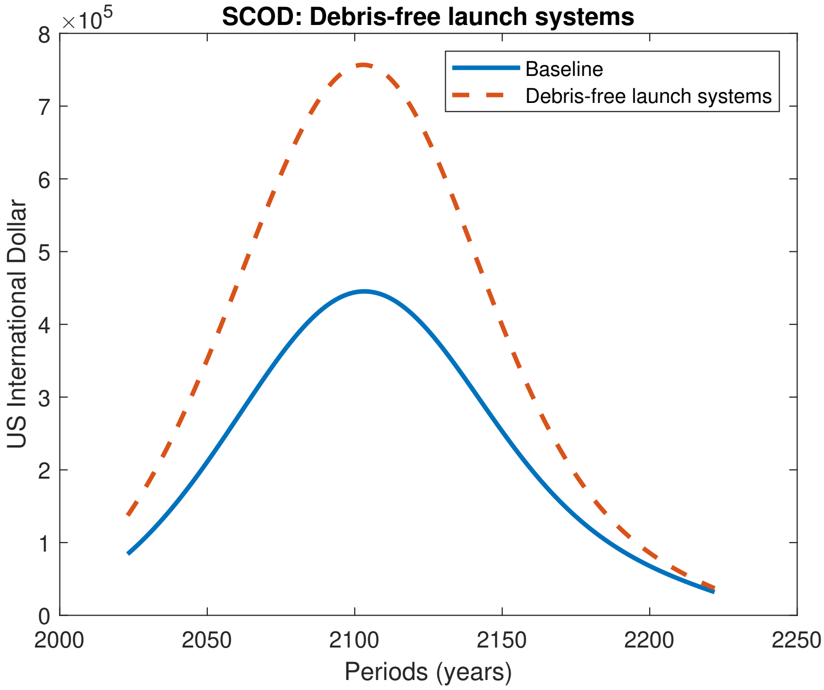

Figure 4: The social cost of orbital debris: Debris-free launch systems

main source of debris are launches. However, over time, the relative importance of launches for debris emissions declines, and the main source of emissions turns out to be in-orbit collisions. Second, the use of debris-free launch vehicles increases the number of launches and hence, the use of space. The number of satellites in orbit increases, leading to a rise in the number of collisions. Although the population of orbital debris in any period is lower compared to the baseline scenario, the trajectory is similar but shifted a few years. The combination of these two elements explains why the social cost of orbital debris is higher for debris-free launch vehicles.

6.2. Collision avoidance

One of the debris mitigation guidelines calls for the implementation of collision avoidance measures as a strategy for reducing debris emissions. Collision avoidance systems used by spacefaring companies are technologies designed to prevent spacecraft from colliding with other objects in space. These systems typically use a combination of radar, lidar, optical sensors, and advanced algorithms to detect potential hazards. When a collision risk is identified, the system can automatically calculate the necessary trajectory adjustments, often referred to as "collision avoidance maneuvers." Collision avoidance has two implications. First, it can prevent the destruction of valuable space assets. Second, preventing collisions also reduces the creation of additional pieces of debris. Private firms are implementing collision avoidance systems because the cost of losing satellites to collisions is high. Space agencies and private companies such as SpaceX and Blue Origin employ such systems to ensure the safety and longevity of their spacecraft, especially in busy orbital environments. These systems rely on real-time data, predictive modeling, and coordinated maneuvering to minimize the risks of damage to spacecraft and other space assets.

We introduce collision avoidance systems by modifying the damage function as follows:

$$X_t = (1 - v)\theta D_t S_t \tag{35}$$

where v represents the reduction in the risk of collision through the implementation of collision avoidance systems, that is, the percentage of collisions prevented. We assume that the implementation of collision avoidance systems is at no cost and is implemented by space operators when its cost is lower than the cost of losing space capital assets. Figure 5 plots the SCOD for different levels of collision avoidance. For a collision avoidance rate of 25% the SCOD declines to around \$45,700. If the probability of collision is reduced by 50% the SCOD declines to around \$17,290, whereas for a reduction of 75%, the SCOD stays at about \$2,960.

The significant impact of collision avoidance systems on SCOD is explained by the fact that they reduce the damage caused by debris while simultaneously preventing further increases in the debris population resulting from the endogenous in-orbit collision process.

6.3. Further sensitivity analysis

The SCOD is determined by debris emissions as a function of space activity. The evolution of orbital debris depends on two parameters: the number of debris pieces generated per launch and the number of debris pieces produced per collision. The value of these two parameters depends on technical and operational factors, as well as on the implementation of the debris mitigation guidelines.

The number of fragments from a collision depends on several factors, as the mass and size of the impacting objects, their velocity, spacecraft design, the level of shielding, etc. In the baseline calibration we use the value estimated by Farinella and Cordelli (1991) and Lafleur (2011). Similarly, the number of debris from launches depends on a large number of factors, including the type of launch vehicle, the operational procedures for inserting satellites into orbit, the deorbiting policy and the passivization of intact objects to avoid explosions and breakups. All these factors add uncertainty about the number of pieces of debris produced by launches and collisions.

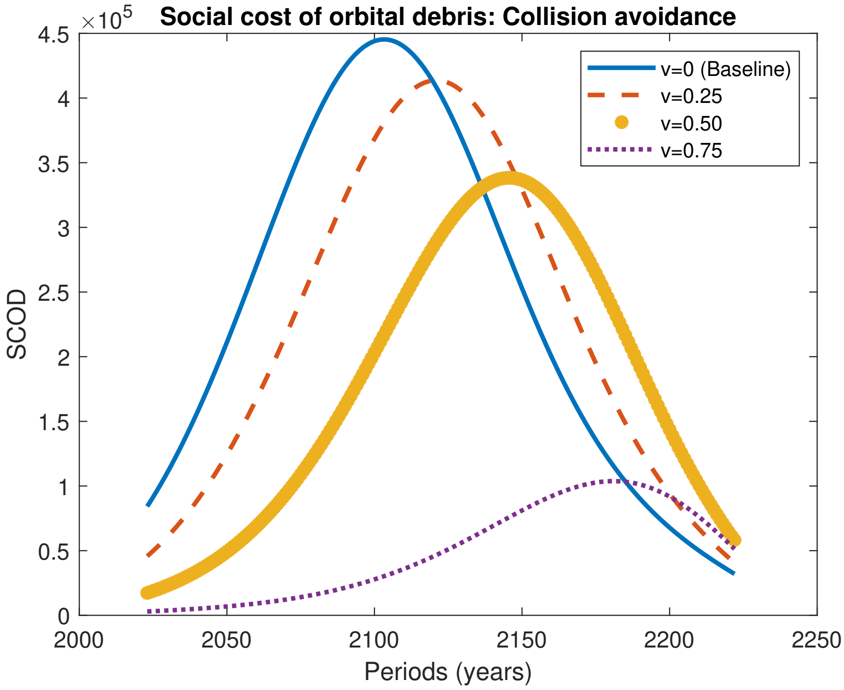

Figure 5: The social cost of orbital debris as a function of collision avoidance

Table 2 shows the SCOD for alternative values of these two parameters. We consider a ranger for the number of debris produced by launch (ω) from zero (debris-free launch systems) to 250 (the baseline is 70). For the case of the number of debris produced by collision (γ), we use a range of values from 1,000 to 10,000 (the baseline). We find that SCOD increases with γ but decreases with ω. This opposite relationship is explained by the fact that both sources of debris have different implications on social welfare. Whereas the number of launches contribute to increases the number of satellites with a positive impact on output and consumption, the endogenous in-orbit emission of debris from collision has a negative effect on the space environment and on the number of satellites.

	$\omega = 0$	$\omega = 70$	$\omega = 150$	$\omega = 250$
$\gamma = 1,000$	8,220	8,208	8,196	8,183
$\gamma = 5,000$	46,334	26,783	21,960	19,327
$\gamma = 10,000$	137,211	**84,200**	63,987	51,993

Table 2: Sensitivity analysis: SCOD as a function of ω and γ

7. Conclusions

This paper estimates the social cost of orbital debris (SCOD). Orbital debris represents a negative environmental externality in space. Research in climate-change economics has shown that the accurate estimation of the social cost of an externality is crucial for designing and implementing effective mitigation policies. Understanding the social cost of a negative externality is essential for policymakers. A key example is the social cost of carbon (SCC), which has become a central tool in climate change policy, particularly in shaping emissions regulatory policies. The social cost of a negative externality is a crucial information for policymakers. An example is the estimates of the social cost of carbon (SCC) which has become a central tool for climate change policy, mainly for the determination of emissions regulatory policies.

AS far as we are aware, this paper is the first to estimate the global social cost of orbital debris (SCOD). It follows the standard approach used in climate-change economics, simulating the paths of consumption and emissions resulting from an Integrated Assessment Model (IAM). For the baseline calibration, the model estimates a SCOD of $86,730 for the year 2024 (in 2023 international dollars). This figure significantly exceeds the cost estimates for removing objects from orbit provided by Colvin et al. (2023). However, it is important to note that this estimate is highly sensitive to key parameter values. For instance, with a pure social discount rate of 3%, the SCOD drops to $14,400, while at 0.1%, it rises sharply to $646,000. Likewise, for an intertemporal marginal consumption rate of 3, the SCOD declines to only $8,460. On the other hand, our findings indicate that the SCOD is also dependent on progress in collision avoidance systems. Implementing these systems can significantly reduce or even eliminate damages caused by debris.

A number of caveats must be considered regarding the estimates presented in this paper. First, our results are based on a 200-year horizon, assuming that the global economic growth rate follows a declining trend and that the shares of Earth-based capital and space-based capital in the production function remain constant over time. While intensive space technological development is accounted for through a satellite-ISCT component, there remains significant uncertainty regarding the future evolution of the space economy. Second, the SCOD is closely tied to the implementation of debris mitigation guidelines established by the IACD, national space agencies, and the ESA's Zero Debris Strategy. These policies have a significant impact on the number of intact objects in orbit and their contribution to debris emissions. Finally, the potential onset of the Kessler Syndrome would have profound implications for this analysis. As noted by Weitzman (2014) in the context of climate change, such a catastrophic event would lower the discount rate applied to mitigation-investment decisions, thereby increasing the social cost of the environmental externality.

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