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Technology Spillovers from the Final Frontier: A Long-Run View of U.S. Space Innovation*

By Luisa Corrado†, Stefano Grassi‡ and Aldo Paolillo§

Recent studies suggest that space activities generate significant economic benefits. This paper attempts to quantify these effects by modeling both business cycle and long-run effects driven by space sector activities. We develop a model in which technologies are shaped by both a dedicated R&D sector and spillovers from space-sector innovations. Using U.S. data from the 1960s to the present day, we analyze patent grants to distinguish between space and core sector technologies. By leveraging the network of patent citations, we further examine the evolving dependence between space and core technologies over time. Our findings highlight the positive impact of the aerospace sector on technological innovation and economic growth, particularly during the 1960s and 1970s.

JEL: A1, C5, E00, O10.
Keywords: Aerospace, Space Economy, Growth.

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I. Introduction

The space sector has experienced significant change, transitioning from its Cold War origins, characterized by public-sector-led geopolitical rivalry, to a dynamic, commercially driven sector. The early space race sparked groundbreaking technological advancements in space transportation systems, satellites, and communication systems, with lasting impacts on scientific research and technology, see Forbes (2020). For instance, Fishman (2020) reports that the Apollo program required the development of a large number of new technologies such as the world's largest rocket, the world's smallest and fastest computer, the world's first high-speed data network, space suits, and space food. The pursuit of space exploration has also led to revolutionary advancements in physics, chemistry, material sciences, and engineering, many of which have been successfully adapted for industrial applications, see Hertzfeld (2002). Today, decreasing costs of spacecraft development and advances in remote sensing have enabled private companies, like SpaceX and Blue Origin, to enter the space sector marking the beginning of a New Space Age (NSA), see Weinzierl and Sarang (2021) and Corrado et al. (2023a). This shift, driven by public-private partnerships (Rausser et al., 2023) has fostered a more decentralized and competitive sector with the potential to influence other industries with new economic activities in the space sector, see Weinzierl (2018) and Crawford (2016).[1] The historical and ongoing impact of space activities requires a comprehensive evaluation of their technological and economic consequences (Beldavs and Sommers, 2018).

This paper examines the technological and economic effects of space activities in the U.S. from the 1960s to the present day, focusing on the diffusion of space-driven innovations across the broader economy.[2] In particular, we examine how technologies originating in the space sector diffuse across other sectors, driving productivity gains that contribute to broader economic growth. For instance, advancements in telecommunication systems, such as satellite-based networks, have revolutionized global connectivity, while innovations in material science, originally developed for spacecraft, have led to the creation of lighter, stronger, and more heat-resistant materials now used in various industrial applications. To quantify these effects, we employ a business cycle-endogenous growth model combined with new historical data on patenting activity, to disentangle the role of space-related innovations in driving GDP growth and its fluctuations.

The economic effects of space activities can be classified as direct and indirect. Direct effects are the innovations generated in the space sector for the space sector, such as new

[1] For a detailed discussion of the opportunities and challenges of the space economy, as well as a review of the economic methodologies used to analyze them, see Corrado et al. (2025). Key opportunities include scientific exploration, planetary defense, space settlement, and resource extraction. However, these ventures face technological, financial, and regulatory challenges, as high development costs, unclear property rights, and unregulated competition could lead to geopolitical tensions and negative externalities such as space debris and environmental risks, see Macauley (2015), Adilov et al. (2015), Klima et al. (2016), Rao et al. (2020), and Guyot et al. (2023).

[2] We focus on the U.S. due to its historical leadership in space exploration and its continued prominence in the space sector. Hertzfeld (2007) analyzes the role of the U.S. in the context of globalization in accessing outer space.

satellite technologies or new launch vehicle systems (O'Connor et al., 2019, Voigt et al., 2007). Indirect effects, or spillovers, are innovations generated in the space sector, such as solar cells or memory foam, that find applications in other sectors. The economic effects of space activities can also be distinguished into business cycle effects—stemming from increases in employment, investment, and income generated by the space sector, and long-term effects driven by technological progress. Our paper examines all these dimensions by analyzing both the short-term macroeconomic fluctuations linked to space sector activity and the long-term impacts on technology, productivity, and growth. This places our study in relation to several existing strands of research, which we review in the following section.

I.A. Literature Review

The economic effects of space activities can be analyzed from both a microeconomic and a macroeconomic perspective. The microeconomic approach examines how space-related innovation and investment influence specific industries and regions, while the macroeconomic perspective studies their impact on broader economic aggregates. From a microeconomic perspective, Jaffe et al. (1998) examine NASA's patenting activity between 1963 and 1994, and analyze trends in space-related innovation and their wider impact. They document a peak in NASA patents in the early 1970s, followed by a decline, attributing these fluctuations to shifts in research funding and patenting incentives. Their study also examines the quality of NASA patents, highlighting that they were broader and very influential until the late 1970s, when their impact waned.

Kantor and Whalley (2023) use historical U.S. county-industry data and a patent-based measure of space technology capability to assess the impact of NASA's R&D investments on local economic outcomes. They find that NASA activity led to greater growth in manufacturing value added, employment, and capital in counties and industries specialized in space technologies, but they detect no significant productivity gains, suggesting limited local technological spillovers. Their microeconomic focus is on the effects of NASA's contractor spending on local manufacturing, providing insight into how space-related investments influence specific industries at the regional level. At the same time, broader technological diffusion can unfold over longer horizons and extend beyond the manufacturing sector through indirect channels such as research collaborations and cross-industry spillovers.

In the macroeconomic strand of the literature, Evans (1976) applies an input-output model to estimate the broader economic impact of NASA's R&D expenditures, distinguishing between short-term demand effects and long-term productivity gains. More recently, Highfill and MacDonald (2022) employs supply-use tables, from national accounts, to quantify the direct and indirect economic contributions of the space sector. Their study tracks space-related activity across industries; however, it does not incorporate spillovers from technological advancements. Corrado et al. (2023b) develop a real business cycle model with endogenous growth to examine technological spillovers from the space sector to the economy. They find that technological progress from space sector activity has a positive impact on economic growth.

I.B. Contribution and findings

Building on these studies, we introduce a microfounded R&D sector in a macro model characterized by space sector and a core sector. Technologies emerge from both generic R&D and space sector activities, featuring a distinct spillover mechanism from space to core technologies. For model estimation, we combine a large patent and citation network dataset in addition to aggregate macroeconomic variables. Our macroeconomic model, which includes both business cycle and endogenous growth elements, helps distinguish short- and long-term effects of space activities. Business cycle effects are temporary fluctuations in income and consumption triggered by increases in space sector demand. Endogenous growth effects involve the creation of new patents in the space sector, adopted by the core sector to build new technologies, thus enhancing productivity and long-term economic growth.

Our paper connects to the broader literature on endogenous growth in general equilibrium models (e.g., Romer, 1990; Grossman and Helpman, 1991; Aghion and Howitt, 1992). It extends medium-scale macroeconomic models with an R&D sector (e.g., Comin and Gertler, 2006; Bianchi et al., 2019; Anzoategui et al., 2019) by explicitly modeling space activity as a distinct driver of technological progress. This framework enables us to analyze the impact of space sector spillovers on economic growth and examine counterfactual scenarios with different degrees of spillovers. To estimate the model, we exploit a novel dataset of U.S. patent data from Berkes (2018) which provides insights on technological innovation in the space and core sectors.

From the patent data point of view, our contribution is twofold. By leveraging the information on patents generated in the space sector from the dataset, we empirically measure the development of new space technologies over time. Moreover, using the citation network of the patent dataset, we measure the spillover effects into the core sector of patents generated from space activities and, through our model, evaluate their impact on technology and economic growth.

Our main finding is that space activities generate positive economic effects, with different intensities over time. The strongest effects are observed in the 1960s, decline significantly in later decades. In particular, the impact of space activities on the creation of new technologies in the space sector (defined as space innovation productivity) reached its peak in the 1960s and the lowest levels in the 2000s. We perform a simulation exercise to evaluate the economic impact of a space sector shock (a given increase in space sector production) under scenarios of high and low space innovation productivity. We simulate a 1% increase in space sector production and compare its long-term effects during the high space innovation productivity of the 1960s and the lower space innovation productivity of the 2000s. In the 1960s, when space innovation productivity was at its peak, such a shock results in a long-run increase in real GDP by 0.51 basis points, boosting potential output permanently. Conversely, from the 1980s onward, with reduced space innovation productivity, the same shock leads to a smaller long-term increase in real GDP of 0.27 basis points. These findings indicate that the overall economic impact of space activities has waned over time, emphasizing the need to understand the changing role of technological spillovers from the space sector.

Our model also evaluates the economic returns of space sector spillovers by analyzing fiscal multipliers across different time horizons, distinguishing between short-term, medium-term, and long-term effects. We find that in the first part of the space race, space-related investments had significantly higher multipliers than in more recent periods. In particular, during the high space innovation productivity of the 1960s, the long-run total multiplier exceeds one, reaching 2.2 when discounted and 6.0 when non-discounted. This implies that space expenditures have generated permanent economic gains beyond their initial stimulus, with long-lasting effects on technological progress and economic growth.

The paper proceeds as follows. Section II describes the patents data and the construction of the citation network. Section III describes the endogenous growth model. The macroeconomic dataset with the identification strategy is presented in Section IV. Section V presents the empirical results. Finally, Section VI draws the conclusions.

II. Patent Data and Citation Network

Patent data are widely used to assess the impact of R&D activities on technological progress. Despite potential limitations, such as noise in patent counts (Jaffe et al., 1998), patents remain a valuable indicator of knowledge diffusion and technological change, see (Griliches, 1990). Until now, patent data have not been used to quantify both the direct impact of space activities in generating innovations in the space sector and their indirect impacts (spillovers) on other sectors. By analyzing space technology patents, along with their classifications and citations network, we quantify the extent to which innovations from the space sector spread throughout the industry.

II.A. Description of Patent Data

Our analysis is based on the Comprehensive Universe of U.S. Patents (CUSP) database of Berkes (2018), which provides a complete historical record of patents granted by the

United States Patent and Trademark Office (USPTO) from 1836 to 2015. Given the patent data coverage, we focus on patents granted between 1920 and 2015, which aligns our analysis with the development of the modern aerospace industry. The dataset we use includes over 7.5 million patents and approximately 71 million citation links. In the CUSP dataset, each patent is classified using the U.S. Patent Classification (USPC) system. We merge the patent data classified according to USPC with the North American Industry Classification System (NAICS) using the 2014 USPTO–NAICS concordance table.[3] This mapping allows us to assign patents to specific economic sectors, including the space sector, and to track their technological evolution and interconnections over time. In the context of our model, this classification enables us to distinguish between space-sector and core-sector innovations and to study how technological developments in the space sector propagate to the rest of the economy.

To assess the dynamics of innovation in the space sector, we define the *space innovation intensity* ($F_{s,t}^{data}$) as the ratio of space sector to core sector patents within a quarter.[4] This measure considers the technological classification of each patent to determine its sectoral contribution. Details about the construction of this measure, including weighting procedures, aggregation rules, and sectoral assignment, are in Appendix VII. The resulting series is plotted in the upper panel of Figure 2.1. The plot indicates that space sector innovation reached a peak in 1960:Q2 at about 2.8%, followed by a gradual decline, hitting a low of 0.80% in 1999:Q1.

II.B. Network-Based Spillover Measurement

To analyze the technological spillovers from the space sector to other economic sectors, we use patent citations as indicators of knowledge transfer. For example, when a patent cites another patent, it signals a knowledge spillover from the cited innovation to the citing one. A terrestrial communication patent citing a satellite communication patent, for instance, suggests that advancements in satellite technology have contributed to improvements in terrestrial communication systems. A direct citation occurs when a patent cites a space sector patent. Indirect citations occur when a patent cites another patent that references space-related technologies, capturing indirect knowledge spillovers. To measure these effects, we construct a citation network in which each patent is a node and citations form directed links. This network structure allows us to track knowledge diffusion over time. To illustrate how the citation network captures technological diffusion, we present an example centered on a key patent granted in 1973—*U.S. Patent 3,781,647*—which

[3]The concordance table links the USPC, as of December 31, 2014, to 26 NAICS product fields. It is available from the U.S. Patent and Trademark Office: `https://www.uspto.gov/web/offices/ac/ido/oeip/taf/data/naics_conc/2014/`.

[4]We use the superscript '*data*' to distinguish this empirical measure from its model counterpart, defined in Section IV.

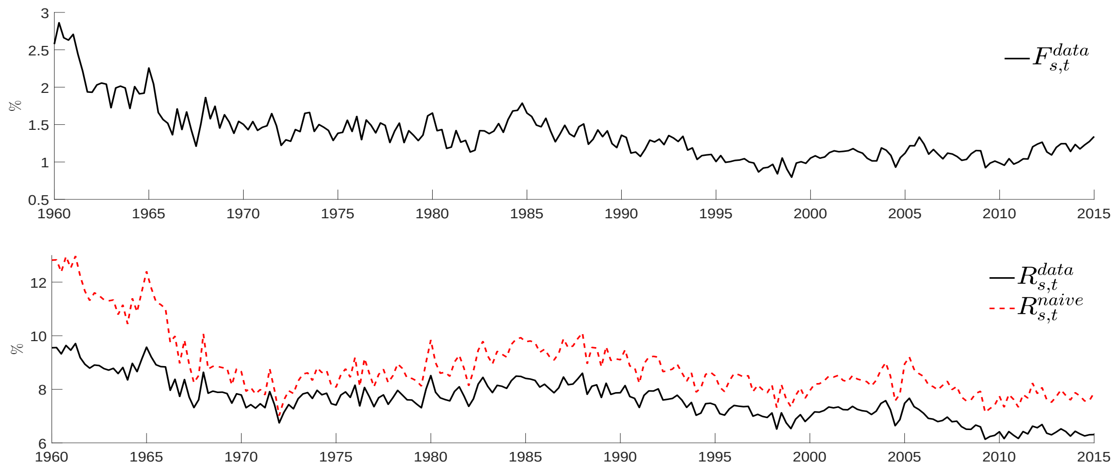

Figure 2.1. : In the upper panel, the space innovation intensity ($F_{s,t}^{data}$) is the ratio of space sector to core sector patents. In the lower panel, the naive spillover measure ($R_{s,t}^{naive}$) is the fraction of core sector patents that directly cite at least one space sector patent. The network-based spillover measure ($R_{s,t}^{data}$) accounts for indirect knowledge diffusion through the full citation network. All measures are computed quarterly based on the grant dates of the corresponding patents.

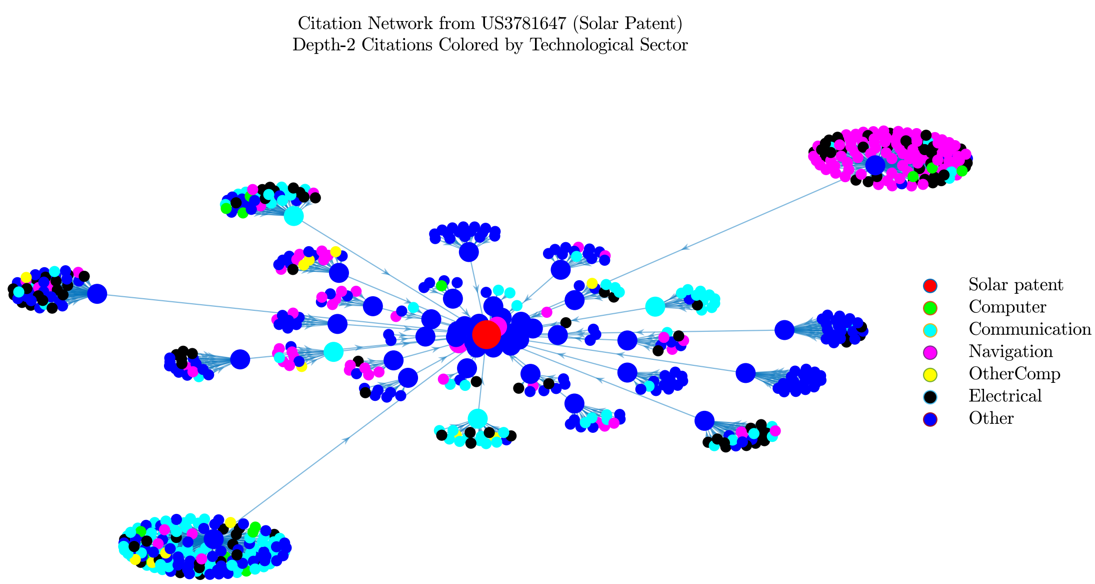

Figure 2.2. : Citation network centered on the solar patent —U.S. Patent 3,781,647— (large red node). The graph displays all patents that directly cite the central patent (medium-sized nodes), and indirect citations (smaller nodes), forming a two-generation network. Nodes are colored by the technological sector. For clarity, we restrict the visualization to the shortest citation paths, omitting multiple linkages to the central patent and cross-citations among citing patents.

proposes a system for transmitting solar power from space.[5] This patent belongs to the space sector (as classified by NAICS code 3364) and ranks among the most influential in our dataset based on network centrality measures. Its prominence makes it a useful case for visualizing how knowledge propagates from a space-related innovation through successive generations of citations. Figure 2.2 displays the solar patent in the center (big red node) and the network of patents that directly cite it (medium-sized nodes), as well as the indirect citations (smaller nodes). All the nodes are colored according to their technological sector. This example provides an intuitive visualization of how innovation spreads across technological domains.

We extend the analysis from a single patent to the entire set of space-sector patents, to measure how core-sector innovations rely on space-related knowledge through both direct and indirect citation linkages.[6] We then construct time-aggregated measures of these spillovers, which are used to feed the technological component of our macroeconomic model. A naive spillover measure ($R_{s,t}^{naive}$) computed as the fraction of core sector patents that directly cite at least one space sector patent is reported in the lower panel of Figure 2.1. However, this measure overlooks the broader structure of technological diffusion, where influence can also flow through indirect linkages. To address this limitation, we apply the PageRank algorithm developed by Brin and Page (1998). Originally introduced to rank webpages by analyzing the structure of hyperlinks, PageRank has been successfully applied to other sparse and fragmented networks, including scientific and patent citation networks (Gleich, 2015). In our context, we apply the PageRank algorithm to the network of patent citations to measure the relevance of patents based on both direct and indirect technological influence.

PageRank generalizes the $R_{s,t}^{naive}$ by capturing each patent's position in the broader citation network (see Appendix VIII). While the naive measure counts only direct citations to space-sector patents, PageRank also considers indirect linkages by assigning each patent a dependency score based on the patents it cites. A patent receives a high dependency score if it cites other patents with high scores. As a result, a core-sector patent shows stronger reliance on space-related knowledge if it builds upon core technologies that themselves cite space-sector patents. This recursive structure allows us to track the diffusion of space-related innovations through multiple layers of the citation network. To derive the dependency scores, we apply the PageRank algorithm under two initialization schemes: one that highlights patents citing space-sector technologies, and another that assigns equal weight to all patents. The ratio of the two scores defines our spillover in-

[5] *Method and Apparatus for Converting Solar Radiation to Electrical Power*, invented by Peter E. Glaser and assigned to Arthur D. Little Inc. Granted on December 25, 1973. See Glaser (1973).

[6] While one could also compute spillovers from the space sector to itself, these are quantitatively small in our data and fall outside the main focus of this paper. For simplicity and relevance, we restrict attention to spillovers from the space sector to the core economy. Exploring intra-space spillovers may be a valuable direction for future research.

dicator, $R_{s,t}^{data}$, which tracks the *relative* extent to which core-sector patents depend on space knowledge over time. Appendix VIII provides a full description of the algorithm, its implementation, and the relationship between the naive and network measures. The lower panel of Figure 2.1 shows that $R_{s,t}^{data}$ peaks at 9.6% in 1965:Q1 and gradually declines to 6.15% by 2011:Q1.

II.C. An Illustrative Example

In this Section, we use the PageRank methodology to track the technological dependency on space-related patents of four key economic sectors. Rather than focusing on aggregate technological spillovers in the core sector, we provide a zoomed view of industry-specific dependencies on space-sector innovations. We consider four key core sectors that have been historically influenced by space-related innovations (see Hertzfeld, 2002).

These sectors are: (i) Computer and Peripheral Equipment, (ii) Communication Equipment, (iii) Navigation, Measurement, Electromedical, and Control Instruments, and (iv) Electrical Equipment, Appliances, and Components.[7] For each sector, we compute the dependency score $R_{s,t}^{data}$, which quantifies the extent to which patents in that field rely on space-sector technologies. To understand what drives the aggregate spillover to the core sector (shown in the lower panel of Figure 2.1), we perform a counterfactual analysis. We compute $R_{s,t}^{data}$ assuming that spillovers are confined within each key sector (Computer, Communication, Navigation, and Electrical Equipment), while setting spillovers to zero in the remaining core sectors. Average dependency scores of patents in each sector are computed for each quarter. These sectoral spillovers reveal the extent to which these key technological areas contribute to the overall spillover, as illustrated in Figure 2.3, which traces their evolution over time.

The results in Figure 2.3 show distinct diffusion patterns of space technologies into different core economy sectors over time. In the Computer and Peripheral Equipment sector, spillover scores remain below 0.10% and stable until around 1990, after which they dramatically increase to about 0.50% by 2010. This rise coincides with the computing industry's growth during the digital revolution and is mainly driven by increased computer-related patent activity, rather than a greater reliance on space-related knowledge per patent. In the Communication Equipment sector, a similar trend is observed, with spillover measures steadily rising from the early 1990s, linked to the telecommunication technology diffusion during the Internet and mobile communications boom. In the Navigation, Measurement, Electromedical, and Control Instruments sector, there is a consistently high dependency on space technologies, with a continued upward trend in spillovers during the 2000s, albeit less steep than in computing or communications.

[7] These sectors correspond to the following NAICS codes: Computer and Peripheral Equipment (3341), Communication Equipment (3342), Navigational, Measuring, Electromedical, and Control Instruments (3345), and Electrical Equipment, Appliances, and Components (335).

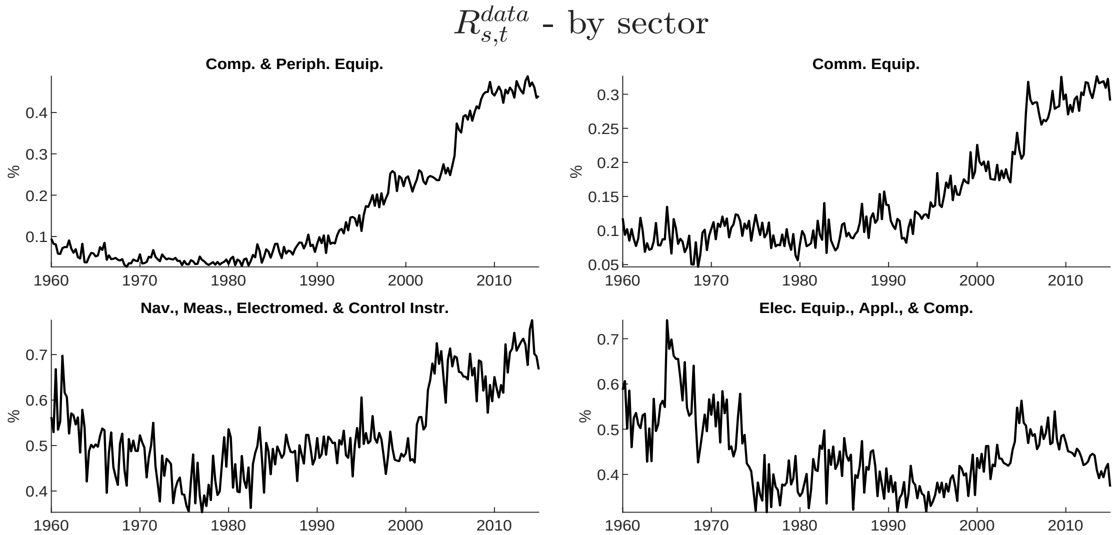

Figure 2.3. : Sectoral dependency scores on space-sector patents ($R^{data}_{s,t}$), computed using the PageRank methodology. Each panel shows the contribution of a key technology sector to the overall core-sector spillover, under a counterfactual in which spillovers are set to zero outside the sector considered. This decomposition highlights how reliance on space knowledge has evolved across distinct domains. $R^{data}_{s,t}$ is computed quarterly based on patent grant dates. Sectors include: (i) Computer and Peripheral Equipment (NAICS 3341), (ii) Communication Equipment (NAICS 3342), (iii) Navigation, Measurement, Electromedical, and Control Instruments (NAICS 3345), and (iv) Electrical Equipment, Appliances, and Components (NAICS 335).

Finally, though the Electrical Equipment, Appliances, and Components sector does not display the most dynamic spillover growth, it maintains high dependency levels, indicating stable integration of space-derived technologies despite not being the primary channel for recent innovation spillovers from space.

Our baseline model captures the effects of space activity on the broader U.S. economy through a representative core sector, focusing on aggregate outcomes. To further explore sector-specific dynamics, we conclude Section V with a counterfactual analysis that translates the granular spillover patterns from Figure 2.3 into differentiated economic impacts, transmitted through key sectors.

III. Baseline Model Description

The economy is composed at each time t by the core sector ($\mathcal{S}_c$), the space sector ($\mathcal{S}_s$), households, the space sector customer, and the $R\&D$ sector. The space sector customer is represented by the public space agency (e.g., NASA) or the private company[8] (e.g., SpaceX) who requires the output (e.g., rockets) produced by the space sector (e.g., Boeing or SpaceX itself). The firms in the two sectors are divided internally into intermediate

[8]Although many large private companies are involved in recent space activities, the majority of SpaceX's early contracts were public contracts, and both NASA and the Department of Defense remain its main customers. The same applies to Blue Origin and the majority of launch companies.

and retail branches. Figure 2.4 shows a flowchart of the economy, where time t subscripts are omitted for convenience.

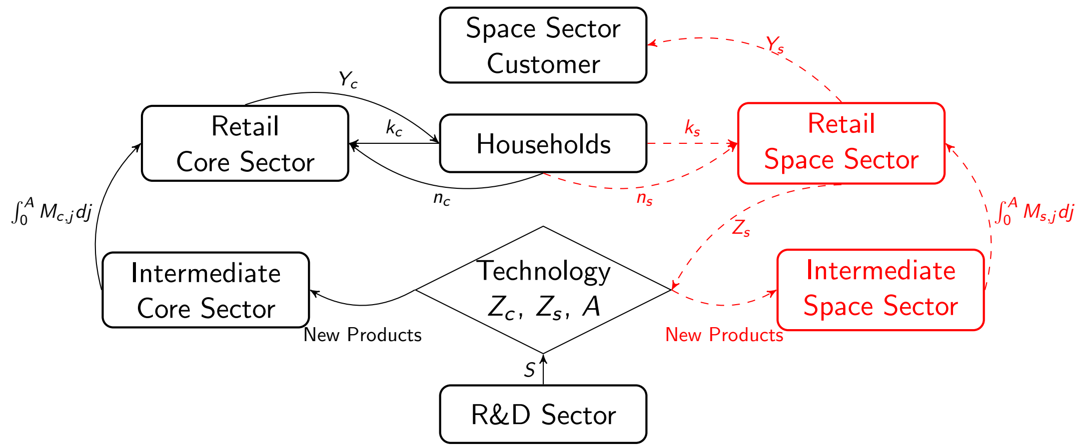

Figure 2.4. : The flowchart of the economy. The arrows represent the flow of the indicated variables. Y_c and Y_s are the final goods produced by firms and demanded by households and the space sector customer, respectively; k_c and k_s represent the capital stocks rented by households to the core sector and space sector firms; n_c and n_s are the hours of work supplied by the households to the core sector and space sector firms; the number of intermediate technologies used in production is denoted as A, whose growth depends on adoption of existing technologies in the two sector, Z_c and Z_s; finally, S denotes the resources allocated by the R&D sector for developing new technologies.

Households consume the core sector goods (Y_c), and the space sector customer sets the demand for the space sector goods (Y_s). The demand for space sector goods is funded with the resources provided by the households through taxation (T_s).[9] The households also supply labor (n_c, n_s) and lend capital (k_c, k_s) to firms in the two sectors. Firms in both sectors operate the production processes that take as input intermediate goods produced by intermediate firms (M_c, M_s), in addition to labor and capital. Innovators in the R&D sector operate in a perfectly competitive environment and develop new technologies, selling the rights to produce them (i.e., blueprints) to intermediate firms. The number of intermediate goods (A), which is a proxy for technological progress, increases over time due to three main forces: R&D by innovators, the development of new space technologies, and spillovers from the space sector to the core economy.

Space Sector

DEMAND

The space sector customer exogenously sets the demand for space sector goods, choosing the amount of space sector production at time t ($Y_{s,t}$) and by fixing it as a share ($g_{s,t}$) of

[9]The paper does not consider political factors or market-driven incentives that may affect space investment. Likewise, the geopolitical determinants of space investment are outside the scope of this study.

core goods production ($Y_{c,t}$):

$$\frac{Y_{s,t}}{Y_{c,t}} = g_{s,t}. \tag{2.1}$$

The space sector share ($g_{s,t}$) follows an exogenous autoregressive (AR) process:

$$\log(g_{s,t}) = (1-\rho_s)\log(\chi) + \rho_s \log(g_{s,t-1}) + \epsilon_{s,t}, \tag{2.2}$$

where χ is the steady state of the space sector share, ρ_s is the AR coefficient, and $\varepsilon_{s,t}$ is a zero mean Gaussian white noise representing the space activity shock with standard deviation equal to σ_s.

Supply

The supply of space sector goods is provided by the space sector firms. Space sector firms rent space sector capital ($k_{s,t}$) and demand labor ($n_{s,t}$) from households and employ the intermediate input goods ($M^j_{s,t}$, in number A_t) from intermediate space sector firms. Space sector firms take the prices of these inputs (the wage rate $w_{s,t}$, the capital rental rate $r_{k_s,t}$) and the intermediate goods price ($P^{m,j}_{s,t}$) as given to maximize their nominal profits:

$$\max_{\{n_{s,t},k_{s,t},M^j_{s,t}\}} P_{s,t}Y_{s,t} - P_{s,t}w_{s,t}n_{s,t} - P_{s,t}r_{k_s,t}u_{k_s,t}k_{s,t-1} - \int_0^{A_t} P^{m,j}_{s,t}M^j_{s,t}dj, \tag{2.3}$$

where $P_{s,t}Y_{s,t}$ are the total revenues ($P_{s,t}$ is the final space sector price), $w_{s,t}n_{s,t}$ is the labor cost, $r_{k_s,t}u_{k_s,t}k_{s,t-1}$ is the capital rental cost and $\int_0^{A_t} P^{m,j}_{s,t}M^j_{s,t}dj$ is the cost of purchasing the intermediate goods. The firm is subject to the production function:

$$Y_{s,t} = a_{z_s,t}\left[(n_{s,t})^{1-\alpha_s}(u_{k_s,t}k_{s,t-1})^{\alpha_s}\right]^v [G_{s,t}]^{1-v}, \tag{2.4}$$

where $G_{s,t}$ is a constant elasticity of substitution (CES) aggregator of intermediate inputs with an elasticity of substitution equal to θ_m:

$$G_{s,t} = \left(\int_0^{A_t}\left(M^j_{s,t}\right)^{\frac{\theta_m-1}{\theta_m}}\right)^{\frac{\theta_m}{\theta_m-1}}, \tag{2.5}$$

where $Y_{s,t}$ is the output of the space sector, $a_{z_s,t}$ represents the short-term fluctuations in the productivity of the space sector, which adds to the long-term productivity component A_t; α_s is the share of capital in the production function, v is a weight parameter for intermediate goods in production,[10] and $u_{k_s,t}$ the capacity utilization of the capital stock used for space sector production. The solution to this problem gives the optimal demand schedule and is reported in Appendix IX.

Intermediate firms

The supply of intermediate goods in the space sector is provided by monopolistically competitive intermediate firms. Each intermediate firm in the space sector produces a differentiated variety j of the intermediate good ($M^j_{s,t}$), using a production technology that transforms one unit of the final good ($Y^j_{s,t}$) into one unit of the intermediate good, according to the linear function $M^j_{s,t} = Y^j_{s,t}$ (see Anzoategui et al., 2019). Each intermediate firm maximizes its profits, which are equal to revenues ($P^{m,j}_{s,t} M^j_{s,t}$) minus costs ($P_{s,t} M^j_{s,t}$). In real terms, the profits of the intermediate firm j in the space sector ($D^j_{s,t}$) are expressed as:

$$D^j_{s,t} = \frac{\left(P^{m,j}_{s,t} - P_{s,t}\right)}{P_{s,t}} M^j_{s,t}. \tag{2.6}$$

The intermediate firm maximizes these profits subject to the demand from space sector firms, Appendix IX reports these demand equations. The solution (in a symmetric equilibrium) to this problem pins down the relative price of intermediate goods over final goods ($p^m_{s,t} \equiv P^m_{s,t}/P_{s,t}$) as to fix a constant markup ($\frac{\theta_m}{\theta_m - 1}$) between the marginal revenue (the price of one unit of the intermediate good, $P^m_{s,t}$) over marginal costs (the cost of transforming one unit of the final good into one unit of intermediate good, $P_{s,t}$):

$$p^m_{s,t} = \frac{P^m_{s,t}}{P_{s,t}} = \frac{\theta_m}{\theta_m - 1}. \tag{2.7}$$

Combining the intermediate inputs demand (eq. A2.4 in Appendix IX) with the supply (eq. 2.7) and imposing a symmetric equilibrium ($M^j_{s,t} \equiv M_{s,t}$), an expression for the quantity of each intermediate good can be found, allowing us to rewrite production (2.4) as a function of labor and capital only. We report this derivation in Appendix IX.

The space sector customer finally buys the space sector goods from retailers and finances this expenditure by levying taxes on households. The expression for space sector taxes is:

$$T_{s,t} = w_{s,t} n_{s,t} + u_{k_s,t} r_{k_s,t} k_{s,t-1} + A_t \left(p^m_{s,t} M_{s,t}\right),$$

where the right-hand side (r.h.s.) equals the costs paid to produce space sector goods (see eq. 2.3), after imposing symmetry (i.e., $M^j_{s,t} = M_{s,t}$) and substituting $\frac{P^m_{s,t}}{P_{s,t}} = p^m_{s,t}$.

[10]To ensure the existence of a balanced-growth path, v must satisfy the following relationship: $v = 1/(\alpha_s(1 - \theta_m) + \theta_m)$, see Annicchiarico and Pelloni (2021).

Core Sector

The core sector is symmetric to the space sector and is also divided into the retail and intermediate branches. It faces an analogous maximization problem subject to a production technology that is isomorphic to that of the space sector:

$$Y_{c,t} = a_{z_c,t}\left[(n_{c,t})^{1-\alpha_c}\left(u_{k_c,t}k_{c,t-1}\right)^{\alpha_c}\right]^{v}\left[G_{c,t}\right]^{1-v}, \tag{2.8}$$

where $G_{c,t}$ is a CES aggregator of core sector intermediate inputs ($M^j_{c,t}$):

$$G_{c,t} = \left(\int_0^{A_t}\left(M^j_{c,t}\right)^{\frac{\theta_m-1}{\theta_m}}\right)^{\frac{\theta_m}{\theta_m-1}}.$$

Appendix IX provides a detailed derivation of the decision problem of firms in the core sector.

Households

The households choose the sequence of consumption (c_t), hours worked ($n_{c,t}$ and $n_{s,t}$), amounts of investment in the capital stocks ($i_{c,t}$ and $i_{s,t}$) and fractions of capital to be used in production ($u_{k_c,t}$ and $u_{k_s,t}$) in the two sectors, to maximize lifetime utility:

$$\mathbb{E}_0\sum_{t=0}^{\infty}(\beta\Gamma)^t a_{\zeta,t}\left[\log(c_t) - \varphi_t\varphi^c\frac{n_{c,t}^{1+\nu_c}}{1+\nu_c} - \varphi_t\varphi^s\frac{n_{s,t}^{1+\nu_s}}{1+\nu_s}\right]. \tag{2.9}$$

Eq. (2.9) describes the discounted flow of utility coming from consuming the core goods, less the disutility of supplying labor to the two sectors. The parameter β is the intertemporal discount rate, which is scaled by the gross growth rate of the economy (Γ) to take into account technological progress. The parameter $a_{\zeta,t}$ is the discount factor shock, and φ_t is the labor supply shock. Parameters ν_c and ν_s determine the curvature of the labor disutility and measure the elasticity of labor supply to the wage rate. The weights φ^c and φ^s are scale coefficients that impose steady-state values for hours worked that are consistent with historical averages in the data.

Households satisfy the following budget constraint while maximizing utility:

$$\begin{aligned} i_{c,t} + p_{s,t}i_{s,t} + c_t + b_t = {} & \frac{R_{t-1}b_{t-1}}{\pi_{c,t}} + w_{c,t}n_{c,t} + p_{s,t}w_{s,t}n_{s,t} + r_{k_c,t}u_{k_c,t}k_{c,t-1} \\ & + p_{s,t}r_{k_s,t}u_{k_s,t}k_{s,t-1} - p_{s,t}T_{s,t} + D_t - \Psi_t. \end{aligned} \tag{2.10}$$

In eq. (2.10), the elements on the r.h.s represent the net source of funds coming from wage income in the core sector ($w_{c,t}n_{c,t}$) and in the space sector ($p_{s,t}w_{s,t}n_{s,t}$), returns on capital rented to core firms ($r_{k_c,t}u_{k_c,t}k_{c,t-1}$) and space firms ($p_{s,t}r_{k_s,t}u_{k_s,t}k_{s,t-1}$), and liquidity from assets represented by expiring bonds (b_{t-1}). Bonds are issued in nominal units in terms of the numeraire (the core good) and have a risk-free gross yield equal to R_t, so the real gross returns are given by $R_{t-1}b_{t-1}/\pi_{c,t}$, where $\pi_{c,t}$ denotes the inflation rate of the numeraire ($P_{c,t}/P_{c,t-1}$). Households also provide the space sector customer with the resources needed to finance the demand for space sector goods ($p_{s,t}T_{s,t}$). The term D_t contains profits from intermediate firms in the two sectors. The variable Ψ_t collects the convex adjustment costs related to investment and capacity utilization.[11] The elements on the left-hand side (l.h.s.) show how available funds are allocated between consumption (c_t), investment in core sector capital ($i_{c,t}$) and investment in space sector capital ($i_{s,t}$) and new bonds (b_t). Investments in both sectors, $i_{c,t}$ and $i_{s,t}$, are equal to the difference between the new capital minus the previous period capital stock, net of depreciation:

$$i_{c,t} = k_{c,t} - (1-\delta_{k_c})\, k_{c,t-1}, \quad \text{and} \quad i_{s,t} = k_{s,t} - (1-\delta_{k_s})\, k_{s,t-1},$$

where the parameters δ_{k_c} and δ_{k_s} are the capital depreciation rates for the core and space sectors. The first-order conditions related to the household problem are presented in the Appendix IX.

Technology

Based on the literature that integrates business cycle dynamics and endogenous growth (Comin and Gertler, 2006; Bianchi et al., 2019; Anzoategui et al., 2019), we model technology as an endogenous variable that drives the long-run evolution (trend) of real variables. Following Comin and Gertler (2006) and Anzoategui et al. (2019), we assume that new technologies need time to be adopted. In line with these authors, we distinguish between existing technologies (Z_t) and adopted technologies (A_t). As outlined in eq. (2.5), A_t represents the technologies actively used in production processes in both sectors, which directly affect productivity. Unlike Anzoategui et al. (2019), we extend the model by introducing a two-sector technology. We assume that the aggregate stock of existing technologies (Z_t) consists of space-sector ($Z_{s,t}$) and core-sector ($Z_{c,t}$):

$$Z_t = Z_{c,t} + Z_{s,t}.$$

[11] Ψ_t contains the adjustment costs related to investment in the core sector ($\Psi_{k_c,t}$), the adjustment costs related to investment in the space sector ($\Psi_{k_s,t}$), capacity utilization in the core sector ($\Psi_{u_c,t}$) and capacity utilization in the space sector ($\Psi_{u_s,t}$):

$$\Psi_t = \Psi_{k_c,t} + p_{s,t}\Psi_{k_s,t} + \Psi_{u_c,t}k_{c,t-1} + p_{s,t}\Psi_{u_s,t}k_{s,t-1}.$$

These adjustment costs depend on the parameters η_k, η_{u_c}, and η_{u_s}. The parameter η_k determines how costly it is to adjust the capital stock in both sectors, while η_{u_c} and η_{u_s} govern the costs associated with changing the utilization rate of capital in the core and space sectors, respectively. We provide the complete functional forms for these costs in Appendix IX.

The law of motion for adopted technologies links A_t with the technology from the previous period (ϕA_{t-1}) that survived, and with the (unadopted) existing technologies, defined as the difference between total existing technologies and those that are adopted ($Z_{t-1}-A_{t-1}$), following the same specification used by Anzoategui et al. (2019):

$$A_t = \lambda\phi\left(Z_{t-1} - A_{t-1}\right) + \phi A_{t-1}, \tag{2.11}$$

where ϕ denotes the quarterly survival rate of technologies. Eq. (2.11) implies that, at each time t, an adopted technology has a probability ϕ to survive, and that a technology in the pool of unadopted technologies ($Z_{t-1} - A_{t-1}$) has a probability λ of being adopted, conditional on its survival. The adoption probability (λ) is inversely related to the average adoption lag (τ), according to the formula $\lambda = \frac{1}{4\tau}$. Therefore, when τ increases, the probability λ decreases and adopted technologies (A_t) respond less to new technologies generated in the core and space sectors.[12] Dividing eq. (2.11) by A_{t-1} we obtain its stationary form which gives the stochastic growth rate of the economy (x_t):

$$\exp\left(x_t\right) \equiv \frac{A_t}{A_{t-1}} = \lambda\phi\left(\tilde{Z}_{t-1} - 1\right) + \phi,$$

where $\tilde{Z}_{t-1}$ represents detrended existing technologies (Z_{t-1}/A_{t-1}). The growth rate x_t determines the balanced growth path of the real variables in the model and its steady-state value is equal to the net growth rate of the economy, $\gamma = \log(\Gamma)$.

Space technologies

We assume that space technologies are related to space sector activities. The stock of existing space sector technologies ($Z_{s,t}$) depends on the number of technologies that survive from the previous period ($\phi Z_{s,t-1}$) and on production in the space sector ($Y_{s,t}$):

$$Z_{s,t} = \phi Z_{s,t-1} + \xi_{s,t-1} Y_{s,t-1}, \tag{2.12}$$

where $\xi_{s,t-1}$ denotes the productivity of space sector activities in generating new technologies. We assume, similarly to Comin and Gertler (2006), that $\xi_{s,t}$ evolves according to the following equation:

$$\xi_{s,t} = a_{\xi_s,t}\hat{\xi}_s\left(\frac{A_t}{Y_{s,t}}\right)^{1-\epsilon_s} = a_{\xi_s,t}\hat{\xi}_s\tilde{Y}_{s,t}^{\epsilon_s-1},$$

[12] Differently from Anzoategui et al. (2019), we assume a constant λ. Explaining the procyclicality of technology adoption (i.e., endogenous λ_t; see Comin and Gertler, 2006 and Anzoategui et al., 2019) is outside the scope of this paper. To avoid being too restrictive in selecting this parameter, we estimate the adoption lag rather than calibrating it (see Section IV). Note that, since λ and ϕ enter the model multiplicatively, they cannot be jointly identified. We fix ϕ and estimate λ.

where $a_{\xi_s,t}$ is time-varying space innovation productivity, that quantifies how activity in the space sector influences technological development over time. The parameter ϵ_s determines the diminishing returns of technology to space activity. Finally, $\tilde{Y}_{s,t} = Y_{s,t}/A_t$ represents the space sector activity detrended by the technology level A_t, to ensure a balanced growth path (see Appendix X). Given the above specification, space technology can be expressed as:

$$Z_{s,t} = \sum_{k=0}^{\infty} \phi^k a_{\xi_s,t-k} \xi_{s,t-k} Y_{s,t-1-k}, \tag{2.13}$$

which is a convolution of past space activity and its productivity.

R&D sector

Innovators in the R&D sector generate new technologies that directly increase the stock of existing technologies in the core sector ($Z_{c,t}$). Furthermore, technologies in the core sector gain indirectly from ideas first developed in the space sector, demonstrating the spillover effect from space sector advancements to the core sector.

In our notation, the stock of existing core sector technologies ($Z_{c,t}$) depends on the number of technologies that survive from the previous time period ($\phi Z_{c,t-1}$), the R&D resources (S_{t-1}), and the technological spillover from the space sector to the core sector ($Spill_{sc,t}$):

$$Z_{c,t} = \phi Z_{c,t-1} + \xi_{c,t-1} S_{t-1} + \xi_{sc}^{spill} Spill_{sc,t}, \tag{2.14}$$

where $\xi_{c,t-1}$ is the productivity of R&D resources, and ξ_{sc}^{spill} is a scaling constant for the spillover $Spill_{sc,t}$.[13] The productivity of R&D resources ($\xi_{c,t}$) has the following expression:

$$\xi_{c,t} = a_{\xi_c,t} \hat{\xi}_c \left(\frac{A_t}{S_t} \right)^{1-\epsilon_c} = a_{\xi_c,t} \hat{\xi}_c \tilde{S}_t^{\epsilon_c - 1}, \tag{2.16}$$

where $a_{\xi_c,t}$ is the time-varying productivity of R&D resources in producing new technologies, and $\hat{\xi}_c$ is a constant that controls the steady-state growth rate of technologies and $\tilde{S}_t \equiv S_t/A_t$ represents detrended R&D resources.[14] According to Comin and Gertler (2006), in the numerator of eq. (2.16), the technology level (A_t) represents intertemporal

[13] The problem of an individual innovator p is:

$$Z_{c,t}^p = \phi Z_{c,t-1}^p + \xi_{c,t-1} S_{t-1}^p + \xi_{sc}^{spill} Spill_{sc,t}^p, \tag{2.15}$$

where the p superscripts denote the decision variables of the innovator p. Following Comin and Gertler (2006), the productivity of R&D resources ($\xi_{c,t}$) is taken as given by the individual innovator p and depends on economy-wide quantities, so the aggregation of individual R&D efforts in eq. (2.15) is possible.

[14] In Appendix XI we show how the steady state of the growth rate of technologies depends on $\hat{\xi}_c$. To see that $\xi_{c,t}$ is needed to have a balanced growth path, see Appendix X.

spillovers in innovation, indicating how previous discoveries enable future advancements. The R&D expenditure (S_t) in the denominator reflects diminishing returns in knowledge creation, meaning that increasing R&D efforts leads to less than proportional gains in research output. The decreasing returns are consistent with the empirical evidence and generate a realistic relationship between research effort and growth, see Griliches (1990) and Jones (1995).

Innovators sell the right to produce a new technology (a blueprint) to intermediate firms. Under the assumptions of perfect competition in the R&D sector (Comin and Gertler, 2006), this right is sold at a price equal to the value it generates, denoted by J_t. This value corresponds to the present discounted profits that the intermediate firm earns by producing and selling the associated intermediate good to wholesale firms (see subsection on intermediate firms, eq. 2.6).

The evolution of J_t takes into account the probability that the innovation (i) becomes adopted and generates profits (with a probability equal to λ and an expected value equal to V_{t+1}), (ii) remains among the existing and unadopted technologies (with a probability equal to $1-\lambda$ and an expected value equal to J_{t+1}), or (iii) becomes obsolete before becoming adopted (with a probability of $1-\phi$ and a value of zero):[15]

$$J_t = \phi\beta\Gamma\mathbb{E}_t \left\{ \frac{u_{c,t+1}}{u_{c,t}} \left[\lambda V_{t+1} + (1-\lambda) J_{t+1}\right] \right\}. \tag{2.17}$$

The value of an adopted innovation (V_t) in eq. (2.17) is given by the discounted summation of the profits generated by intermediate firms in both the space and the core sector ($D_{s,t}$ and $D_{c,t}$, see eqs. 2.6), namely:

$$V_t = p_{s,t} D_{s,t} + D_{c,t} + \phi\beta\Gamma\mathbb{E}_t \left(\frac{u_{c,t+1}}{u_{c,t}} V_{t+1} \right).$$

The innovators choose the amount of R&D (S_t) in eq. 2.14 to maximize expected profits. Under the free-entry condition (Comin and Gertler, 2006), the expected marginal revenue from a new blueprint equals its marginal cost:

$$\beta\Gamma\mathbb{E}_t \left(\frac{u_{c,t+1}}{u_{c,t}} J_{t+1} \right) = \frac{1}{\xi_{c,t}}.$$

This zero-profit condition equates the expected discounted value of a new technology (left-hand side) to its marginal cost, given by the inverse of the marginal product of R&D (right-hand side).

[15]The future values are discounted by the stochastic discount factor, namely $\beta\Gamma\mathbb{E}_t \frac{u_{c,t+1}}{u_{c,t}}$.

Spillover dynamics

To capture the flow of knowledge for the space technologies to the core sector, we introduce the spillover variable $Spill_{sc,t}$. This variable corresponds to the number of new core-sector patents in a given quarter that cite earlier innovations from the space sector. We measure it empirically using the network-based spillover indicator described in Section II. To reflect the gradual flow of citations across sectors observed in the data, we assume that $Spill_{sc,t}$ evolves according to an adoption process similar to Equation 2.11. To match the empirical evidence on citation links, we assume that there is a probability that space technologies not yet spilled over to the core sector will eventually do so. The law of motion for the spillover, $Spill_{sc,t}$, is:

$$Spill_{sc,t} = \lambda_{sp}\phi\left[Z_{s,t-1} - Z^{spill}_{c,t-1}\right], \tag{2.18}$$

where $Z^{spill}_{c,t}$ represents the stock of technologies that have spilled over from the space sector to the core sector, and $(Z_{s,t-1} - Z^{spill}_{c,t-1})$ denotes the pool of technologies in the space sector that have not yet spilled over to the core sector. As in Equation 2.11, ϕ denotes the survival rate of technologies from the previous period, ensuring that only those still in use can generate spillovers. Similarly, λ_{sp} is the quarterly probability that each surviving technology in the pool generates a spillover.

This formulation requires tracking the technologies that have spilled over ($Z^{spill}_{c,t}$) as a state variable, which evolves according to the following law of motion:

$$Z^{spill}_{c,t} = \phi Z^{spill}_{c,t-1} + Spill_{sc,t}. \tag{2.19}$$

Combining (2.18) and (2.19), we obtain the following expression for the stock of spillover technologies:

$$Z^{spill}_{c,t} = \phi(1-\lambda_{sp})Z^{spill}_{c,t-1} + \lambda_{sp}\phi Z_{s,t-1}, \tag{2.20}$$

spillover technologies, similarly to space technologies, are a convolution of past space activity and its past spillovers.

Iterating Equation (2.20) and substituting the expression of existing space technologies $Z_{s,t}$ in Equation (2.13), we get:

$$Z^{spill}_{c,t} = \sum_{k=0}^{\infty}\left[\phi(1-\lambda_{sp})\right]^k \lambda_{sp}\phi\left[\sum_{j=0}^{\infty}\phi^j \xi_{s,t-1-k-j} Y_{s,t-2-k-j}\right].$$

This expression shows that the stock of core-sector technologies resulting from spillovers is a convolution of past space activity and its productivity, with geometrically declining weights that depend on the spillover probability λ_{sp}. This recursive structure mirrors the indirect transmission patterns we analyze in the citation network, where technological influence propagates through chains of citations beyond direct links.[16]

Aggregation and Equilibrium

The resource constraint for the core sector is given by:

$$c_t + i_{c,t} + p_{s,t} i_{s,t} + S_t + A_t M_{c,t} + p_{s,t} A_t M_{s,t} = Y_{c,t} - \Psi_t. \tag{2.21}$$

Equation (2.21) ensures that the amount of consumption (c_t), investment ($i_{c,t}$ and $i_{s,t}$), R&D resources (S_t), and intermediate goods ($M_{c,t}$ and $M_{s,t}$) are equal to core sector production ($Y_{c,t}$), net of losses due to adjustment costs (Ψ_t). [17]

The exogenous demand requirement in eq. (2.1) and the supply given by the production function (2.4) enforce equilibrium in the space sector. The model is closed by assuming that a central bank sets the nominal interest rate according to a simple Taylor rule:[18]

$$R_t = R_{ss} \pi_{c,t}^{r_\pi}.$$

where $R_{ss} = 1/\beta$ represents the steady-state gross interest rate, and r_π denotes the policy response to consumer price inflation. We define total production in the economy (GDP_t) as the sum of core sector and space sector production:

$$GDP_t = Y_{c,t} + p_{s,t} Y_{s,t}.$$

We also define aggregate investment in the economy as:

$$i_t = i_{c,t} + p_{s,t} i_{s,t}.$$

Finally, the evolution of the relative price of the space sector good is linked to the evolution of the inflation rates in the two sectors:

$$\frac{p_{s,t}}{p_{s,t-1}} = \frac{P_{s,t}/P_{c,t}}{P_{s,t-1}/P_{c,t-1}} = \frac{\pi_{s,t}}{\pi_{c,t}}.$$

Exogenous Processes

The remaining exogenous processes of the model determine the evolution of the intertemporal preference shock ($a_{\zeta,t}$), core sector productivity ($a_{z_c,t}$), space sector productivity

[16] Note that in the extreme case where $\lambda_{sp} = 0$ (no spillover), $Z_{c,t}^{spill}$ remains at zero for all t. Conversely, if $\lambda_{sp} = 1$ (immediate spillover), all space technologies are fully transferred to the core sector with a one-period lag, yielding $Z_{c,t}^{spill} = \phi Z_{s,t-1}$.

[17] The term Ψ_t collects all the real adjustment costs and their expressions are given in Appendix IX

[18] In this model without nominal rigidities, the nominal interest rate does not play any role in determining real quantities.

($a_{z_s,t}$), labor supply shock (φ_t), the time-varying space innovation productivity ($a_{\xi_s,t}$), and the time-varying productivity of R&D resources in developing new technologies ($a_{\xi_c,t}$). They are modeled as AR(1) processes:

$$\log(a_{\zeta,t}) = \rho_\zeta \log(a_{\zeta,t-1}) + \varepsilon_{\zeta,t}, \qquad \log(a_{z_c,t}) = \rho_{z_c} \log(a_{z_c,t-1}) + \varepsilon_{z_c,t},$$
$$\log(a_{z_s,t}) = \rho_{z_s} \log(a_{z_s,t-1}) + \varepsilon_{z_s,t}, \qquad \log(\varphi_t) = \rho_\varphi \log(\varphi_{t-1}) + \varepsilon_{\varphi,t},$$
$$\log(a_{\xi_s,t}) = \rho_{\xi_s} \log(a_{\xi_s,t-1}) + \varepsilon_{\xi_s,t}, \qquad \log(a_{\xi_c,t}) = \rho_{\xi_c} \log(a_{\xi_c,t-1}) + \varepsilon_{\xi_c,t},$$

where ρ_ζ, ρ_{z_c}, ρ_{z_s}, ρ_φ, ρ_{ξ_s}, and ρ_{ξ_c} are the AR coefficients, and $\varepsilon_{\zeta,t}$, $\varepsilon_{z_c,t}$, $\varepsilon_{z_s,t}$, $\varepsilon_{\varphi,t}$, $\varepsilon_{\xi_s,t}$, and $\varepsilon_{\xi_c,t}$ are Gaussian white noises with standard deviations equal to σ_ζ, σ_{z_c}, σ_{z_s}, σ_φ, σ_{ξ_s}, and σ_{ξ_c}, respectively.

IV. Model Solution and Estimation

The model features non-stationary variables due to endogenous growth in technology. In particular, the number of adopted technologies A_t follows a stochastic trend and directly contributes to production by expanding the variety of intermediate inputs used in final goods (Romer, 1990). As a result, all real variables inherit the same trend, which drives their long-run dynamics. To ensure a well-defined steady state, we express the model in terms of deviations from this common trend. This stationary model is reported in Appendix X and its steady state is derived in Appendix XI.

Macroeconomic series

We estimate the model using six real macroeconomic variables (GDP; aggregate consumption; aggregate investment; hours worked in the core sector; industrial production index of the space sector; R&D resources), all these variables are measured in growth rates. The dataset starts in 1960:Q1, capturing the early years of space activity, and ends in 2015:Q1, the last quarter for which patent data are available. A detailed description of the data sources and applied transformations is provided in Appendix XII. The following measurement equations connect the macroeconomic data series (on the left-hand side) to the model variables (on the right-hand side):

$$\begin{aligned}
\Delta GDP_t^{data} &= \log(\widetilde{GDP}_t) - \log(\widetilde{GDP}_{t-1}) + x_t + \varepsilon_t^{GDP}, \\
\Delta c_t^{data} &= \log(\tilde{c}_t) - \log(\tilde{c}_{t-1}) + x_t + \varepsilon_t^{c}, \\
\Delta i_t^{data} &= \log(\tilde{i}_t) - \log(\tilde{i}_{t-1}) + x_t + \varepsilon_t^{i}, \\
\Delta n_{c,t}^{data} &= \log(n_{c,t}) - \log(n_{c,t-1}) + \varepsilon_t^{n_c}, \\
\Delta Y_{s,t}^{data} &= \log(\tilde{Y}_{s,t}) - \log(\tilde{Y}_{s,t-1}) + x_t + \varepsilon_t^{Y_s}, \\
\Delta S_t^{data} &= \log(\tilde{S}_t) - \log(\tilde{S}_{t-1}) + x_t + \varepsilon_t^{S},
\end{aligned} \tag{2.22}$$

where ε_t^{GDP}, ε_t^c, ε_t^i, $\varepsilon_t^{n_c}$, $\varepsilon_t^{Y_s}$, ε_t^S are measurement errors. A tilde indicates the business cycle components of nonstationary variables, and x_t is the stochastic growth rate defined as $\log(A_t/A_{t-1})$, see Section III.[19]

Technology series

In addition to macroeconomic series, we estimate the model using two technology series: the space innovation intensity ($F_{s,t}^{data}$) and the space spillover measure ($R_{s,t}^{data}$). These technology indicators are constructed from patent data, as described in Section II. First, we denote the model counterpart of $F_{s,t}^{data}$ as F_t, and define it as the share of new space-sector technologies relative to the total number of new technologies (space and core). We define $Q_{s,t} = \xi_{s,t-1}Y_{s,t-1}$ as the number of new space-sector technologies (see Equation 2.12), and $Q_{c,t} = \xi_{c,t-1}S_{t-1} + \hat{\xi}_{sc}^{spill}Spill_{sc,t}$ as the total number of new core-sector technologies, including spillovers from space technologies (see Equation 2.14). Therefore, the expression for F_t is:

$$F_t = \frac{Q_{s,t}}{Q_{s,t} + Q_{c,t}}. \tag{2.23}$$

Second, we denote the model counterpart of the space spillover measure $R_{s,t}^{data}$ as $R_{s,t}$, which represents the relative reliance of core-sector technologies on space-sector spillovers. We define $C_{spill,t} = \xi_{sc}^{spill}Spill_{sc,t}$ as the number of core-sector patents that build on space-sector technologies (see Equation 2.14), and $C_{total,t} = \xi_{c,t-1}S_{t-1} + \xi_{sc}^{spill}Spill_{sc,t}$ as the total number of new core-sector patents. The model-based spillover measure $R_{s,t}$ is then defined as:

$$R_{s,t} = \frac{C_{spill,t}}{C_{total,t}}.$$

The following measurement equations connect the technology series to the model variables:

$$F_{s,t}^{data} = F_{s,t} + \varepsilon_t^F, \qquad R_{s,t}^{data} = R_{s,t} + \varepsilon_t^R, \tag{2.24}$$

where ε_t^F, and ε_t^R are errors, that capture the imperfect measurement of technological variables based on patent data (see Jaffe et al., 1998). Technology variables are in levels, as they are already measured in percentage terms. They are observed in the same time span as the macroeconomic series (1960:Q1-2015:Q1).

[19]The stochastic growth rate x_t does not appear in the equation for hours worked, since these are stationary variables in the model.

Estimation

The measurement errors ε_t^{GDP}, ε_t^c, ε_t^i, $\varepsilon_t^{Y_s}$, ε_t^S, ε_t^F, and ε_t^R appering in equations (2.22) and (2.24) are distributed as Gaussian white noises with standard deviations equal to σ_{GDP}^{ME}, σ_c^{ME}, σ_i^{ME}, $\sigma_{n_c}^{ME}$, $\sigma_{Y_s}^{ME}$, σ_S^{ME}, σ_F^{ME} and σ_R^{ME}, respectively. The measurement errors in Equations (2.22) and (2.24) reflect imprecision in data collection and imperfect alignment between the model and the observed variables (Herbst and Schorfheide, 2015). Following Borağan Aruoba et al. (2018), we set their standard deviations to 10% of the corresponding series. To estimate the model, we use the standard Random Walk Metropolis-Hastings algorithm (RWMH) implemented in Dynare, see Adjemian et al. (2022). Consistent with standard practice in the DSGE literature (see, e.g., Smets and Wouters, 2007 and Herbst and Schorfheide, 2015), we calibrate a subset of parameters based on economic theory, see Table 2.1. The parameters for the capital share in tech-

Table 2.1—: Calibrated parameters. The table reports the calibrated parameter's name (Full Name), the associated symbol (Symbol), and the calibrated value (Value).

Full Name	Symbol	Value	Full Name	Symbol	Value
Capital share $\mathcal{S}_c$	α_c	0.350	Inverse Frisch el. $\mathcal{S}_s$	ν_s	2.000
Capital share $\mathcal{S}_s$	α_s	0.350	Steady-state hours $\mathcal{S}_c$	n_c	1.000
Discount factor	β	0.991	Steady-state hours $\mathcal{S}_s$	$n_s \times 10$	0.056
Obsolescence interm. goods	ϕ	0.990	Elast. interm. goods	θ_m	2.670
Depreciation $\mathcal{S}_c$	δ_{k_c}	0.025	Depreciation $\mathcal{S}_s$	δ_{k_s}	0.025
Space share	$\chi \times 100$	0.560	Average growth rate	$\gamma \times 100$	0.450
Inverse Frisch el. $\mathcal{S}_c$	ν_c	2.000	Investment rigidity	η_k	10.000
Capacity rigidity $\mathcal{S}_c$	η_{u_c}	0.500	Capacity rigidity $\mathcal{S}_s$	η_{u_s}	0.500
Taylor rule inflation reaction	r_π	1.500	Probability of spillover	λ_{sp}	0.050
$\mathcal{S}_s$ techn. over $\mathcal{S}_c$ techn.	$\chi_A \times 100$	1.360	Spill. techn. over R&D techn.	$\chi_{spill} \times 100$	7.600

nology are set equal to $\alpha_s = \alpha_c = 0.35$ to match a labor share of income of 0.65, see eqs. (2.4) and (2.8). The quarterly intertemporal discount rate (β) in eq. (2.9) is set at 0.991, giving an annual interest rate of 3.60% at the steady state. The quarterly capital depreciation rates are equal to $\delta_{k_c} = \delta_{k_s} = 0.025$, implying an annual depreciation rate of 10%. The steady state of the space sector share (g_s) in eq. (2.2) equals $\chi = 0.56/100$, to match the historical average of the sectoral output ratio for the *Aerospace Product and Parts Manufacturing Sector (NAICS 3364)* relative to U.S. nominal GDP over the sample.

In the calibration, we also impose a relative price of the space good (p_s) normalized to 1 at the steady state (see Appendix XI). The average growth rate of the economy is calibrated to an annual steady-state growth rate of 1.80%, so the quarterly growth rate is $\gamma = 0.45/100$, to match the average growth rate of U.S. real GDP per capita over the sample period, as in Anzoategui et al. (2019). For the labor disutility curvature parameters ν_c and ν_s we follow the microeconomic evidence and set them at 2.00, which is the prior mean value used by Anzoategui et al. (2019). As in Comin and Gertler (2006), we set $\theta_m = 2.67$, so the gross markup in the intermediate goods sector is 1.60. In addition, following Comin and Gertler (2006), we set an annual obsolescence rate of intermediate technologies equal to 3%, implying a quarterly survival rate $\phi = (1 - 0.03)^{1/4} = 0.99$.

We set the parameters governing investment rigidity and capacity utilization to $\eta_k = 10$ and $\eta_{u_c} = \eta_{u_s} = 0.50$, following Iacoviello and Neri (2010). We fix the quarterly spillover probability from space technologies to core technologies (λ_{sp}) at 0.05, implying an average spillover lag of 20 quarters (5 years). We define the steady-state ratio of technologies in the space sector to technologies in the core sector as $\chi_A = \frac{Z_s}{Z_c}$ and set it to 1.36%, which corresponds to the average share of patents in the space sector relative to patents in the core sector in our sample. Similarly, we define χ_{spill} as the steady-state share of new core-sector technologies that originate from space-sector spillovers (spillover share) and set it to 7.60%, based on the average value of the empirical spillover measure over the estimation sample, see Figure 2.1 in Section II.

In the Taylor rule, the response parameter to inflation is $r_\pi = 1.50$, see Iacoviello and Neri (2010). The weights φ^c and φ^s in eq. (2.9) are chosen to normalize hours worked in the core sector to $n_c = n_c^{ss} = 1$ and set hours worked in the space sector to $n_s = n_s^{ss} = \chi$. This ensures that the steady-state ratio of labor across sectors matches the relative size of space sector production to core sector production (Y_s/Y_c). The weights φ^c and φ^s depend on other calibrated values, and their expressions are provided in Appendix XI. The technological scaling factors ($\hat{\xi}_s$, $\hat{\xi}_c$, and ξ_{sc}^{spill}) are calibrated to ensure consistency with three steady-state moments: the long-run growth rate of the economy (γ), the steady-state ratio of space to core technologies (χ_A), and the spillover share (χ_{spill}). The expressions for these parameters are reported in Appendix XI.

The priors are in line with the DSGE literature, see Smets and Wouters (2007) and are reported in Table 2.2. For the elasticity of new technologies to R&D (ϵ_c) and space activity (ϵ_s), we use the Beta ($\mathcal{B}$) prior as in Anzoategui et al. (2019), with a mean of 0.60 and a standard deviation of 0.15. For the average adoption lag τ, we specify a Normal ($\mathcal{N}$) prior with mean equal to 5.00 (five years adoption lag) and standard deviation of 1.00, as in Anzoategui et al. (2019). For the exogenous processes, we use Inverse-Gamma ($\mathcal{IG}$) priors for the standard deviations and $\mathcal{B}$ priors for the AR coefficients as in Smets and Wouters (2007). The RWMH chain runs for 1,500,000 iterations and the first half is discarded as a burn-in period. Convergence is assessed by running multiple chains and considering the statistics of Brooks and Gelman (1998), provided by Dynare, see Adjemian et al. (2022).

The last two columns of Table 2.2 report the posterior estimates and standard deviation of the parameters. We estimate $\epsilon_c = 0.16$ and $\epsilon_s = 0.26$, suggesting lower coefficients and more diminishing returns to R&D and space activity than the prior. We estimate the

Table 2.2—: Estimation Results. The table reports the parameter's name (Full Name) with the associated symbol (Symbol). The table also reports the prior shape (Prior), prior mean and standard deviation (Mean, St. Dev), and the posterior mean (Post. Mean) and the posterior standard deviation (Post. St. Dev) for the estimated parameters. The $\mathcal{B}$ is the Beta distribution; $\mathcal{N}$ is the Normal distribution; $\mathcal{IG}$ is the Inverse-Gamma distribution.

Full Name	Symbol	Prior	Prior Mean	Prior St. Dev	Post. Mean	Post. St. Dev
R&D elasticity	ϵ_c	$\mathcal{B}$	0.60	0.15	0.16	0.01
Space activity elasticity	ϵ_s	$\mathcal{B}$	0.60	0.15	0.26	0.09
Adoption lag	τ	$\mathcal{N}$	5.00	1.00	7.08	0.92
Persistence space Demand	ρ_s	$\mathcal{B}$	0.50	0.10	0.94	0.01
Persistence space innovation productivity	ρ_{ξ_s}	$\mathcal{B}$	0.50	0.10	0.93	0.01
Persistence Prod. S_c	ρ_{z_c}	$\mathcal{B}$	0.50	0.10	0.91	0.01
Persistence Prod. S_s	ρ_{z_s}	$\mathcal{B}$	0.50	0.10	0.95	0.01
Persistence Lab. Supply	ρ_{φ}	$\mathcal{B}$	0.50	0.10	0.91	0.01
Persistence Preference	ρ_{ζ}	$\mathcal{B}$	0.50	0.10	0.99	0.00
Persistence R&D technology	ρ_{ξ_c}	$\mathcal{B}$	0.50	0.10	0.96	0.00
St. Dev. S_s Demand	$100 \times \sigma_{g_s}$	$\mathcal{IG}$	1.00	1.00	3.91	0.19
St. Dev. S_s technology	$100 \times \sigma_{\xi_s}$	$\mathcal{IG}$	1.00	1.00	9.30	0.42
St. Dev. Prod. S_c	$100 \times \sigma_{z_c}$	$\mathcal{IG}$	1.00	1.00	0.37	0.02
St. Dev. Prod. S_s	$100 \times \sigma_{z_s}$	$\mathcal{IG}$	1.00	1.00	8.22	0.50
St. Dev. Lab. Supply	$100 \times \sigma_{\varphi}$	$\mathcal{IG}$	1.00	1.00	2.24	0.13
St. Dev. Preference	$100 \times \sigma_{\zeta}$	$\mathcal{IG}$	1.00	1.00	4.17	0.50
St. Dev. S_c technology	$100 \times \sigma_{\xi_c}$	$\mathcal{IG}$	1.00	1.00	2.87	0.15

average adoption lag τ to 7 years, which is in line with Comin and Gertler (2006). This gives a quarterly adoption probability of existing technologies ($\lambda = \frac{1}{4\tau}$) of around 3.60%. We find a high persistence of the space sector share ($\rho_s = 0.94$), and of space innovation productivity ($\rho_{\xi_s} = 0.93$). The other AR parameters (ρ_{z_c}, ρ_{z_s}, ρ_{φ}, ρ_{ζ}, and ρ_{ξ_c}) also point to high degrees of persistence.

V. Economic Results

Figure 2.5 shows the smoothed estimate of the space innovation productivity ($a_{\xi_s,t}$), using the parameters' posterior mean. Overall, we can notice persistent fluctuations of $a_{\xi_s,t}$, in line with the estimated AR parameter ($\rho_{a_{\xi_s}}$), see Table 2.2. The vertical lines mark major missions and key technological achievements in U.S. space history, as descriptive references for the reader, see NASA (2024). Space innovation productivity begins at a trend value of approximately 1.40 in the initial decades and exhibits a decline from the early 1980s, declining to about 0.30 in the last two decades.

Our estimates suggest that space sector activity was considerably more effective at generating new technologies during the early stages of space exploration than it is today. The trend in space innovation productivity ($a_{\xi_s,t}$) reached approximately 1.60 in the 1960s, during the early era of space exploration (e.g., Mercury program — Event 1 and the Apollo 11 Moon landing - Event 2). It remained relatively high throughout the 1970s, averaging around 1.4, and was still at 1.3 at the time of the first Space Shuttle launch (Event 4). From the 1980s, $a_{\xi_s,t}$ entered a prolonged downward trajectory, implying a

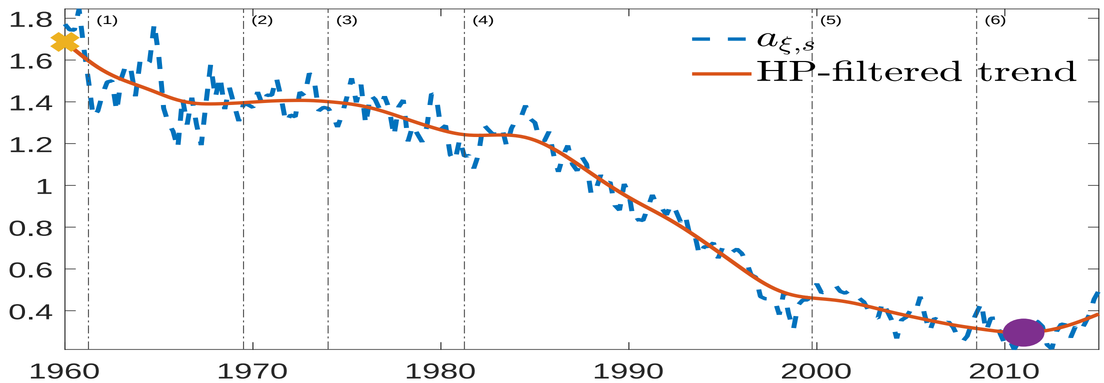

Figure 2.5. : The smoothed dynamics of space innovation productivity ($a_{\xi_s,t}$, blue dashed line) and its Hodrick-Prescott filtered trend using $\lambda^{HP} = 16000$ (HP-filtered, red solid line). The five vertical dash-dotted lines mark major U.S. space technology and mission milestones: (1) 1961:Q2 – Mercury Redstone 3 (first U.S. human spaceflight); (2) 1969:Q3 - Apollo 11 Moon landing; (3) 1974:Q1 – grant of the original U.S. GPS patent; (4) 1981:Q2 – first Space Shuttle launch (STS-1); (5) 1999:Q4 – launch of NASA's Terra satellite (Earth Observing System); (6) 2008:Q3 – Falcon 1 reaches orbit. The star (yellow) and the circle (purple) show the values used for the simulations in the next subsections, and they represent the highest value of 1960 ($a_{\xi_s,t} = 1.72$) and the lowest value ($a_{\xi_s,t} = 0.25$) of 2011, respectively.

decline in the productivity of space activities in generating new technologies. The most recent private initiative, SpaceX's Falcon 1 launch in 2008:Q3 (Event 6), was associated with a value of approximately 0.25. Following this event, space innovation productivity continued to decline, reaching its lowest point in the sample, around 0.25 in 2011.

Impulse Responses

Given the parameter estimates in Table 2.2 and the evolution of space innovation productivity in Figure 2.5, we now study the generalized impulse response functions (GIRFs) of key variables to a space sector shock that unexpectedly increases the share of the space sector ($g_{s,t}$), and the level of production in the space sector ($Y_{s,t}$). The GIRFs measure the impact that an exogenous increase in space sector activity (e.g., the launch of a new satellite program) has on the discovery of new technologies and GDP.

Specifically, the GIRFs are calculated by comparing the evolution of key variables in the case where the share of the space sector ($g_{s,t}$) receives an impulse from its shock ($\varepsilon_{s,t}$) to the case where it does not.

Figure 2.6 shows the estimated GIRFs in two scenarios: the first one is associated with the higher space innovation productivity of 1960:Q2 ($a_{\xi_s,t} = 1.72$, red dashed line), while the second is associated with the lower space innovation productivity of 2011:Q1 ($a_{\xi_s,t} = 0.25$, blue solid line). The GIRFs are computed using a second-order solution of the model.[20] Our analysis considers a space sector shock ($\varepsilon_{s,t}$) that hits the economy with the same size (a one percent increase in detrended space activity $\tilde{Y}_{s,t}$) in both scenarios. The first panel of Figure 2.6 shows that this shock increases the space sector share ($g_{s,t}$), as described in eq. (2.2). The exogenous increase in the space sector share is identical in both high and low space innovation productivity cases, raising the share by approximately 0.55 basis points above its steady-state level. Since the steady-state share is 0.56% ($g_s = \chi$), this shock corresponds to roughly a 1% increase relative to steady-state. The middle-left panel shows that after the shock, increased production in the space sector generates new space technologies ($Z_{s,t}$), as implied by equation (2.12). The plot indicates that these technological effects are significantly more pronounced under high space innovation productivity. Under this scenario, $Z_{s,t}$ peaks at around 5 basis points after 30 quarters, whereas in the low space innovation productivity scenario, it reaches 3 basis points.

We observe similar differences in the response of core sector technologies, which increase due to the space sector spillover described in equation (2.14). Under the high space innovation productivity scenario, $Z_{c,t}$ peaks at approximately 0.12 basis points above the steady state, whereas under the low space innovation productivity scenario, it is at 0.05 basis points. Similarly, the aggregate stock of existing technologies ($Z_t = Z_{s,t} + Z_{c,t}$) peaks at 0.18 and 0.09 basis points for high and low space innovation productivity scenarios, respectively. The relatively small responses of the technological variables reflect the modest size of the simulated shock, a 1% increase in space sector activity used as a benchmark. For reference, a shock large enough to raise the space sector's share to its historical peak (0.80% in 1967:Q2) would be approximately 43 times larger.[21] Assuming the response scales proportionally with the size of the shock, this historical peak-level shock would translate into an increase in existing technologies (Z_t) of about 7.90 basis points under the high-productivity scenario, and about 4.00 basis points under the low-productivity scenario.

Trend and Business Cycle Effects of Space Activity

To disentangle the impact of a space sector shock on technology and economic growth, we examine its joint effect on the trend and business cycle components of GDP. Figure 2.7 presents the GIRFs of adopted technologies in the production processes (A_t) and the stationary component of GDP ($\widetilde{GDP}_t$), which together determine the overall response of nonstationary GDP ($GDP = A_t\widetilde{GDP}_t$).

As shown in Figure 2.6, we examine a space sector shock which results in a 1% increase

[20] To compute the GIRFs (Koop et al., 1996), we simulate positive and negative shocks to $\varepsilon_{\xi_s,t}$ that raise or lower the value of space innovation productivity from its steady-state level of $a_{\xi_s,t} = 1$, to the highest value of $a_{\xi_s,t} = 1.72$ and lowest value equal of $a_{\xi_s,t} = 0.25$. The GIRFs are computed using a second-order perturbation with Dynare, see Adjemian et al. (2022), and are averaged over 100 iterations and make use of a pruned solution to the model, to rule out possible explosive paths generated by the nonlinear solution, see Andreasen et al. (2018).

[21] This larger shock would raise the space sector share by 23.9 basis points above its steady-state value of 0.56%, compared to just 0.55 basis points in the smaller shock shown in Figure 2.6.

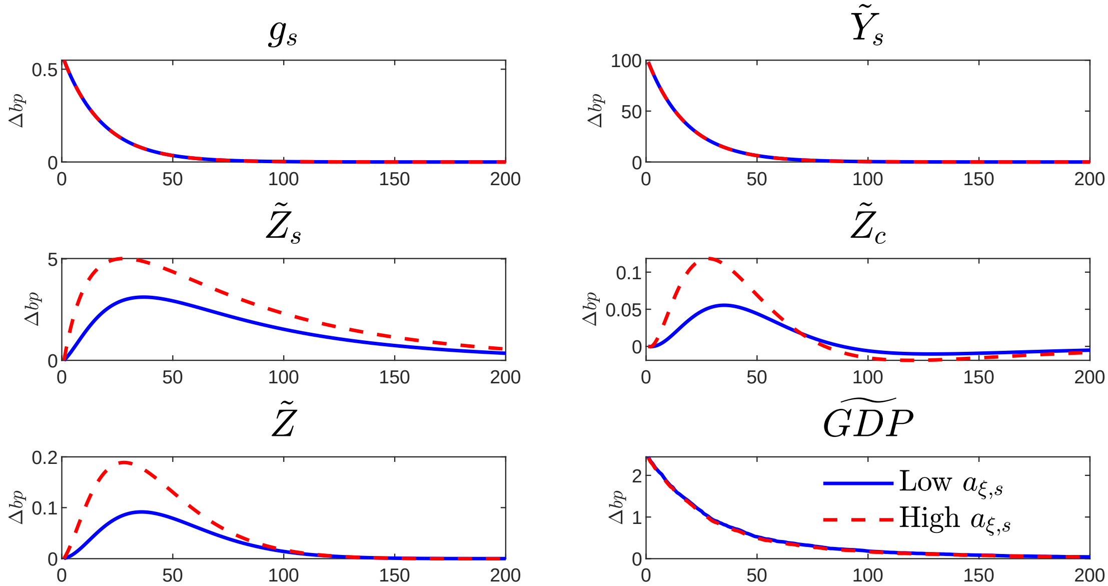

Figure 2.6. : The GIRFs of stationary variables to a positive space sector shock. The GIRFs are associated with higher space innovation productivity of the beginning of the sample ($a_{\xi_s,t} = 1.72$, red dashed line) and lower space innovation productivity of the recent years ($a_{\xi_s,t} = 0.25$, blue solid line). The upper left panel reports the response of the space sector share ($g_{s,t}$) in deviations from the steady state (namely, $g_{s,t} - \chi$), expressed in basis points (Δbp); the upper right panel reports the response of space sector production ($Y_{s,t}$) expressed in basis points deviations (Δbp) from the steady state; the middle left panel reports the response of productivity space sector technologies ($\tilde{Z}_{s,t}$) in basis points deviations (Δbp) from the steady state; the middle right panel reports the response of core sector technologies ($\tilde{Z}_{c,t}$) in basis points deviations (Δbp) from the steady state; the lower left panel reports the response of existing technologies ($\tilde{Z}_t$) in basis points deviations (Δbp) from the steady state; and the lower right panel reports response of GDP ($\widetilde{GDP}_t$) in basis points deviations (Δbp) from the steady state. Horizontal axes report the quarters.

in space sector production ($\tilde{Y}_{s,t}$). The top panel displays how adopted technologies (A_t) react under varying levels of space innovation productivity. In the high space innovation productivity scenario of 1960, A_t responds more robustly, reaching roughly 0.51 basis points, while in the low space innovation productivity scenario of 2011, the response is weaker, at about 0.27 basis points. The response of A_t emerges only in the long run, starting from zero and exhibiting a permanent effect. The lower panel of the figure shows the response of the business cycle component ($\widetilde{GDP}_t$) following a space sector shock. On impact, $\widetilde{GDP}_t$ increases by approximately 2.35 basis points before gradually reverting to its steady-state level. The initial rise is mechanically driven by the expansion in space sector production and the corresponding increase in aggregate income. The response of $\widetilde{GDP}_t$ is nearly identical in the high and low space innovation productivity scenarios. This distinction highlights the fundamental difference between the persistent effects of technological shocks and the transitory nature of business cycle fluctuations.

Figure 2.8 shows the overall response of GDP (blue solid line), which results from the combined effects of the business cycle component ($\widetilde{GDP}_t$) and the technology level (A_t)

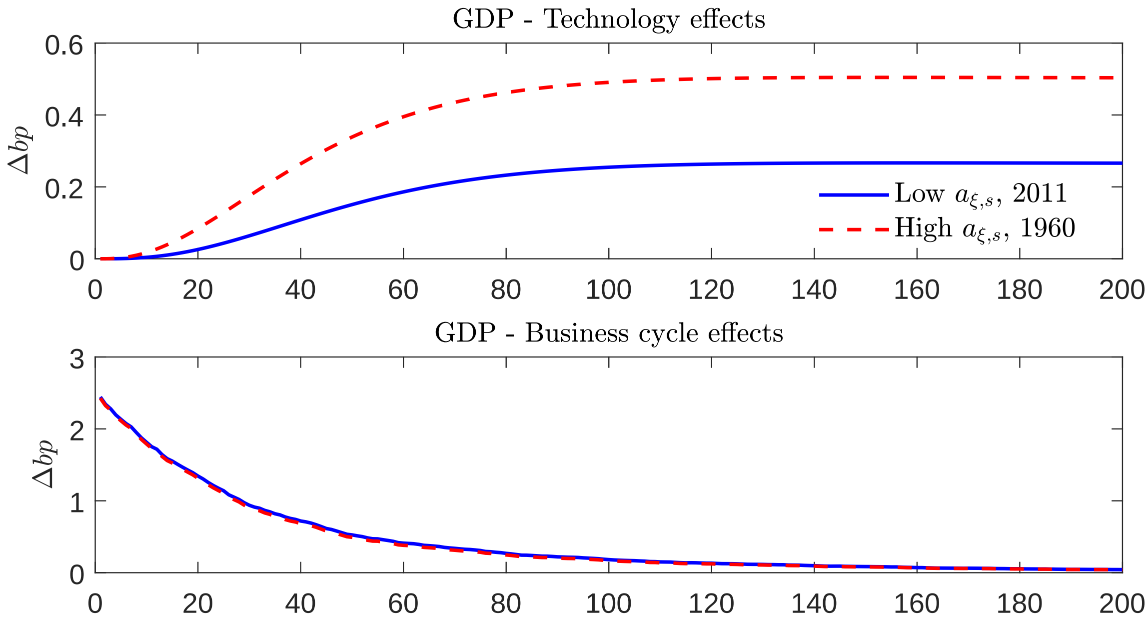

Figure 2.7. : The GIRFs of GDP to a positive space sector shock, distinguishing between trend and business cycle components. The GIRFs are associated with higher space innovation productivity of the beginning of the sample ($a_{\xi_s,t} = 1.72$, red dashed line) and lower space innovation productivity of the recent years ($a_{\xi_s,t} = 0.25$, blue solid line). The upper panel reports the response of the technological component of GDP (A_t) expressed in basis points deviations (Δbp) from its trajectory without the space sector shock; the lower panel reports the response of the business cycle component of GDP, namely $\tilde{GDP}_t$ in basis points deviations (Δbp) from the steady state. Horizontal axes report the quarters.

following a space sector shock of the same magnitude as in Figure 2.7. This shock is associated with the high space innovation productivity scenario of 1960 ($a_{\xi_s,t} = 1.72$). The initial response of GDP is entirely driven by the business cycle component; in the long run, it converges to the technological component, as technological improvements are the only persistent effects of the shock.

To assess the economic significance of the results, we analyze the spending multipliers associated with space activity. At each time period i after the shock, we compute (a) the response of GDP (GDP_{t+i}, shown in Figures 2.7 and 2.8), (b) the response of space expenditure ($p_{s,t+i}Y_{s,t+i}$), and (c) the response of the interest rate (R_{t+i}). We then compare the economic gains (the discounted cumulative increase in GDP) against the economic costs (the discounted cumulative increase in space expenditure), over any given time horizon h. Following Mountford and Uhlig (2009) and Zubairy (2014), the cumulative space spending multiplier $M_{s,h}$ is given by:

$$M_{s,h} = \frac{\mathbb{E}_t \sum_{i=0}^{h} \Delta \left(\frac{1}{R_{t|t+i}} \right) GDP_{t+i}}{\mathbb{E}_t \sum_{i=0}^{h} \Delta \left(\frac{1}{R_{t|t+i}} \right) (p_{s,t+i}Y_{s,t+i})}. \tag{2.25}$$

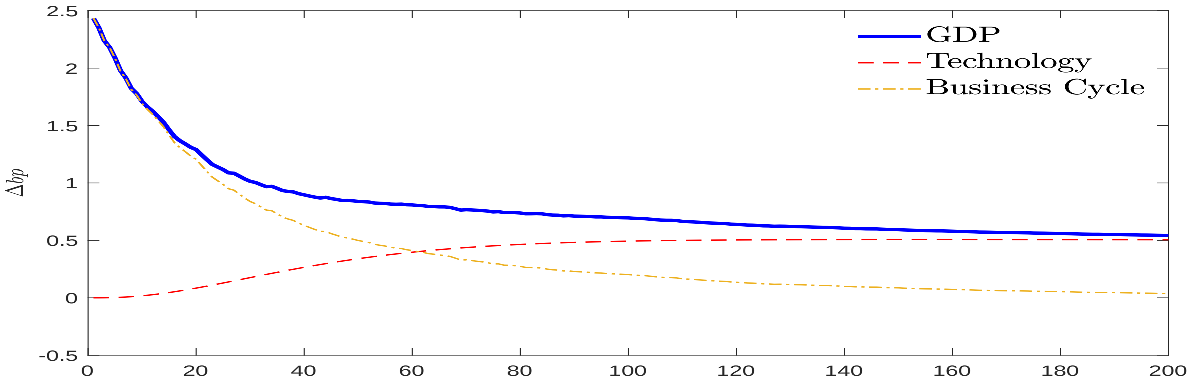

Figure 2.8. : The GIRFs of GDP to a positive space sector shock. All the GIRFs in this plot are associated with higher space innovation productivity of the beginning of the sample ($a_{\xi_s,t} = 1.72$). The GIRFs are expressed in percentage deviations with respect to the case where no shock realizes. The horizontal axis reports the quarters.

In eq. (2.25), $1/R_{t|t+i}$ represents the discount factor for future gains and expenses, occurring i periods ahead in the future.[22]

Table 2.3 reports the cumulative space spending multipliers at different horizons: 20, 100, 200, and 400 quarters.[23] The table presents two versions of the multipliers: one where discounting of future gains is applied, based on the equilibrium interest rate (as shown in Equation 2.25), and one where the discount factor is set to unity ($1/R_{t|t+i} = 1$ for all i). This distinction is important because the technological effects unfold over the long run, where discounting can significantly alter the estimated impact, see Ramey (2020). By considering these two cases, market-based discounting and no discounting, we provide a useful range for interpreting long-run multipliers in the spirit of Millner and Heal (2023).

Table 2.3—: Cumulative space spending multipliers at different time horizons. Values without parentheses correspond to the high space innovation productivity at the beginning of the sample ($a_{\xi_s,t} = 1.72$), while values in parentheses indicate the lower space innovation productivity of recent years ($a_{\xi_s,t} = 0.25$). The table reports discounted (Disc) and non-discounted (Not Disc) multipliers over 20-, 100-, 200-, and 400-quarter horizons.

	20q	100q	200q	400q
Disc	1.1 (1.1)	1.4 (1.3)	1.8 (1.4)	2.2 (1.6)
Not Disc	1.1 (1.1)	1.5 (1.3)	2.4 (1.8)	6.0 (3.7)

[22]The discount factor is given by the product of risk-free gross policy rates from t to $t+i$:

$$R_{t|t+i} = \prod_{j=0}^{i} R_{t+j}.$$

Analyzing whether the multipliers may vary depending on different discount factors ($R_{t|t+i}$) between public or private space customers is left for future research.

[23]The reason for using this very long horizon (400 quarters, or 100 years) is to show the theoretical effect of slow-moving technological spillovers, consistent with the nearly century-long span of our patent data from 1920 to 2015.

Table 2.3 highlights the dynamic effects of space sector spending on GDP across different time horizons. In the medium run (20 quarters), the multipliers are slightly above one and are similar across the high and low space innovation productivity cases, suggesting that short-term effects are mainly driven by business cycle fluctuations. Over the long term (100 quarters) and especially in the very long run (200 and 400 quarters), the divergence between the scenarios increases significantly. In the high space productivity scenario, multipliers are significantly higher than in the low productivity case, showing that in the long run, technological advancements from space investment drive GDP growth. At the 400-quarter horizon, the high non-discounted multiplier is 6.0, nearly three times larger than the corresponding discounted value (2.2). These results show how discounting significantly affects the assessment of returns from space investments. Since the economic effects of space activity emerge gradually over time, the way future gains are discounted plays a crucial role in determining their perceived value today. Moreover, these findings highlight the importance of the technological impacts from space activities, as the larger economic benefits of space spending emerge primarily through sustained innovation and diffusion over the long run, rather than from short-term demand effects.

Sectoral Spillovers

We use our model to analyze the sector-specific spillovers discussed in Section II. In particular, we conduct a counterfactual analysis that isolates the effects of spillovers from space technologies in each of the four key technological sectors shown in Figure 2.3.

We compute the response of the nonstationary technological component of GDP, A_t, assuming that the spillover from space operates through only one sector at a time. To do so, we calibrate the sector-specific spillover shares (χ_{spill}) to match the observed sectoral spillover series in Figure 2.3, instead of the aggregate measure for the core sector (bottom panel of Figure 2.1). We fix space innovation productivity ($a_{\xi_s,t} = 1$) to keep the number of new space technologies constant across simulations, isolating only differences in their diffusion to other sectors. χ_{spill} are set to match the empirical values in Figure 2.3 at two points in time: 1960 and 2011. These years are selected to represent, respectively, the pioneering phase of space activity and the more recent period marked by lower space innovation productivity.

We report the GIRFs of nonstationary GDP in Figure 2.9, following a one-percent increase in activity of the space sector ($Y_{s,t}$). The results reveal heterogeneous dynamics across sectors and over time. In the case of the Computer and Peripheral Equipment sector (top-left panel), the impact on GDP is substantially higher in 2011 than in 1960, reflecting the sector's growing importance as a recipient of space-related innovation. A similar pattern is observed for the Communication Equipment sector (top-right panel). By contrast, the Navigation, Measurement, Electromedical, and Control Instruments sector (bottom-left panel) exhibits a more stable contribution over time, with nearly identical GDP responses in both periods, mirroring the relatively constant spillover measure shown in Figure 2.1. Finally, the Electrical Equipment sector (bottom-right panel) displays a declining influence, with a weaker GDP response in 2011 than in 1960, in line with the diminishing spillover measure from space technologies in the data. These findings show the evolving and uneven transmission of space-sector innovation to the broader economy. By isolating each sector's role in turn, the counterfactuals provide a clearer picture of how specific technological channels have mediated the macroeconomic impact of space activities across different historical periods.

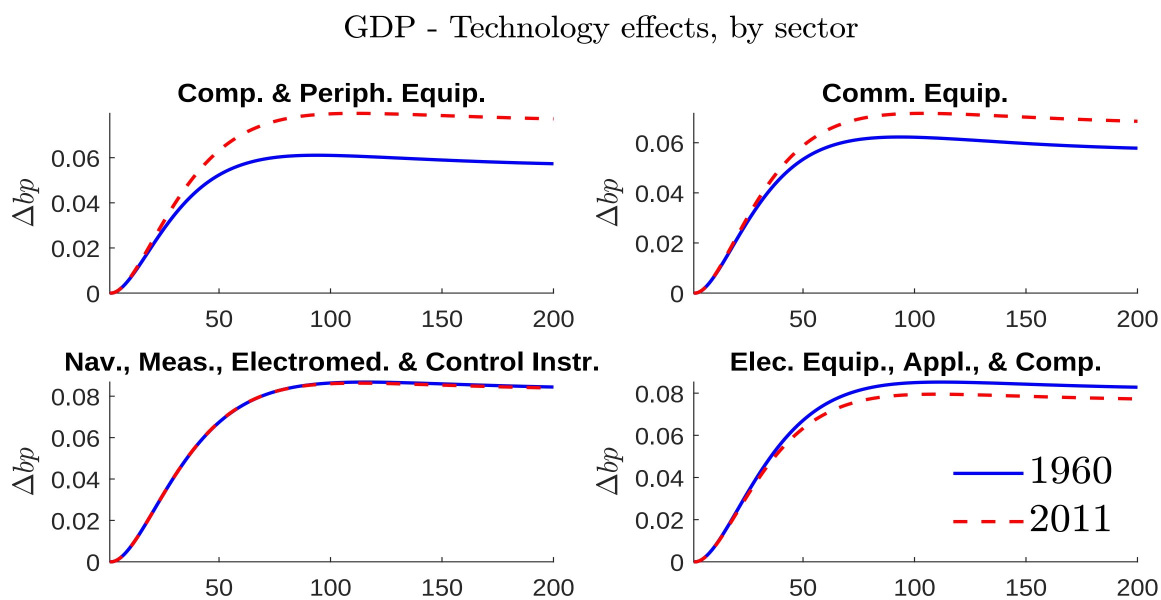

Figure 2.9. : The panels show the response of the nonstationary technological component of GDP_t (A_t), measured in basis points deviations (Δbp) from its no-shock trajectory, after a one-percent increase in space sector activity ($Y_{s,t}$). Each panel focuses on a specific spillover channel (Computer, Communication, Navigation, and Electrical) and compares responses using spillover shares (χ_{spill}) equal to the spillover measures $R^{data}_{s,t}$ observed in 1960 (blue solid line) and 2011 (red dashed line). Space innovation productivity is held constant at its steady-state value ($a_{\xi_s,t} = 1$) to isolate the role of sector-specific spillover transmission. The responses are computed from a second-order approximation of the model with pruning. The horizontal axis denotes quarters.

VI. Conclusion

The renaissance of space exploration that we are witnessing is paving the way for a number of potential technological developments that may produce significant economic spillovers. This paper addresses this evidence by building and estimating a two-sector general equilibrium growth model with a space sector, using a novel dataset on U.S. patents. To analyze technological dependencies among patents, we construct a citation network and use network-based metrics to capture both direct and indirect linkages. Relative to earlier work, our model features a richer technology block, where technological progress can stem from generic R&D or space innovation, and where spillovers from space to the core sector are modeled explicitly. Our results can be summarized as follows. Space activities lead to positive spillovers to the broader economy, boosting productivity and long-term growth. These spillovers are larger in the earlier stages of aerospace activity (1960s) compared to today (2010s), due to lower innovation productivity of space activity. We find that the economic effects of space activity give the highest returns in the long term, since business cycle effects are temporary and associated with lower multipliers. Whilst the overall technology generated in the aggregate U.S. economy by space activity has reduced over the decades, the effects on specific sectors show distinct patterns. Focusing on sectors like Computer and Peripheral Equipment and Communication Equipment, we show that the spillover from space has increased over time.

As space activities expand and data availability improves, both granular and aggregate approaches can be used to explore the economic implications of specific space-related initiatives. Future research could leverage the granularity of patent data to isolate the spillovers generated by specific activities within the space sector, such as satellite development, launch services, or space science missions. Distinguishing between public and private contributions (e.g., NASA vs. commercial firms) would allow researchers to investigate incentive structures, coordination issues, and potential inefficiencies in the allocation of resources. This line of research could also shed light on negative externalities and policy trade-offs, particularly as competition intensifies and property rights remain underdeveloped. Embedding these features into macroeconomic models, possibly through richer input-output networks (as McNerney et al., 2022 and Highfill and MacDonald, 2022) would offer a more comprehensive view of how space technologies propagate through the economy and how their benefits and risks are distributed.

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VII. Patent data description

This appendix describes the data sources, transformations, and methodology used to construct the patent and citation datasets employed in the analysis.

The patent data come from the Comprehensive Universe of U.S. Patents (CUSP) database provided by Berkes (2018), which compiles historical records of patents issued by the United States Patent and Trademark Office (USPTO) from 1836 to 2015. For this study, we use the subset of data available from 1920 to 2015, aligning with the focus of our analysis on the aerospace sector. The dataset integrates multiple sources, including USPTO records, digitized historical archives, Optical Character Recognition (OCR)-processed documents, and Google Patents. It provides detailed information on patent grants, technological classifications, and backward citations, allowing for a comprehensive examination of innovation patterns over time. The dataset includes a total of 7,584,773 patents from 1920 onward.

Each patent in the dataset is classified using the U.S. Patent Classification (USPC) system, which can assign multiple technology classes to a single patent. Among these, one main class is designated to capture the core inventive concept of the patent. To map patents to economic sectors, we merge the U.S. Patent Classification (USPC) system with the North American Industry Classification System (NAICS) using the 2014 USPTO-NAICS concordance table provided by the U.S. Patent and Trademark Office (USPTO).[24] This concordance table links each USPC class and subclass to one or more NAICS sectors based on technological relevance. Since some USPC classes correspond to multiple NAICS sectors, we retain all valid associations in our dataset to fully account for the potential economic domains influenced by a given patent. This approach ensures that patents classified under multiple applicable industries contribute proportionally across all linked NAICS sectors. To measure the extent to which a patent belongs to the space sector, we compute a fractional weight for each patent based on its technological classification. Let p denote a patent, and let T_p be the set of technology classes assigned to p, with cardinality $|T_p|$. For each technology class $T \in T_p$, let $w_s(T)$ denote the share of T that maps to the space sector s. The fractional assignment of patent p to the space sector is then given by:

$$\alpha_s(p) = \frac{1}{|T_p|} \sum_{T \in T_p} w_s(T).$$

The total number of space sector patents at time t is computed by summing over all patents granted in the period t. Let P_t be the set of patents granted in quarter t, then

[24] Available at https://www.uspto.gov/web/offices/ac/ido/oeip/taf/data/naics_conc/2014/.

the total weighted count of space patents is:

$$Q_{s,t}^{data} = \sum_{p \in P_t} \alpha_s(p).$$

To construct a relative measure of new space technologies in a given quarter, we compute the ratio of space sector patents to total patents (space plus core sector). The number of core sector patents at time t is denoted as:

$$Q_{c,t}^{data} = \sum_{p \in P_t} \alpha_c(p),$$

where $\alpha_c(p) = 1 - \alpha_s(p)$ is the fraction of patent p assigned to the core sector.

The final ratio of space sector patents to core sector patents (space innovation intensity), which serves as our main measure of space technological activity, is then given by:

$$F_t^{data} = \frac{Q_{s,t}^{data}}{Q_{s,t}^{data} + Q_{c,t}^{data}}.$$

This measure, plotted in Figure 2.1 in the main text, represents the flow of new space technologies relative to core technologies in each period and is the empirical counterpart of the model variable F_t defined in Eq. (2.23). Patent data are dated using the grant date (year, month, and day), and observations are aggregated at the quarterly frequency to ensure comparability with macroeconomic data. The series in Figure 2.1 in the main text shows that the share of space-related technologies peaked in 1960 at approximately 2.8%, followed by a long-term decline, reaching its lowest value of 0.80% in 1999.

Secondly, we study technological spillovers through patent citations, where a citation indicates that the citing patent builds on the technological content of the cited one. Citation data are obtained from the `cit_given_from_1920.csv` file of the CUSP database, which records citation relationships between patents. The data are filtered to retain only citations between patents included in our dataset to ensure consistency.[25]

To quantify spillovers, we define the set of citations made by patent p as $C(p)$. Each cited patent $q \in C(p)$ has a space sector weight $\alpha_s(q)$. We define the subset of citations that reference at least one space sector patent as:

$$C_s(p) = \{q \in C(p) \mid \alpha_s(q) > 0\}.$$

We define a dummy variable $d_{s,p}$ that indicates whether patent p cites at least one space

[25]The percentage of retained patents is 99.08%.

sector patent:

$$d_{s,p} = \begin{cases} 1, & \text{if } |C_s(p)| > 0 \\ 0, & \text{otherwise.} \end{cases}$$

Focusing on the core sector, we weight each patent by its degree of core-sector relevance $\alpha_c(p)$, and define the naive space to core spillover measure as:

$$R^{naive}_{s,t} = \frac{\sum_{p \in P_t} \alpha_c(p) \cdot d_{s,p}}{\sum_{p \in P_t} \alpha_c(p)}.$$

This expression computes the share of core-sector patents that cite at least one space-sector patent, using sectoral weights and is plotted in the lower panel of Figure 2.1 in the main text. While this measure captures direct citation links, it does not account for the broader network of indirect technological dependencies. To address this, the next section introduces a centrality-based approach that incorporates the full structure of the citation network.

VIII. PageRank algorithm

This appendix describes the methodology used to compute spillovers from the space sector to the core sector using a PageRank-based algorithm applied to the patent citation network. Unlike the simpler dummy-based method, this approach captures the full structure of direct and indirect linkages across the network.

To capture technological dependency, rather than influence, we use the Reverse PageRank variant, which ranks patents based on the citations they make instead of those they receive. In this setting, each patent i is assigned a dependency score PR_i, which is higher when the patents it cites j also have high scores PR_j. This reflects the idea that a patent is more dependent when it builds upon prior work that itself relies heavily on earlier innovations. The recursive structure of the algorithm allows it to incorporate indirect pathways of technological transmission.

To implement the algorithm, we define the citation matrix A, where each element indicates whether patent i cites patent j:

$$A_{ij} = \begin{cases} 1, & \text{if patent } i \text{ cites patent } j, \\ 0, & \text{otherwise.} \end{cases}$$

Based on this matrix, Reverse PageRank computes the dependency score of each patent i (PR_i) iteratively, using the following equation:

$$PR_i = (1-d)v_i + d \sum_{j:A_{ij}=1} \frac{PR_j}{C_j}, \tag{A2.1}$$

where d is the damping factor, which controls how much weight is given to the network structure; v is the teleportation vector (Brin and Page, 1998), which assigns baseline weights across patents, with v_i denoting its ith element; and C_j is the in-degree of patent j, representing the total number of citations it receives.

The first term in Eq. (A2.1), which includes the teleportation vector, assigns a baseline level of dependency to each patent independently of the citation network. This ensures that all patents receive some initial dependency score, preventing the measure from being entirely driven by citation links alone and improving numerical stability. The second term captures the recursive component of the algorithm, summing the dependency scores of all patents cited by i, with each contribution inversely weighted by the number of other patents that cite them (C_j). This means that if a cited patent j is only referenced by i ($C_j = 1$), its full score PR_j is transferred to i. Conversely, if j is widely cited ($C_j > 1$), its influence is diluted and distributed across all citing patents.

The algorithm is parameterized by several tuning parameters. The damping factor d determines the relative weight given to the teleportation and network part. Lower values of d reduce the influence of network links, while higher values increase it.[26] We calibrate the damping factor to $d = 0.50$, the standard choice in the literature on technological diffusion (see Chen et al., 2007, Mariani et al., 2019). This value balances the influence of the citation network with baseline scores from the teleportation vector.[27] The PR scores are computed by starting from an initial distribution and repeatedly updating them based on the scores of connected nodes, until the values converge. The algorithm iterates until the difference between two consecutive iterations falls below a convergence tolerance tol, which we set to 10^{-6} to ensure numerical stability; we cap the number of iterations at $max\_iter = 1000$, although convergence is typically achieved in less than 40 iterations.

To quantify the relative importance of citations to space-sector patents versus generic patents, the algorithm employs two different initializations for teleportation. The first captures the dependency on space sector patents and uses a teleportation vector v based on the naive spillover definition: each patent receives a weight of 1 if it cites at least one space-sector patent, and 0 otherwise.[28] This is defined as:

$$v_i = \begin{cases} 1, & \text{if patent } i \text{ cites a space-sector patent,} \\ 0, & \text{otherwise.} \end{cases} \tag{A2.2}$$

[26] Technically, Brin and Page (1998) show that the damping factor d controls the probability that a random walker on the network follows an existing link between nodes rather than 'teleporting' to a random node. A higher d thus places greater weight on the network's linkage structure.

[27] This value is lower than the original damping factor used for web pages by Brin and Page (1998), who set $d = 0.85$. Scientific citation networks tend to exhibit shorter path lengths on average than the web graph, motivating a lower value of d, see Chen et al. (2007).

[28] Additionally, the teleportation term can be modified to analyze reliance on specific technologies or individual patents. In this case, we assign $v_i = 1$ only for patents within a targeted technological category or for a single patent of interest, while setting $v_i = 0$ elsewhere. This approach allows us to isolate the propagation of influence from a particular technology or innovation throughout the citation network, see the next subsection.

The second initialization captures the dependency on generic patents and uses a uniform teleportation scheme, where all patents receive the same teleport weight regardless of citations. This is defined as:

$$v_i = 1, \quad \forall i. \tag{A2.3}$$

The spillover measure is obtained by taking the ratio of the Reverse PageRank scores computed using the naive teleportation (A2.2) and the uniform teleportation (A2.3):

$$S_i = \frac{PR_i^{\text{naive}}}{PR_i^{\text{uniform}}}.$$

This ratio measures the extent to which each patent depends on space-sector knowledge relative to generic knowledge. By aggregating over all patents belonging to the core sector in each quarter t, the network spillover measure —presented in Figure 2.1 of the main text— is obtained. Formally, it is computed as:

$$R_{s,t}^{data} = \frac{1}{|P_t|} \sum_{i \in P_t} \alpha_c(i) S_i.$$

where as before $|P_t|$ is the number of patents granted at time t and $\alpha_c(i)$ is the fraction of patent i assigned to the core sector. When the damping factor is set to zero ($d = 0$), the PageRank scores reduce to the teleportation terms, ignoring the network structure. In this case, under naive initialization (A2.2), the teleportation term becomes a dummy for whether a patent cites a space-sector patent; under uniform initialization (A2.3), all patents receive equal weight. As a result, the spillover measure ($R_{s,t}^{data}$) simplifies to the naive measure ($R_{s,t}^{naive}$), which captures only direct citations. The network spillover series ($R_{s,t}^{data}$), plotted in the lower panel of Figure 2.1, captures the evolution of technological reliance on space patents over time. The series shows that the overall dependency of core-sector patents on space-sector patents peaked in the 1960s at 9.6%, reflecting the high diffusion of space technology innovations. A gradual decline in spillover intensity is observed over subsequent decades, reaching its lowest value of 6.15% in 2010. These spillover measures are incorporated into the endogenous growth model in the main text, linking space-sector technological diffusion to macroeconomic outcomes.

A granular example: the solar power patent

To demonstrate the effectiveness of our citation network approach, we analyze the technological diffusion of the solar power patent already shown in the main text in Section II. The solar power plant patent *U.S. Patent 3,781,647* was granted on December 25, 1973. This invention describes a system for collecting solar radiation in outer space, converting it into microwave energy, and transmitting it back to Earth for conversion into electrical power. Over time, the underlying concept has inspired innovations in wireless power transmission, satellite-based energy systems, and renewable energy technologies, with applications in both terrestrial and space-based infrastructure. Figure 2.2 in the main text displays the directed network of patents that directly cite the solar energy patent, along with those that cite its immediate successors. The figure reveals the presence of successor patents across the Communication, Navigation, and Electrical sectors, highlighting the diverse technological footprint of the original solar power innovation. Building on this evidence, we apply our Reverse PageRank methodology to track how patents in different sectors have relied on the technology of this patent over time. Similar to our analysis of space-sector patents, we now compute dependency scores using a teleport term that reflects the direct successors of the original solar power plant patent only. Figure A2.1 illustrates the evolution of sectoral dependency scores ($R^{data}_{sol,t}$), capturing the extent to which key sectors rely on the solar power patent over time. Spillover effects from the

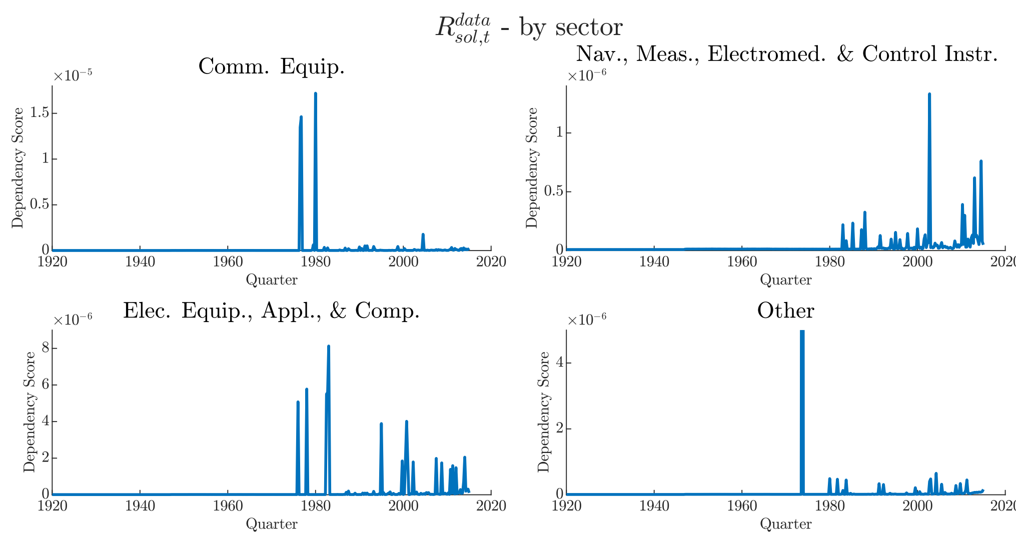

Figure A2.1. : Sectoral dependency scores on the solar power patent ($R^{data}_{sol,t}$), computed using the Reverse PageRank methodology. The measure captures the reliance of patents in key economic sectors on GPS over time. $R^{data}_{sol,t}$ is computed quarterly based on patent grant dates. Sectors include: (i) Communication Equipment (NAICS 3342), (ii) Navigation, Measurement, Electromedical, and Control Instruments (NAICS 3345), (iii) Electrical Equipment, Appliances, and Components (NAICS 335), and (iv) Other sectors.

solar energy patent are visible across the Communication Equipment and Navigation-related sectors, reflecting its downstream relevance in space-based power systems and control technologies. The Navigation sector, in particular, shows sustained reliance into the 2000s and 2010s. Electrical Equipment and Other sectors also display diffusion, though with distinct sectoral patterns. As expected, dependency scores are correctly zero prior to the patent's introduction, since only subsequent inventions can cite it.

This case study highlights the broader capacity of our citation-based approach, combined with granular patent data, to trace the cascading effects of innovations across sectors and over time. Our methodology is flexible and can be applied to analyze spillovers from various aggregates of patents, bridging the gap between the sector-wide analysis presented in the main text and the single-patent case explored in this appendix. Future research could leverage this approach to examine the diffusion of technologies originating from specific institutional sources (e.g., NASA-funded patents or private sector innovations) or from particular technological domains within the space sector. These extensions would further enrich our understanding of how space-related advancements influence the broader economy.

IX. The Model Equations

Wholesale Space Firms

The optimal factor demand schedules derived from the maximization problem of wholesale space sector firms are the following:

- Labor demand by $\mathcal{S}_s$:

$$(1-\alpha_s)vY_{s,t} = w_{s,t}n_{s,t}.$$

- Capital demand by $\mathcal{S}_s$:

$$\alpha_s v Y_{s,t} = r_{k_s,t}u_{k_s,t}k_{s,t-1}.$$

- Intermediate input demand by $\mathcal{S}_s$:

$$(1-v)Y_{s,t}\left(\frac{1}{G_{s,t}}\right)^{\frac{\theta_m-1}{\theta_m}}\left(\frac{1}{M^j_{s,t}}\right)^{\frac{1}{\theta_m}} = \frac{P^{m,j}_{s,t}}{P_{s,t}}. \tag{A2.4}$$

Combining the intermediate inputs demand (eq. A2.4) with the supply (eq. 2.7) and imposing a symmetric equilibrium ($M^j_{s,t} = M_{s,t}$), we obtain an expression for the quantity of each intermediate good:

$$M_{s,t} = \left[(1-v)\frac{a_{z_{s,t}}}{p^m_{s,t}}\right]^{\frac{1}{v}} A_t^{\frac{1-v\theta_m}{v(\theta_m-1)}} n_{s,t}^{1-\alpha_s}\left(u_{k_s,t}k_{s,t-1}\right)^{\alpha_s}.$$

After some algebra, this also allows us to rewrite the production function (2.4) as a function of the labor and capital inputs only:

$$Y_{s,t} = \left(a_{z_{s,t}}\right)^{\frac{1}{v}} \left[(1-v)\frac{1}{p^m_{s,t}}\right]^{\frac{1-v}{v}} n_{s,t}^{1-\alpha_s} \left(u_{k_s,t}k_{s,t-1}\right)^{\alpha_s} A_t^{\frac{1-v}{v(\theta_m-1)}}.$$

Wholesale Core Firms

The problem of wholesale core firms mirrors the one regarding the space sector shown in eq. (2.3):

$$\max_{n_{c,t},k_{c,t},M^j_{c,t}} Y_{c,t} - w_{c,t}n_{c,t} - r_{c,t}u_{k_c,t}k_{c,t-1} - \int_0^{A_t} \frac{P^{m,j}_{c,t}}{P_{c,t}} M^j_{c,t}dj,$$

subject to the production technology

$$Y_{c,t} = a_{z_{c,t}} \left[(n_{c,t})^{1-\alpha_c} \left(u_{k_c,t}k_{c,t-1}\right)^{\alpha_c}\right]^v \left[G_{c,t}\right]^{1-v},$$

where $G_{c,t}$ is a CES aggregator of intermediate inputs:

$$G_{c,t} = \left(\int_0^{A_t} \left(M^j_{c,t}\right)^{\frac{\theta_m-1}{\theta_m}}\right)^{\frac{\theta_m}{\theta_m-1}}.$$

The variable $a_{z_c,t}$ represents technology in the core sector, and the variable $u_{k_c,t}$ capacity utilization of the capital stock used for core sector production. Similarly to the space sector side, the optimal factor demand schedules are then:

- Labor demand by $\mathcal{S}_c$:

$$(1-\alpha_c)vY_{c,t} = w_{c,t}n_{c,t},$$

- Capital demand by $\mathcal{S}_c$:

$$\alpha_c vY_{c,t} = r_{k_c,t}u_{k_c,t}k_{c,t-1},$$

- Intermediate input demand by $\mathcal{S}_c$:

$$(1-v)Y_{c,t}\left(\frac{1}{G_{c,t}}\right)^{\frac{\theta_m-1}{\theta_m}}\left(\frac{1}{M^j_{c,t}}\right)^{\frac{1}{\theta_m}} = \frac{P^{m,j}_{c,t}}{P_{c,t}}. \tag{A2.5}$$

The supply of intermediate core goods is delegated to monopolistic competitive intermediate core sector firms. Intermediate core sector firms transform one unit of the final good into one unit of the intermediate good. Each intermediate firm maximizes its profits, which are equal to:

$$D_{c,t}^{j} = \frac{\left(P_{c,t}^{m,j} - P_{c,t}\right)}{P_{c,t}} M_{c,t}^{j},$$

subject to the demand from the wholesalers in the core sector (eq. A2.5). The solution (in a symmetric equilibrium) to the above problem pins down the relative price of intermediate core goods:

$$\frac{P_{c,t}^{m}}{P_{c,t}} \equiv p_{c,t}^{m} = \frac{\theta_m}{\theta_m - 1}.$$

As for the space sector problem, it is possible to write the equilibrium quantity of the intermediate core sector good,

$$M_{c,t} = \left[(1-v)\frac{a_{z_{c,t}}}{p_{c,t}^{m}}\right]^{\frac{1}{v}} A_t^{\frac{1-v\theta_m}{v(\theta_m-1)}} n_{c,t}^{1-\alpha_c} \left(u_{k_c,t} k_{c,t-1}\right)^{\alpha_c},$$

and to plug it into the final good production function:

$$Y_{c,t} = \left(a_{z_{c,t}}\right)^{\frac{1}{v}} \left[(1-v)\frac{1}{p_{c,t}^{m}}\right]^{\frac{1-v}{v}} n_{c,t}^{1-\alpha_c} \left(u_{k_c,t} k_{c,t-1}\right)^{\alpha_c} A_t^{\frac{1-v}{v(\theta_m-1)}}.$$

Households

The functional forms of the investment and capacity utilization costs appearing in the households' budget constraint (eq. 2.10) are the following:

$$\Psi_{k_c,t} = \frac{\eta_k}{2}\left(\frac{k_{c,t}}{k_{c,t-1}} - \Gamma\right)^2 k_{c,t-1},$$

$$\Psi_{k_s,t} = \frac{\eta_k}{2}\left(\frac{k_{s,t}}{k_{s,t-1}} - \Gamma\right)^2 k_{s,t-1},$$

$$\Psi_{u_c,t} = \left[\frac{1}{\beta} - (1-\delta_{k_c})\right]\left[\frac{\frac{\eta_{u_c}}{1-\eta_{u_c}}}{2} + \frac{\frac{\eta_{u_c}}{1-\eta_{u_c}}}{2} u_{k_c,t}^2 + \left(1 - \frac{\eta_{u_c}}{1-\eta_{u_c}}\right) u_{k_c,t} - 1\right],$$

$$\Psi_{u_s,t} = \left[\frac{1}{\beta} - (1-\delta_{k_s})\right]\left[\frac{\frac{\eta_{u_s}}{1-\eta_{u_s}}}{2} + \frac{\frac{\eta_{u_s}}{1-\eta_{u_s}}}{2}u_{k_s,t}^2 + \left(1 - \frac{\eta_{u_s}}{1-\eta_{u_s}}\right)u_{k_s,t} - 1\right].$$

The term Ψ_t in the budget constraint of households (eq. 2.10) is given by:

$$\Psi_t = \Psi_{k_c,t} + p_{s,t}\Psi_{k_s,t} + \Psi_{u_c,t}k_{c,t-1} + p_{s,t}\Psi_{u_s,t}k_{s,t-1}.$$

Finally, in the budget constraint the term D_t sums the profits of intermediate firms in the two sectors:

$$D_t = D_{c,t} + p_{s,t}D_{s,t}.$$

The households' optimization leads then to the following first-order conditions:

- Euler equation:

$$u_{c,t} = \beta\Gamma R_t \mathbb{E}_t \frac{u_{c,t+1}}{\pi_{c,t+1}}.$$

- Labor supply to $\mathcal{S}_c$:

$$a_{\zeta,t}\varphi_t\varphi^c n_{c,t}^{\nu_c} = w_{c,t}u_{c,t}.$$

- Labor supply to $\mathcal{S}_s$:

$$a_{\zeta,t}\varphi_t\varphi^s n_{s,t}^{\nu_s} = p_{s,t}w_{s,t}u_{c,t}.$$

- Capital supply to $\mathcal{S}_c$:

$$\begin{aligned} &u_{c,t}\left[1 + \eta_k\left(\frac{k_{c,t}}{k_{c,t-1}} - \Gamma\right)\right] \\ &= \beta\Gamma\mathbb{E}_t u_{c,t+1}\left[1 - \delta_{k_c} + r_{k_c,t+1}u_{k_c,t+1} - \Psi_{u_c,t+1} + \frac{\eta_k}{2}\left(\frac{{k_{c,t+1}}^2}{{k_{c,t}}^2} - \Gamma^2\right)\right]. \end{aligned}$$

- Capital supply to $\mathcal{S}_s$:

$$\begin{aligned} &p_{s,t}u_{c,t}\left[1 + \eta_k\left(\frac{k_{s,t}}{k_{s,t-1}} - \Gamma\right)\right] \\ &= \beta\Gamma\mathbb{E}_t p_{s,t+1}u_{c,t+1}\left[1 - \delta_{k_s} + r_{k_s,t+1}u_{k_s,t+1} - \Psi_{u_s,t+1} + \frac{\eta_k}{2}\left(\frac{{k_{s,t+1}}^2}{{k_{s,t}}^2} - \Gamma^2\right)\right]. \end{aligned}$$

- Capacity utilization in $\mathcal{S}_c$ condition:

$$\frac{r_{k_c,t}}{\frac{1}{\beta}-(1-\delta_{k_c})}=1-\frac{\eta_{u_c}}{1-\eta_{u_c}}+\frac{\eta_{u_c}}{1-\eta_{u_c}}u_{k_c,t}.$$

- Capacity utilization in $\mathcal{S}_s$ condition:

$$\frac{r_{k_s,t}}{\frac{1}{\beta}-(1-\delta_{k_s})}=1-\frac{\eta_{u_s}}{1-\eta_{u_s}}+\frac{\eta_{u_s}}{1-\eta_{u_s}}u_{k_s,t}.$$

The marginal utility of consumption above ($u_{c,t}$) is defined as follows:

$$u_{c,t}=\frac{a_{\zeta,t}}{c_t}.$$

X. Stationarizing the Model

As stated in the main text, the model incorporates stochastic growth (x_t) in the number of existing technologies across the space sector ($Z_{s,t}$), the core sector ($Z_{c,t}$), the aggregate economy (Z_t), and the set of adopted technologies (A_t). The following variables reflect the resulting stochastic trend and are proportional to A_t along the balanced growth path: core sector production ($Y_{c,t}$); space sector production ($Y_{s,t}$); consumption (c_t); the inverse of the marginal utility of consumption ($1/uc_t$); core capital ($k_{c,t}$); space sector capital ($k_{s,t}$); R&D expenditure (S_t); gross domestic product (GDP_t); real core sector wages ($w_{c,t}$); real space sector wages ($w_{s,t}$); profits from intermediate goods producers ($D_{c,t}$ and $D_{s,t}$); and investment adjustment costs ($\Psi_{k_c,t}$ and $\Psi_{k_s,t}$). To stationarize the model around the balanced growth path, the non-stationary variables are rewritten as the product of their detrended components (denoted with the tilde sign) and the number of adopted technologies (A_t). After rewriting the equations in this form, the model relationships can be reformulated in terms of stationary variables and the stochastic growth rate, so that the variables have a proper steady state, and the model can be solved. The derivations are the following:

- Adopted technologies:

$$\frac{A_t}{A_{t-1}}\equiv\exp(x_t)=\lambda\phi\left[\frac{\tilde{Z}_{t-1}A_{t-1}}{A_{t-1}}-\frac{A_{t-1}}{A_{t-1}}\right]+\phi\frac{A_{t-1}}{A_{t-1}}=\lambda\phi\left[\tilde{Z}_{t-1}-1\right]+\phi.$$

- Existing technologies:

$$Z_t=\tilde{Z}_tA_t=\phi Z_{t-1}+\xi_{t-1}S_{t-1}=\phi\tilde{Z}_{t-1}A_{t-1}+\xi_{t-1}\tilde{S}_{t-1}A_{t-1},$$

so that

$$\tilde{Z}_t \exp(x_t) = \phi \tilde{Z}_{t-1} + \xi_{t-1} \tilde{S}_{t-1}.$$

- R&D spending:

$$\beta \Gamma \mathbb{E}_t \frac{u_{c,t+1}}{u_{c,t}} J_{t+1} = \beta \Gamma \mathbb{E}_t \frac{\tilde{u}_{c,t+1}}{\tilde{u}_{c,t}} \frac{1}{x_{t+1}} J_{t+1} = \frac{1}{\xi_t}.$$

- Definition of effective capital:

$$\bar{k}_{s,t} = \tilde{\bar{k}}_{s,t} A_t = u_{k_{s,t}} k_{s,t-1} = u_{k_{s,t}} \tilde{k}_{s,t-1} A_{t-1},$$

so that

$$\tilde{\bar{k}}_{s,t} = u_{k_{s,t}} \tilde{k}_{s,t-1} \frac{1}{\exp(x_t)}.$$

Similarly,

$$\bar{k}_{c,t} = \tilde{\bar{k}}_{c,t} A_t = u_{k_{c,t}} k_{c,t-1} = u_{k_{c,t}} \tilde{k}_{c,t-1} A_{t-1},$$

so that

$$\tilde{\bar{k}}_{c,t} = u_{k_{c,t}} \tilde{k}_{c,t-1} \frac{1}{\exp(x_t)}.$$

- Space sector production:

$$\begin{aligned} Y_{s,t} &= \tilde{Y}_{s,t} A_t \\ &= \left(a_{z_{s,t}}\right)^{\frac{1}{v}} \left[(1-v)\frac{1}{p^m_{s,t}}\right]^{\frac{1-v}{v}} n_{s,t}^{1-\alpha_s} \left(\bar{k}_{s,t}\right)^{\alpha_s} A_t^{\frac{1-v}{v(\theta_m-1)}} \\ &= \left(a_{z_{s,t}}\right)^{\frac{1}{v}} \left[(1-v)\frac{1}{p^m_{s,t}}\right]^{\frac{1-v}{v}} n_{s,t}^{1-\alpha_s} \left(\tilde{\bar{k}}_{s,t} A_t\right)^{\alpha_s} A_t^{\frac{1-v}{v(\theta_m-1)}}. \end{aligned} \tag{A2.6}$$

Under the restriction for the existence of a balanced growth path:

$$v = \frac{1}{\alpha_s (1-\theta_m) + \theta_m},$$

$$\tilde{Y}_{s,t} = \left(a_{z_{s,t}}\right)^{\frac{1}{v}} \left[(1-v)\frac{1}{p^m_{s,t}}\right]^{\frac{1-v}{v}} n_{s,t}^{1-\alpha_s} \left(\tilde{\bar{k}}_{s,t}\right)^{\alpha_s}. \tag{A2.7}$$

- Core sector production:

$$\begin{aligned} Y_{c,t} &= \tilde{Y}_{c,t} A_t \\ &= \left(a_{z_{c,t}}\right)^{\frac{1}{v}} \left[(1-v)\frac{1}{p^m_{c,t}}\right]^{\frac{1-v}{v}} n_{c,t}^{1-\alpha_c} \left(\bar{k}_{c,t}\right)^{\alpha_c} A_t^{\frac{1-v}{v(\theta_m-1)}} \\ &= \left(a_{z_{c,t}}\right)^{\frac{1}{v}} \left[(1-v)\frac{1}{p^m_{c,t}}\right]^{\frac{1-v}{v}} n_{c,t}^{1-\alpha_c} \left(\tilde{\bar{k}}_{c,t} A_t\right)^{\alpha_c} A_t^{\frac{1-v}{v(\theta_m-1)}}, \end{aligned} \tag{A2.8}$$

so that

$$\tilde{Y}_{c,t} = \left(a_{z_{c,t}}\right)^{\frac{1}{v}} \left[(1-v)\frac{1}{p^m_{c,t}}\right]^{\frac{1-v}{v}} n_{c,t}^{1-\alpha_c} \left(\tilde{\bar{k}}_{c,t}\right)^{\alpha_c}. \tag{A2.9}$$

- Core sector labor demand:

$$(1-\alpha_c)vY_{c,t} = (1-\alpha_c)v\tilde{Y}_{c,t}A_t = w_{c,t}n_{c,t} = \tilde{w}_{c,t}A_t n_{c,t},$$

so that

$$(1-\alpha_c)v\tilde{Y}_{c,t} = \tilde{w}_{c,t}n_{c,t}.$$

- Space sector labor demand:

$$(1-\alpha_s)v\ Y_{s,t} = (1-\alpha_s)v\tilde{Y}_{s,t}A_t = w_{s,t}n_{s,t} = \tilde{w}_{s,t}A_t n_{s,t},$$

so that

$$(1-\alpha_s)v\tilde{Y}_{s,t} = \tilde{w}_{s,t}n_{s,t}.$$

- Core sector capital demand:

$$\alpha_c v Y_{c,t} = \alpha_c v \tilde{Y}_{c,t} A_t = r_{k_c,t}\bar{k}_{c,t} = r_{k_c,t}\tilde{\bar{k}}_{c,t} A_t,$$

so that

$$\alpha_c v \tilde{Y}_{c,t} = r_{k_c,t}\tilde{\bar{k}}_{c,t}. \tag{A2.10}$$

- Core sector intermediate input demand:

$$\begin{aligned} M_{c,t} &= \left[(1-v)\frac{a_{z_{c,t}}}{p^m_{c,t}}\right]^{\frac{1}{v}} A_t^{\frac{1-v\theta_m}{v(\theta_m-1)}} n_{c,t}^{1-\alpha_c}\left(\bar{k}_{c,t}\right)^{\alpha_c} \\ &= \left[(1-v)\frac{a_{z_{c,t}}}{p^m_{c,t}}\right]^{\frac{1}{v}} A_t^{\frac{1-v\theta_m}{v(\theta_m-1)}} n_{c,t}^{1-\alpha_c}\left(\tilde{\bar{k}}_{c,t}A_t\right)^{\alpha_c} \\ &= \left[(1-v)\frac{a_{z_{c,t}}}{p^m_{c,t}}\right]^{\frac{1}{v}} n_{c,t}^{1-\alpha_c}\left(\tilde{\bar{k}}_{c,t}\right)^{\alpha_c}. \end{aligned} \tag{A2.11}$$

- Space sector intermediate input demand:

$$\begin{aligned} M_{s,t} &= \left[(1-v)\frac{a_{z_{s,t}}}{p^m_{s,t}}\right]^{\frac{1}{v}} A_t^{\frac{1-v\theta_m}{v(\theta_m-1)}} n_{s,t}^{1-\alpha_s}\left(\bar{k}_{s,t}\right)^{\alpha_s} \\ &= \left[(1-v)\frac{a_{z_{s,t}}}{p^m_{s,t}}\right]^{\frac{1}{v}} A_t^{\frac{1-v\theta_m}{v(\theta_m-1)}} n_{s,t}^{1-\alpha_s}\left(\tilde{\bar{k}}_{s,t}A_t\right)^{\alpha_s} \\ &= \left[(1-v)\frac{a_{z_{s,t}}}{p^m_{s,t}}\right]^{\frac{1}{v}} n_{s,t}^{1-\alpha_s}\left(\tilde{\bar{k}}_{s,t}\right)^{\alpha_s}. \end{aligned} \tag{A2.12}$$

- Space sector capital demand:

$$\alpha_s v Y_{s,t} = \alpha_s v \tilde{Y}_{s,t} A_t = r_{k_s,t}\bar{k}_{s,t} = r_{k_s,t}\tilde{\bar{k}}_{s,t} A_t,$$

so that

$$\alpha_s v \tilde{Y}_{s,t} = r_{k_s,t} \tilde{\bar{k}}_{s,t}. \tag{A2.13}$$

- Marginal utility of consumption:

$$\begin{aligned} u_{c,t} &= \frac{\tilde{u}_{c,t}}{A_t} \\ &= \frac{a_{\zeta,t}}{c_t} \\ &= \frac{a_{\zeta,t}}{\tilde{c}_t A_t} \\ &= \frac{1}{A_t} \frac{a_{\zeta,t}}{\tilde{c}_t}, \end{aligned} \tag{A2.14}$$

so that

$$\tilde{u}_{c,t} = \frac{a_{\zeta,t}}{\tilde{c}_t}. \tag{A2.15}$$

- Budget constraint:

(A2.16)

$$\begin{aligned} k_{c,t} + p_{s,t} k_{s,t} + c_t + b_t &= \tilde{k}_{c,t} A_t + p_{s,t} \tilde{k}_{s,t} A_t + \tilde{c}_t A_t + \tilde{b}_t A_t \\ &= \frac{R_{t-1} b_{t-1}}{\pi_{c,t}} + w_{c,t} n_{c,t} + p_{s,t} w_{s,t} n_{s,t} \\ &\quad + k_{c,t-1} \left(1 - \delta_{k_c} + u_{k_c,t} r_{k_c,t}\right) \\ &\quad + p_{s,t} k_{s,t-1} \left(1 - \delta_{k_s} + u_{k_s,t} r_{k_s,t}\right) - \Psi_{k_c,t} - p_{s,t} \Psi_{k_s,t} \\ &\quad - \Psi_{u_c,t} k_{c,t-1} - p_{s,t} \Psi_{u_s,t} k_{s,t-1} - p_{s,t} T_{s,t} + D_{c,t} + p_{s,t} D_{s,t} \\ &= \frac{R_{t-1} \tilde{b}_{t-1} A_{t-1}}{\pi_{c,t}} + \tilde{w}_{c,t} A_t n_{c,t} + p_{s,t} \tilde{w}_{s,t} A_t n_{s,t} \\ &\quad + \tilde{k}_{c,t-1} A_{t-1} \left(1 - \delta_{k_c} + u_{k_c,t} r_{k_c,t}\right) \\ &\quad + p_{s,t} \tilde{k}_{s,t-1} A_{t-1} \left(1 - \delta_{k_s} + u_{k_s,t} r_{k_s,t}\right) \\ &\quad - \tilde{\Psi}_{k_c,t} A_t - p_{s,t} \tilde{\Psi}_{k_s,t} A_t - \Psi_{u_c,t} \tilde{k}_{c,t-1} A_{t-1} \\ &\quad - p_{s,t} \Psi_{u_s,t} \tilde{k}_{s,t-1} A_{t-1} - p_{s,t} \tilde{T}_{s,t} A_t + \tilde{D}_{c,t} A_t + p_{s,t} \tilde{D}_{s,t} A_t, \end{aligned}$$

so that

(A2.17)

$$
\begin{aligned}
\tilde{k}_{c,t} + p_{s,t}\tilde{k}_{s,t} + \tilde{c}_t + \tilde{b}_t = {} & \frac{R_{t-1}\tilde{b}_{t-1}}{\pi_{c,t}\exp(x_t)} + \tilde{w}_{c,t}n_{c,t} + p_{s,t}\tilde{w}_{s,t}n_{s,t} \\
& + \frac{\tilde{k}_{c,t-1}}{\exp(x_t)}\left(1-\delta_{k_c} + u_{k_c,t}r_{k_c,t}\right) \\
& + p_{s,t}\frac{\tilde{k}_{s,t-1}}{\exp(x_t)}\left(1-\delta_{k_s} + u_{k_s,t}r_{k_s,t}\right) \\
& - \tilde{\Psi}_{k_c,t} - p_{s,t}\tilde{\Psi}_{k_s,t} - \Psi_{u_c,t}\frac{\tilde{k}_{c,t-1}}{\exp(x_t)} \\
& - p_{s,t}\Psi_{u_s,t}\frac{\tilde{k}_{s,t-1}}{\exp(x_t)} - p_{s,t}\tilde{T}_{s,t} + \tilde{D}_{c,t} + p_{s,t}\tilde{D}_{s,t}.
\end{aligned}
$$

- Resource constraint:

(A2.18)

$$
\begin{aligned}
& c_t + k_{c,t} - (1-\delta_{k_c})\,k_{c,t-1} + p_{s,t}k_{s,t} + (1-\delta_{k_s})\,p_{s,t}k_{s,t-1} + S_t + A_tM_{c,t} + p_{s,t}A_tM_{s,t} = \\
& \quad \tilde{c}_tA_t + \tilde{k}_{c,t}A_t - (1-\delta_{k_c})\,\tilde{k}_{c,t-1}A_{t-1} + p_{s,t}\tilde{k}_{s,t}A_t \\
& \qquad + (1-\delta_{k_s})\,p_{s,t}\tilde{k}_{s,t-1}A_{t-1} + \tilde{S}_tA_t + A_tM_{c,t} + p_{s,t}A_tM_{s,t} \\
& \quad = Y_{c,t} - p_{s,t}Y_{s,t} - \frac{\eta_k}{2}\left(\frac{k_{c,t}}{k_{c,t-1}} - \Gamma\right)^2 k_{c,t-1} \\
& \qquad - \frac{\eta_k}{2}\left(\frac{k_{s,t}}{k_{s,t-1}} - \Gamma\right)^2 p_{s,t}k_{s,t-1} - \Psi_{u_c,t}k_{c,t-1} - \Psi_{u_s,t}p_{s,t}k_{s,t-1} \\
& \quad = \tilde{Y}_{c,t}A_t - \frac{\eta_k}{2}\left(\frac{\tilde{k}_{c,t}A_t}{\tilde{k}_{c,t-1}A_{t-1}} - \Gamma\right)^2 \tilde{k}_{c,t-1}A_{t-1} \\
& \qquad - \frac{\eta_k}{2}\left(\frac{\tilde{k}_{s,t}A_t}{\tilde{k}_{s,t-1}A_{t-1}} - \Gamma\right)^2 p_{s,t}\tilde{k}_{s,t-1}A_{t-1} \\
& \qquad - \Psi_{u_c,t}\tilde{k}_{c,t-1}A_{t-1} - \Psi_{u_s,t}p_{s,t}\tilde{k}_{s,t-1}A_{t-1},
\end{aligned}
$$

so that

(A2.19)

$$
\begin{aligned}
& \tilde{c}_t + \tilde{k}_{c,t} - (1-\delta_{k_c})\frac{\tilde{k}_{c,t-1}}{\exp x_t} + p_{s,t}\tilde{k}_{s,t} + (1-\delta_{k_s})\frac{p_{s,t}\tilde{k}_{s,t-1}}{\exp x_t} + \tilde{S}_t + M_{c,t} + p_{s,t}M_{s,t} \\
& \quad = \tilde{Y}_{c,t} - \frac{\eta_k}{2}\left(\frac{\tilde{k}_{c,t}}{\tilde{k}_{c,t-1}}\exp(x_t) - \Gamma\right)^2 \frac{\tilde{k}_{c,t-1}}{\exp x_t} \\
& \qquad - \frac{\eta_k}{2}\left(\frac{\tilde{k}_{s,t}}{\tilde{k}_{s,t-1}}\exp(x_t) - \Gamma\right)^2 p_{s,t}\frac{\tilde{k}_{s,t-1}}{\exp x_t} - \Psi_{u_c,t}\frac{\tilde{k}_{c,t-1}}{\exp x_t} - \Psi_{u_s,t}p_{s,t}\frac{\tilde{k}_{s,t-1}}{\exp x_t}.
\end{aligned}
$$

- Investment adjustment costs:

$$
\begin{aligned}
\Psi_{k_c,t} &= \tilde{\Psi}_{k_c,t} A_{t-1} \\
&= \frac{\eta_k}{2}\left(\frac{k_{c,t}}{k_{c,t-1}} - \Gamma\right)^2 k_{c,t-1} \\
&= \frac{\eta_k}{2}\left[\frac{\tilde{k}_{c,t}}{\tilde{k}_{c,t-1}}\left(\frac{A_t}{A_{t-1}}\right) - \Gamma\right]^2 \tilde{k}_{c,t-1} A_{t-1},
\end{aligned} \tag{A2.20}
$$

so that

$$
\tilde{\Psi}_{k_c,t} = \frac{\eta_k}{2}\left(\frac{\tilde{k}_{c,t}}{\tilde{k}_{c,t-1}} \exp(x_t) - \Gamma\right)^2 \tilde{k}_{c,t-1}. \tag{A2.21}
$$

Similarly,

$$
\begin{aligned}
\Psi_{k_s,t} &= \tilde{\Psi}_{k_s,t} A_{t-1} \\
&= \frac{\eta_k}{2}\left(\frac{k_{s,t}}{k_{s,t-1}} - \Gamma\right)^2 k_{s,t-1} \\
&= \frac{\eta_k}{2}\left[\frac{\tilde{k}_{c,t}}{\tilde{k}_{c,t-1}}\left(\frac{A_t}{A_{t-1}}\right) - \Gamma\right]^2 \tilde{k}_{s,t-1} A_{t-1},
\end{aligned} \tag{A2.22}
$$

so that

$$
\tilde{\Psi}_{k_s,t} = \frac{\eta_k}{2}\left(\frac{\tilde{k}_{s,t}}{\tilde{k}_{s,t-1}} \exp(x_t) - \Gamma\right)^2 \tilde{k}_{s,t-1}. \tag{A2.23}
$$

- Euler equation:

$$
u_{c,t} = \frac{\tilde{u}_{c,t}}{A_t} = \beta \Gamma R_t \mathbb{E}_t \frac{u_{c,t+1}}{\pi_{c,t+1}} = \beta \Gamma R_t \mathbb{E}_t \frac{\tilde{u}_{c,t+1}}{\pi_{c,t+1}} \frac{1}{A_{t+1}},
$$

so that

$$
\tilde{u}_{c,t} = \beta \Gamma R_t \mathbb{E}_t \frac{\tilde{u}_{c,t+1}}{\pi_{c,t+1}} \left(\frac{1}{\exp(x_{t+1})}\right).
$$

- Labor supply to core sector:

$$
a_{\zeta,t} \varphi_t \varphi^c n_{c,t}^{\nu_c} = w_{c,t} u_{c,t} = \frac{\tilde{w}_{c,t} A_t \tilde{u}_{c,t}}{A_t} = \tilde{w}_{c,t} \tilde{u}_{c,t}. \tag{A2.24}
$$

- Labor supply to space sector:

(A2.25)
$$a_{\zeta,t}\varphi_t\varphi^s n_{s,t}^{\nu_s} = p_{s,t}w_{s,t}u_{c,t} = \frac{p_{s,t}\tilde{w}_{s,t}A_t\tilde{u}_{c,t}}{A_t} = p_{s,t}\tilde{w}_{s,t}\tilde{u}_{c,t}.$$

- Capital supply to core sector:

$$\begin{aligned}
&u_{c,t}\left[1+\eta_k\left(\frac{k_{c,t}}{k_{c,t-1}}-\Gamma\right)\right]\\
&=\frac{\tilde{u}_{c,t}}{A_t}\left[1+\eta_k\left(\frac{\tilde{k}_{c,t}A_t}{\tilde{k}_{c,t-1}A_{t-1}}-\Gamma\right)\right]\\
&=\beta\Gamma\mathbb{E}_t u_{c,t+1}\left[1-\delta_{k_c}+r_{k_c,t+1}u_{k_c,t+1}-\Psi_{u_c,t+1}+\frac{\eta_k}{2}\left(\frac{{k_{c,t+1}}^2}{{k_{c,t}}^2}-\Gamma^2\right)\right]\\
&=\beta\Gamma\mathbb{E}_t\frac{\tilde{u}_{c,t+1}}{A_{t+1}}\left[1-\delta_{k_c}+r_{k_c,t+1}u_{k_c,t+1}-\Psi_{u_c,t+1}+\frac{\eta_k}{2}\left(\frac{\tilde{k}_{c,t+1}^2{A_{t+1}}^2}{\tilde{k}_{c,t}^2{A_t}^2}-\Gamma^2\right)\right],
\end{aligned}$$

so that

(A2.26)
$$\tilde{u}_{c,t}\left[1+\eta_k\left(\frac{\tilde{k}_{c,t}}{\tilde{k}_{c,t-1}}\exp x_t-\Gamma\right)\right]=$$
$$\beta\Gamma\mathbb{E}_t\tilde{u}_{c,t+1}\left(\frac{1}{\exp x_{t+1}}\right)\left[1-\delta_{k_c}+r_{k_c,t+1}u_{k_c,t+1}-\Psi_{u_c,t+1}+\frac{\eta_k}{2}\left(\frac{\tilde{k}_{c,t+1}^2}{\tilde{k}_{c,t}^2}\left(\exp x_{t+1}\right)^2-\Gamma^2\right)\right].$$

- Capital supply to space sector:

$$\begin{aligned}
&p_{s,t}u_{c,t}\left[1+\eta_k\left(\frac{k_{s,t}}{k_{s,t-1}}-\Gamma\right)\right]\\
&=\frac{\tilde{u}_{c,t}}{A_t}\left[1+\eta_k\left(\frac{\tilde{k}_{s,t}A_t}{\tilde{k}_{s,t-1}A_{t-1}}-\Gamma\right)\right]\\
&=\beta\Gamma\mathbb{E}_t p_{s,t+1}u_{c,t+1}\left[1-\delta_{k_s}+r_{k_s,t+1}u_{k_s,t+1}-\Psi_{u_s,t+1}+\frac{\eta_k}{2}\left(\frac{{k_{s,t+1}}^2}{{k_{s,t}}^2}-\Gamma^2\right)\right]\\
&=\beta\Gamma\mathbb{E}_t p_{s,t+1}\frac{\tilde{u}_{c,t+1}}{A_{t+1}}\left[1-\delta_{k_s}+r_{k_s,t+1}u_{k_s,t+1}-\Psi_{u_s,t+1}+\frac{\eta_k}{2}\left(\frac{\tilde{k}_{s,t+1}^2{A_{t+1}}^2}{\tilde{k}_{s,t}^2{A_t}^2}-\Gamma^2\right)\right],
\end{aligned}$$

so that

(A2.27)

$$p_{s,t}\tilde{u}_{c,t}\left[1+\eta_k\left(\frac{\tilde{k}_{s,t}}{\tilde{k}_{s,t-1}}\exp x_t-\Gamma\right)\right]=$$

$$\beta\Gamma\mathbb{E}_t p_{s,t+1}\tilde{u}_{c,t+1}\left(\frac{1}{\exp x_{t+1}}\right)\left[1-\delta_{k_s}+r_{k_s,t+1}u_{k_s,t+1}-\Psi_{u_s,t+1}+\frac{\eta_k}{2}\left(\frac{\tilde{k}^2_{s,t+1}}{\tilde{k}^2_{s,t}}(\exp x_{t+1})^2-\Gamma^2\right)\right].$$

- Definition of nominal wage inflation:

$$\omega_{c,t}=\frac{w_{c,t}}{w_{c,t-1}}\pi_{c,t}=\frac{\tilde{w}_{c,t}}{\tilde{w}_{c,t-1}}\exp(x_t)\pi_{c,t}.$$

Similarly,

$$\omega_{s,t}=\frac{w_{s,t}}{w_{s,t-1}}\pi_{c,t}=\frac{\tilde{w}_{s,t}}{\tilde{w}_{s,t-1}}\exp(x_t)\pi_{c,t}.$$

XI. Steady State

This section derives the deterministicsteady state for the variables in the stationarized-model presented in Appendix X. Variables without the time subscript denote steady-state values.

First, we impose that the steady-state rate of growth of the economy (x) is equal to the parameter γ, or equivalently that the gross rate, $\exp(x)$, is equal to the parameter Γ:

$$x=\gamma,\quad \text{and}\quad \exp x=\Gamma.$$

The capital supply conditions, eq. (A2.26) and eq. (A2.27), give the steady-state values of the rental rates of capital in the two sectors:

$$r_{k_c}=(1/\beta-1+\delta_{k_c}),\quad \text{and}\quad r_{k_s}=(1/\beta-1+\delta_{k_s}). \tag{A2.28}$$

Adjustment costs of investment and capacity utilization costs are zero:

$$\tilde{\Psi}_{k_c}=\tilde{\Psi}_{k_s}=\tilde{\Psi}_{u_c}=\tilde{\Psi}_{u_s}=0,$$

since it holds that:

$$u_{k_c}=u_{k_s}=1,\quad \omega_c=1+\gamma,\quad \omega_s=1+\gamma.$$

The steady state of the inflation rates, the space sector share, and the markups are as follows:

$$\pi_c = 1, \quad \pi_s = 1, \quad g_s = \chi.$$

Using the capital demand conditions, eq. (A2.10) and eq. (A2.13), together with the steady-state values for the rental rates of capital, eq. (A2.28), it is possible to find the ratios of core sector capital and space sector capital to output (denoted, respectively, with ζ_0 and ζ_1):

$$\zeta_0 \equiv \frac{\tilde{\tilde{k}}_c}{\tilde{Y}_c} = \frac{\alpha_c}{(1/\beta - 1 + \delta_{k_c})}, \quad \zeta_1 \equiv \frac{\tilde{\tilde{k}}_s}{\tilde{Y}_s} = \frac{\alpha_s}{(1/\beta - 1 + \delta_{k_s})}.$$

From the equations of intermediate goods producers, we obtain the following steady-state relationships:

$$p_c^m = p_s^m = \frac{\theta_m}{\theta_m - 1}.$$

$$\zeta_2 \equiv \frac{M_c}{\tilde{Y}_c} = \frac{v}{p_c^m}, \quad \text{and} \quad \zeta_3 \equiv \frac{M_s}{\tilde{Y}_s} = \frac{v}{p_s^m}.$$

The amount of hours worked in the two sectors is imposed according to the ratio observed in the data, and set equal to the two parameters n_c^{ss} and n_s^{ss}:

$$n_c = n_c^{ss}, \quad \text{and} \quad n_s = n_s^{ss},$$

where n_c^{ss} is normalized to $n_c^{ss} = 1$ and n_c^{ss} to $n_s^{ss} = 0.56/100$ (the steady-state share of the space sector in the economy (χ), see the main text). To ensure that the equilibrium value of hours worked is equal to n_c^{ss} and n_s^{ss}, the labor disutility weights φ^c and φ^s are calibrated accordingly (see below). From the equations of wholesale firms, we obtain the following steady-state values:

$$\tilde{Y}_c = \left(\frac{1-v}{p_c^m}\right)^{\frac{1-v}{v(1-\alpha_c)}} \zeta_0^{\frac{\alpha_c}{(1-\alpha_c)}} n_c, \text{ and } \tilde{Y}_s = \left(\frac{1-v}{p_s^m}\right)^{\frac{1-v}{v(1-\alpha_s)}} \zeta_1^{\frac{\alpha_s}{(1-\alpha_s)}} n_s.$$

From these values, the steady state of the other endogenous variables is easily obtained:

$$M_c = \zeta_2 \tilde{Y}_c, \qquad M_s = \zeta_3 \tilde{Y}_s,$$

$$\tilde{\tilde{k}}_c = \zeta_0 \tilde{Y}_c, \qquad \tilde{\tilde{k}}_s = \zeta_1 \tilde{Y}_s,$$

$$\tilde{k}_c = \Gamma \tilde{\tilde{k}}_c, \qquad \tilde{k}_s = \Gamma \tilde{\tilde{k}}_s,$$

$$p_s = \frac{\chi \tilde{Y}_c}{\tilde{Y}_s} = 1,$$

$$D_c = (p_c^m - 1) M_c, \qquad D_s = (p_s^m - 1) M_s,$$

$$V = \frac{1}{1-\phi-\beta}(D_c + p_s D_s),$$

$$J = \frac{1}{1-\phi\beta(1-\lambda)}(\phi\beta\lambda V),$$

From the first order condition of the R&D sector, we have:

$$\xi_c = \frac{1}{\beta J},$$

From the equation connecting adopted technologies (A) to existing ones (Z):

$$\tilde{Z} = \frac{1}{\lambda\phi}(\lambda\phi + \Gamma - \phi),$$

We target the steady-state ratio between space sector existing technologies and all existing technologies (χ_A):

$$\tilde{Z}_c = \frac{1}{1+\chi_A}\tilde{Z}.$$

Using the fact that total technologies are space sector technologies plus core sector technologies:

$$\tilde{Z}_s = \tilde{Z} - \tilde{Z}_c.$$

From the relationship:

$$\tilde{Z}_s = \frac{\hat{\xi}_s \tilde{Y}_s^{\epsilon_s}}{\Gamma - \phi_s},$$

we obtain the steady-state value for $\hat{\xi}_s$:

$$\hat{\xi}_s = (\tilde{Z} - \tilde{Z}_c)\frac{\Gamma - \phi_s}{\tilde{Y}_s^{\epsilon_s}}.$$

From the equation determining the spillover from space to core technologies, eq. (2.20), we get an expression for the stock of spillover technologies ($\tilde{Z}_c^{spill}$):

$$\tilde{Z}_c^{spill} = \lambda_{sp}\phi_c\tilde{Z}_s\frac{\Gamma}{\Gamma - \phi_c(1-\lambda_{sp})}.$$

Therefore, it is possible to determine the steady-state value of the spillover flow $\widetilde{Spill}_{sc}$:

$$\widetilde{Spill}_{sc} = \frac{1}{\Gamma}\lambda_{sp}\phi_c\left(\tilde{Z}_s - \tilde{Z}_c^{spill}\right).$$

Through equation (2.14), we then find the steady-state value for $\tilde{Z}_c$:

$$\tilde{Z}_c\Gamma = \phi_c\tilde{Z}_c + \xi_c\tilde{S} + \hat{\xi}_{sc}^{spill}\widetilde{Spill}_{sc}\Gamma. \tag{A2.29}$$

We target the steady-state ratio between new technologies due to the spillover and new technologies due to R&D to be equal to χ_{spill}, which allows us to find $\hat{\xi}_{sc}^{spill}$:

$$\hat{\xi}_{sc}^{spill} = \chi_{spill}\frac{\xi_c\tilde{S}}{\widetilde{Spill}_{sc}\Gamma}.$$

By rearranging (A2.29), the steady-state amount of R&D resources ($\tilde{S}$) is given by:

$$\tilde{S} = \frac{1}{\xi_c}\left[\tilde{Z}_c(\Gamma - \phi_c) - \hat{\xi}_{sc}^{spill}\widetilde{Spill}_{sc}\Gamma\right].$$

From the steady-state value of $\tilde{S}$, we are able to find the constant $\hat{\xi}_c$ in steady-state core sector innovation productivity:

$$\hat{\xi}_c = \frac{\xi_c}{\tilde{S}^{\epsilon_c} - 1}.$$

We define the following two ratios for convenience:

$$\zeta_4 \equiv \frac{\tilde{S}}{\tilde{Y}_c},$$

$$\zeta_5 \equiv \frac{\tilde{c}}{\tilde{Y}_c} = 1 + \zeta_0\left(1 - \delta_{k_c} - \Gamma\right) + \zeta_1\left(1 - \delta_{k_s} - \Gamma\right)\chi - \zeta_2 - \zeta_3\chi - \zeta_4.$$

Therefore, steady-state consumption ($\tilde{c}$) and steady-state marginal utility of consumption are given by, respectively:

$$\tilde{c} = \zeta_5\tilde{Y}_c, \quad \text{and} \quad \tilde{u}_c = \frac{1}{\tilde{c}}.$$

The values of $\tilde{c}$ and $\tilde{u}_c$ allow us to find the expression for the labor disutility weights φ^c and φ^s:

$$\varphi^c = \frac{1}{n_c^{1+\nu_c}}\left[\frac{(1-\alpha_c)\,v}{\zeta_5}\right], \quad \text{and} \quad \varphi^s = \frac{1}{n_s^{1+\nu_s}}\left[\chi\frac{(1-\alpha_s)\,v}{\zeta_5}\right].$$

From these values and the labor supply conditions (A2.24) and (A2.25), we find the wages in the two sectors:

$$\tilde{w}_c = \frac{\varphi^c n_c^{\nu_c}}{\tilde{u}_c}, \quad \tilde{w}_s = \frac{\varphi^s n_s^{\nu_s}}{p_s\tilde{u}_c}.$$

Finally, the expression for space sector taxes ($\tilde{T}_s$) is the following:

$$\tilde{T}_s = \tilde{w}_s n_s + r_{k_s}u_{k_s}\tilde{k}_s/\Gamma + p_s^m M_s.$$

XII. Data Construction

Gross Domestic Product

Real gross domestic product (GDP) is retrieved from the U.S. Bureau of Economic Analysis series GDPC1. The series is seasonally adjusted and expressed in billions of chained 2012 dollars. The GDP is divided by the Civilian Noninstitutional Population (series CNP16OV from the U.S. Bureau of Labor Statistics) to transform it in per capita terms. As shown in the measurement equations, the series is connected to the model in log differences. These rates are not demeaned so that information on growth is retained.

Consumption

Aggregate real consumption in billions of chained 2012 dollars is provided by the U.S. Bureau of Economic Analysis in the PCECC96 series. The series is seasonally adjusted and is divided by the Population Level (CNP16OV) to get per capita consumption. As for GDP, the growth rates are not demeaned.

Investment

Real Gross Private Domestic Investment is retrieved from the U.S. Bureau of Economic Analysis series GPDIC1. It is seasonally adjusted and measured in billions of chained 2012 dollars. It is divided by the Population Level (CNP16OV) to get per capita investment. Also for this series, the growth rates are not demeaned.

Hours worked

Data on hours worked is obtained from the U.S. Bureau of Labor Statistics' Current Employment Statistics (Establishment Survey). The series of hours worked per capita is obtained by multiplying the average Weekly Hours of Production and Nonsupervisory Employees (AWHNONAG) by the number of employees on nonfarm payrolls (PAYEMS) and dividing by the Population Level (CNP16OV). The original monthly series are filtered to the quarterly frequency by applying the arithmetic mean. All series are seasonally adjusted. As shown in the measurement equations, the series is fed to the model in log differences.

Aerospace activity

Data on aerospace industrial production is obtained from the Board of Governors of the Federal Reserve System in the IPG3364S series. The series represents an index of industrial production of Aerospace Product and Parts, and it is seasonally adjusted and taken in non-demeaned growth rates. The aerospace IP between 1960:Q1 and 1972:Q1 is imputed using aerospace capacity utilization. This is because the aerospace industrial production has a shorter sample than aerospace capacity utilization, and the two series are closely correlated.

Research and Development expenditure

Research and Development Output is obtained from the U.S. Bureau of Economic Analysis series Y694RX1Q020SBEA: Real Gross Domestic Product: Research and Development. It is divided by the Population Level (CNP16OV) to get per capita R&D. The series is connected to the model in log differences. Also for this series we do not perform demeaning.