Authoritarian Surveillance, Innovation and Growth

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Abstract

How do authoritarian political institutions influence the ability of an economy to innovate? The existing literature identifies a mostly negative effect of autocracy on innovation. In this paper, we build a theoretical model to investigate if this premise still holds in autocracies that rely on digital surveillance for political control, and that use the data obtained through surveillance as a subsidy for innovation in fields such as artificial intelligence. Our model illustrates the trade-off between the negative effect of surveillance on research and creativity, and the positive effect of the availability of large amounts of data. We find that while on average the effect of authoritarian institutions on innovation remains negative, in fields such as artificial intelligence where large amounts of data are important, autocracies can – under specific circumstances – achieve better results than competitive democracies.

Keywords: endogenous growth, authoritarian innovation, surveillance, artificial intelligence, China

JEL:E02, L52, O11, O38, O43

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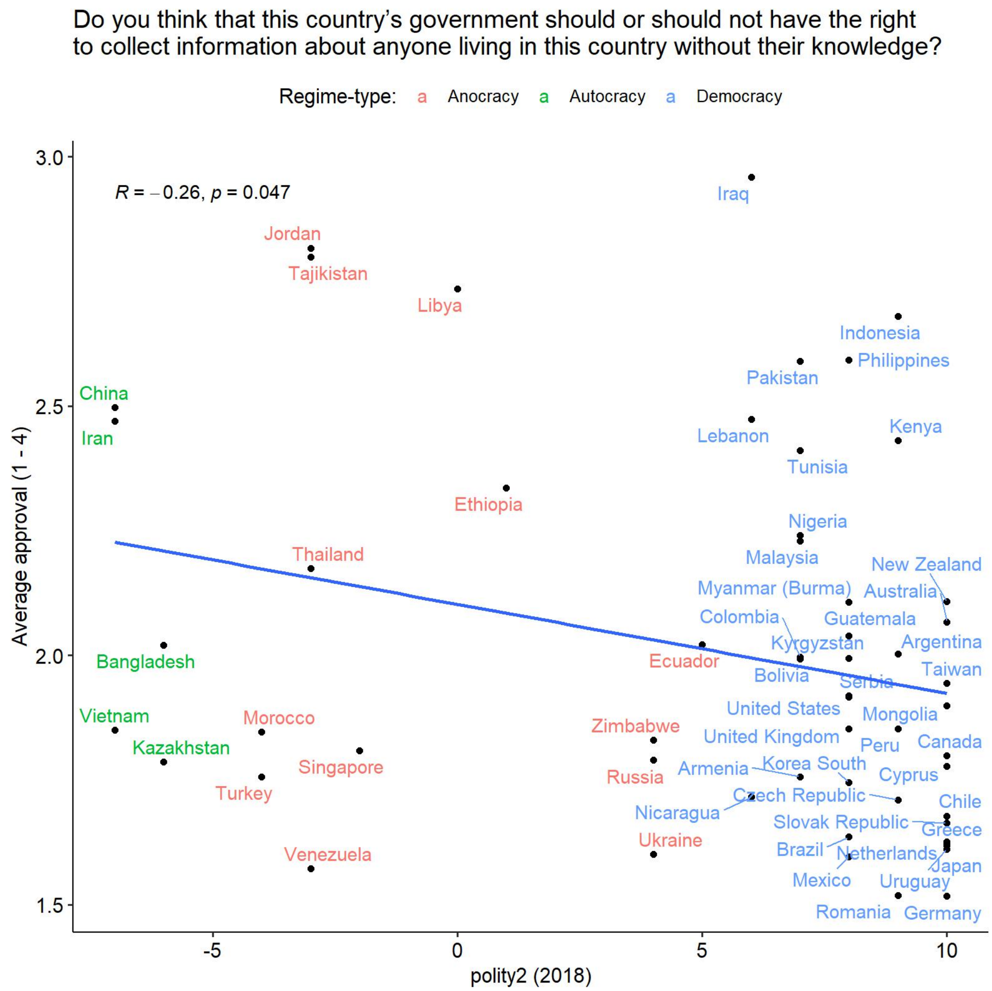
1 Introduction

It is generally assumed that democratic institutions are more likely to encourage innovative activities that lead to higher productivity and, hence, higher economic growth than authoritarian institutions (Acemoglu and Robinson 2012; Acemoglu et al. 2019; Wang et al. 2021). However, does this conclusion still hold if we focus on data-intensive industries that heavily rely on large amounts of data produced by an autocratic state?

In this paper, we develop an endogenous growth model with a myopic government to illustrate the trade-off between surveillance and data availability in an autocracy. In traditional autocracies, surveillance and repression harm innovation, as these activities render scientists and researchers less creative and productive. In modern informational autocracies (see Guriev and Treisman 2022 for a conceptual discussion), however, surveillance can also be used to gather and bundle large amounts of data, which can then be used as an input – provided by the state – to accelerate innovation in data-intensive fields, such as artificial intelligence (Beraja et al. 2022).

Recent contributions such as Cong et al. (2021) that focus on the growth aspects of a data economy point out that consumers might suffer from data misuse or privacy violations that come as a consequence of surveillance by the state. However, as we argue in this paper, higher levels of government surveillance might also entail potential benefits for households, such as lower crime rates, fewer terrorist attacks, or smoother government services. There is evidence that in particular in autocracies, people accept a certain level of government surveillance in exchange for more security and better government services (Kostka 2019; Habich-Sobiegalla and Kostka 2022; see also Figure 1).

Figure 1: Approval for government surveillance and institutional environment



Note: Data on average approval is from wave 7 of the World Value Survey; to measure institutional quality we take the polity2 indicator from https://www.systemicpeace.org/polityproject.html

A general finding of the recent literature on the data economy and economic growth is that data are either underused due to their non-rivalry and property rights owned by consumers (Jones and Tonetti 2020) or overused as a result of an inefficiently small R&D sector (Cong et al. 2021). We complement this literature by showing that R&D misallocation tends to zero, if households that own their data put a large weight on governmental surveillance relative to private data misuse, i.e. the costs of surveillance are sufficiently low. We argue that in the race for primacy in data-intense technologies between large democracies such as the US and large autocracies such as China (see Lee 2018 for a discussion), the ability of a state to gather and bundle data at a sufficiently low social cost and use it as an input for R&D could well play the role of a game changer, providing autocracies with an advantage over democratic political systems.

Our paper and model speak to several different strands of literature. First, we present an endogenous growth model that builds directly on Veldkamp (2005); Jones and Tonetti (2020); Cong et al. (2021, 2022) and Beraja et al. (2022). Like in Cong et al. (2021) we let innovator firms develop and supply differentiated varieties of data-intensive goods, such as algorithms. These goods are used to produce the final good. In contrast to Veldkamp (2005); Jones and Tonetti (2020); Cong et al. (2021) and Cong et al. (2022), we also introduce a myopic government that produces governmental data as a by-product of surveillance and assume that households derive positive utility from surveillance. Hence, we have governmental as well as private data in the economy.

Second, in contrast to Beraja et al. (2022), the government is self-interested in that it tries to secure its power. For this reason, it raises taxes to finance surveillance. One major point this paper makes is that from a socially optimal point of view, as in Cong et al. (2021), data are overused at the expense of R&D labor. The misallocation of R&D labor is particularly pronounced if the degree of knowledge spillover is large and/or the importance of data for the development of new algorithms is low. However, we show that governmental surveillance can moderate this distortion towards zero. This finding complements the work of Cong et al. (2021). Another finding is that rent-seeking governments tend to set a tax above zero. For a reasonable parameter calibration, this accelerates the negative impact of underemployment in the R&D sector, which is still present due to data overuse.

Third, a potential productivity impact of governmental surveillance relative to output on the growth rate of algorithms is only transitory, but has no long-run effects on the growth rate and labor market allocations. More surveillance reduces creativity, but generates new data, thereby increasing output via new algorithms that in turn contribute to productivity in the R&D sector. We show that in the long run, both effects exactly cancel each other out, as aggregate governmental surveillance grows at the same rate as aggregate output.

Our paper is organized as follows. Section 2 motivates the paper, by providing a brief overview of the existing literature on the effect of democratic and authoritarian political institutions on innovation, and by outlining how recent breakthroughs in big data technologies such as artificial intelligence may have changed the trade-off between authoritarian control and innovation. Section 3 presents our baseline model. Section 4 introduces the social planner's problem, and section 5 the action of the rent-seeking government. Section 6 performs a calibration exercise to illustrate the steady-stage labor market allocations, and section 7 concludes.

2 Motivation

2.1 Democracy, Autocracy and Innovation

Theoretically and empirically, the literature on the effect of political institutions on economic growth remains divided. While there is growing support for the idea that democracy is good for growth (Jamali et al. 2007; Acemoglu and Robinson 2012; Knutsen 2013, 2015; Acemoglu et al. 2019), other studies find ambiguous or no effects (Olson 1982; Libman 2012; Piatek et al. 2013; Murtin and Wacziarg 2014; Pozuelo et al. 2016; Truex 2017; Ghardallou and Sridi 2020).

A subset of this literature studies innovation as one possible mechanism why democracies might outperform autocracies (Huang and Xu 1999; Carayannis and Campbell 2014; Knutsen 2015; Silve and Plekhanov 2018; Tang and Tang 2018; see Gao et al. 2017 for a dissenting view). One potential channel is the effect of democracy on human capital, which in turn can positively affect innovation (Tebaldi and Elmslie 2008; Klomp and de Haan 2012). Other studies find a positive effect of political freedom on innovation in high-tech sectors, while the effect remains ambiguous or negative for low-tech sectors (Aghion et al. 2007; Zuazu 2019).

With respect to natural resources, the effect seems clearer, as they seems to have a negative effect on innovation in autocracies, but not in democracies (Rosenberg and Tarasenko 2020). Finally, a literature based on case studies argues that, even though on average authoritarian regimes lag behind democracies when it comes to generating innovation, sometimes pockets of competence exist where autocracies were able to successfully compete with liberal democracies (Graham 1987, 1993; Stokes 2000; Josephson 2005; Gomez and Canales 2015). Overall, the existing literature suggests the long-term effect of authoritarian institutions on innovation to be either negative or ambiguous.

Our paper introduces two innovations to this literature. First, we focus on highly digitized autocracies, i.e. authoritarian regimes that use sophisticated methods to censor, monitor, and control the internet and other sources of information (King et al. 2013, 2014; Shadmehr and Bernhardt 2015; Roberts 2018; Strittmatter 2020; Guriev and Treisman 2022), rather than relying on repression and more traditional methods of control. We show that surveillance in such autocracies still introduces distortions for both scientific research and the economy in general, and thus comes at an economic cost. However, the fact that large amounts of data are gathered, bundled and made available in a centralized way can also offer potential advantages, in particular with respect to research in data-intense fields such as deep learning. Building on this trade-off, our second innovation is to investigate how informational autocracies fare with respect to research and innovation in technologies that rely on large amounts of data. Section 2.2 briefly introduces the specific features of data-intense technologies, and explains why they might have the potential to change the way authoritarian institutions affect innovation.

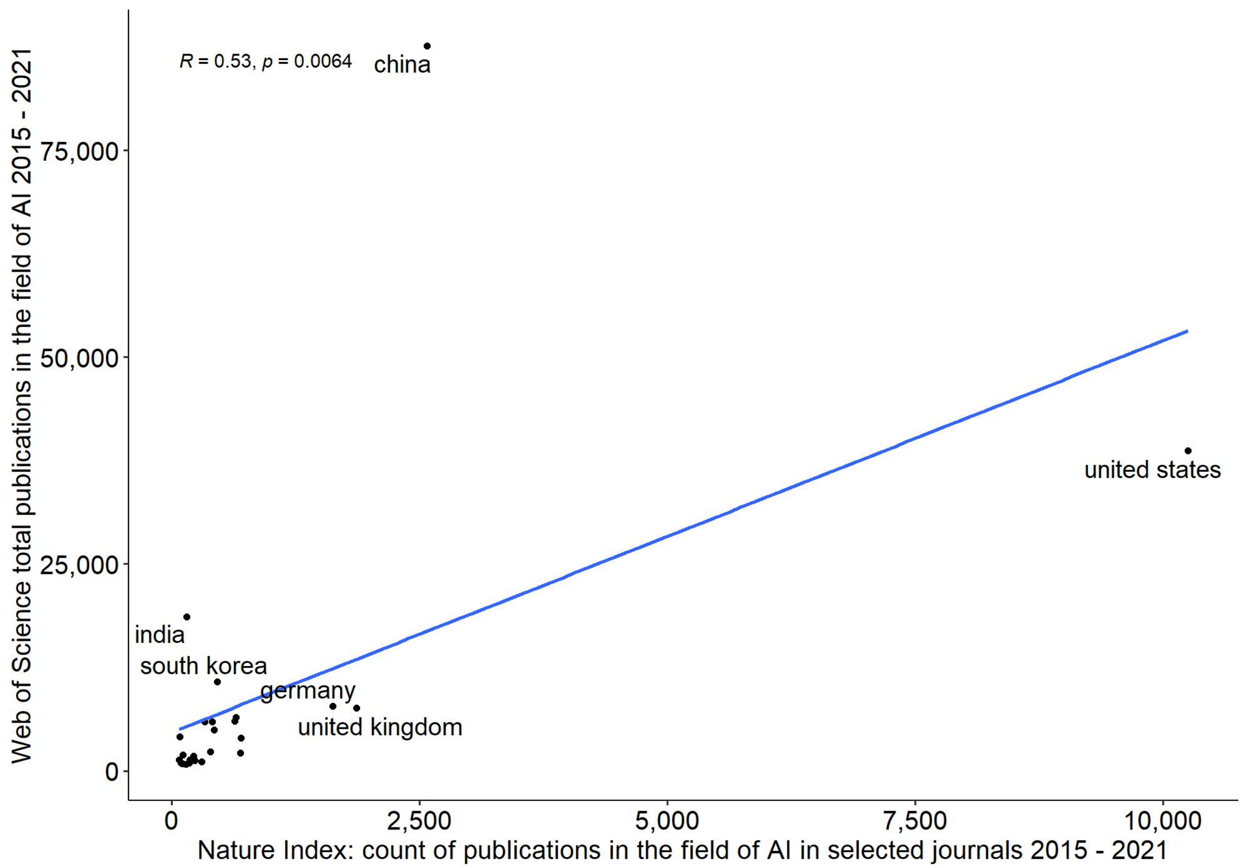
2.2 Artificial Intelligence and Deep Learning

In 2006, two publications on recursive learning in many-layered neuronal networks gave a boost to research in the field of machine learning (Hinton and Salakhutdinov 2006; Hinton et al. 2006). Building on this breakthrough, researchers concentrated on developing algorithms that were able to learn from large amounts of data, without giving the algorithm any detailed previous instructions. Instead, the algorithm relies solely on artificial multi-layered neural networks, which in their functioning resemble the neural networks of the human brain. After some time, these algorithms were able to classify and learn from large amounts of data with high levels of precision (Krizhevsky et al. 2012; He et al. 2016). Importantly, the amount of data available and the depth of the network (measured by the number of layers) are positively correlated with the ability of the algorithm to learn and self-improve, hence *deep* learning (Hey 2009; Domingos 2015). It is this feature which lead some researchers to describe the quantity of data available for researchers as the "new oil" of the knowledge economies of the 21st century (Spitz 2017; Lee 2018; Taffel 2023).

Once the initial breakthrough in machine learning had been made, the new technology was rapidly applied to various fields, such as image recognition, natural language processing, toxicology, medical image analysis, management, bioinformatics, financial fraud detection, as well as surveillance and military technologies. For our argument it is important that in the *application* phase of these technologies, the type of cutting-edge research abilities where US elite-universities still have an absolute advantage have become relatively less important. Instead, the training and incremental improvement of existing algorithms with large amounts of data has become central to advance innovation in these sectors (Agrawal et al. 2018; Cockburn et al. 2018; Beraja et al. 2021). Such processes can also be carried out by well-qualified specialists, even if they are not competing at the absolute frontier of global knowledge production.

Figure 2 illustrates this point, and shows that with respect to the overall amount of AI-related publications (as measured by the total number of publications in the field of AI that are indexed by Web of Science), China has already an advantage over all other countries in the world. We take this number as an indication that already today, China is leading when it comes to the overall amount of researchers that are able to do applied work in the field. When it comes to top-level publications (proxied by the Nature index of high-quality publications in AI), however, the United States are still ahead (Wagner et al. 2020, 2022).

Figure 2: Quality vs Quantity of Publications in the Field of AI



It is thus with respect to the training of existing technology with large amounts of data that autocracies might have an advantage. First, authoritarian states are using surveillance systems that can gather larger amounts of data about the behavior and characteristics of the population than most democracies (Qiang 2019; Strittmatter 2020), despite surveillance also playing a role in many democratic countries (Zuboff 2019). Second, as a result of less stringent privacy laws, this data can be shared by the government with private firms, similar to a subsidy, providing them with an advantage over firms in democratic political contexts (Jones and Tonetti 2020; Beraja et al. 2021, 2022, 2023). Third, population size does matter, as in states with a larger population the amount of data that can be provided as input is also larger. Finally, digital technology penetration through a society is playing a role as well. The larger is the number of digital services and devices that are used, the more data is generated, and the higher the amount of data that can be collected by the government. In the next section, we introduce a simple model to illustrate how these specific features can influence the speed of innovation in a digital autocracy.

3 Baseline Model

3.1 Households

Our economy is populated with a fixed number of infinitely-lived, homogeneous representative households. Each household has $L(t) = L(0)\exp[nt]$ members, with $n0$ denoting the exogenous growth rate of the population. Further, $L(0) = L_0 > 0$. In every period, each member inelastically supplies one unit of labor per time unit. We normalize the number of households to one. We further follow Veldkamp (2005) and Jones and Tonetti (2020) and assume that consumers produce data as a by-product of consumption.

These data can be sold to the research sector (Jones and Tonetti 2020). However, data commonly comprises personal information and, thus, the potential misuse of data leads to a disutility that households consider when they sell their data.

The instantaneous utility function introduced below captures in a stylized manner the utility costs and benefits of state surveillance. The household's instantaneous utility function $u(t)$ is given by

$$u(t) = \left[\frac{[G(t)^{\epsilon}c(t)^{1-\epsilon}]^{1-\theta}}{1-\theta} - \iota[d_c(t)^{\kappa}G(t)^{1-\kappa}]^{\chi}\right], \tag{1}$$

with $\theta > 0$, $\kappa \in (0, 1]$ and $\theta \neq 1$ as the magnitude of the elasticity of marginal utility of consumption. χ parameterizes the weighted average of disutility of data misuse (with weight κ) or privacy violation due to governmental surveillance $G(t)$ weighted with the parameter $1 - \kappa$. $\epsilon \in [0, 1)$ weights the utility derived from governmental surveillance, $G(t)$ relative to private consumption, $c(t)$. For the special case that $\kappa = \epsilon = 1$, a household does not derive utility and disutility from governmental surveillance. While Cong et al. (2021) focus on this special case ($\kappa = \epsilon = 1$), our paper goes further by focusing explicitly on governmental surveillance activities.

Beyond being consistent with a balanced growth path, (1) captures in a stylized manner the utility costs and benefits of surveillance. More surveillance leads to more (subjective) security and stability, such as lower crime rates and fewer terrorists attacks, but, on the other hand, restricts civil liberties. Thus, as long as $[G(t)^{\epsilon}c^{1-\epsilon}]^{1-\theta}\epsilon < \iota\chi[d_c(t)^{\kappa}G(t)^{1-\kappa}]^{\chi}$, the marginal utility of G turns out to be negative, as the marginal costs of surveillance exceeds the marginal benefits in utility terms. In the following, we impose that $\chi > 1$ in order to guarantee the convexity of disutility in (1).

Given $\theta > 0$ and $\rho > 0$, the representative household's problem is to choose a plan $\{c(t), d_c(t)\}_{t=0}^{\infty}$ so as to

$$\max_{\{c(t),d_c(t)\}} \int_0^{\infty} \exp[-(\rho - n)t] \left[\frac{[G(t)^{\epsilon}c(t)^{1-\epsilon}]^{1-\theta}}{1-\theta} - \iota[d_c(t)^{\kappa}G(t)^{1-\kappa}]^{\chi} \right] dt \tag{2}$$

subject to

$$c(t) \geq 0 \tag{3}$$

$$d_c(t) \geq 0 \tag{4}$$

$$\dot{a}(t) = (r(t) - n)a(t) + w(t) + p_{dc}(t)d_c(t) - c(t) \tag{5}$$

$$\frac{\dot{d}_c(t)}{d_c(t)} \leq \frac{\dot{c}(t)}{c(t)}, \frac{\dot{d}_g(t)}{d_g(t)} \leq \frac{\dot{G}(t)}{G(t)} \tag{6}$$

and the No-Ponzi game condition

$$\lim_{t \Rightarrow \infty} a(t) \exp[-\int_0^t (r(s) - n)ds] \geq 0. \tag{7}$$

Here, $r(t)$ is the risk-free interest rate, $a(t)$ is the per capita financial wealth that consists of raw capital and perpetual patents as will become clearer below. Moreover, the constraint

(38) requires that the growth rate of data is bounded by the growth rate of consumption. Restriction (38) also implies that data is a by-product of consumption: $d_c(t) \leq \zeta c(t)$ for some arbitrary constant $\zeta \in (0, 1)$ (see Cong et al. (2021)). As usual, ρ is the consumer's subjective discount rate, while $p_{dc}(t)$ shows the price per data unit $d_c(t)$ that can be realized by selling data (as a by-product of consumption) to intermediate good producers (see Veldkamp (2005) or Cong et al. (2021)). $w(t)$ is the wage rate for labor supply.

Solving the optimization problem delivers the Euler equations for consumption (8) and data (9), respectively as

$$\frac{\dot{c}(t)}{c(t)} = \frac{1}{\tilde{\theta}}\left(r - n - \rho + (1-\theta)\epsilon\frac{\dot{G}(t)}{G(t)}\right) \tag{8}$$

$$\frac{\dot{p_c}(t)}{p_c(t)} + (1-\chi\kappa)\frac{\dot{d_c}(t)}{d_c(t)} - (1-\kappa)\chi\frac{\dot{G}(t)}{G(t)} = r - n - \rho, \tag{9}$$

and the transversality condition (tvc)

$$\lim_{t\Rightarrow\infty} a(t)\exp[-\int_0^t (r(s) - n)ds] = 0. \tag{10}$$

This follows directly from applying Pontryagin's maximum principle to the problem. Note further that $\tilde{\theta} \equiv [1 - (1-\theta)(1-\epsilon)]$ denotes the effective rate of the intertemporal elasticity of substitution. Note that for $\epsilon = 0$, we have $\tilde{\theta} = \theta$.

3.2 Surveillance and the Government

In order to keep the model analytically tractable, we model the governmental sector as simple as possible. We assume that a fraction $m(t) \in (0, 1)$ of governmental surveillance activities $G(t)$ generates aggregate governmental data $D_g(t) = m(t)G(t) = d_g(t)L(t)$. We allow $m(t)$ to decrease (or $\frac{1}{m(t)}$ to increase) over time to include the possibility that governmental surveillance becomes more efficient over time, in the sense that more data can be generated with a given level of surveillance activities due to technological improvements.

Governmental surveillance activities are financed via two sources. First, the government imposes a profit tax on final goods producers with a constant tax rate $\tau \in (0,1)$. Second, the government exclusively sells data-sets $d_g(t)$ to the research sector (where data firms operate) at price $p_{dg}(t)$. For simplicity, we do not allow data sharing across data firms. Moreover, the government cannot lend or borrow. The budget is thus always balanced. Taken together, the governmental constraint reads as

$$G(t) = \tau Y(t) + p_{dg}(t) d_g(t) L(t). \tag{11}$$

From equation (11), an implicit assumption is that governmental data are not shareable across firms. The reasons for this assumption are twofold. First, we focus on the normative and positive implications of data shareability within a firm.[1] Second, as shown by (Beraja et al. (2022)), from an empirical perspective this case is more relevant for authoritarian regimes. Like in Beraja et al. (2022)), governments collect their own data and sell them to a specific firm for analysis, while simultaneously excluding other firms from using the same data.

3.3 Production Side of the Economy

3.3.1 Final Goods Sector

The production side of our economy borrows elements from Romer (1990) and Jones (1995). The final goods sector produces the consumption aggregate with labor and intermediate goods as factor inputs in an environment with perfect competition. The production of the final goods sector is written as

$$Y(t) = L_Y(t)^{1-\alpha} \int_0^{N(t)} x_{i,t}^{\alpha} di, \tag{12}$$

[1] The implications of non-rival data have already been studied by Jones and Tonetti (2020), although we have to point out that data shareability across firms would strengthen the importance of governmental surveillance data in our model.

where $Y(t)$ indicates the output of the consumption aggregate. $L_Y(t)$ represents labor used in the final goods production, and $N(t)$ is the technological frontier. $x_{i,t}$ is the amount of a specific, i indexed intermediate good $x_{i,t}$ (e.g. a machine for instance) that is used in final goods production at time t. $\alpha \in (0,1)$ indicates the share of intermediate inputs.

Let $p_i(t)$ be the price paid for the ith intermediate good. Profit maximization together with the assumption of perfect competition implies that factors are paid their marginal products:

$$w_Y(t) = (1-\tau)(1-\alpha)\frac{Y(t)}{L_Y(t)}, \tag{13}$$

$$p_i(t) = (1-\tau)\alpha L_Y(t)^{1-\alpha} x_{i,t}^{\alpha-1}, \tag{14}$$

where w_i stands for the wage rate paid in the final goods sector.

3.3.2 Intermediate Goods Sector

From (14), we obtain the downward-sloping demand function of intermediate goods as:

$$x_{i,t} = L_Y(t)\left(\frac{\alpha(1-\tau)}{p_i(t)}\right)^{\frac{1}{1-\alpha}} \tag{15}$$

In the spirit of Dixit and Stiglitz (1977), we assume that the intermediate goods sector is monopolistically competitive. This implies that each firm produces exactly one of the differentiated intermediate goods. For production, each firm producing intermediate goods has to purchase one intermediate goods-specific blueprint from the R&D sector that will be introduced below. After the intermediate goods producer has purchased the blueprint, she is able to convert one unit of capital into one unit of intermediate good: $k_{i,t} = x_{i,t}$. The costs of the blueprint are the fixed costs for each firm. Moreover, the assumption of free entry ensures that fixed costs equal operating profits. This, in turn, implies that overall profits are zero. We assume that the marginal and average costs of production are constant. Hence, the operating profit's flow is given by

$$\begin{aligned}\pi_{i,t} &= (p_{i,t}-r)k_{i,t} \\ &= ((1-\tau)\alpha L_Y(t)^{1-\alpha}x_{i,t}^{\alpha-1}-r(t))k_{i,t} \qquad (16)\end{aligned}$$

Profit maximization yields the usual markup pricing:

$$p_{i,t}=p(t)=\frac{r(t)}{\alpha}, \qquad (17)$$

where $\frac{1}{\alpha}>1$ is the markup over marginal costs. Using (17) in (14), we find that

$$x_{i,t}=\left[\frac{(1-\tau)\alpha^2}{r(t)}\right]^{\left(\frac{1}{1-\alpha}\right)}L_Y(t)\equiv x(t), \qquad (18)$$

which implies that the quantity of intermediate goods production is independent of the variety. Thus, using (17) in (15), the aggregate capital stock is simply $K(t)=\int_0^N x_{i,t}di=N(t)x(t)$, so that (12) can be written as

$$Y(t)=L_Y(t)N(t)\left[\frac{(1-\tau)\alpha^2}{r(t)}\right]^{\left(\frac{\alpha}{1-\alpha}\right)}. \qquad (19)$$

Inspecting (19) reveals that final output decreases with an increasing profit tax rate τ.

3.3.3 Data Firms in the Research Sector

The novelty of our paper is that private as well as governmental data enter R&D when new blueprints are developed. This distinguishes our contribution from Jones and Tonetti (2020) or Beraja et al. (2022), where data only enter directly into the production of final goods. These contributions implicitly focus on data-driven industries by assuming that exclusively data intermediate goods are used for final good production. While this seems reasonable for industries such as Google or Facebook, more traditional industries still use non-data intermediate goods, where data can be used to improve the quality of such intermediate goods. As we focus on surveillance as well, our paper is also different from Cong et al. (2021, 2022), who neglect data from government surveillance as a potential driver of innovation.

In our paper, data firms operate in the R&D sector that employs scientists, $L_N(t)$ as well as a weighted average of private and governmental data. Hence, total data employed in the research sector at time t to discover new blueprints (or algorithms) is given by

$$D(t) \equiv [D_c(t)]^{\beta}[D_g(t)]^{1-\beta} = (d_c)^{\beta}(d_g)^{1-\beta}L(t), \tag{20}$$

with weighting factor $\beta \in [0, 1]$. Two points in (20) are worth mentioning. First, if $\beta = 1$, the research sector only employs private data, i.e. $D(t) = D_c(t)$ (see Cong et al. (2021) for instance). Second, there is a scale effect. The size of aggregate data $D(t)$ depends on the size of the population $L(t)$, which means that more people (larger countries) produce more private as well as governmental data.

The aggregate technological frontier evolves according to:

$$\dot{N}(t) \quad = \quad \bar{\eta}N(t)^{\phi}(D(t))^{\xi}L_N(t)^{1-\xi}, \tag{21}$$

where $\bar{\eta} > 0$ is an efficiency term of innovation. $\xi \in (0, 1)$ represents the relative contribution of data $D(t)$ and R&D scientists $L_N(t)$ in the production process of new varieties (or algorithms) $N(t)$, while $0 < \phi < 1$ captures the "standing on the shoulders of giants" effect of technology on the change in technology which can be interpreted as knowledge spillovers.[2]

We further assume that surveillance reduces the efficiency of innovation. This can be justified by the underlying psychological pressure of the government on researchers. Authoritarian surveillance entails targeted repression and makes citizens adhere to social or legal norms (Roberts 2018). Repression, however, also disincentives innovation activities on the

[2]For $\phi < 0$, we have the "fishing out effect" effect, i.e. it is harder to find a new blueprint if the number of already discovered blueprints $N(t)$ is very large. For $\phi = 0$, both effects offset each other.

entrepreneurial level (Acemoglu and Robinson 2012) and on the level of the individual, where it hinders the creativity that is crucial in the innovation process (Karpa et al. 2022). On the other hand, more governmental surveillance also implies more data and more varieties that can in turn enhance research productivity. To capture this idea in a parsimonious way, in contrast to Cong et al. (2021) or Cong et al. (2022), the research productivity term is endogenously explained by governmental surveillance activities $G(t)$ relative to output $Y(t)$:

$$\eta(t) = \bar{\eta}\left(\frac{G(t)}{Y(t)}\right)^{-\omega} = \bar{\eta}\left(\frac{d_g(t)L(t)}{m(t)Y(t)}\right)^{-\omega}, \tag{22}$$

with $\omega \in [0,1)$ that reflects the strength of negative influence of surveillance activities on research productivity. $m(t)$ is an exogenously growing (with constant rate) efficiency parameter. Because researchers are socialized in a given regime, they take the value of η as given by neglecting the negative influence of surveillance activities. For $\omega = 0$, (5) collapse to $\eta(t) = \bar{\eta}$, i.e. an exogenously given and time-independent efficiency term of innovation.

We assume that data firms develop new blueprints for new varieties of capital goods under conditions of free market entry and perfect competition. Hence, data firms enter as long as marginal benefits equals marginal costs of production. In other words, data firms maximize their profits $\pi_N(t)$ according to

$$\begin{aligned}\max_{\{L_N(t),d_c(t),d_g(t)\}} \pi_N(t) &= p_N(t)\eta(t)N(t)^{\phi}(D(t))^{\xi}L_N(t)^{1-\xi} - w_N(t)L_N(t)\\ &\quad - p_{dc}(t)d_c(t)L(t) - p_{dg}(t)d_g(t)L(t),\end{aligned} \tag{23}$$

where $p_N(t)$ represents the price of a blueprint. The first order conditions pin down the R&D sector's demand function of data from private households and government as well as the wages in the research sector. The free-entry conditions are:

$$p_N(t)(1-\xi)\eta N(t)^{\phi}(D(t))^{\xi}L_N(t)^{-\xi} = w_N(t), \tag{24}$$

$$p_N(t)\beta\xi\eta(t)N^{\phi}(t)(D(t))^{\xi-1}\frac{D(t)}{d_c(t)}L_N(t)^{1-\xi} = p_{dc}(t)L(t), \tag{25}$$

$$p_N(t)(1-\beta)\xi\eta(t)N(t)^{\phi}(D(t))^{\xi-1}\frac{D(t)}{d_g(t)}L_N(t)^{1-\xi} = p_{dg}(t)L(t). \tag{26}$$

3.4 Equilibrium

A competitive equilibrium is a set of allocations $\{c(t), Y_t, a(t), \{x_{i,t}\}_{i\in[0,N_t]}, d_c(t), d_g(t), L_Y(t),$ $L_N(t), L(t), N(t), G(t), D_c(t), D_g(t)\}_{t=0}^{\infty}$, a price system $\{w(t), r_t, \{p_{i,t}\}_{i\in[0,N_t]}, p_{cd}(t), p_{gd}(t),$ $P_N(t)\}$ and an imposed policy scalar $\{\tau\}$ such that for all t:

(i) $\{c(t)\}$ and $\{a(t)\}$ solve the household problem (37)-(7), $\{x_{i,t}\}_{i\in[0,N_t]}$ and $\{L_Y(t)\}$ solve the final goods producer problem, $\{p_{i,t}\}_{i\in[0,N_t]}$ and $\{\pi_{i,t}\}_{i\in[0,N_t]}$ solve the intermediate goods producers problem for all $i \in [0, N_t]$, $\{L_N(t), d_c(t), d_g(t)\}$ solve the data firm's R&D problem (23).

(ii) $\{w(t)\}$ clears the labor market $L_N(t)+L_Y(t) = L(t)$, {r(t)} clears the asset market with $a(t)L(t) = N(t)p_N(t)$, $\{p_{gd}(t)\}$ clears the surveillance data market $d_g(t)L(t) = D_g(t)$, $\{p_{cd}(t)\}$ clears the consumption data market $d_c(t)L(t) = D_c(t)$, {N(t)} follows from the R&D production function (21). $G(t)$ follows from $\{\tau, Y(t), p_{dg}(t), d_g(t), L(t)\}$. In every point in time, the governmental budget (11) is balanced.

3.5 Governmental Surveillance and Growth: A Balanced Growth Path Characterisation

In this section, we solve the model along the balanced growth path (bgp). A bgp is a trajectory such that all variables grow at a constant exponential (but not necessarily equal) rate forever. In Appendix 1, we derive the growth rate for the decentralized economy on the bgp. This growth rate is different for private and governmental data provision. We summarize this finding in the following proposition:

Proposition 1. *As in Jones (1995), the decentralized economy does not exhibit a scale effet. As shown in Appendix 8.2, the bgp growth rates for* $y(t) \equiv \frac{Y(t)}{L(t)}$*,* $N(t)$*,* $c(t)$ *and* $g(t) \equiv \frac{G(t)}{L(t)}$ *are given by*

$$\hat{g} = \left\{ \frac{\xi[(1-\theta)\epsilon - (1-\kappa)\chi] + \kappa\chi}{\xi[\theta - 1 + \chi(1-\kappa)] + (1-\phi)\chi\kappa} \right\} n. \tag{27}$$

The bgp growth rates for private and public data sets $d_c(t)$ *and* $d_g(t)$*, respectively, are given by*

$$\begin{aligned} \hat{g}_d &= \frac{1-\phi}{\xi}\hat{g} - \frac{n}{\xi} \\ &= \left\{ \frac{[1-\theta][1+\epsilon(1-\phi)] - (1-\kappa)(2-\phi)]}{\xi[\theta - 1 + \chi(1-\kappa)] + (1-\phi)\chi\kappa} \right\} n. \end{aligned} \tag{28}$$

Remark 1. Cong et al. (2021): For the special case that the government is absent, i.e. $\epsilon = \omega = 0$ and $\kappa = 1$, the bgp growth rate for the decentralized economy collapses to $\hat{g}|_{\epsilon=\omega=0,\kappa=1} = \frac{\chi}{\xi(\theta-1)+\chi(1-\phi)}$, *while the bgp growth rate of data-sets reads as* $\hat{g}|_{\epsilon=\omega=0,\kappa=1} = \frac{1-\theta}{\xi(\theta-1)+\chi(1-\phi)}$. For the special case that the government is absent and, additionally, preferences are logarithmic ($\theta = 1$), the bgp growth rate collapses to $\hat{g} = \frac{n}{1-\theta}$. This growth rate is larger compared to Jones (1995) as in our setting the diminishing returns of research labor $(1 - \xi < 1)$ are directly offset by data usage within the R&D sector.

Remark 2. Appendix 8.2 shows that for the parameter restriction

$$\chi > \hat{\chi} \equiv \frac{\epsilon(\theta - 1)\xi}{\kappa - (1-\kappa)\xi} \tag{29}$$

the bgp growth rate (27) exists and is positive, while the bgp growth rate for data sets, (28), exists but is negative.

In other words, (29) ensures the convexity of the disutility term χ in the representative household's utility function originating from private data production and governmental surveillance. In contrast to Cong et al. (2021), the restriction is more severe due to the presence of government surveillance activities affecting directly positively ($\xi\epsilon$) as well as negatively ($(1-\kappa)\xi$) the representative household's utility function.

Proposition 2. *As shown in Appendix 8.3, for the decentralized economy, on the bgp, the share of employed R&D is constant and reads as*

$$\hat{l}_n(t) \equiv \frac{\hat{L_N(t)}}{L(t)} = 1 - \hat{l}_y(t) = \hat{l}_n = \frac{\alpha(1-\xi)}{\left[\frac{g_d^*+n-g^*}{g^*}\right]\epsilon(\theta-1)+\theta+\alpha(1-\xi)+\frac{\rho}{g^*}} \in (0,1), \tag{30}$$

where g^* is given by (27) and g_d^* by (28) and $1-\xi > \phi$. Note that the ladder condition restricts the knowledge spillover effect in order to ensure that $l_r \in (0,1)$ for the empirically plausible value $\theta > 1$ (see Jones (2016)).

Further, (30) is independent of the tax rate because its positive effect (lower wages in the final goods sector makes employment in the R&D sector more attractive) and the negative effect (higher taxes in the final goods sector reduces the demand for intermediate goods (see (18)), thus reduces profits in the intermediate good sector and, hence, leads to lower wages in the R&D sector) via the intermediate goods cancel each other.

3.6 Comparative Statics

Before we proceed with deriving the social planner's problem, it is worth deriving some insights from comparative statics.

Proposition 3. *For $\theta > 1$, the bgp growth rate (27) decreases with the increasing importance of data usage in the R&D sector, ξ, while the effect of the increasing importance of dis-utility stemming from private data usage or governmental surveillance, χ on the bgp* *is undetermined. Finally, if the importance of utility from governmental surveillance ϵ increases, households prefer lower bgp growth rates. In formal terms we have:*

$$\frac{\partial \hat{g}}{\partial \xi} = \left\{ \frac{[(1-\theta)(1+\epsilon(1-\phi)) - (1-\kappa)(2-\phi)\chi]n\kappa\chi}{\xi[\theta - 1 + \chi(1-\kappa)] + (1-\phi)\chi\kappa]^2} \right\} < 0, \tag{31}$$

$$\frac{\partial \hat{g}}{\partial \chi} = \left\{ \frac{(\theta-1)[\kappa(1+\epsilon(1-\phi)) - \xi(1-\epsilon)(1-\kappa)]n\xi}{[\xi(\theta - 1 + \chi(1-\kappa)) - (1-\phi)\chi\kappa]^2} \right\} \lesseqqgtr 0, \tag{32}$$

$$\frac{\partial \hat{g}}{\partial \epsilon} = \left\{ \frac{(1-\theta)n\xi}{\xi[\theta - 1 + \chi(1-\kappa)] - (1-\phi)\chi\kappa]} \right\} < 0. \tag{33}$$

Some comments regarding Proposition 3 are in order. First, from inspecting (31) we see that an increase of ξ that mirrors the importance of data usage in the innovation of new data algorithms decreases the bgp growth rate. This counter-intuitive result can be explained with a general equilibrium effect. An increase of ξ increases the usage of data at the cost of R&D employment in the production of new algorithms. To produce more data in the present, surveillance and/or private consumption in the present has to go up at the cost of future consumption. Alternatively, households might invest in new algorithms that increase their future consumption potential and also produce more future data as a by-product. Due to the tendency of consumption smoothing (note that $\theta > 1$), the first effect dominates the second, and, hence, households require a lower bgp growth rate if ξ goes up.[3] Next, (32) for $\theta > 1$ shows that if the importance of dis-utility from private data use and/or governmental surveillance increases, households accept lower bgp growth rates if the negative impact of governmental surveillance on utility is sufficiently small, i.e. if $1 - \kappa < \frac{(1-\epsilon)\xi}{1+\xi(1-\epsilon)+\epsilon(1-\phi)}$. This finding contrasts and complements recent studies such as Cong et al. (2021), which propose that consumers have to be compensated with higher bgp growth rates for the disutility from private data use. In our setting, where households also

[3] Cong et al. (2021) state on p. 6484 that an increase of ξ increases the gbp growth rate if $\theta > 1$. We believe that this is a typo as their bgp growth rate in fact decreases if ξ goes up, provided that the consumption smoothing motive is sufficiently large, i.e. $\theta > 1$.

derive positive utility from surveillance, i.e. a higher subjective feeling of security, under some conditions, in equilibrium smaller growth rates are required even if governmental surveillance as well as private data misuse is present. Finally, from (33) we observe that an increase of ϵ reduces the bgp growth rate as, unsurprisingly, households accept lower bgp growth rates if the importance of the utility-enhancing effect of governmental surveillance increases and the consumption smoothing motive is sufficiently pronounced.

4 The Social Planner's Problem

The equilibrium characterized in the decentralized economy is not socially optimal due to, (i) monopolistic competition, (ii) knowledge spillovers in the R&D production function as well as a (iii) reduction of R&D productivity due to government surveillance that is taken as given by the agents as reflected by (21) and (5).

In turn, a benevolent social planner maximizes the utility of the representative household subject to the rouse constraint. The latter requires that aggregate net output $Y(t) - \int_0^{N(t)} r(t)x_{i,t}di$ equals aggregate consumption and governmental surveillance expenditures, $G(t)$:

$$C(t) = c(t)L(t) = Y(t) - \int_0^{N(t)} r(t)x_{i,t}di - G(t), \tag{34}$$

where $G(t) = \frac{d_g(t)L(t)}{m(t)}$. Given $N(t)$, the social planner solves a static optimization problem that is at each point in time t she chooses the optimal level of intermediate goods given $N(t)$. In other words, she optimizes the following resource constraint:

$$C(t) + G(t) = L_Y(t)^{1-\alpha} \int_0^{N(t)} x_{i,t}^{\alpha}di - \int_0^{N(t)} r(t)x_{i,t}di \equiv Y_n(t). \tag{35}$$

From this optimization problem, we derive the optimal net output, $Y_n(t)$ as:

$$Y_n(t) = (1-\alpha)L_Y(t)N(t)\left(\frac{\alpha}{r(t)}\right)^{\frac{\alpha}{1-\alpha}}. \tag{36}$$

Unsurprisingly, given the same level of technology and labor input, compared to the decentralized economy, the output is larger. The difference is due to monopolistic competition in the intermediate goods sector in the decentralized economy. Given (36), the social planer solves the following problem:

$$\max_{\{c(t),d_c(t),G(t),l_y(t)\}} \int_0^\infty \exp[-(\rho - n)t] \left[\frac{[G(t)^\epsilon c(t)^{1-\epsilon}]^{1-\theta}}{1-\theta} - \iota [d_c(t)^\kappa G(t)^{1-\kappa}]^\chi \right] dt$$

subject to

$$c(t) \geq 0,$$

$$G(t) \geq 0,$$

$$d_c(t) \geq 0,$$

$$m(t) \geq 0,$$

$$\dot{N}(t) = \bar{\eta} \left[\frac{G(t)}{Y_n(t)} \right]^{-\omega} N(t)^\phi \left[(d_c(t)L(t))^\beta \left(G(t)m(t) \right)^{1-\beta} \right]^\xi L_N(t)^{1-\xi}, \tag{37}$$

$$\frac{\dot{d}_c(t)}{d_c(t)} \leq \frac{\dot{c}(t)}{c(t)}, \frac{\dot{d}_g(t)}{d_g(t)} \leq \frac{\dot{G}(t)}{G(t)}$$

$$c(t) + \frac{G(t)}{L(t)} = (1-\alpha) l_y(t) N(t) \left(\frac{\alpha}{r(t)} \right)^{\frac{\alpha}{1-\alpha}}, \tag{38}$$

$$l_y(t) + l_n(t) = 1. \tag{39}$$

Equation (39) represents the labor market clearing condition, while equation (38) shows the simplified resource constraint. After solving the social planner's problem in Appendix 8.4, we can summarize our main findings with the following proposition:

Proposition 4. *In Appendix 8.4 it is shown that the bgp growth rates coincide with the bgp growth rates for the decentralized economy presented in Proposition 1. In other words,* *we have*

$$g^* = \hat{g} \leq \frac{n[\xi(1-(1-\kappa)\chi) - \chi\kappa] - \xi\rho}{\xi[1-\phi-\chi(1-\kappa)] - \kappa(1-\phi)\chi}. \tag{40}$$

One remark regarding the last (in)equality shown in Proposition 3 is in order. Although the social optimal and decentral bgp growth rates are identical, nevertheless we have to impose an upper limit on the social optimal growth rate in order to guarantee that the fraction of R&D workers does not exceed the value of one.

From an intuitive point of view, the result presented in Proposition 4 directly relates to Jones (1995), who shows that a focus on growth rates per se is not sufficient to fully describe a country's economic performance.[4] For instance, an increase of governmental surveillance decreases the efficiency of R&D, thus leading to an immediate reduction of the growth of new ideas. However, more surveillance implies more governmental data that in turn can be used to generate new ideas that manifest themselves in new intermediate goods and an increase in the final output. Hence, in the medium run, growth rates return to the initial growth rates if the positive effect of additional data exactly offsets the negative effect of surveillance on creativity, as it is the case in our model.[5]

However, as we show below, we have *level effects*, i.e. the social optimal fraction of labor employed in the R&D sector is larger compared to the fraction of R&D workers employed in the decentralized economy. This, in turn, leads to a sub-optimal overuse of data in the decentralized economy. We show this in Proposition 5:

[4]The not surprising finding that the bgp growth rates between the decentralized and centralized economy coincide is also made by e.g. Cong et al. (2021) and Jones and Tonetti (2020), who both use a semi-endogenous growth setting with data usage.

[5]This can be seen directly inspecting equation (21) together with (5). As on the bgp, $G(t)$ grows with the same rate as $Y(t)$, the fraction $\frac{G(t)}{Y(t)}$ remains constant. Hence on the bgp, η in equation (5) does not grow. Hence, off the bgp, we expect transitional dynamics of $\eta(t)$, which dynamics is governed by ω. Hence, even if we modify (5) to $\eta(t) = \bar{\eta}\left(\frac{G(t)}{Y(t)}\right)^{-\omega} = \bar{\eta}\left(\frac{(d_g(t)L(t))^{-\omega_1}}{(m(t)Y(t))^{-\omega_2}}\right)$, with $\omega_1 \in [0,1)$ with $\omega_2 \in [0,1)$ and $\omega_1 \neq \omega_2$, on the bgp, the gap between $G(t)$ and $Y(t)$ is constant (and not zero as in our case for $\omega_1 = \omega_1 = \omega$). In other words, on the bgp, the finding that $\hat{g} = g^s$ remains valid even for the case that $\omega_1 \in [0,1)$, $\omega_2 \in [0,1)$ and $\omega_1 \neq \omega_2$.

Proposition 5. *In Appendix 8.5, it is shown that the bgp fraction of R&D labor in the centrally planned economy is constant and given condition (29) holds, the social fraction of R&D employed labor exceeds the fraction of R&D labor in the decentralized economy. The bgp social fraction of R&D labor can be formally derived as*

$$l_n^*(t) = l_n^* = \frac{1}{1 + \frac{(1-\phi)(\xi-\chi\kappa)-\chi(1-\kappa)\xi}{(1-\xi)\xi} + \frac{\xi\rho - n[\xi-(\kappa-(1-\kappa)\xi)\chi]}{g(1-\xi)\xi}}. \tag{41}$$

Remark 3. In Appendix 8.5 it is also verified that given the inequality (40) holds, we have $l^* \in (0,1)$, which is automatically fulfilled for the empirically plausible case $\theta > 1$.

5 Rent-Seeking Government

In the preceding sections, we have contrasted the decentralized with the central planning solution. We can interpret the social planner as a benevolent government. We found that bgp growth rates are the same, but the allocation of the labor force between the R&D sector and the final goods sector differs due to monopolistic competition in the decentralized economy's intermediate goods sector. This results in a sub-optimal overuse of data in the decentralized economy and hence excessive surveillance activities from a social's planner point of view. To obtain the socially optimal labor market allocation for the decentralized economy, a wage subsidy scheme with subsidy rate $s(t)$ has to be imposed in the intermediate goods sector, i.e.

$$p_N(t)(1-\xi)\eta N(t)^{\phi}(D(t))^{\xi} L_N(t)^{-\xi} = w_N(t)s(t). \tag{42}$$

A suited tax scheme brings down the sub-optimal use of data, and reduces surveillance activities by altering the R&D labor share towards an optimal level. In turn, as shown by Cong et al. (2021), a data tax addresses the miss-allocation in the labor market. This is also the case in our model. The same applies to the taxation of the final goods market with tax rate τ (see (11)). Hence, a tax rate greater than zero reduces welfare further. Therefore, the benevolent planner sets the tax rate to zero.

However, what happens with the tax rate if the government is self-interested, and how does this impact the economy? Allen (2011, p. 15) notes that “economic success is the result of secure property rights, low taxes, and minimal government. Arbitrary government is bad for growth because it leads to high taxes [...] and rent-seeking.” In the context of our model, the tax rate $\tau(t)$ can be interpreted as a characteristic of an authoritarian state, where self-interested elites control the government and use tax revenues as an additional source for financing surveillance activities in order to consolidate their hold on power (see 11). For simplicity, we first assume that the elites are myopic and have a static objective function:

$$W(t) = \iota \ln[\tau Y(t)] + (1 - \iota) \ln[c(t)], \tag{43}$$

where $\iota \in [0, 1]$ reflects the weight that the elites place on surveillance with direct expenses of the representative household in terms of consumption loss. We proceed by showing that on the bgp, consumption is a constant fraction of output:

$$\frac{c(t)}{y(t)} = [1 - \tau] \underbrace{\left[1 - \alpha^2 - \frac{\xi(1-\alpha)(1-\beta)}{(1-\xi)} \left(\frac{l_n(t)}{l_y(t)}\right)\right]}_{>0}, \tag{44}$$

as $\frac{l_n(t)}{l_y(t)}$ is constant on the bgp. The latter results help to ensure that the bgp tax rate that is chosen by the myopic government is constant. Next, substitution of (44) and (19) in (43), and after having dropped all exogenous and pre-determined variables, we have

$$W(t) = \iota \ln[\tau] + (1 - \iota) \ln[1 - \tau] + \left(\frac{\alpha}{1-\alpha}\right) \ln[1 - \tau]. \tag{45}$$

Finally, differentiating (45) with respect to the tax rate τ yields:

$$\tau = \iota(1 - \alpha). \tag{46}$$

Thus, the tax rate chosen by the ruling elites is stationary and depends on two parameters: first, on the ruling elites' chosen degree ι of surveillance, and, second, on the intensity α of intermediate goods in final good production. (46) shows that the tax rate is increasing in the degree ι, i.e. the more important is surveillance for the ruling elites, the higher is the chosen tax rate. Moreover, the tax rate is decreasing in α, because a larger α increases the effect of the tax wedge on the production of intermediate goods as visualized in (18).

Now consider the case of forward-looking, dynamic optimization elites. These elites choose τ_t in order to maximize

$$W = \int_0^\infty \exp[-(\rho - n)t][\iota \ln[\tau Y(t)] + (1-\iota)\ln[c(t)]dt. \tag{47}$$

Again using (44) and (19) and noting the fact that the labor market outcome is not affected by the tax rate, dropping exogenous variables, we can rewrite (47) as

$$W = \frac{1}{\rho - n}\left[\iota \ln[\tau] + (1-\iota)\ln[1-\tau] + \left(\frac{\alpha}{1-\alpha}\right)\ln[1-\tau]\right]. \tag{48}$$

Hence, the tax rate that is chosen by the government under a dynamic rent-seeking regime is the same as that under a static rent-seeking regime and given by (46). We summarize the result with the following proposition.

Proposition 6. *Under some conditions, the tax rate chosen by a myopic government under static rent-seeking corresponds to the tax rate under dynamic rent-seeking.*

Hence, if the government is benevolent, the chosen tax rate τ is zero. While a tax rate greater than zero leaves the bgp growth rate unaffected, it nevertheless increases the R&D labor market distortion further that already exists due to data overuse.[6]

[6] The fraction of R&D labor in the decentralized economy decreases with decreasing α. In turn, τ is increasing with a decreasing α.

Table 1: Summary of parameterization for the baseline economy

Variable	Description	Value	Source
α	Intensity of intermediate goods in production	$\frac{1}{3}$	Standard
ϵ	Utility weight of governmental surveillance	0.2	Discretionary
θ	Relative risk aversion of consumption in utility	2.5	Standard
ξ	Contribution of data in innovation frontier	0.5	Cong et al. (2021)
χ	Disutility weight of data misuse or privacy violation	1.5	Cong et al. (2021)
ϕ	Degree of knowledge spillover in innovation frontier	0.85	Cong et al. (2021)
ρ	Subjective discount factor	0.03	Standard
n	Population growth rate	0.02	Standard
κ	Relative disutillity from private data misuse and from governmental surveillance	0.80	Discretionary

6 Calibration

Similar to Jones (1995), in our model the sub-optimal allocation of R&D labor in the decentralized economy is due to monopolistic competition in the production of intermediate goods. To compensate for the lower production and usage of intermediate goods, the final good producers employ more labor that in turn crowds out R&D labor. However, in our model the R&D labor market distortion is less severe than in Jones (1995), as data can be used as a direct substitute for R&D labor to produce new algorithms. Thus, like in Cong et al. (2021), the crowding-out of R&D labor is paralleled by a socially sub-optimal crowding-in of data.

To obtain a better understanding of the steady-stage labor market allocations, we perform a calibration exercise. In other words, we use calibrated values that are consistent with the relevant literature (see table (1) for an overview) and calculate the difference between labor that is allocated in the R&D sector between the social planner's problem and the decentralized economy by varying the parameter space $\{\phi, \kappa, \epsilon, \xi\}$[7].

The result of this exercise is presented in the first row of figure (3). In this exercise, we focus in particular on κ that weights the household's relative disutillity from private data misuse and from governmental surveillance.[8] We find that, (i), if household's derive

[7]Note that κ is calibrated in the way to insure a positive bgp growth rate (see Remark 2).

[8]For $\kappa = 0$ ($\kappa = 1$) household's members suffer only from governmental surveillance (private data misuse).

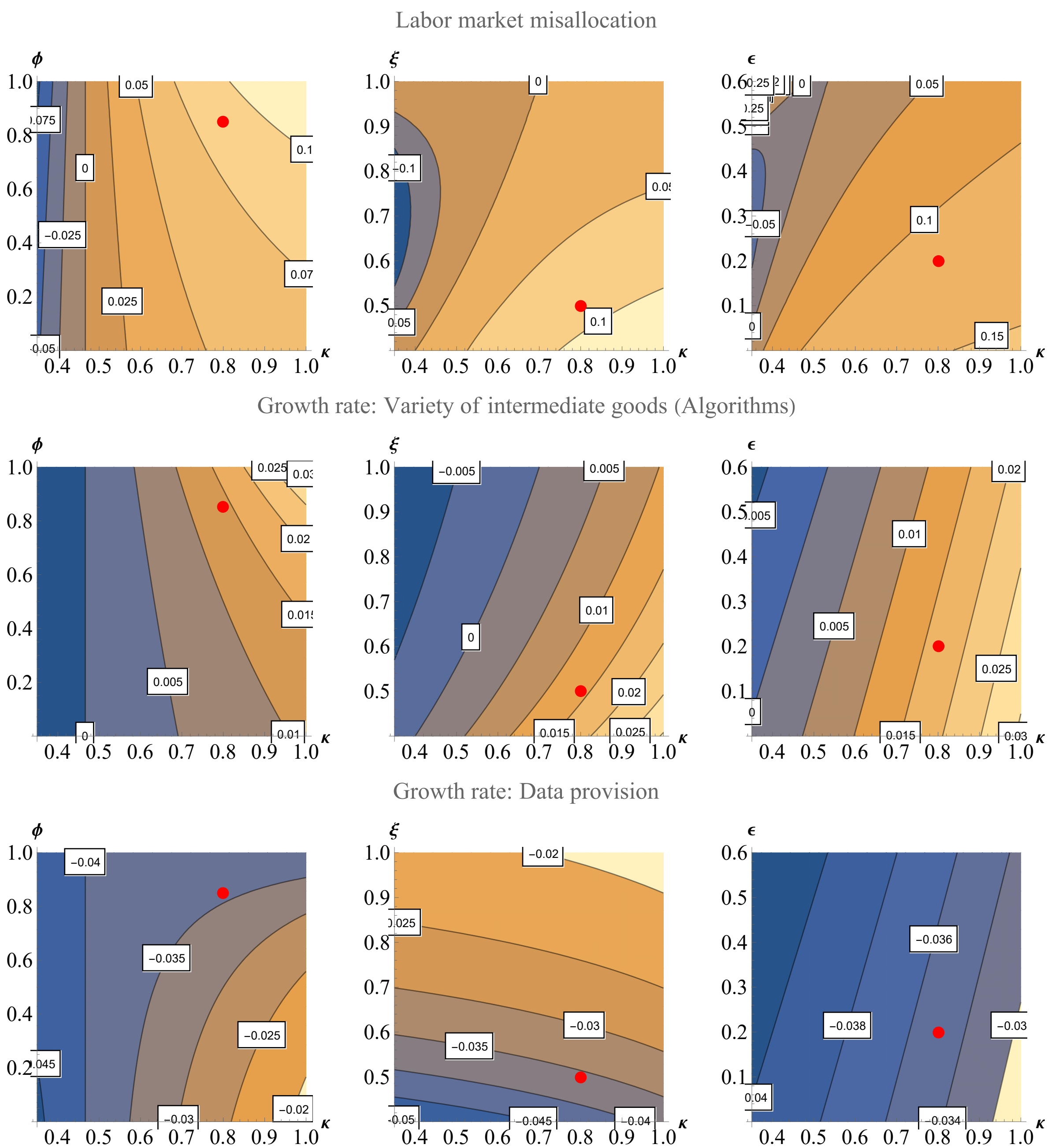
sufficient utility from governmental surveillance (high ϵ), the R&D misallocation of labor tends to zero, even if households put a large weight on governmental surveillance relative to private data misuse (small κ). The reason is that for a small κ and large ϵ, the social planner optimally allocates more people in the final goods sector, thereby reducing the R&D labor misallocation between the social planner's solution and the solution of the decentralized economy. On the other side, R&D labor misallocation increases with decreasing ϵ for constant κ. Moreover, (ii), we also observe that R&D misallocation is particularly pronounced if the degree of knowledge spillover ϕ is large and/or the importance of data for the development of new algorithms ξ is low. Importantly, we find that for a specific combination of utility and disutility from governmental surveillance, the decentralized labor market allocation coincides with the social optimal allocation. Hence, if households also derive utility from governmental surveillance, it is not necessarily the case that the decentralized data economy overuses data at the cost of an insufficiently small R&D sector. This finding complements the work of Cong et al. (2021).

To complement our exercise, the second row of figure (3) shows the equilibrium growth rates of the variety of intermediate goods which can be interpreted as algorithms. These figures confirm our findings summarized with Propositions 1 and 3. For empirically plausible values, we find that the growth rate of intermediate goods ranges between zero and 3 percent.

7 Conclusion

In this paper, we develop a political economy model to illustrate the trade-off between surveillance and data availability in an autocracy. As in traditional autocracies, surveillance and repression have a negative effect on innovation, as they render scientists and researchers less creative and productive. In modern informational autocracies, surveillance can however also be used to gather and bundle large amounts of data, which can then be used as an input – provided by the state – to accelerate innovation in data-intensive fields, such as

Figure 3: Decentralized economy vs. social planner's problem: Differences in R&D labor allocation



Notes: The first row shows the difference of R&D labor allocation between the central planner's problem and the decentralized economy. For the case of the first row, a positive (negative) value indicates a sub-optimal small (large) R&D sector for the decentral data economy. The printed numbers quantify the exact differences. The second (third) row computes the bgp growth rates of the variety of intermediate goodss (data provision) for different vales $\{\phi, \xi, \epsilon, \kappa\}$. For the second and third row: Yellow ocker shows larger bgp growth rates, while blue color reflects smaller bgp growth rates. The printed numbers reflect the bgp growth rates. The calibration ensures the convexity of the consumer's disutility function as well as the existence of the bgp. Finally, a red dote in each figure indicates the benchmark calibration based on Table 1.

artificial intelligence. Under certain conditions, this second effect might outweigh the first effect, rendering autocracies more productive than democracies when it comes to generating new blueprints and applied research, for example in the form of more precise and better performing algorithms.

Which effect ultimately prevails depends to a large extent on the future technological evolution of the field of artificial intelligence. If the technology remains roughly at the same level during the next couple of years, then informational autocracies such as China might well have an advantage in the new systemic competition of the 21st century. By leveraging large amounts of data – that might at least partially gathered through state surveillance – they will be better able to put applied solutions to the market than democratic states, where firms and research institutions are hampered by more restrictive data and privacy regulations.

If, however, cutting-edge scientist in some of the leading research institutions in the world come up with another breakthrough and paradigm shift in the field, the world's democracies might win the race once again, as – at least for now – most cutting-edge research institutions in the field of AI are still located in democracies, and in particular in the United States.

8 Appendix

8.1 Proof of Proposition 1: BGP growth rate for the decentralized economy

In this Appendix, we derive the bgp growth rates (27) and (28). In our model, there is perfect labor mobility between final goods and the research sector. In equilibrium, mobility between sectors comes to a halt if $w_N(t) = w_Y(t)$ or equivalently,

$$p_N(t)(1-\xi)\eta N(t)^{\phi}(D(t))^{\xi} L_N(t)^{-\xi} \quad = \quad (1-\tau)(1-\alpha)\frac{Y(t)}{L_Y(t)}. \tag{49}$$

Next, we want to pin down the operating profits of intermediate goods producers. We start with,

$$p_N(t) = \pi(t) + \dot{p_N}(t) \tag{50}$$

which is the no-arbitrage condition that the market value of a patent $p_N(t)$ has to meet in equilibrium. In the absence of asset price bubbles (which we assume), condition (50) says that the market value of a patent equals the fundamental value of the patent, i.e. the present value of the expected future accounting profits from using the new invented algorithm in the intermediate goods sector. Hence, we have

$$p_N(t) = \int_t^{\infty} \exp[-(\Gamma(\tau))]\pi(t)d\tau, \tag{51}$$

with $\Gamma(\tau) = \int_t^{\tau} r(s)ds$ so that the discount rate is the market interest rate. With perfect foresight and the absence of uncertainty, the no-arbitrage condition can be handled as a differential equation for $p_N(t)$. The solution to the differential equation (50) is given by (51). In bgp, interest rates are constant, i.e. $r(t) = r$, while the operating profits have to grow with rate n (which becomes clear in the following analysis). Thus, (51) reduces to

$$p_N(t) = \frac{\pi(t)}{r-n}, \tag{52}$$

where operating profits are obtained as

$$\pi(t) = (1-\tau)(1-\alpha)\alpha\frac{Y(t)}{N(t)}. \tag{53}$$

With a constant interest rate r, $\frac{Y(t)}{N(t)}$ grows with a constant rate n (see (19)). Thus, in bgp, operating profits also grow with rate n (see equation (53)) as the price for blueprints does:

$$p_N(t) = \frac{(1-\tau)(1-\alpha)\alpha Y(t)}{(r-n)N(t)} \tag{54}$$

Thus, using (54) in (49) yields:

$$\alpha(1-\xi)\eta N(t)^{\phi-1}(D(t))^{\xi}L_N(t)^{-\xi} \quad = \quad \frac{r-n}{L_Y(t)}. \tag{55}$$

Now, we are prepared to derive the growth rate of $N(t)$ and $d_c(t)$. Writing (55) in growth rates gives (and assuming that r is constant on the the bgp):

$$(\phi+\omega-1)\frac{\dot{N}(t)}{N(t)} + \xi\beta\frac{\dot{d}_c(t)}{d_c(t)} + (\xi(1-\beta)-\omega)\frac{\dot{d}_g(t)}{d_g(t)} + \omega\frac{\dot{m}(t)}{m(t)} + n \quad = \quad 0. \tag{56}$$

The free-entry condition of private data (25) can be also written in growth rates, yielding the growth rate of the price for private data sets:

$$\frac{\dot{p}_{dc}(t)}{p_{dc}(t)} = (\xi\beta-1)\frac{\dot{d}_c(t)}{d_c(t)} + (\phi+\omega)\frac{\dot{N}(t)}{N(t)} + (\xi(1-\beta)-\omega)\frac{\dot{d}_g(t)}{d_g(t)} + \omega\frac{\dot{m}(t)}{m(t)} + n. \tag{57}$$

Similarly, the free-entry condition of governmental data (26) can be written in growth rates to obtain the growth rate of the price for governmental data sets from surveillance activities:

$$\frac{\dot{p}_{dg}(t)}{p_{dg}(t)} = (\xi(1-\beta)-1-\omega)\frac{\dot{d}_g(t)}{d_g(t)} + (\phi+\omega)\frac{\dot{N}(t)}{N(t)} + \xi\beta\frac{\dot{d}_c(t)}{d_c(t)} + \omega\frac{\dot{m}(t)}{m(t)} + n. \tag{58}$$

Combining (25) and (26), we can re-express this relationship in growth rates as

$$\frac{\dot{p}_{dc}(t)}{p_{dc}(t)} = \frac{\dot{p}_{dg}(t)}{p_{dg}(t)} + \frac{\dot{d}_g(t)}{d_g(t)} - \frac{\dot{d}_c(t)}{d_c(t)}. \tag{59}$$

As in the steady-state the data markets clear, we must have $p_{dc}(t) = p_{dg}(t)$. Hence, on the bgp, governmental data must grow with the same rate as the prices of private data. Therefore, from (59) we find that on the bgp, the growth rates of private and governmental data sets are equal and grow with the constant rate $\hat{g}_d$, i.e.

$$\hat{g}_d = \frac{\dot{d}_g(t)}{d_g(t)} = \frac{\dot{d}_c(t)}{d_c(t)}. \tag{60}$$

Using (8) and (9) together with (57), we obtain

$$\frac{\dot{c}(t)}{c(t)} \quad = \quad \frac{1}{\tilde{\tilde{\theta}}}\left(\frac{\dot{p}(t)_{dc}}{p_{dc}(t)} - \chi\left[(\kappa - \frac{1}{\chi})\frac{\dot{d}_c(t)}{d_c(t)} + (1-\kappa)\frac{\dot{G}(t)}{G(t)}\right] + (1-\theta)\epsilon\frac{\dot{G}(t)}{G(t)}\right) \tag{61}$$

Expressing $G(t)$ in growth rates, using this and (60) in (61), and, moreover, exploiting the fact that on the bgp, per capita consumption $c(t)$ and $N(t)$ grows with the same rate as $\hat{g}$, we arrive at

$$\hat{g}[1-(1-\theta)-\phi+(1-\kappa)\chi] = [\xi - \kappa\chi]\hat{g}_d + a_1 n \tag{62}$$

with $a_1 \equiv [1-\omega+(1-\theta)\epsilon-\chi(1-\kappa)]$. Note that in the absence of the government, we have that $a_1 = 1$.

To obtain (27) and (28) in Proposition 1, we make use of two equations, namely (56) and (62). We have two equations with two unknowns, $\hat{g}$ and $\hat{g}_d$. Inserting (62) in (56) delivers (27) and (28). Moreover, from (19), we find that output grows with rate $\hat{g}+n$. Together with the goods market clearing condition $Y(t) = C(t) + G(t)$, this implies that $C(t) = c(t)L(t)$

and $G(t)$ have to grow with rate $\hat{g}+n$, while $y(t)$, $c(t)$ and $N(t)$ each grow with the rate $\hat{g}$.

8.2 Proof of Remark 2: Existence of the bgp

To make sure that a bgp exists, two conditions have to be fulfilled. The first has to make sure that $\hat{g} > 0$ which is satisfied as long as the parameter restriction (29) is fulfilled. The second condition requires that the bgp growth rate also satisfies the transversality condition (10) under balanced growth. Along the bgp, (10) considerably simplifies. As along as long as $r > \hat{g}+n$, along the bgp, (10) is satisfied. On the bgp, using (8) we find that $\theta\hat{g}+\rho = r-n$. This implies that as long as $\rho > \hat{g}(1-\theta)$ the bgp growth rate (27) derived with Proposition 1 fulfills the tvc. For the empirically plausible value $\theta > 1$ condition $\rho > \hat{g}(1-\theta)$ is automatically satisfied as $\rho > 0$. Hence, for $\theta > 1$ the bgp growth rate (27) is unique and exists as long as the parameter restriction (29) holds.

8.3 Proof of Proposition 2: BGP labor allocations for the decentralized economy

We start with the insight that the ratios employed in the final goods and research sectors are constant on the bgp. The proof is simple. Using the full employment condition, we have $L_Y(t) = L(t) - L_N(t)$ or expressed in ratios $l_Y(t) = 1 - l_n(t)$ with $L_Y(t) = l_y(t)L(t)$ and $L_N = l_n(t)L(t)$. If on the bgp, $l_y(t)$ and/or $l_n(t)$ grow with a constant rate (as other endogenous variables do), it might be that $l_y(t)$ become larger than one. On contrary, if one of the fractions grow with a negative rate on the bgp, the fractions might reach zero (or even become negative), which implies that all people work either in the final goods sector but do not innovate, or all people innovate but do not produce any final goods. These scenarios obviously contradicts with Proposition 1. Hence, to ensure that both sectors can produce on the bgp, wages have to equalize across sectors and this implies that the fractions $l_y(t)$ and $l_n(t)$ have to be constant on the bgp.

Next, we determine the constant fractions of the research and final goods sectors for the decentralized economy. Using the full employment condition $L_Y(t) = L(t) - L_N(t)$ in (49) together with (53) and (54) delivers on the bgp

$$
\begin{aligned}
L_Y(t)\alpha(1-\xi)g^* &= (r-n)L_N(t), \\
\alpha(1-\xi)g^*\left(\frac{L_Y(t)}{L(t)-L_Y(t)}\right) &= r-n.
\end{aligned} \tag{63}
$$

Moreover, inserting (63) in (8), on the bgp, we find

$$
\begin{aligned}
g^* &= \frac{1}{\tilde{\theta}}\left[\alpha(1-\xi)g^*\left(\frac{L_Y(t)}{L(t)-L_Y(t)}\right)-\rho+(1-\theta)\epsilon\left(g_d^*+n\right)\right] \\
\Rightarrow \quad l_n(t) &\equiv \frac{L_R(t)}{L(t)} = \hat{l}_n = \frac{\alpha(1-\xi)}{\left[\frac{g_d^*+n-g^*}{g^*}\right]\epsilon(\theta-1)+\theta+\alpha(1-\xi)+\frac{\rho}{g^*}},
\end{aligned} \tag{64}
$$

where g^* is given by (27) and g_d^* by (28). Finally, $\hat{l}_y = 1-\hat{l}_n$.

8.4 Proof of Proposition 3: Bgp growth rates for the socially planned economy

The corresponding current-value Hamiltonian for the social planner's problem is given by

$$
\begin{aligned}
\mathcal{H}(d_c(t),G(t),N(t),l_n(t)\lambda_1(t),\lambda_2(t)) \quad := &\quad \left[\frac{[G(t)^\epsilon c(t)^{1-\epsilon}]^{1-\theta}}{1-\theta}-\iota[d_c(t)^\kappa G(t)^{1-\kappa}]^\chi\right] \\
&+ \quad \lambda_1(t)\left[\left(\frac{\alpha}{r}\right)^{\frac{\alpha}{1-\alpha}}(1-\alpha)N(t)l_y(t)-c(t)-\frac{G(t)}{L(t)}\right] \\
&+ \quad \lambda_2(t)\left[\bar{\eta}\left[\frac{G(t)}{L(t)(1-l_n(t))\left(\frac{\alpha}{r}\right)^{\frac{\alpha}{1-\alpha}}}\right]^{-\omega}N^{\omega+\phi}[d_c(t)^\beta(m(t)G(t))^{1-\beta}]^\xi l_n(t)^{1-\xi}L(t)\right]
\end{aligned} \tag{65}
$$

The derivation of the necessary first order conditions is straightforward and skipped here in order to safe space[9]. We proceed by showing with a brief sketch that the bgp growth rate of the decentralized economy corresponds to the bgp growth rate of the centralized economy. Writing the necessary first order condition for consumption $c(t)$ in growth rates yields

$$
(1-\theta)\left[\epsilon\frac{\dot{G}(t)}{G(t)}+(1-\epsilon)\frac{\dot{c}(t)}{c(t)}\right] = \frac{\dot{\lambda}_1(t)}{\lambda_1(t)}+\frac{\dot{c}(t)}{c(t)} \tag{66}
$$

[9]Details are of course available upon request from the authors.

Moreover, reformulating the necessary first order condition for $l_n(t)$ in growth rates, we arrive at

$$\frac{\dot{\lambda}_1(t)}{\lambda_1(t)} = \frac{\dot{\lambda}_2(t)}{\lambda_2(t)}. \tag{67}$$

Thus, on the bgp, the shadow prices grow with the same rate. Next, writing the necessary first order condition for $G(t)$ or $d_c(t)$ in growth rates, using (67) in (66), we arrive at a bgp growth rate g^* that is identical to the bgp growth rate $\hat{g}$ given in (27). Using the necessary first order conditions for $N(t)$ and $l_n(t)$, on the bgp, we obtain

$$g_d^* = \frac{1-\phi}{\xi} g^* - \frac{n}{\xi}$$

which is obviously identical to the first line given in (28). Thus, also the social bgp growth rate of data sets is identical to those derived for the decentralized economy.

8.5 Proof of Proposition 4: BGP labor allocations for the socially planned economy

We first assume that $l_n(t)$ and $l_y(t)$ are constant on the bgp (guess and verify). Solving the necessary first order condition of $l_n(t) = l_n$ for the fraction of shadow prices $\frac{\lambda_1(t)}{\lambda_2(t)}$, inserting this expression in the the necessary first order conditions for $N(t)$ yields on the bgp:

$$g^* l_1^{-1}[\phi l_n + (1-l_n)(1-\xi] = \frac{\dot{\lambda}_2(t)}{\lambda_2(t)} + \rho - n. \tag{68}$$

Next, using the necessary first order condition for $G(t)$ or $d_c(t)$, turning them in growth rates, and make use of the resulting expression in (68) in order to eliminate the growth rate of the shadow price. Finally, using first line given in (28), on the bgp we have

$$g^* \left[(1-\xi)(1-l_n) + l_n \chi(1-\kappa)\right] = l_n \left[(\xi - \kappa\chi)\left(\frac{g^*(1-\phi)}{\xi} - \frac{n}{\xi}\right) + \rho - n\chi(1-\kappa)\right]. \tag{69}$$

Finally, inserting (27) in this expression, after solving for l_n yields expression (41) in the text. Hence, we have verified that l_n and l_y are indeed constant on the bgp.

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