Firm Dynamics under Industrial Policy

by

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ABSTRACT

Designing an effective industrial policy is a critical issue for governments. How does the policy's effect on an industry as a whole vary with the attributes of the supported firms and with the nature of the supported industry? To answer this question, this thesis develops a model describing firm dynamics under government support in the form of tax credits and conducts simulation experiments while varying policy scenarios and parameters representing the industry's nature.

The results show that the impact of government support on an industry varies greatly depending on a parameter representing one of the nature of the industry: inertia to the past market share. For industries where the inertia is within a certain degree, there is a particular trend in the impact of government support on an industry, a clear trade-off depending on the target of the support: the support to large firms has the effect of increasing the size of the largest firms but reduces competition and widens the gap between firms, while the support to small and medium-sized firms has the effect of increasing competition and narrowing the gap, but reduces the size of the largest firm in the industry. However, in industries where the inertia is greater than a certain level, the effect of such policies disappears. The inertia dominates the growth dynamics of the firms, and the policy becomes unable to change the state of the industry.

These results highlight the importance of identifying the nature of the industries to be supported when designing industrial policies. They also show that even when targeting the industries that policies can affect, it is difficult to find a single policy scenario that simultaneously improves the state of an industry from all perspectives. Policymakers need to design industrial policies that meet their purposes with an understanding of the benefits and sacrifices that result from different targets of government support.

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Chapter 1

Introduction

In this chapter, we first review trends in industrial policy. Next, the motivation and scope of this research, as well as the choice of research method, are explained. Finally, the structure of this thesis is described.

1.1 Trends in Industrial Policy

What is industrial policy? Warwick [1] offers the following comprehensive definition after reviewing the various definitions of industrial policy in the prior literature.

> "Any type of intervention or government policy that attempts to improve the business environment or to alter the structure of economic activity toward sectors, technologies or tasks that are expected to offer better prospects for economic growth or societal welfare than would occur in the absence of such intervention." (p.47)

In other words, industrial policy, in a broad sense, refers to government intervention aimed at changing the economy for the better, whether through subsidies, tax cuts, regulation, or other policy measures. On the other hand, one definition of industrial policy in a narrower sense is, for example,

> "Government efforts to promote specific industries that policymakers have identified as critical for national security or economic competitiveness." [2, p. 3]

When people use the term industrial policy without any academic context in mind, they may often use it in the latter sense.

Industrial policy is often discussed as a factor in the economic development of Asian countries such as Japan, China, Taiwan, and Korea [3]–[5]. On the other hand, industrial policy has also been the subject of criticism. One of the most common criticisms concerns "targeting." Industrial policy usually involves government targeting, which is focused investment in specific industries deemed important [6]. Traditionally, the criticism has been that governments are likely to waste policy resources because they cannot make the right choices about which firms and industries to support [7], [8]. Another criticism has been that fostering homegrown industries may cause problems with foreign governments because of the potential for increased international competition, which could negatively affect other countries' industries in the short run [9]. The current trade friction between the U.S. and China can be said to fit this very criticism. In the past, Japan's industrial policy was criticized by the U.S., which reportedly led to a reduction of the Japanese government's industrial policy [10].

Nevertheless, attention to industrial policy has increased worldwide in recent years [3], [4], [9], [11]. The following reasons are cited as contributing factors in the literature.

- The financial crisis of 2008-2009 has led to a drive to restore growth by supporting industries that have been particularly adversely affected [1].
- With the growing awareness of the enormous damage caused by future climate change [12], a greater role of the government is expected to achieve a clean economy with virtually zero emissions, especially in terms of innovation [8], [13], given the risk of market failure for green technologies [8] and the limited time left to avoid such damage [14].
- China's economy has actually grown rapidly due to the government's industrial development support, including large-scale investments in advanced technologies, and China

has become a competitive threat to the U.S. and other developed countries [3], [15].

- Concern that trade friction between the U.S. and China will disrupt global supply chains has increased demand for the development of home-grown industries such as semiconductors [9].

- The COVID-19 pandemic has necessitated large-scale government intervention in the economy to secure vaccines, medicines, and other supplies and to provide assistance to adversely affected companies [9], [16].

These recent changes in the situation have not eliminated criticism of industrial policy. However, it is true that governments are now implementing industrial policies [9]. It is also said that many countries have been engaged in some form of industrial policy for some time, whether intentionally or not, and whether they name it industrial policy or not [4].

1.2 Motivation and Research Scope

Given that countries are already engaged in industrial policy, as pointed out in the literature [4], [17], the key question is not whether industrial policy should be implemented, but how to effectively implement industrial policy. In what follows, I use the term "industrial policy" to refer to government support, such as subsidies and tax breaks, for specific industries and firms with specific attributes, to move the discussion toward the substance of this research. Many empirical studies have examined the effects of industrial policy (for literature reviews, see [9], [18]). However, there are several important points that have not been adequately covered in these studies.

The first point is the impact of a policy on an entire industry through interactions among firms. When empirical studies examine the effects of government support, they usually evaluate the impact of the policy on the productivity, growth, etc., of the firms that received the support. However, there are interactions, or competitions, among firms in a market. Therefore, when a firm receives government support, other firms operating in the same market are affected, at least through the competition, and this may cause some changes in the state of the industry, such as the distribution of firm size. Changing the attributes, e.g., size, of the firms that receive government support may also affect the changes that occur in the industry. The second is the heterogeneity of the industries targeted by government support [9]. Government support for different industries may have different effects, even if the support is of the same type. Some industries may benefit more from the policy, while others may not.

These points lead to the following question:

> When a government supports firms in an industry with limited policy resources, how does the state of the industry change? How do the effects of such policies vary with the attributes of the supported firms and with the nature of the supported industry?

The objective of industrial policy is to change an entire industry to a state that is somehow desirable, and which industries to focus government support on is always a matter of debate when making industrial policy. Therefore, answering this question will help policymakers to design industrial policies that meet their objectives. To contribute to answering this question, I use computer simulations to examine the dynamics of firms under government support and its impact on the state of an entire industry.

1.3 Research Method

To perform this simulation, I use agent-based modeling (ABM), a modeling method that generates a large number of agents that make up a population on a computer and allows each agent to evolve over time according to specific rules that simplify real-world dynamics to investigate how the behavior of the population as a whole changes. Other than ABM, statistical models and differential equation models can also be used. However, the purpose of this study is not to examine the average impact of government support on the firms that receive it, but to examine how the state of the industry as a whole changes. For this purpose, I treat each firm as an agent, construct a model that simply approximates the growth process of firms in reality, and conduct simulation experiments using the model.

As a means of government support, I consider tax credits, one of the most typical industrial policy tools. Four policy scenarios are set up according to the attributes of the firms to be supported: no support, support for all firms, support for large firms, and support for small and medium-sized enterprises (SMEs). Under each policy scenario, Monte Carlo simulations are performed by varying probability distribution parameters that represent the nature of an industry, to investigate how the state of the industry changes under each scenario.

1.4 Structure of the Thesis

The structure of this thesis is as follows: Chapter 2 briefly discusses previous studies on firm dynamics and firm size distribution, and then constructs a mathematical model describing the process of firm growth under government support, explaining the components of the model in detail. Chapter 3 describes the policy scenarios and parameter settings used when running simulations with the model constructed in the previous chapter. By running simulations with a parameter setting, we confirm that the model can generate a firm size distribution that is consistent with a basic empirical fact about the firm size distribution and that the firm size distribution changes depending on the policy scenario. In Chapter 4, I conduct comprehensive simulation experiments while varying the parameters of the model. First, I define three industry indicators to evaluate the state of an industry. Next, Monte Carlo simulations are conducted while varying the policy scenarios and the probability distribution parameters for the nature of industries. By showing the time series behaviors of the model, the sensitivity to the probability distribution parameters, and the relations between the industry indicators, I investigate how the industry state changes depending on the policy scenarios and the industry's nature. Chapter 5 summarizes the thesis and describes the policy implications that can be drawn from it. Appendix presents the results of the simulation experiments performed in this research, including those not included in Chapter 4.

Chapter 2

A Model for Firm Dynamics under Government Support

In this chapter, a mathematical model to describe the process of firm growth under government support is developed. First, we review studies on the distribution of firm size and the dynamics that generate it and then show the need to construct a new model. Next, the components of the model developed for this study are described in detail.

2.1 Research on Firm Dynamics and Size Distribution

A lot of studies have been conducted on models of firm size dynamics and the size distributions that these dynamics produce. The most famous early work was done by Gibrat [19], who modeled the growth of firm size under the simple rule that the expected increment in firm size in each period is proportional to the current firm size. This is called Gibrat's law or the law of proportionate effect, which also implies that the growth rate of a firm is independent of its size.

Following Sutton [20], the implications of the Gibrat's model can be derived as follows. Let x_t be the firm size at time t and ϵ_t be the random variable representing the growth rate of the firm,

$$x_t - x_{t-1} = \epsilon_t x_{t-1} \Leftrightarrow x_t = (1 + \epsilon_t) x_{t-1} \quad (2.1)$$

By taking the logarithm of both sides of Equation (2.1) and taking a sufficiently small interval between times t, using the approximation $\ln(1 + \epsilon_t) \sim \epsilon_t$ and the assumption that the term $\ln x_0$ about initial values is sufficiently small compared to $\ln x_t$,

$$\ln x_t \sim \sum_{u=1}^{t} \epsilon_u \quad (2.2)$$

When ϵ_t is an independent random variable with mean and variance in each period, applying the central limit theorem to Equation (2.2), it follows that the distribution of firm size x_t is approximated by a lognormal distribution.

Since Gibrat's work, many studies on the firm size distribution have been accumulated. Although no conclusion has been reached on the exact shape of the distribution, one of the best known empirical facts about it at this point is that the distribution has heavy tails, especially the upper tail, which follows a power law (e.g., see [21], [22]). A lot of models describing the time evolution of firm size that reproduce such distributions have also been proposed, ranging from simple modifications of the Gibrat's model to more complex models (for a literature review on the models, see [21]).

2.2 Model Building

As mentioned in the previous section, a number of models have been proposed to explain the dynamics of firm size. The firm size in this context includes sales, number of employees, assets, and so on, with sales in particular often used. However, these models are mainly concerned with reproducing the empirically confirmed distribution of firm size and growth rate, rather than the relationship between firm size and policy. For this reason, these models usually do not explicitly take into account the link between firm size and other firm financial variables.

Tax credits, which are considered in this study as the government support tool, contribute to an increase in total assets by reducing the tax burden of firms and increasing their net profit. Therefore, it is difficult to evaluate the impact of tax credits on firm growth in a model that does not consider the link via profits between sales and total assets.

For this reason, I build a simple stochastic model with core relationships between financial variables in a firm to be able to account for government support such as tax credits. In the following, I explain the model with particular attention to sales and total assets.

2.2.1 Formulation of Sales

Denote each firm by a subscript i and the number of firms at time t by N_t. First, I denote the sales $S_{i,t}$ of firm i in period t using the total assets $A_{i,t-1}$ of the firm at the end of period $t-1$, which is equal to the total assets held at the beginning of period t.

For simplicity, I begin the discussion by considering a market with no cap on demand. In this case, sales will continue to increase over time. In addition, since firms can supply as many products and services as they wish within their capacity, there is no interaction, i.e., no competition, among firms to obtain the demand. Sales under these assumptions are called potential sales, denoted by $S_{p,i,t}$.

Next, assume that the potential sales $S_{p,i,t}$ in period t is determined only by the firm's total assets $A_{i,t-1}$ held at the beginning of period t. Under this assumption, expressing the capability of firm i to generate sales from one unit of total assets held at the beginning of t, i.e., the efficiency of total assets in generating sales, using a random variable $r_{ea,i,t}$, $S_{p,i,t}$ can be written as follows.

$$S_{p,i,t} = r_{ea,i,t} A_{i,t-1} \tag{2.3}$$

Since $S_{p,i,t}$ is non-negative, $r_{ea,i,t}$ should be a non-negative random variable. Therefore, $r_{ea,i,t}$ is assumed to be a random variable that follows a lognormal distribution, and we denote its mean and variance by μ_{rea} and σ^2_{rea}, respectively.

Equation (2.3) implies that potential sales $S_{p,i,t}$ are determined solely by total assets held by the firm and the non-negative random variable, but in reality, firms' sales depend on their past sales. In particular, consumers have shown that, in many cases, they are more likely to purchase a product when they have previously purchased that product [23]. To reflect the effect of such an inertia, I rewrite Equation (2.3) as follows.

$$S_{p,i,t} = r_{ea,i,t}A_{i,t-1} + r_{in,i,t}S_{p,i,t-1} \tag{2.4}$$

where $r_{in,i,t}$ is a random variable that represents the degree to which potential sales, the capability to generate sales, in period t depends on itself in the previous period $t-1$. As can be seen from the Equation (2.5) shown below, $S_{p,i,t}$ determines the market share of sales that firm i will obtain when firms compete under the demand with cap. Therefore, $r_{in,i,t}$ can be said to represent inertia to past market share and thus takes on non-negative values. Then, $r_{in,i,t}$ is assumed to be a random variable that follows a lognormal distribution, and we denote its mean and variance by μ_{rin} and σ^2_{rin}, respectively.

In Equation (2.4), $S_{p,i,t}$ takes a form similar to the Gibrat model of Equation (2.1) in markets where $r_{ea,i,t}$ is very small and potential sales are determined only by itself in the previous period and stochastic variations. However, even in such a case, this model differs from the Gibrat model in the following two respects: First, $S_{p,i,t}$ and $S_{i,t}$ do not necessarily coincide because competitions among firms are introduced into the model, as described later. Second, the model deals with changes in total assets $A_{i,t}$ as well as sales $S_{i,t}$, and assumes that firms with $A_{i,t} \leq 0$ exit the market at the end of period t. Then, even if we assume a market in which $S_{p,i,t}$ does not depend on total assets and is determined by sales in the previous period and stochastic variations, sales do not necessarily follow a lognormal distribution.

So far, we have considered a market with no cap on demand. However, in the real world, there is a cap, and companies compete to capture the demand. Here, I exogenously set the total demand D_t at time t. Rahmandad [24] presents a model in which, in a market such that total demand is constant, a firm's sales are the smaller of its potential output or its demand allocated in proportion to its own potential output. We follow this idea by using the total demand D_t and potential sales $S_{p,i,t}$ to denote sales $S_{i,t}$ as follows.

$$S_{i,t} = \min\left\{S_{p,i,t}, D_t \frac{S_{p,i,t}}{\sum_{j=1}^{N_t} S_{p,j,t}}\right\} \tag{2.5}$$

Equation (2.5) implies the following: The allocation of demand among firms is determined in proportion to their potential sales. If the potential sales are smaller than the allocated demand, the potential sales become sales, while if the potential sales are larger than the allocated demand, the allocated demand becomes sales. This means that the potential sales determine the market share of sales that the firm will earn.

As shown in Equation (2.4), $S_{p,i,t}$ is expressed using $S_{p,i,t-1}$ and $A_{i,t-1}$. Thus, a firm's sales are determined by the firm's potential sales and total assets in the previous period, the total assets of all firms, the total demand in the market, and firm-independent stochastic variations.

2.2.2 Formulation of Total Assets

Next, express total assets $A_{i,t}$ at the end of the t period using sales $S_{i,t}$.

Let a random variable $r_{Pb,i,t}$ be the pre-tax profit ratio of firm i in period t, profit before taxes $P_{b,i,t}$ is expressed using $S_{i,t}$ and $r_{Pb,i,t}$ as follows.

$$P_{b,i,t} = r_{Pb,i,t} S_{i,t} \tag{2.6}$$

$P_{b,i,t}$, unlike $S_{p,i,t}$, can be negative. Then, $r_{Pb,i,t}$ is assumed to be a random variable that follows a normal distribution with mean μ_{rPb} and variance σ^2_{rPb}.

Deducting corporate income taxes from the profit before taxes yields net profit $P_{i,t}$.

$$P_{i,t} = P_{b,i,t} - T_{i,t} \tag{2.7}$$

Net profit is divided into dividends paid to shareholders and retained earnings retained within the firm. Here, the dividends paid are ignored for simplicity. Let $R_{i,t}$ be the retained earnings at the end of t period, then the change in retained earnings from the end of $t-1$ period to the end of t period, $\Delta R_{i,t}$, is equal to $P_{i,t}$: $\Delta R_{i,t} = R_{i,t} - R_{i,t-1} = P_{i,t}$.

Next, we consider the corporate income tax. Only firms with positive taxable income in a given period pay the corporate income tax. Assuming that profit before taxes $P_{b,i,t}$ equals the taxable income, the corporate income tax $T_{i,t}^{(n)}$ paid by firm i in period t in the normal case without any tax credit is

$$T_{i,t}^{(n)} = \max\left\{\tau P_{b,i,t}, 0\right\} \tag{2.8}$$

where τ is the corporate income tax rate, which is assumed to be constant for all firms over the entire period.

Next, consider the case where the government provides financial support to firms through tax credits. Let $T_{c,i,t}$ be the amount of tax credits applicable to firm i in period t. Assuming that the portion of $T_{c,i,t}$ that cannot be fully deducted from the corporate income tax before tax credits cannot be carried forward to the next period or later, the corporate income tax after applying tax credits $T_{i,t}$ is

$$T_{i,t} = \max\left\{\tau P_{b,i,t} - T_{c,i,t}, 0\right\} \tag{2.9}$$

As can be seen from this equation, only firms that generated positive profit before taxes can take advantage of tax credits, and of these, only firms that generated profit before taxes of $T_{c,i,t}/\tau$ or more can fully utilize the amount of the applicable tax credits. Thus, the tax credits applied to firm i in period t are as follows: $T_{c,i,t}^{(a)} = T_{i,t}^{(n)} - T_{i,t}$.

Assuming that the firm does not raise additional financings, such as debt or equity financing, total assets at the end of the current period are the sum of total assets at the end of the previous period and the change in retained earnings. As already mentioned, since

$\Delta R_{i,t} = R_{i,t} - R_{i,t-1} = P_{i,t}$, the total assets at the end of t period are as follows.

$$\begin{aligned} A_{i,t} &= A_{i,t-1} + \Delta R_{i,t} \\ &= A_{i,t-1} + P_{b,i,t} - T_{i,t} \\ &= A_{i,t-1} + P_{b,i,t} - \max\left\{\tau P_{b,i,t} - T_{c,i,t}, 0\right\} \end{aligned} \tag{2.10}$$

As shown in Equation (2.6), $P_{b,i,t}$ is expressed using $S_{i,t}$. Thus, a firm's total assets at the end of the period are determined by its total assets at the end of the previous period, its sales in the current period, government support through tax credits, and firm-independent stochastic variations.

The total assets represented by Equation (2.10) can become negative depending on the value of $r_{Pb,i,t}$. For this reason, we assume that firms with $A_{i,t} \leq 0$ exit the market at the end of period t. Note that since sales $S_{i,t}$ are non-negative, it is irrelevant to the exit condition.

2.2.3 Assumptions on Demand Growth

As already mentioned, the total demand D_t is given exogenously in this model, so it is necessary to model changes in D_t. It has been empirically confirmed that the growth of demand for various new products can be described by a logistic curve [25]. Then, D_t is assumed to grow according to a logistic curve.

There are several ways to determine what to treat as parameters in the logistic curve. Here, D_t is expressed as follows, using three parameters: the ceiling of the demand D_c, the time when the demand reaches half of its ceiling t_m, and the time interval between the times when 10% and 90% of the ceiling are reached [26], [27].

$$D_t = \frac{D_c}{1 + \exp\left(-ln(81)\dfrac{t - t_m}{\Delta t_{10,90}}\right)} \tag{2.11}$$

From Equation (2.11), the initial demand D_0 is automatically determined by setting the three parameters D_c, t_m, and $\Delta t_{10,90}$.

$$D_0 = \frac{D_c}{1 + \exp\left(ln(81)\frac{t_m}{\Delta t_{10,90}}\right)} \tag{2.12}$$

In this model, the total demand and total sales of all firms do not necessarily coincide at the beginning of the market launch. At some point, sales will catch up with the total demand, and thereafter, the two will coincide.

Chapter 3

Simulation Settings and Basic Model Behaviors

This chapter describes the policy scenarios and parameter settings used when running simulations with the model constructed in the previous chapter. Next, simulations are run under a parameter setting to demonstrate the size distribution generated by the model. This confirms that the model can generate a distribution consistent with a basic empirical fact about the firm size distribution, and that the size distribution changes depending on the policy scenario.

3.1 Policy Scenarios on Tax Credits

In this section, we consider setting policy scenarios for tax credits. Assuming that the government grants tax credits to firms in period t up to corporate income tax revenue $\sum_{i=1}^{N_{t-1}} T_{i,t-1}$ in period $t-1$, the following four policy scenarios are set.

- TcType = 0: No support
- TcType = 1: Support for all firms
- TcType = 2: Support for large firms

- TcType = 3: Support for SMEs

where TcType is a parameter that distinguishes between policy scenarios.

In this study, we consider all firms to fall into two categories: large firms and SMEs. If the government is to implement support for either large firms or SMEs, it needs to identify whether each firm is a large firm or an SME. Then, we set the percentile rank (PR), which is the criterion for large firms in the distribution of firm sales, as Large_{PR}, and the government considers firms with a PR of Large_{PR} or higher as large firms and all other firms as SMEs.

Putting these settings together, the flow of the government support is as follows: First, at the beginning of period t, the government classifies all firms as either large firms or SMEs based on the PR of each firm in the distribution of sales $S_{i,t-1}$ in period $t-1$. Firm i is allowed to deduct an amount up to $T_{c,i,t}$ from its corporate income tax calculated without considering the tax credits.

However, as discussed in the previous chapter, only firms that generate positive profit before taxes are eligible to take advantage of the tax credits. Of those firms, only firms that generated profit before taxes of $T_{c,i,t}/\tau$ or more can take advantage of the full amount of applicable tax credits. Therefore, considering the tax credits actually applied to firm i in period t, $T^{(a)}_{c,i,t}$, the total amount of $T^{(a)}_{c,i,t}$ is always less than or equal to the corporate income tax revenue in period $t-1$: $\sum_{i=1}^{N_t} T^{(a)}_{c,i,t} \leq \sum_{i=1}^{N_{t-1}} T_{i,t-1}$.

3.2 Parameter Settings

This section describes how to set parameters to run simulations using the model constructed in the previous chapter.

3.2.1 Probability Distribution Parameters for Industry Nature

The model includes three random variables, $r_{ea,i,t} \geq 0$, $r_{in,i,t} \geq 0$, and $r_{Pb,i,t}$, that are independent of the state of the firm. The first two of these random variables follow a lognormal distribution and the last one a normal distribution. Thus, the model has the following six probability distribution parameters: μ_{rea}, σ_{rea}, μ_{rin}, σ_{rin}, μ_{rPb}, and σ_{rPb}.

The values of these parameters can be viewed as representing the nature of the industry described by the model. For example, a model with a large value of μ_{rea} corresponds to an industry where a firm's capability to generate sales heavily depends on the size of its assets. A model with a large μ_{rin} corresponds to an industry with large inertia in which a firm's market share strongly depends on its past market share. A model with a large μ_{rPb} corresponds to an industry with high profitability.

First, we consider the three probability distribution parameters that represent the mean values: μ_{rea}, μ_{rin}, and μ_{rPb}. The $r_{ea,i,t}$ represents the dependence of potential sales on total assets. However, total assets $A_{i,t}$ is actually a concept similar to net assets since the model assumes that firms do not raise additional financings, such as debt or equity financing, as explained in the model building process. For this reason, we set the lower and upper bounds of μ_{rea} to 1 and 5.5, respectively, considering the range that the net asset turnover ratio can normally take. The $r_{in,i,t}$ denotes the dependence of the current period's potential sales on itself in the previous period, i.e., inertia. Therefore, the lower bound of μ_{rin} can be considered to be 0, while too large values of μ_{rin} are unrealistic settings. Here, the upper limit of μ_{rin} is set to 1.2. The $r_{Pb,i,t}$ represents the profitability of a business. Since an industry with μ_{rPb} lower than 0 is not considered sustainable, the lower limit of μ_{rPb} is set to 0. The upper bound of μ_{rPb} is set to 0.6, taking into account the fact that some industries have very high profitability. In summary, the ranges of these three probability distribution parameters are set as follows.

$$1 \leq \mu_{rea} \leq 5.5, \quad 0 \leq \mu_{rin} \leq 1.2, \quad 0 \leq \mu_{rPb} \leq 0.6 \tag{3.1}$$

In the next chapter, we examine how the effect of government support on an industry varies with the nature of the industry by performing a sensitivity analysis for different values of these three probability distribution parameters.

Next, we consider the three probability distribution parameters that represent the standard deviation: σ_{rea}, σ_{rin}, and σ_{rPb}. To perform a sensitivity analysis, the number of the probability distribution parameters included in the model should be reduced as much as possible. For this reason, we assume that the magnitude of variation of the three random variables $r_{ea,i,t}$, $r_{in,i,t}$ and $r_{Pb,i,t}$ is proportional to their mean values, and that their coefficient of variation CV_r is equal for these three. Under this assumption, σ_{rea}, σ_{rin} and σ_{rPb} are as follows.

$$\sigma_{rea} = CV_r \mu_{rea}, \quad \sigma_{rin} = CV_r \mu_{rin}, \quad \sigma_{rPb} = CV_r \mu_{rPb} \tag{3.2}$$

In subsequent simulations, we set $CV_r = 0.5$.

3.2.2 Parameters in Logistic Curve of Demand

To characterize the logistic curve of D_t shown in Equation (2.11), three parameters D_c, t_m, and $\Delta t_{10,90}$ should be set. Here, we set $t_m = 100$ and $\Delta t_{10,90} = 200$ so that $\Delta t_{10,90} = 2t_m$. This means that $D_0 = D_c/10$ and $D_{4t_m} = 729D_c/730 \sim 0.999D_c$ always holds, and t_0 and t_{4t_m} represent the times when the demand is 10% and 99.9% of its ceiling D_c, respectively.

Another parameter D_c, which also characterizes D_t, is set to a rounded value to match the initial number of firms N_0 set in the simulation. Setting $N_0 = 500$, as described later, we set the initial demand to $D_c = 5000$. This gives $D_0 = 500$ under $\Delta t_{10,90} = 2t_m$ and an initial demand of 1 per firm.

3.2.3 Policy-related Parameters

A parameter related to government support is the criterion Large_{PR} of PR to distinguish between large firms and SMEs. Regardless of the country or region, there are far fewer large firms than SMEs. Then, we set Large_{PR} so that 10% of all firms are large firms and the remaining 90% are SMEs.

$$\text{Large}_{PR} = 90 \tag{3.3}$$

The parameters other than Large_{PR} related to the government support are the time at which the support begins and the time at which the simulation ends, i.e., the time at which the effect of the support is observed.

We first consider the start time of the government support. As already mentioned, in the next chapter, we will perform a sensitivity analysis by varying three parameters that represent the nature of the industry. The impact of the support on industries needs to be fairly compared across different industries, but if there is a large difference in the industry size, or total sales of all firms, across industries at the start of the support, then it may not be possible to make a fair comparison. In this model, since demand D_t grows exogenously logistically, the size of an industry matches demand once the total sales of all firms in the industry catch up with the demand. In an industry where its growth is fast and catches up to the demand ceiling early, each firm's growth prospects by the end of the simulation will be small, while in an industry where its growth is slow and there is a large gap to the demand ceiling, each firm's growth prospects will be large. To provide government support under the condition that the industry size is the same across all industries at each time, it is necessary to set the start time of the support to a time after the size of each industry has caught up with demand. One of the times that satisfies this condition under our parameter settings, $t = 101$, is set as the start time of the government support. This is the period following t_m when demand reaches 50% of its ceiling.

Another parameter, the end time of the simulation, is set to $t = 4t_m = 400$ to allow the policy to run long enough to see its effects. This is the period when the demand reaches 99.9% of its ceiling.

3.2.4 Initial Total Assets

The initial value of total assets, A_0, is given by using the initial value of demand, D_0, as follows.

$$A_0 = \frac{D_0}{N_0 \mu_{rea}} \tag{3.4}$$

This means the assumption that, given the initial demand D_0 at $t = 0$, N_0 firms are established at the end of period $t = 0$ with total assets $A_0 = D_0/(N_0\mu_{rea})$ necessary to meet average demand per firm D_0/N_0 in the following period $t = 1$, respectively, and start businesses from period $t = 1$, that is, start generating sales.

3.2.5 Other Settings

The initial number of firms is set to $N_0 = 500$, and the corporate income tax rate is set to $\tau = 0.3 = 30\%$. Since all firms are assumed to be established at the end of period $t = 0$ and to start businesses in period $t = 1$, the initial values of potential sales and sales are set to 0: $S_{p,i,t} = 0$ and $S_{i,t} = 0$.

3.3 Firm Size Distribution Generated by the Model

Under the simulation settings defined so far, we can run the simulation to check the firm size distribution generated by the model. Here, the three probability distribution parameters μ_{rea}, μ_{rin}, and μ_{rPb} are set to the median value in the range of each parameter indicated by Equation (3.1): $\mu_{rea} = 3.25$, $\mu_{rin} = 0.6$, and $\mu_{rPb} = 0.3$. As described in the parameter settings, we first run the simulation without policy up to $t = 100$. Then, from $t = 101$ to $t = 400$, simulations are run under each policy scenario of TcType = 0, 1, 2, and 3.

Figure 3.1 shows the distributions of firms' sales $S_{i,t}$ and total assets $A_{i,t}$ at $t = 400$ obtained from simulations under the four policy scenarios. These distributions are shown in the form of probability density function (PDF) and complementary cumulative distribution function (CCDF). The CCDF is defined as the probability $P(X \geq x)$ that a random variable X takes on a value greater than or equal to x. Each plot shows the results of fitting the data to a power law using the method developed by Clauset et al. [28], [29]. Both the PDF and the CCDF following the power law are straight lines when plotted in both logarithms. Looking at each plot, some plots deviate from the power law at the edges of the distribution, but the upper tails of both the sales and total assets distributions appear to generally follow the straight line of the power law. Since each plot is generated from a single simulation using the stochastic model, these distributions change each time the simulation is run. Therefore, we will not always get distributions that have the same shapes as these. However, this figure shows that under a certain parameter setting, the model can reproduce a basic empirical fact about firm size distribution described in the previous section.

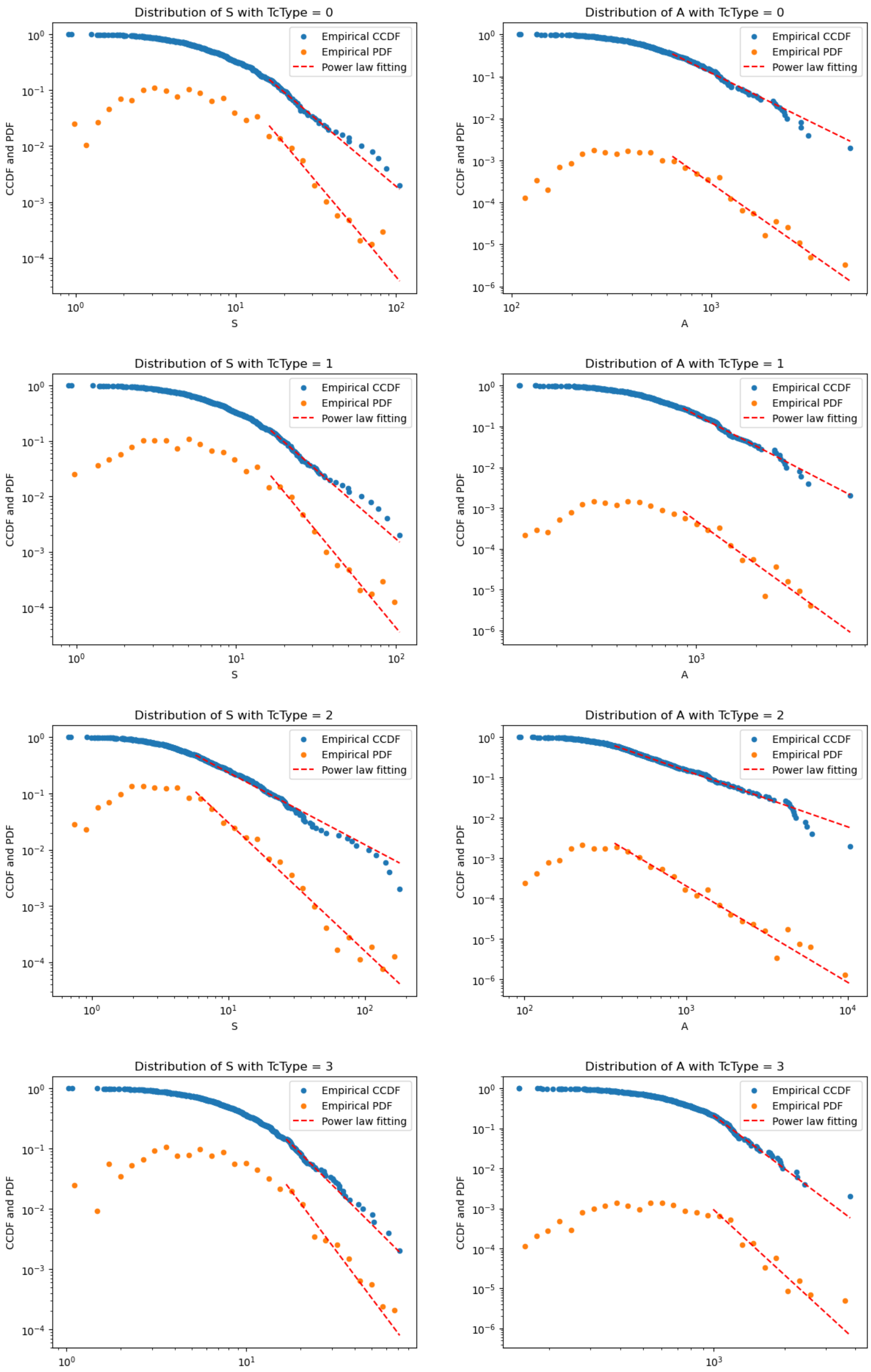

Figure 3.1: PDFs and CCDFs of sales $S_{i,t}$ and total assets $A_{i,t}$ at $t = 400$ obtained by running simulations under four policy scenarios of TcType = 0, 1, 2, and 3, respectively, setting $\mu_{rea} = 3.25$, $\mu_{rin} = 0.6$, and $\mu_{rPb} = 0.3$. The dotted lines indicate power law fitting. x and y axes are both on logarithmic scales.

Figure 3.2 compares the plots under the different policy scenarios shown in Figure 3.1 with one plot for sales and total assets, respectively. The common feature of the plots of sales and total assets is that the distribution is wider both upward and downward under the support for large firms (TcType = 2), while it is narrower both upward and downward under the support for SMEs (TcType = 3). Under all firm support (TcType = 1), the distribution of total assets shifts upward compared to the no support case (TcType = 0), but the distribution of sales changes little. These results may suggest the following. Under the support for large firms, larger and smaller firms arise, widening the gap between firms. Under the support for SMEs, the number of very large and very small firms decreases, while the number of small firms increases. Under the support for all firms, total assets increase, but sales do not change a lot. This difference in the distributions of total assets and sales may be partly due to the assumed demand ceiling under this model.

In this section, we saw how the distribution of firm sizes generated by the model changes by varying the policy scenarios. Since the model's behavior is stochastic, we cannot draw conclusions from this single simulation, but these results are useful for building intuition about the behavior of the model. In the Monte Carlo simulations presented in the next chapter, 10 simulations are run, each with one parameter setting, and conclusions are drawn from these results.

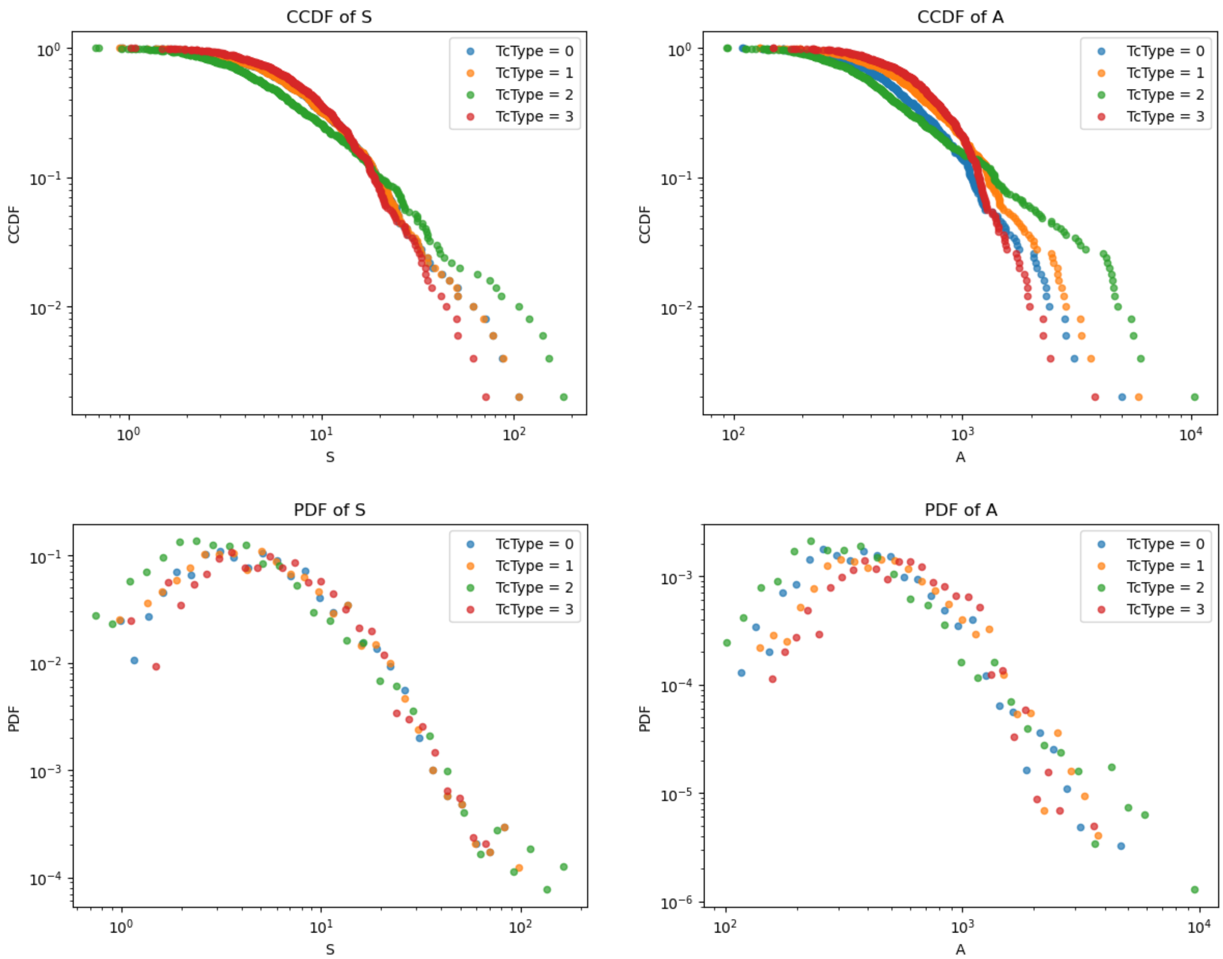

Figure 3.2: PDFs and CCDFs of sales $S_{i,t}$ and total assets $A_{i,t}$ at $t = 400$ obtained by running simulations under four policy scenarios of TcType = 0, 1, 2, and 3, respectively, setting $\mu_{rea} = 3.25$, $\mu_{rin} = 0.6$, and $\mu_{rPb} = 0.3$. x and y axes are both on logarithmic scales.

Chapter 4

Comprehensive Simulation Experiments

In this chapter, we conduct comprehensive simulation experiments by varying the parameters of the model. First, three industry indicators are defined to evaluate the state of an industry. Next, Monte Carlo simulations are conducted while varying the policy scenarios and the probability distribution parameters for industry nature. Based on the simulations, we investigate how the industry state changes depending on the policy scenarios and the nature of the industry by showing the time-series behaviors of the model, the sensitivities to the probability distribution parameters, and the relations between the multiple industry indicators.

The main findings gained from the simulations are summarized as follows.

- The impact of government support through tax credits on an industry varies significantly depending on one of the nature of the industry, the magnitude of inertia to the past market share, represented by the parameter μ_{rin}.

- When the inertia is within a certain degree, the effect of government support on an industry is clear. Large firm support has the effect of significantly increasing the largest firm size in sales. This effect is large for industries with large values of parameters μ_{rea} and μ_{rPb}, i.e., industries with a large dependence of the capability to generate sales on assets and large profitability, while it weakens competition and widens the gap between firms. On the other hand, SME support increases competition and decreases the gap and the largest firm size in the industry. Support for all firms has little effect on such a state of an industry.

- However, as the inertia increases and μ_{rin} reaches around 1, the effect of such a policy disappears. In an industry with strong inertia, such as with $\mu_{rin} \geq 1$, this inertia dominates the growth dynamics of the firms. Some firms grow rapidly, where the largest firm size and the gap become so large, and competition becomes so weak. The policy cannot affect the state of such an industry.

4.1 Industry Indicators

The purpose of this study is not to examine changes in individual firms that directly received government support, but to assess changes that occur in an industry as a whole as a result of those changes and interactions among firms. For this reason, we need industry indicators to assess the state of an industry to interpret the simulation results. Here, we adopt three industry indicators that can reflect changes in the distribution of firm size under different policy scenarios: the largest firm size in sales, the Herfindahl-Hirschman Index (HHI), and the Gini coefficient.

The largest firm size in sales is the sales of the firm with the largest sales in an industry. We refer to this simply as the largest firm size.

The HHI is a widely used measure of market concentration [30]. Market concentration is used to assess the degree of competition in an industry. When market concentration is low, competition is intense, and market power is limited. On the other hand, when market concentration is high, competition is loose, and a few firms have high market power [31]. The HHI is defined by the sum of the squares of the market shares of each firm competing in a given market. It takes a maximum value of 1 when one firm dominates the market and approaches a minimum value of 0 when there are many small firms in the market.

The Gini coefficient is a measure of inequality in a population. It is usually used to measure income inequality, but can also be used to measure inequality in various distributions [32]. Here, it is used as a measure of the gap among firms in terms of sales and market share in an industry. The Gini coefficient is defined as follows using all differences between possible pairs of n observed values x_i, but can be computed faster in practice by sorting x_i and transforming Equation (4.1) [33].

$$G = \frac{\sum_{i=1}^{n} \sum_{j=1}^{n} \left| x_i - x_j \right|}{2n^2 \bar{x}} \tag{4.1}$$

The Gini coefficient takes a minimum value of 0 when all firms have equal sales and market shares, and approaches a maximum value of 1 as the gap among firms increases.

By using these three industry indicators, we can assess the effect of a policy on an industry from different perspectives: the creation of large firms, the degree of competition, and the gap among firms. The three industry indicators can be thought of as objective functions in multi-objective optimization: minimizing the HHI and Gini coefficient while maximizing the largest firm size would be ideal. In reality, however, there are trade-offs between these multiple objective functions, and such an ideal state is often not feasible. By simultaneously assessing changes in multiple industry indicators, we could understand the trade-offs that a policy may have on an industry and select Pareto-optimal policies that are tailored to its purpose and the nature of the industry. In the following, we denote these three industry indicators — the largest firm size, the HHI, and the Gini coefficient — by $\max S$, hhi, and $gini$, respectively.

4.2 Simulation Experiments

In this section, we present the results of comprehensive Monte Carlo simulation experiments in which we vary the parameter TcType, which represents the type of policy scenario, and three probability distribution parameters, μ_{rea}, μ_{rin}, and μ_{rPb}, which represent industry nature. 10

simulations were run for a particular parameter setting. As mentioned in the previous chapter, in each simulation the model was allowed to evolve in time without policy from $t = 0$ to 100, and from $t = 101$ to 400 the simulation was continued under the respective policy scenario with TcType = 0, 1, 2, and 3. The results of the simulation experiments are presented by plotting the three industry indicators, $\max S$, hhi, and $gini$, either as they are or averaged over 10 simulations under the same parameter settings. The figures shown below are selected plots that are necessary to interpret the results of the simulation experiments. The results of the more extensive simulations performed in this study are presented in the Appendix.

4.2.1 Time-series Behaviors

First, we examine the change in the industry indicators over time from $t = 0$ to 400.

Figures 4.1, 4.2, and 4.3 plot the time series of $\max S$, hhi, and $gini$ for each of the four policy scenarios when μ_{rin} is fixed at 0.6.

We first focus on the time series of $\max S$. One thing that can be seen from Figure 4.1 is that large firm support (TcType = 2) has the effect of increasing $\max S$ significantly for all parameter settings shown in this figure. This effect is larger for parameter settings where μ_{rea} and μ_{rPb} have large values. This means that the effect of supporting large firms on the creation of very large firms is larger in industries where the dependence of the capability to generate sales on total assets and the profitability are high.

This result can be interpreted as follows. In this model, the government sets an amount of tax credits applicable to a qualifying firm in proportion to their sales. However, since the amount of tax credits actually applied is limited to profit before taxes multiplied by the corporate income tax rate, firms in industries with low profitability may utilize only a small portion of the applicable tax credits. On the other hand, industries with high profitability could apply much of the amount allocated to them, allowing firms to enjoy greater benefits from the government support. In addition, the financial support provided to firms through tax credits increases their total assets through higher profit after taxes. Therefore, in industries where total assets have a large impact on sales and market share, the effect of the large firm support on sales growth is large.

Turning to the time series of SME support (TcType = 3) in Figure 4.1, $\max S$ is reduced for all parameter settings shown in this figure, contrary to the case of the large firm support. All firm support (TcType = 1) makes little difference compared to the no support case.

We next focus on the time series of *hhi* and *gini*. Comparing Figures 4.2 and 4.3, we find that the effects of each policy scenario are almost the same for *hhi* and *gini*. The large firm support increases *hhi* and *gini* significantly, while the SME support has the effect of decreasing both indicators. This is because under the large firm support, the growth of large firms accelerates and the market share of other firms decreases, which weakens competition and widens the gap between firms, while the SME support has the opposite effect to this by supporting the growth of SMEs. The all firm support makes little difference compared to the no support case, as in the case of $\max S$.

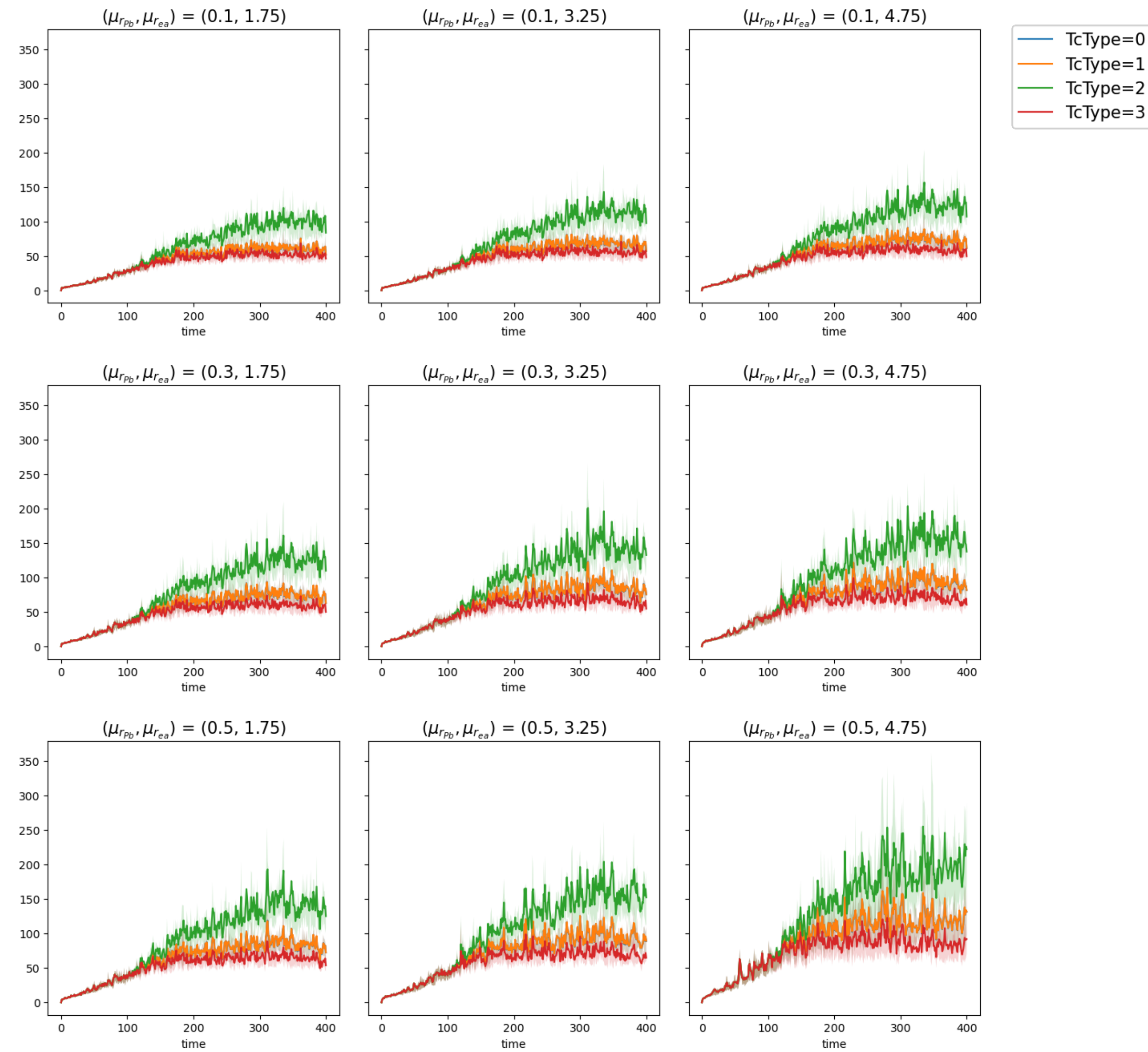

Figure 4.1: Time series of max S from $t = 0$ to 400 with $\mu_{rin} = 0.6$. The curve and the upper and lower bound of the shaded region in each plot are the mean and the 25th and 75th percentiles of the data from 10 simulations for each parameter setting, respectively. The color of each curve and shaded region is set according to the policy scenario, TcType.

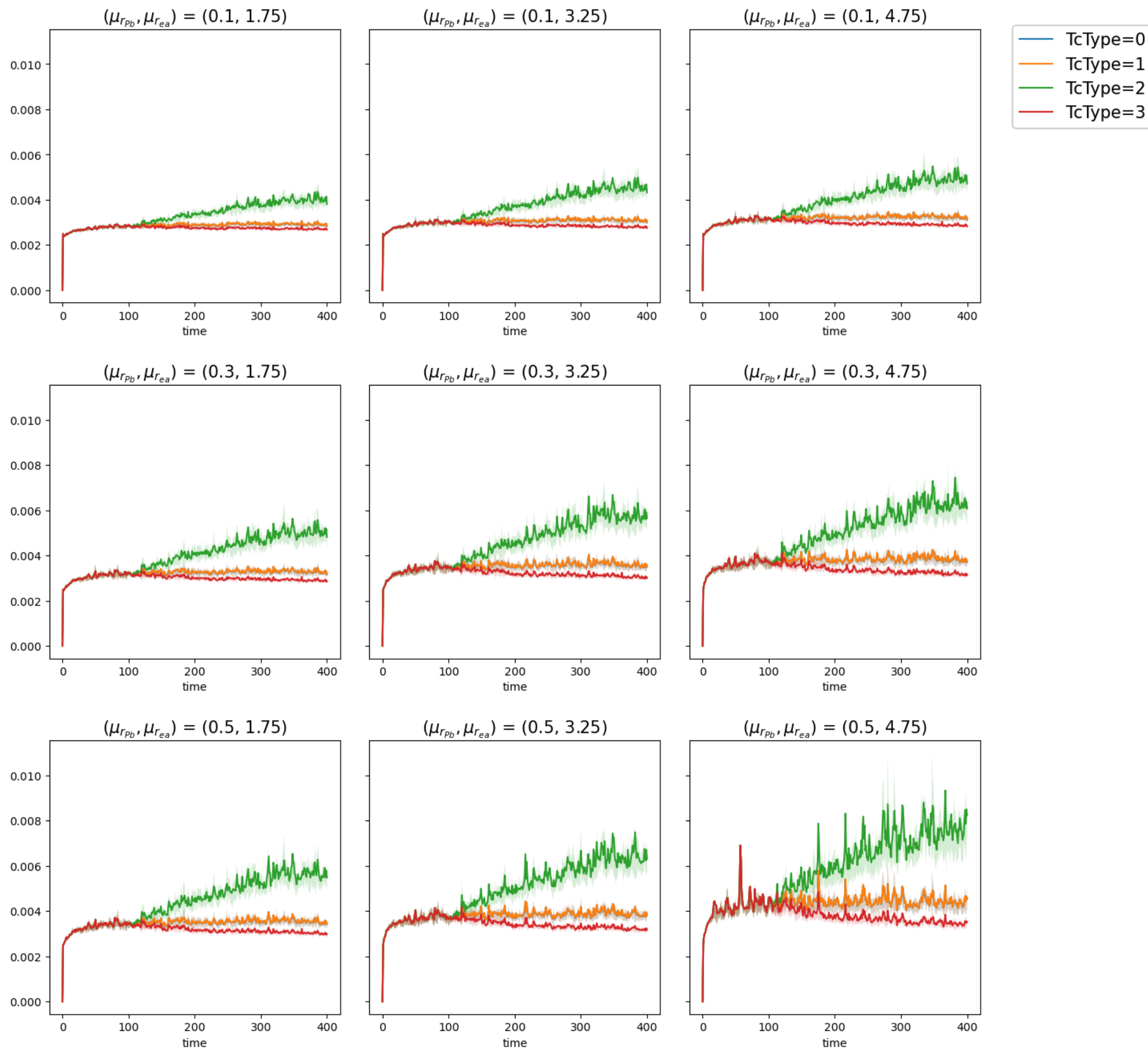

Figure 4.2: Time series of *hhi* from $t = 0$ to 400 with $\mu_{rin} = 0.6$. The curve and the upper and lower bound of the shaded region in each plot are the mean and the 25th and 75th percentiles of the data from 10 simulations for each parameter setting, respectively. The color of each curve and shaded region is set according to the policy scenario, TcType.

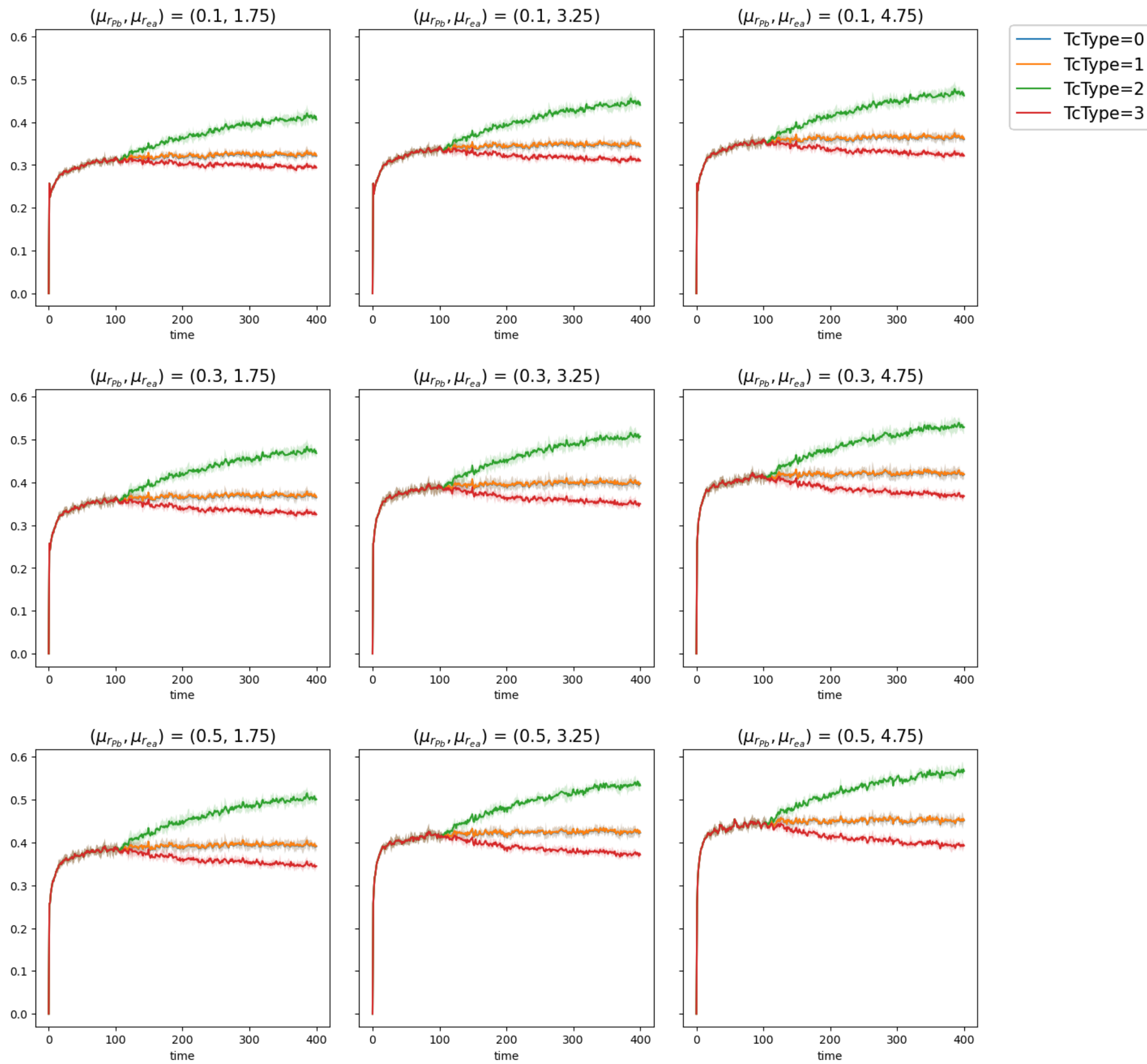

Figure 4.3: Time series of *gini* from $t = 0$ to 400 with $\mu_{rin} = 0.6$. The curve and the upper and lower bound of the shaded region in each plot are the mean and the 25th and 75th percentiles of the data from 10 simulations for each parameter setting, respectively. The color of each curve and shaded region is set according to the policy scenario, TcType.

Next, we increase the value of μ_{rin} and plot the time series of industry indicators for the cases with $\mu_{rin} = 1.0$ in Figures 4.4, 4.5, and 4.6. These figures show completely different results from the cases with $\mu_{rin} = 0.6$.

First, all of these figures have in common that changing the policy scenario has almost no effect on any of the three industry indicators. In addition, if we look at the y-axis scales of

Figures 4.4, 4.5, and 4.6, the three industry indicators are much larger than those of Figures 4.1, 4.2, and 4.3, and *gini* converges to 1 with time. As discussed in the previous chapter, μ_{rin} represents the effect of inertia in that the current period's market share and capability to generate sales depend on those in the previous period. The dynamics of firm growth and industry change are expected to be significantly different in industries with large inertia and those with not so large inertia.

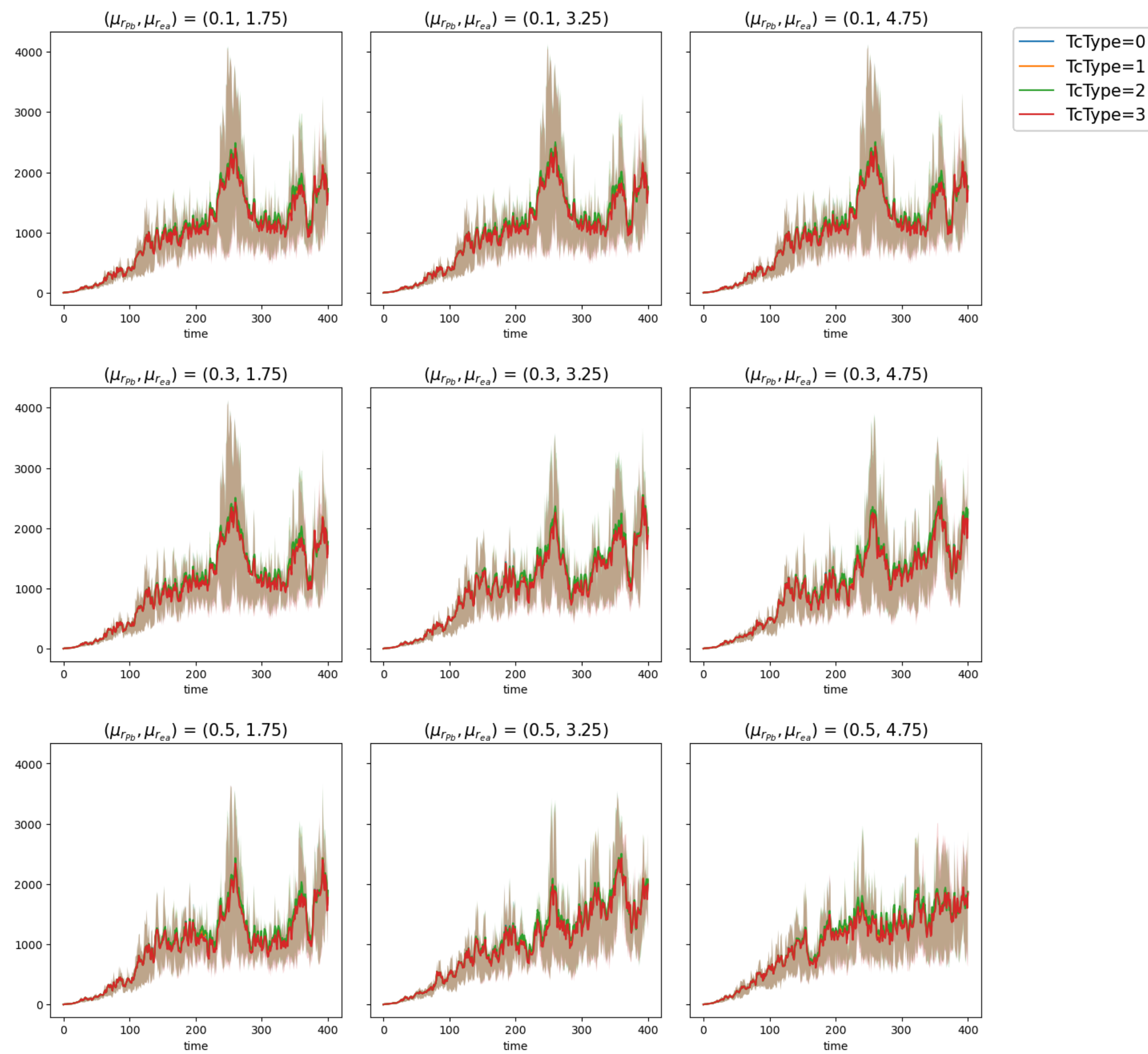

Figure 4.4: Time series of max S from $t = 0$ to 400 with $\mu_{rin} = 1.0$. The curve and the upper and lower bound of the shaded region in each plot is the mean and the 25th and 75th percentiles of the data from 10 simulations for each parameter setting, respectively. The color of each curve and shaded region is set according to the policy scenario, TcType.

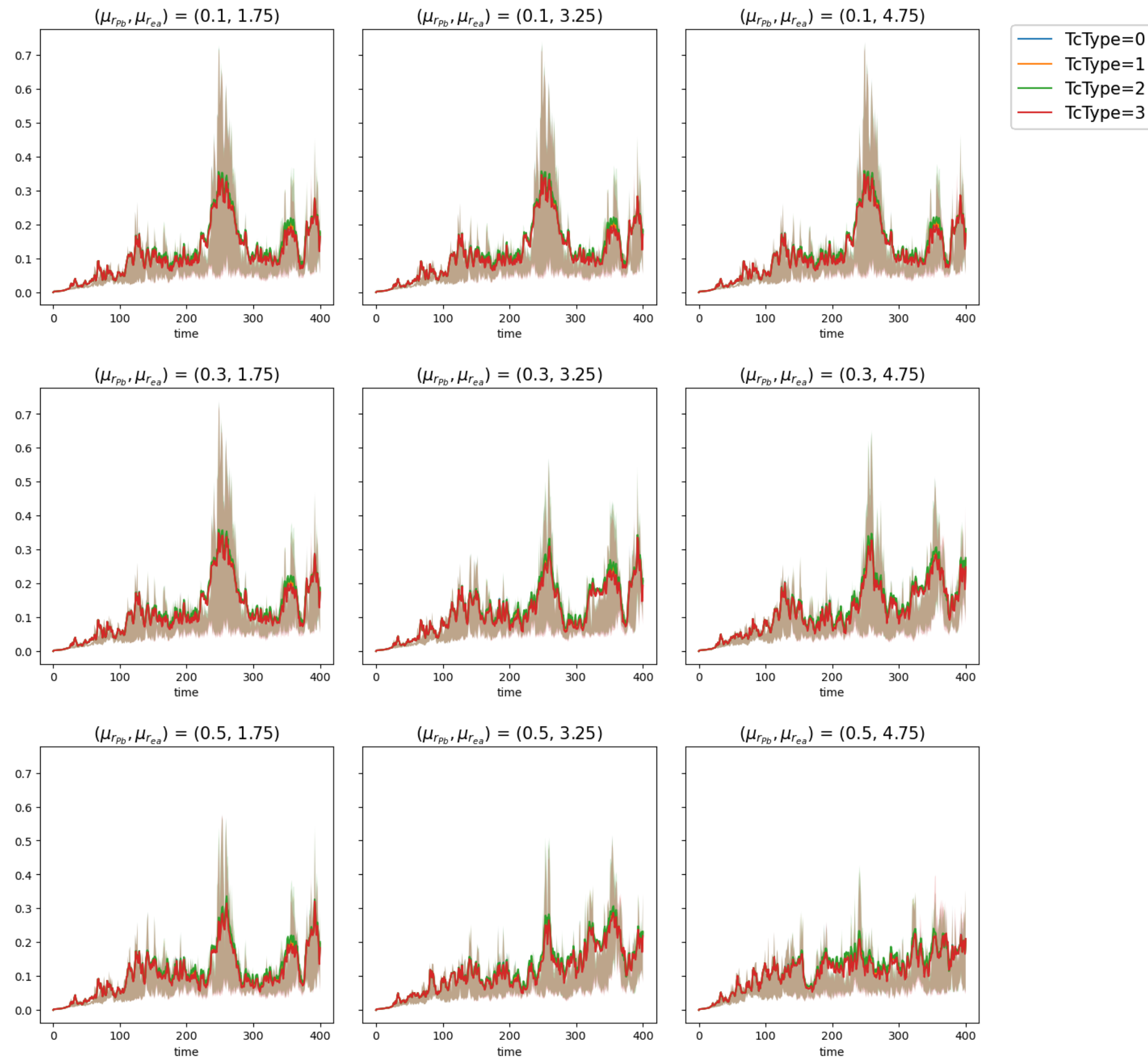

Figure 4.5: Time series of hhi from $t = 0$ to 400 with $\mu_{rin} = 1.0$. The curve and the upper and lower bound of the shaded region in each plot is the mean and the 25th and 75th percentiles of the data from 10 simulations for each parameter setting, respectively. The color of each curve and shaded region is set according to the policy scenario, TcType.

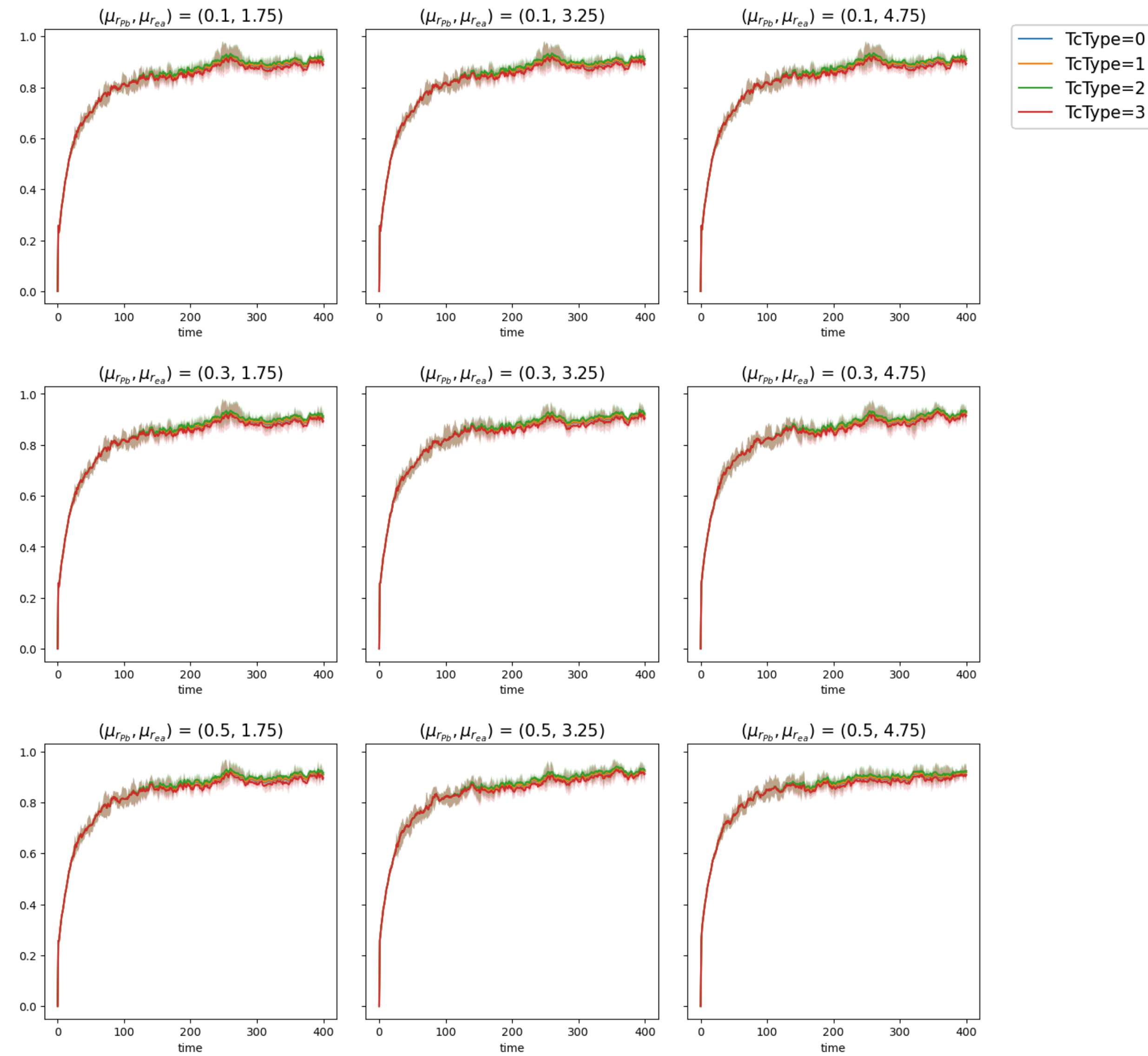

Figure 4.6: Time series of *gini* from $t = 0$ to 400 with $\mu_{rin} = 1.0$. The curve and the upper and lower bound of the shaded region in each plot is the mean and the 25th and 75th percentiles of the data from 10 simulations for each parameter setting, respectively. The color of each curve and shaded region is set according to the policy scenario, TcType.

4.2.2 Sensitivity to Probability Distribution Parameters

To examine the dependence of the industry indicators on the probability distribution parameters presented in the previous section in more detail, sensitivity analyses were performed.

Figures 4.7, 4.8, and 4.9 show the sensitivity of the industry indicators at $t = 400$ to one probability distribution parameter under each policy scenario. Since each data point corresponds to one simulation, this figure gives the change in the distribution of each industry indicator when the policy scenario and each probability distribution parameter are varied.

First, we focus on the plots of sensitivity to μ_{rea} and μ_{rPb}. The distributions of the industry indicators in these plots are all multimodal with multiple peaks. Focusing only on the collections of data points containing the lowest peaks in each plot, they suggest the same implications as those presented in the previous section for the case $\mu_{rin} = 0.6$. Large firm support has the effect of increasing $\max S$, and the magnitude of the increase is large for larger μ_{rea} and μ_{rPb}, while SME support decreases $\max S$. *hhi* and *gini* increase with large firm support and decrease with SME support. All firm support has little effect on any of the industry indicators.

On the other hand, focusing on the collections of data points containing the top peaks in each plot of sensitivity to μ_{rea} and μ_{rPb}, we cannot confirm the change in the industry indicators due to the policy scenario. Turning to the plots of sensitivity to μ_{rin}, we see that the industry indicators increase rapidly as μ_{rin} approaches 1 in every plot.

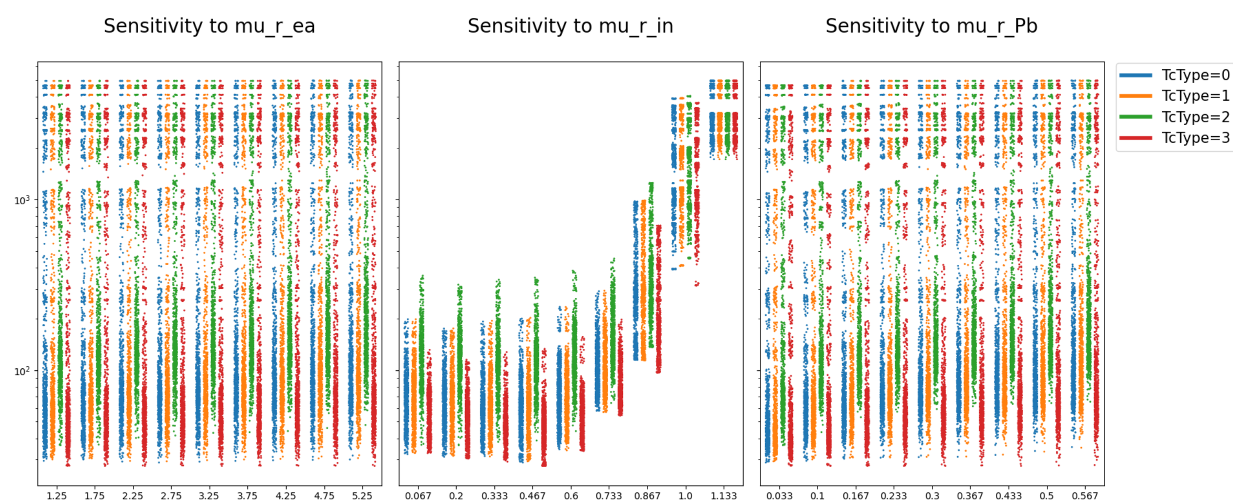

Figure 4.7: Sensitivity of $\max S$ to one of μ_{rea}, μ_{rin}, and μ_{rPb} at $t = 400$. 10 simulations have been performed under one parameter setting, and one data point corresponds to one simulation. The color of each data point is set according to the policy scenario, TcType.

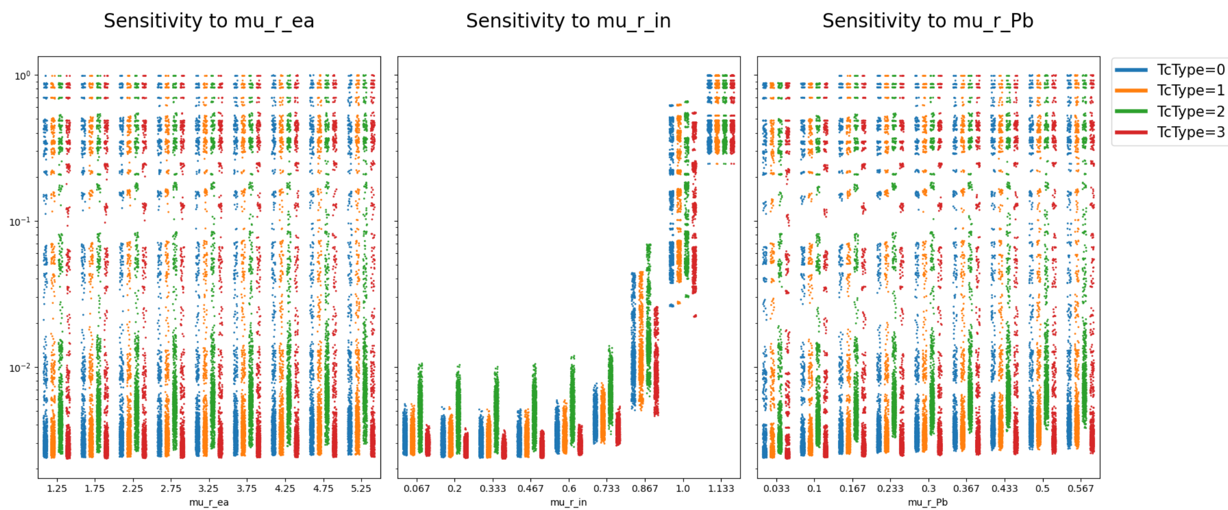

Figure 4.8: Sensitivity of hhi to one of μ_{rea}, μ_{rin}, and μ_{rPb} at $t = 400$. 10 simulations have been performed under one parameter setting, and one data point corresponds to one simulation. The color of each data point is set according to the policy scenario, TcType.

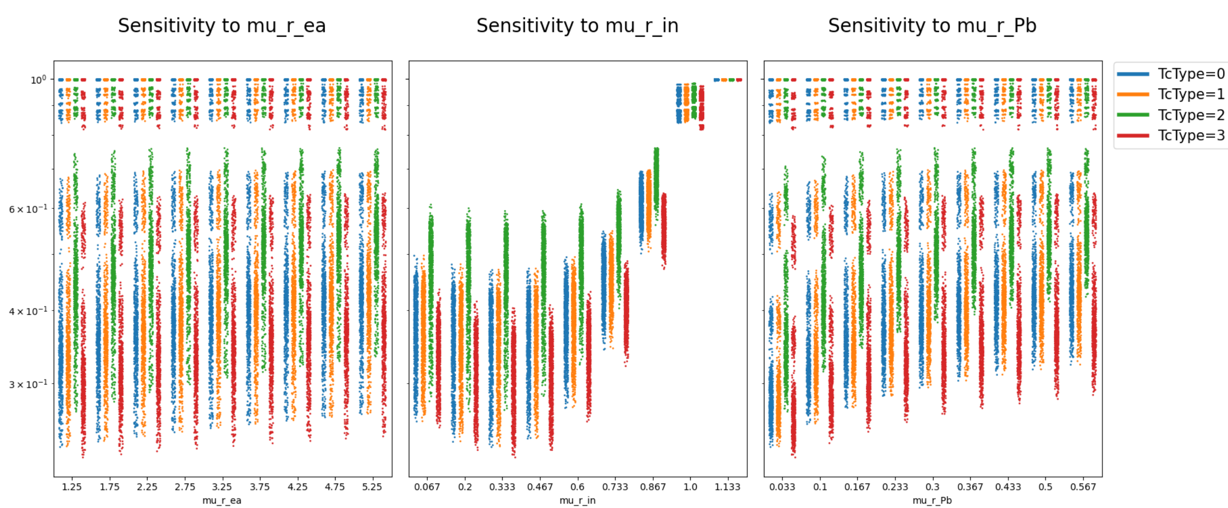

Figure 4.9: Sensitivity of $gini$ to one of μ_{rea}, μ_{rin}, and μ_{rPb} at $t = 400$. 10 simulations have been performed under one parameter setting, and one data point corresponds to one simulation. The color of each data point is set according to the policy scenario, TcType.

The reasons for these results are confirmed by the plots of the sensitivity of the industry indicators to the three probability distribution parameters shown in Figures 4.10, 4.11, and 4.12. In these figures, two-dimensional plots with μ_{rPb} and μ_{rea} on the x- and y-axes are arranged from top to bottom, with μ_{rin} changing from small to large values. The values of μ_{rin} are set to 0.067, 0.733, 0.867, 1.0, and 1.133 so that the changes in the plots around $\mu_{rin} = 1.0$ can be examined.

Looking at Figure 4.10 showing the sensitivity of $\max S$, the dependence of $\max S$ on the policy scenario and on μ_{rea} and μ_{rPb} is clear for μ_{rin} values between 0.067 and 0.733. Large firm support increases the industry indicators, and the larger μ_{rea} and μ_{rPb} are, the larger the increase is. However, when $\mu_{rin} = 0.867$, the dependence on μ_{rea} and μ_{rPb} changes, and the effect of large firm support is no longer maximized when μ_{rea} and μ_{rPb} are large. When μ_{rin} is further increased and reaches 1.133, the effect of the policy on $\max S$ almost completely disappears. Figure 4.11 (hhi) and Figure 4.12 ($gini$) also show such a trend.

This may indicate the following: In industries where the market share and capability to generate sales have strong inertia to themselves in the past, this inertia dominates the growth dynamics of firms. The impact of policy on firms is buried in these dynamics, making it impossible for the policy to change the state of the industry. The color bars in Figures 4.10, 4.11, and 4.12 show that the scales of the industry indicators actually increase with increasing μ_{rin}, corresponding to the fact that with increasing μ_{rin}, the effect of the policy is obscured.

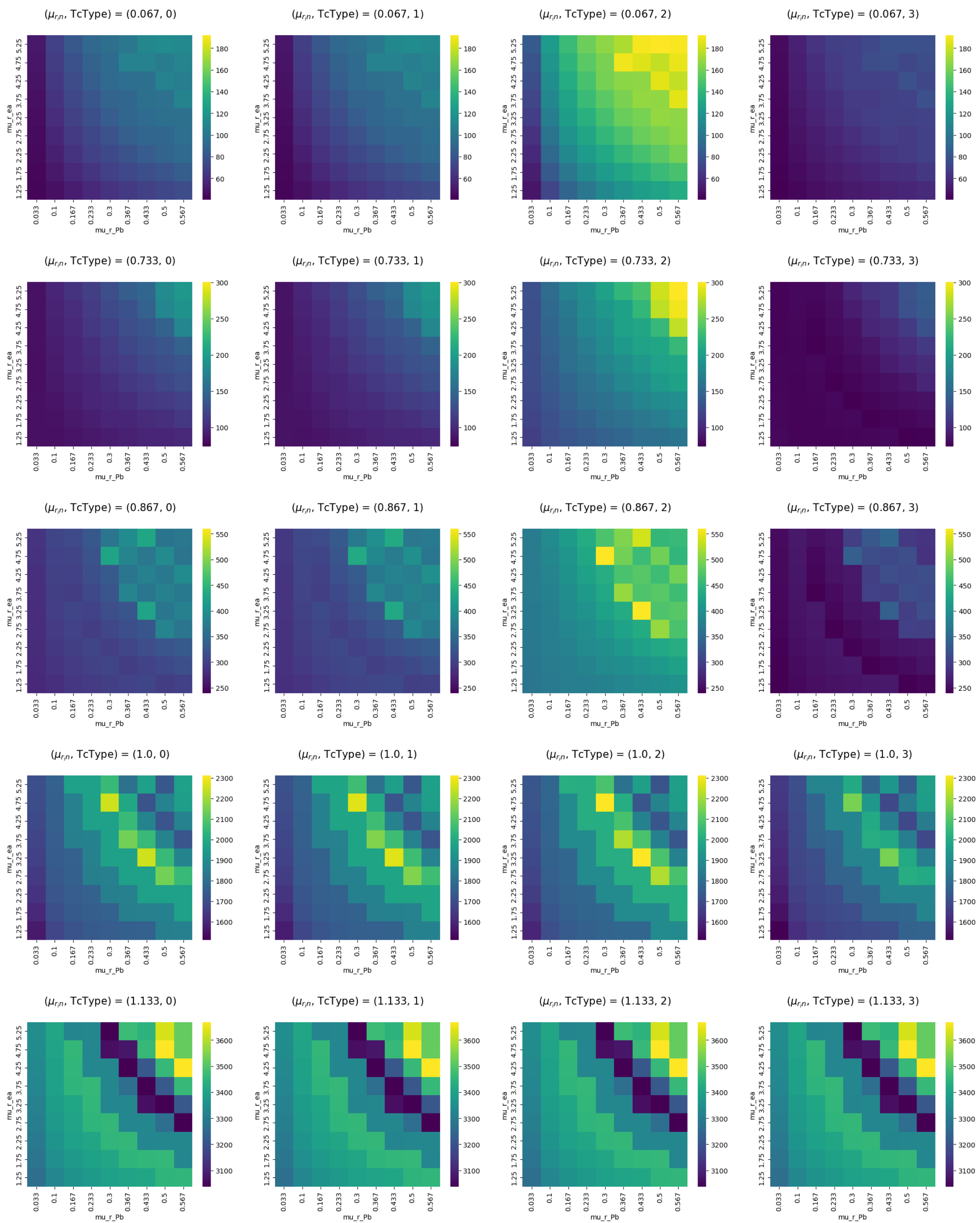

Figure 4.10: Sensitivity of $\max S$ to μ_{rea}, μ_{rin}, and μ_{rPb} at $t = 400$. Each plot is a heatmap of $\max S$ values in μ_{rPb}-μ_{rea} space, with plots in the same row under the same μ_{rin} value and plots in the same column under the same policy scenario, TcType. Plots in the same row have the same scale.

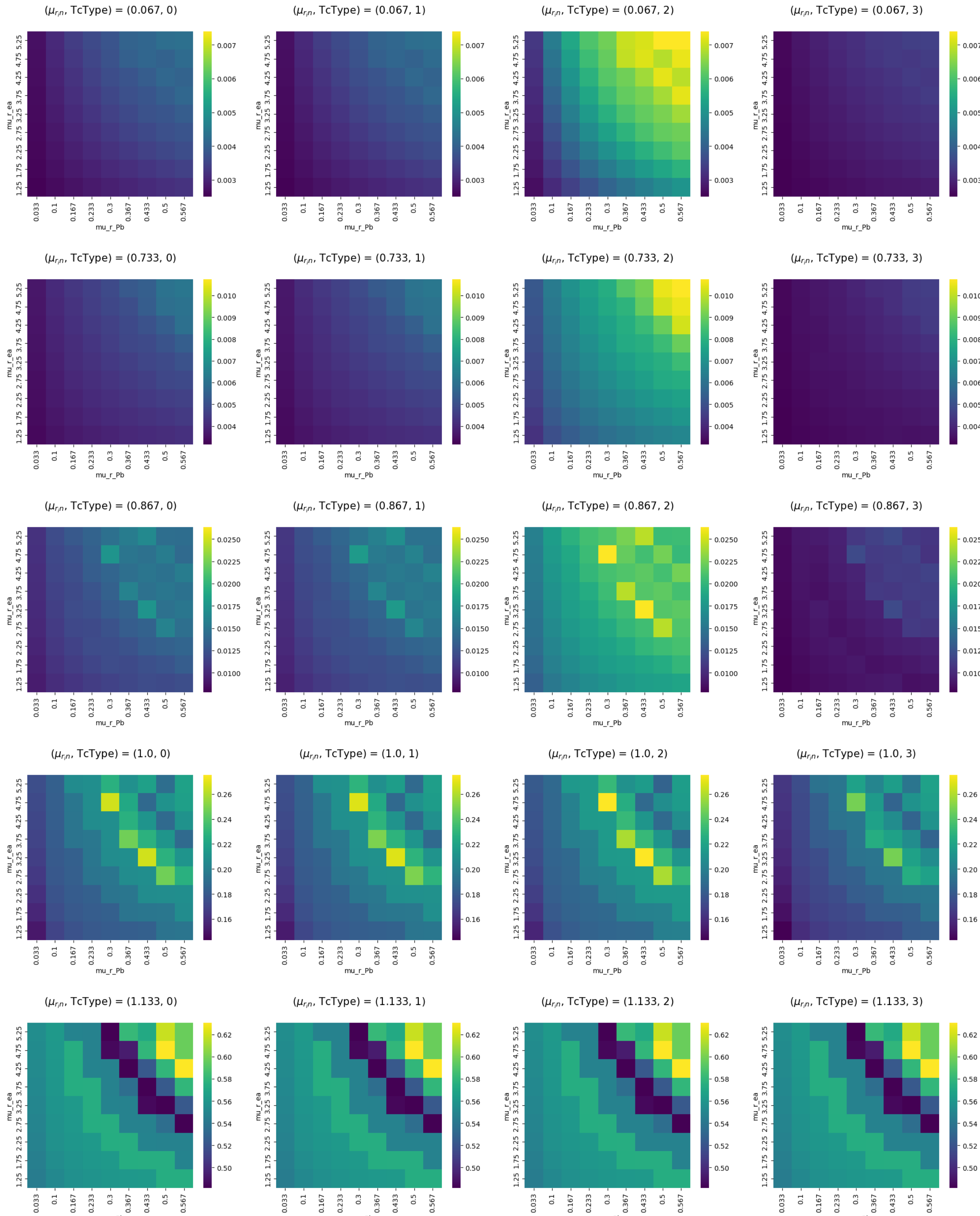

Figure 4.11: Sensitivity of hhi to μ_{rea}, μ_{rin}, and μ_{rPb} at $t = 400$. Each plot is a heatmap of hhi values in μ_{rPb}-μ_{rea} space, with plots in the same row under the same μ_{rin} value and plots in the same column under the same policy scenario, TcType. Plots in the same row have the same scale.

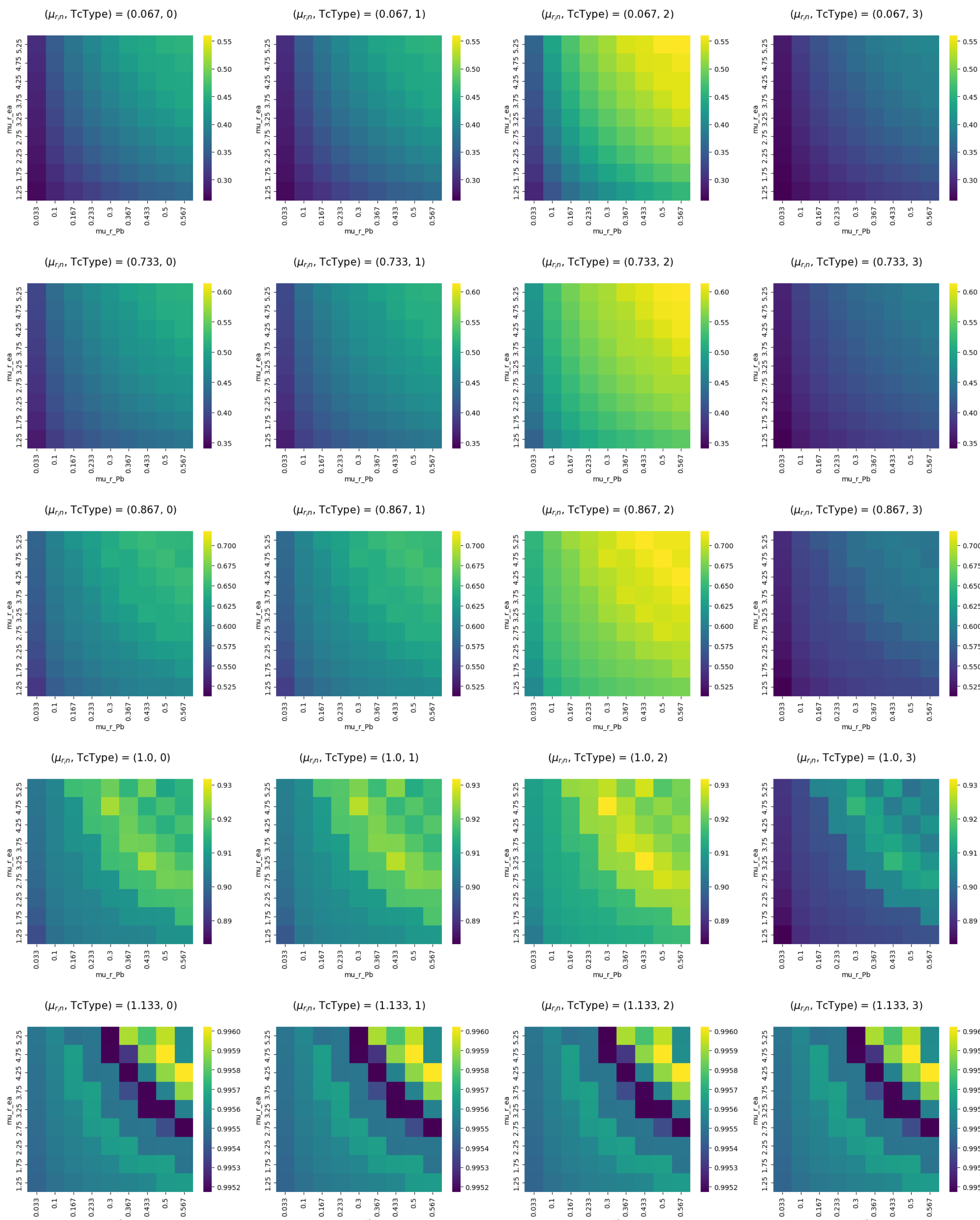

Figure 4.12: Sensitivity of *gini* to μ_{rea}, μ_{rin}, and μ_{rPb} at $t = 400$. Each plot is a heatmap of *gini* values in μ_{rPb}-μ_{rea} space, with plots in the same row under the same μ_{rin} value and plots in the same column under the same policy scenario, TcType. Plots in the same row have the same scale.

4.2.3 Relations between Industry Indicators and Pareto Front

Finally, we examine the relations between the industry indicators $\max S$, *hhi*, and *gini*. As already mentioned, there are usually trade-off relations between these indicators that the policy affects. By considering these indicators as objective functions and obtaining the Pareto front in the objective space, we can explore Pareto-optimal policies under each parameter setting.

Figure 4.13 shows the relations between two industry indicators, from top to bottom, with μ_{rin} changing from small to large values. The values of μ_{rin} are set to $0.067, 0.733, 1.0$, and 1.133 so that the changes around $\mu_{rin} = 1.0$ can be examined. The values of μ_{rea} and μ_{rPb} are set to the median values in the respective parameter ranges: $\mu_{rea} = 3.25$ and $\mu_{rPb} = 0.3$. On each plot, a Pareto front is drawn, connecting the Pareto-optimal data points.

Focusing on the plots of μ_{rin} values between 0.067 and 0.733, we find that there is a clear trade-off between $\max S$ and *hhi* and between $\max S$ and *gini*, respectively. Supporting large firms significantly increases $\max S$, but at the same time worsens *hhi* and *gini*. SME support, on the contrary, improves *hhi* and *gini*, but decreases $\max S$. Support for all firms has little effect on any of the industry indicators. None of the policy scenarios considered here can substantially improve all industry indicators at the same time. This indicates that the optimal target of government support varies depending on the purpose of the policy. In this figure, one data point corresponds to one simulation, so the Pareto front depicted in each plot changes stochastically with each simulation experiment. However, the trend is consistent (for simulation results for a wider range of parameter settings, see Appendix): when $\max S$ is the most important, the optimal policy will be to support large firms, and when *hhi* and *gini* are the most important, the optimal policy will be to support SMEs.

On the other hand, for values of μ_{rin} greater than or equal to 1.0, this trend does not hold. In the $\mu_{rin} = 1.0$ plots, the data points corresponding to different policy scenarios appear to be randomly arranged on the Pareto front, and no specific trend can be read off. In the $\mu_{rin} = 1.133$ plots, the data points under each policy scenario are almost aligned. As discussed in the previous section, this is considered to be because, as μ_{rin} increases, the impact of the policy on firms is buried by the effect of the inertia to the past market share and capability to generate sales, and the policy effect disappears.

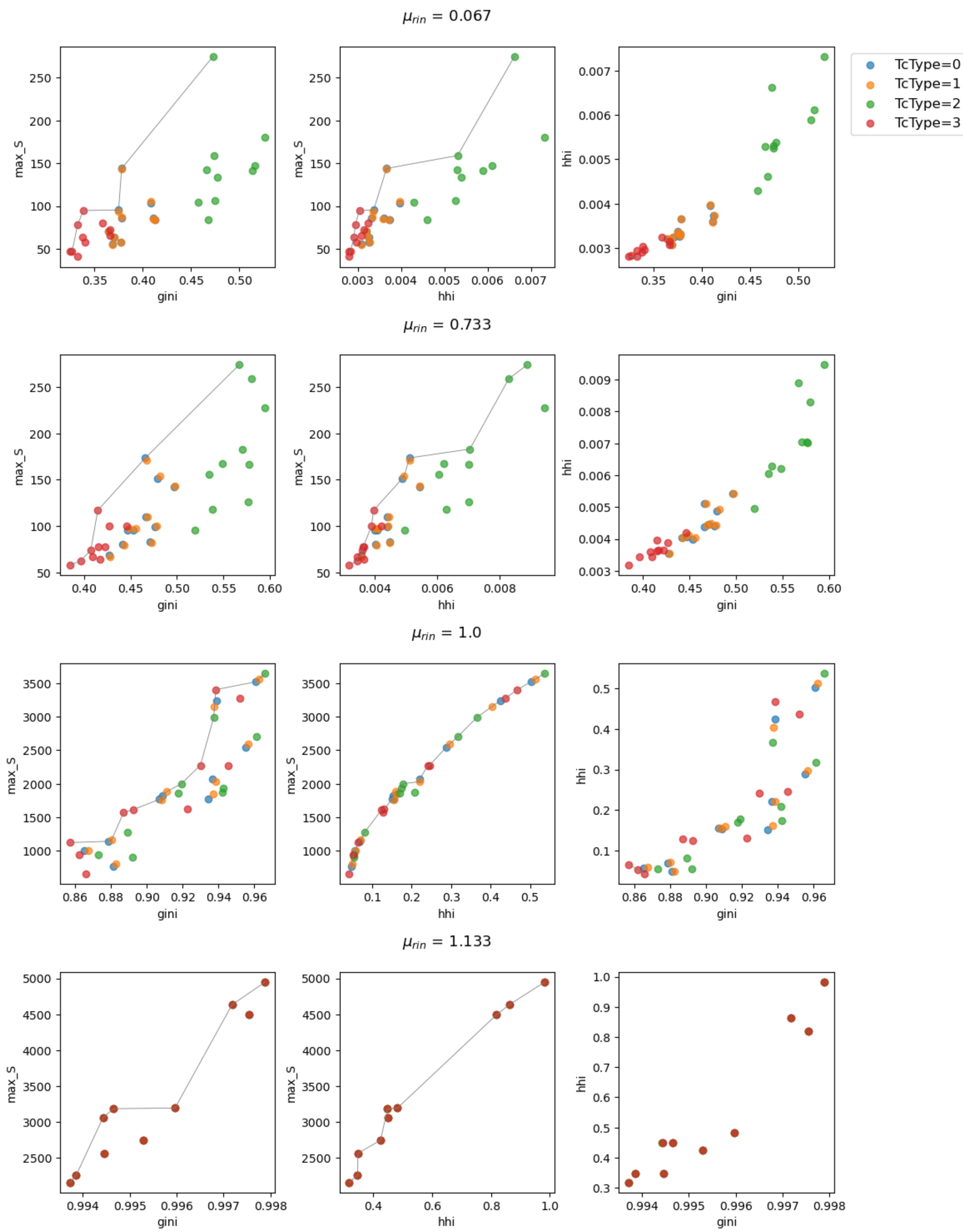

Figure 4.13: Relations between $\max S$ and hhi, $\max S$ and $gini$, and hhi and $gini$ at $t = 400$. The plots in the same row are scatter plots of the two industry indicators under the same μ_{rin} value. The values of μ_{rea} and μ_{rPb} are fixed to 3.25 and 0.3 in all plots, respectively. The color of each data point is set according to the policy scenario, TcType. The gray broken line in each plot is the Pareto front.

Chapter 5

Discussion

This chapter summarizes the contents of this thesis and presents the implications for policy that can be drawn from this study.

5.1 Summary

The chapters of this thesis are summarized as follows.

Chapter 1 provides an overview of recent trends in industrial policy that form the background for this study, and presents the scope and methodology of this study. While industrial policy has traditionally been criticized, the reality is that governments are intervening in industries with the goal of changing the economy to more desirable states. To better understand how to effectively implement industrial policy, I focus on the impact of the policy not on the firms that receive government support, but on the industry as a whole, and the heterogeneity of the industries targeted by the government support, and posed the following research questions: When a government supports firms in an industry with limited policy resources, how does the state of the industry change? How do the effects of such policies vary with the attributes of the supported firms and with the nature of the supported industry? To address this question, I employed ABM to simulate the dynamics of firms and changes in the states of the industry under government support.

Chapter 2 presents a mathematical model describing the process of firm growth under government support. Although a lot of models have been proposed to explain the dynamics of firm size, these models are mainly concerned with reproducing the empirically confirmed distribution of firm size and growth rate rather than the relations between firm size and policy. This makes it difficult to use these models to assess the impact of government support on firm growth. I constructed a simple stochastic model of firm dynamics with the relations between financial variables in the firms to allow for taking into account government support such as tax credits.

Chapter 3 shows the policy scenarios and parameter settings required to run the simulation using the model. There are four policy scenarios for the tax credit: no support, support for all firms, support for large firms, and support for SMEs. The model includes three random variables that are independent of the states of the firms. In this thesis, the mean values of these random variables, μ_{rea}, μ_{rin}, and μ_{rPb}, represent the nature of an industry described by the model: the dependence of the capability to generate sales on total assets, the inertia to the capability and the market share in the past, and the business profitability, respectively. We also find that a simulation run with a parameter setting can produce a distribution that is consistent with a basic empirical fact about the size distribution of firms.

In Chapter 4, comprehensive simulation experiments are conducted. Prior to the results of the simulation experiments, three industry indicators to assess the state of an industry are defined: the largest firm size in sales, the HHI, and the Gini coefficient. We then examined changes in these industry indicators based on the Monte Carlo simulations performed under varying the policy scenarios and the probability distribution parameters representing the nature of the industry. The main findings from the simulation experiments are as follows.

- In the model, the impact of government support through tax credits on an industry varies greatly depending on one of the nature of the industry, i.e., the magnitude of the inertia to the past market share, represented by the parameter μ_{rin}.

- When the inertia is within a certain degree, i.e., at least $\mu_{rin} \leq 0.733$ in the range studied here, the impact of government support on an industry is clear. Large firm support significantly increases the largest firm size. The effect is particularly large for industries with large parameters μ_{rea} and μ_{rPb}, i.e., industries with large dependence of the capability to generate sales on assets and large profitability. However, the support of large firms worsens the HHI and the Gini coefficient. On the contrary, SME support improves the HHI and the Gini coefficient, but decreases the largest firm size. All firm support has no significant effect on these indicators.

- On the other hand, as the inertia increases and μ_{rin} reaches around 1, this trend changes, and the effect of the policy in the model almost disappears. In industries with strong inertia, such as with $\mu_{rin} \geq 1$, the inertia dominates the growth dynamics of firms. In such an industry, some firms grow rapidly with the inertia as a driving force, and all industry indicators, such as the largest firm size, the HHI, and the Gini coefficient, become very large.

5.2 Policy Implications

The main policy implications of this thesis are as follows.

The first implication relates to the effect of a policy on an industry as a whole, taking into account the effect of the policy on firms other than those targeted by the policy. In a market, there are interactions among firms through competition, so government support for firms with a particular attribute has an indirect effect on other firms, changing the distribution of firm size in the industry. Since demand is assumed to be exogenously determined in this study, when the largest firm size increases due to the large firm support, the sales of SMEs decrease, and when the SME support improves the HHI and Gini coefficient, the largest firm size decreases as the sales of large firms decline. In reality, demand is affected by the activities of firms themselves. Although this model ignores such endogenous demand growth, there is no market in which demand grows infinitely due to firm activities, and there would be an upper limit due to factors such as population. Therefore, it is likely that changes in competition due to government support and the resulting changes in an industry as a whole cannot be ignored as a realistic effect of a policy.

The second implication is trade-offs regarding the effects of government support. As the results of the simulation experiments show, it is difficult to substantially improve all industry indicators simultaneously under any of the policy scenarios considered here. Supporting large firms may contribute to creating a small number of huge firms, but it may lead to widening gaps among firms and weakening competition in the domestic market. On the other hand, supporting SMEs may reduce gaps and increase competition, but it may not be suitable for the purpose of creating large, internationally competitive firms. Furthermore, supporting all firms with the multiple objectives of creating super-large firms, reducing inequality, and increasing competition may not actually improve an industry from any perspective in a market where sufficient demand growth is not expected. Policymakers will need to look at these trade-offs, understand the benefits and sacrifices of different targeting, and design industrial policies consistent with their purposes.

The final implication is the importance of considering the industry's nature in policy targeting. Simulation experiments suggest that in industries with strong inertia to past market share, policy cannot substantially affect the state of the industry. This is thought to be because, as already mentioned, this inertia determines the growth dynamics of firms. In such industries, even if government support appears to have affected the creation of super-large firms, gaps among firms, and competition, these may, in fact, have been obtained simply by chance and not as a result of the policy. The resources available for policies are always limited, which is why targeting is always an issue in industrial policy. In designing industrial policy, it is important to identify the nature of the industries to be supported to direct resources to industries where the policy can have a substantial impact.

In this thesis, simulations were conducted using a simplified model of the rules that real firms are expected to follow. For this reason, many factors associated with real business activities and industry development have been omitted. However, because it is a simple model, it is easy to understand the factors that contribute to the dynamics generated by the model and, under certain assumptions, to examine how policies affect firm dynamics and how they change the state of an entire industry. The model could be calibrated to more closely reproduce real industries by combining it with real financial data for firms in different countries. After further incorporating factors such as those on real business activities, if necessary, simulations using this model could contribute to policymakers' decision-making about what industrial policies a country's government should design to achieve their purpose.

Appendix A

Time-series Behaviors and Relations between Industry Indicators

This appendix presents the time-series behaviors and the relations between the industry indicators obtained from the simulation experiments in Chapter 4 for a wider range of probability distribution parameters.

A.1 Time-series Behaviors

In Chapter 4, we presented the time series of $\max S$, hhi, and $gini$ for each of the four policy scenarios when μ_{rin} is fixed at 0.6 and 1.0. In the following figures, the values of μ_{rin} are set at nine equally spaced levels throughout the range, $0.067, 0.2, 0.333, 0.467, 0.6, 0.733, 0.867, 1.0$, and 1.133, to examine the changes in the time series of each industry indicator by changing μ_{rin} in more detail.

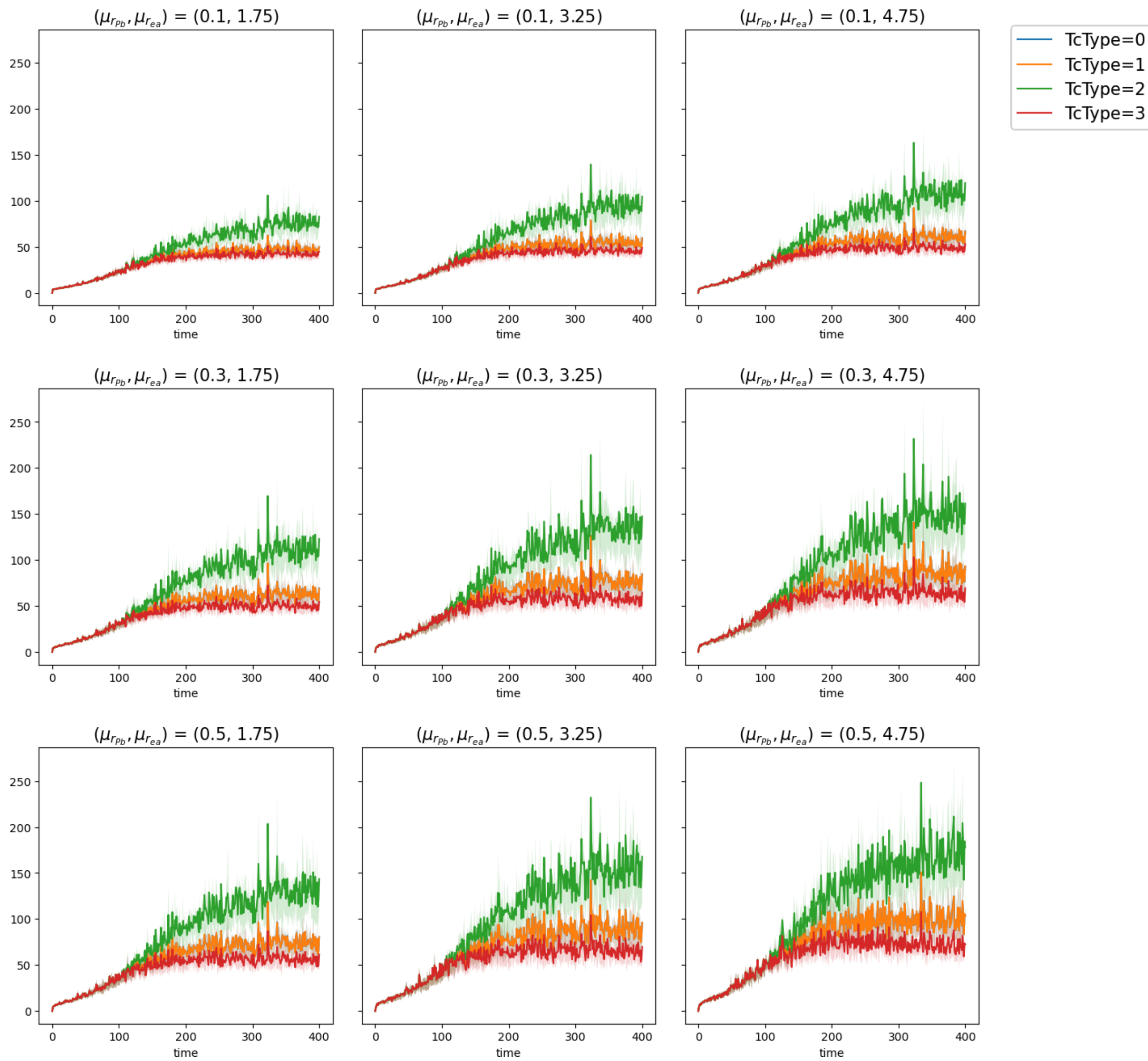

Figure A.1: Time series of $\max S$ from $t = 0$ to 400 with $\mu_{rin} = 0.067$. The curve and the upper and lower bound of the shaded region in each plot are the mean and the 25th and 75th percentiles of the data from 10 simulations for each parameter setting, respectively. The color of each curve and shaded region is set according to the policy scenario, TcType.

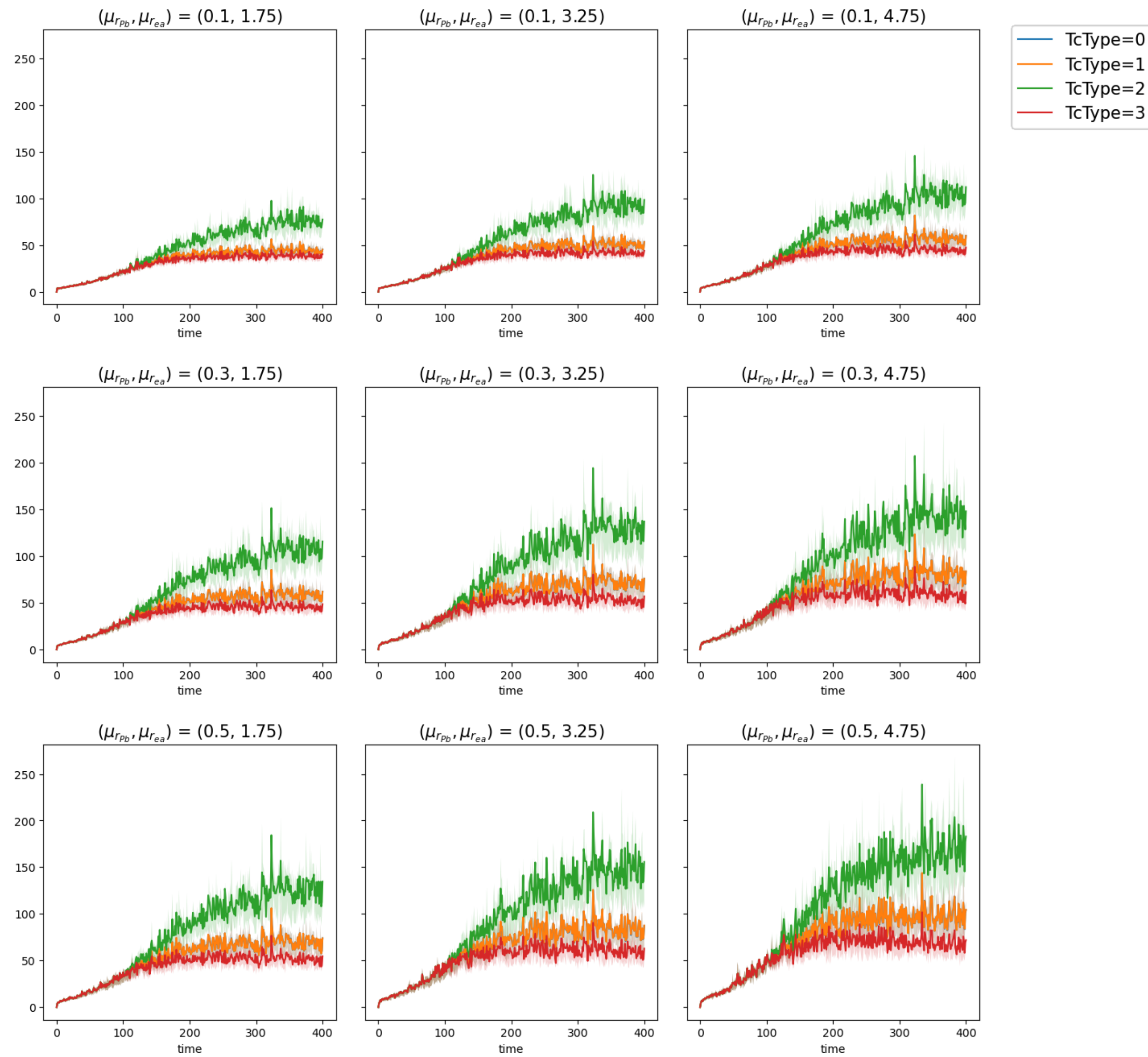

Figure A.2: Time series of max S from $t = 0$ to 400 with $\mu_{rin} = 0.2$. The curve and the upper and lower bound of the shaded region in each plot are the mean and the 25th and 75th percentiles of the data from 10 simulations for each parameter setting, respectively. The color of each curve and shaded region is set according to the policy scenario, TcType.

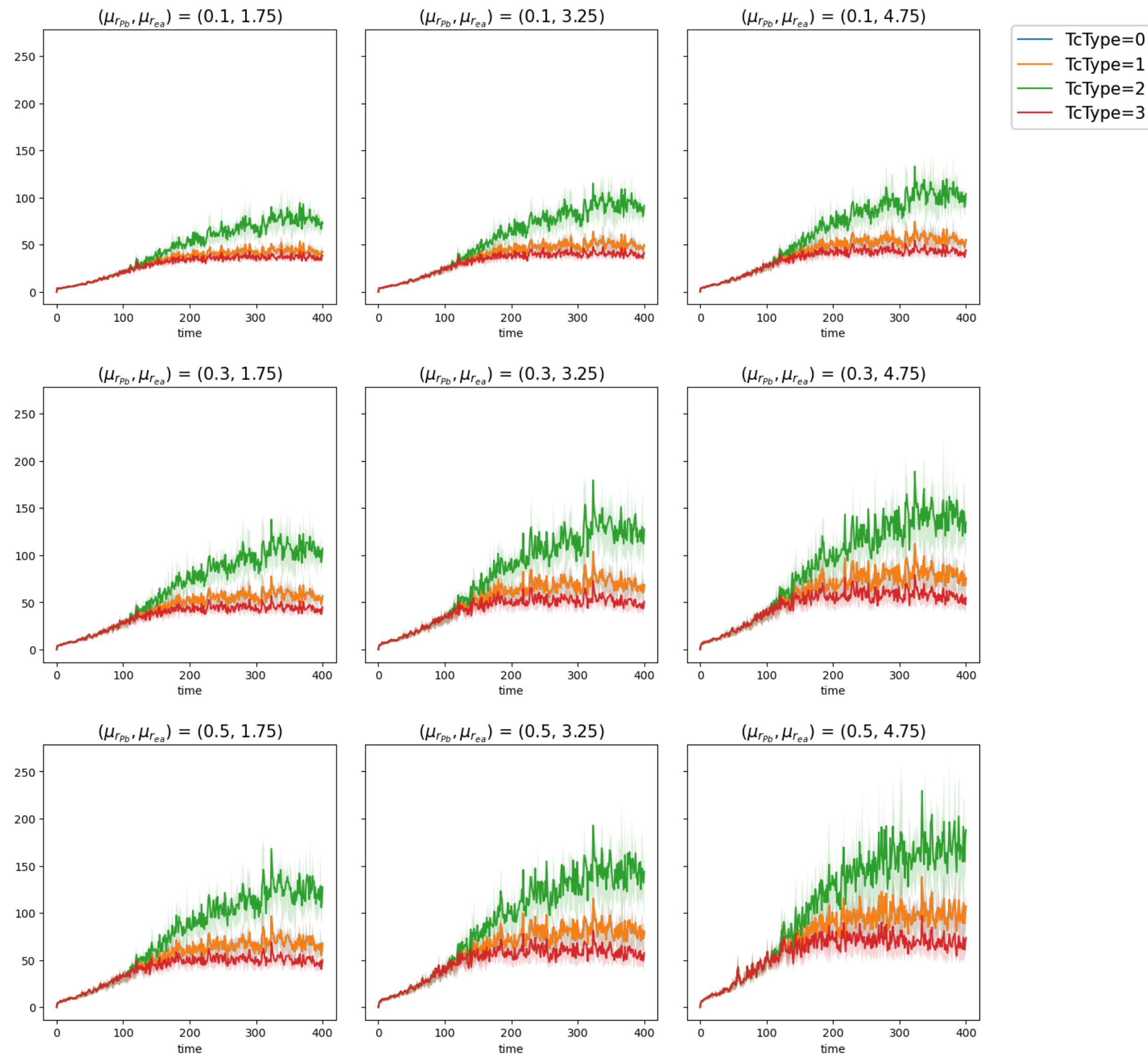

Figure A.3: Time series of $\max S$ from $t = 0$ to 400 with $\mu_{rin} = 0.333$. The curve and the upper and lower bound of the shaded region in each plot are the mean and the 25th and 75th percentiles of the data from 10 simulations for each parameter setting, respectively. The color of each curve and shaded region is set according to the policy scenario, TcType.

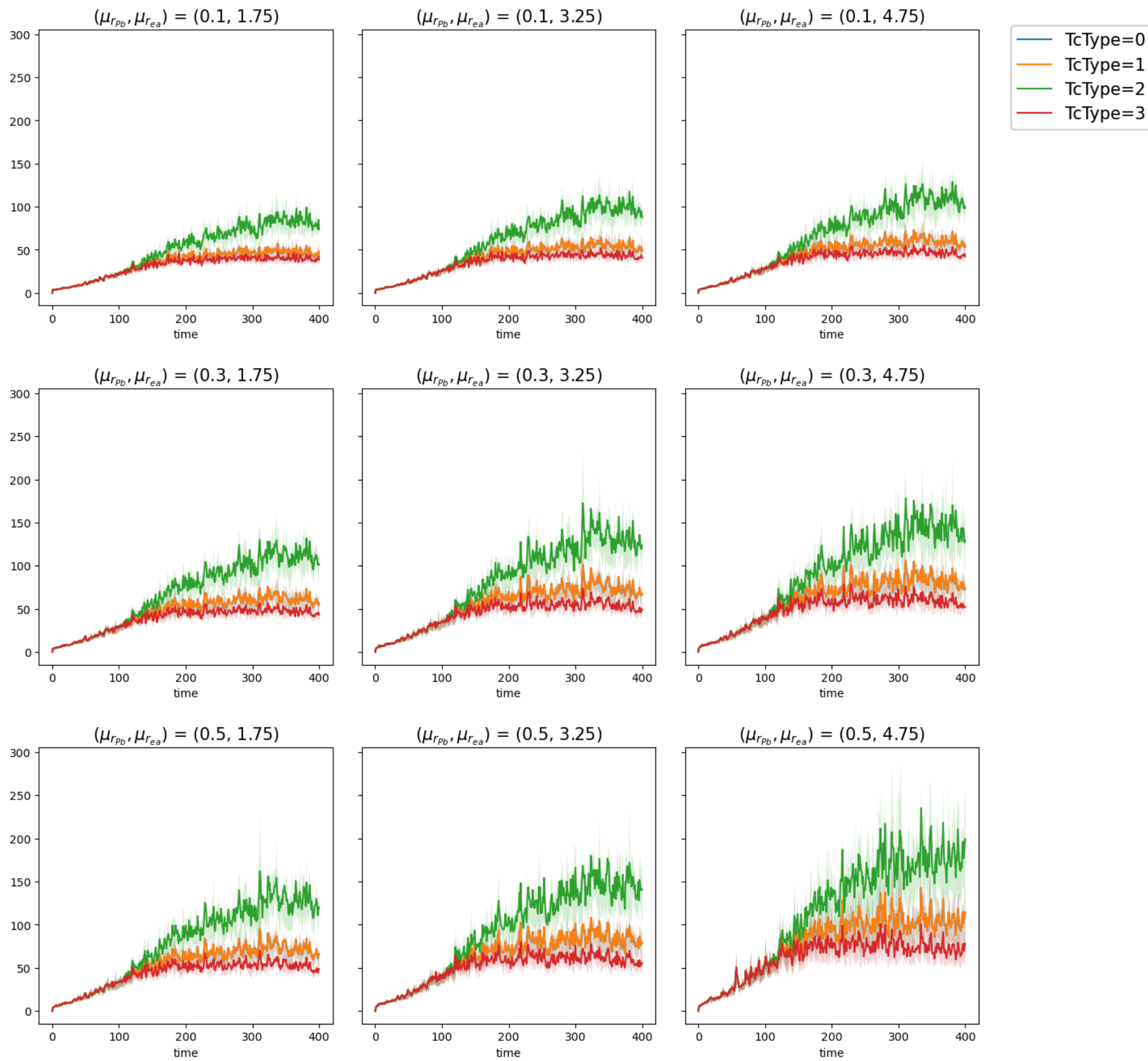

Figure A.4: Time series of $\max S$ from $t = 0$ to 400 with $\mu_{rin} = 0.467$. The curve and the upper and lower bound of the shaded region in each plot are the mean and the 25th and 75th percentiles of the data from 10 simulations for each parameter setting, respectively. The color of each curve and shaded region is set according to the policy scenario, TcType.

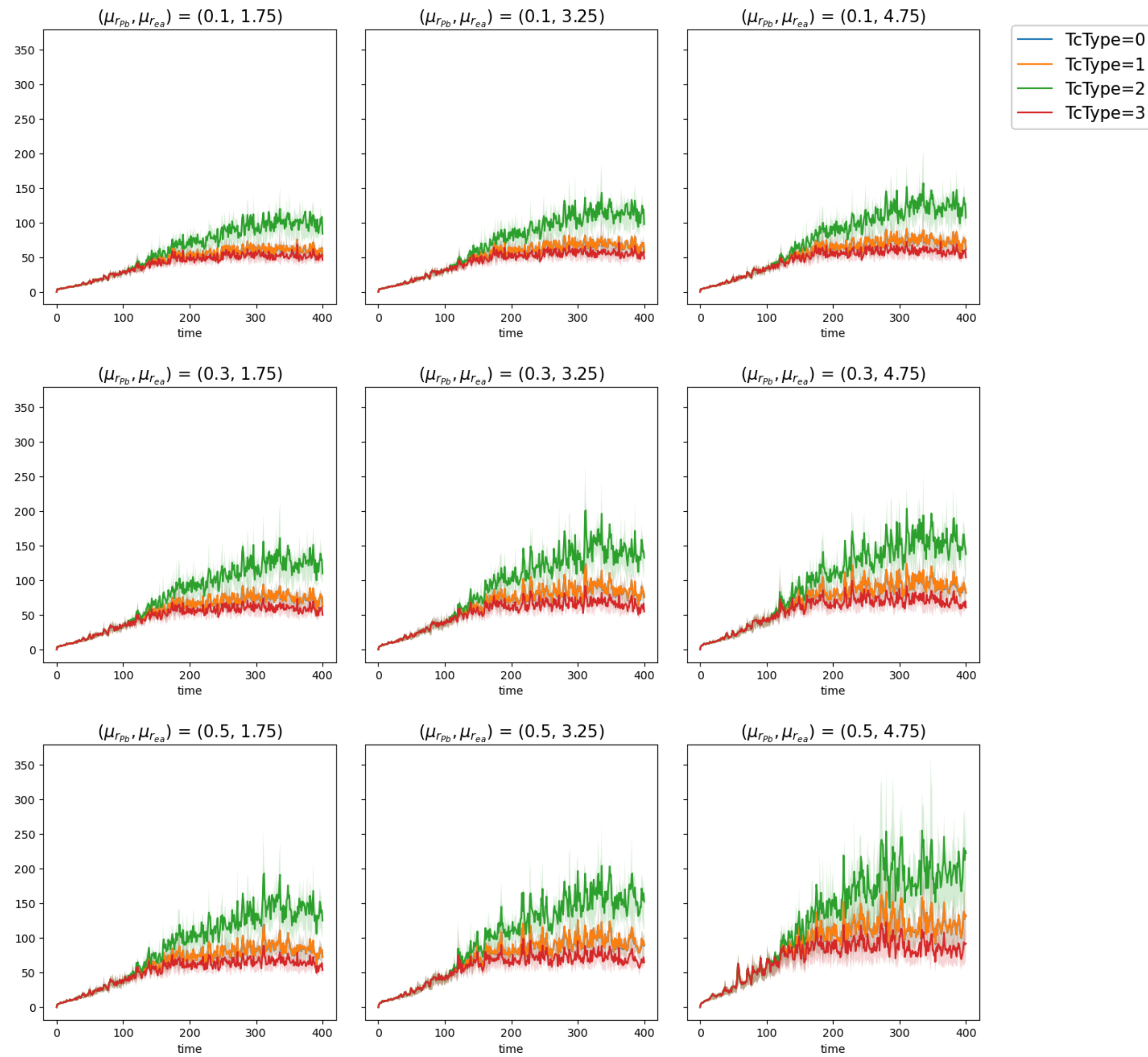

Figure A.5: Time series of max S from $t = 0$ to 400 with $\mu_{rin} = 0.6$. The curve and the upper and lower bound of the shaded region in each plot are the mean and the 25th and 75th percentiles of the data from 10 simulations for each parameter setting, respectively. The color of each curve and shaded region is set according to the policy scenario, TcType.

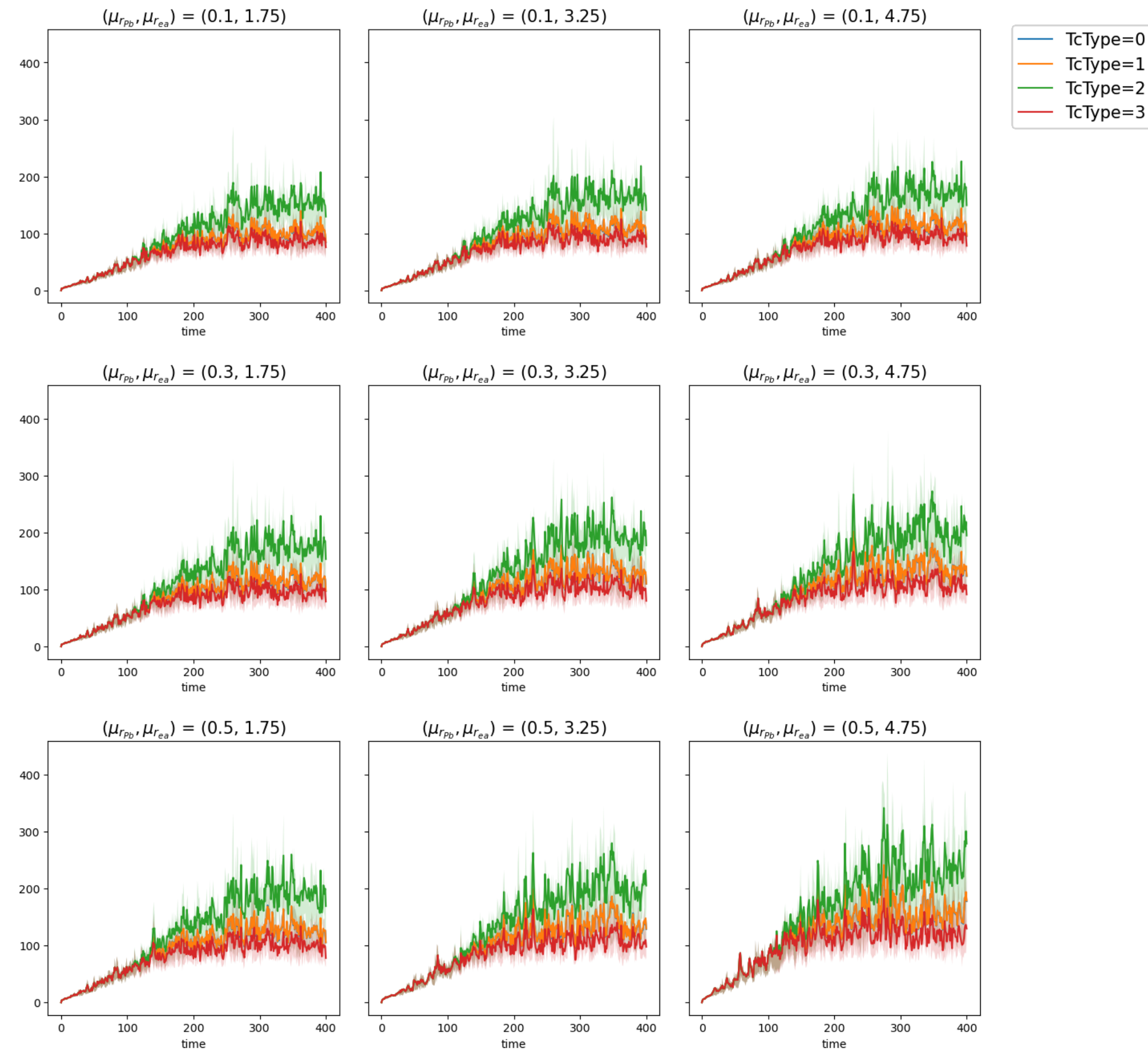

Figure A.6: Time series of $\max S$ from $t = 0$ to 400 with $\mu_{rin} = 0.733$. The curve and the upper and lower bound of the shaded region in each plot are the mean and the 25th and 75th percentiles of the data from 10 simulations for each parameter setting, respectively. The color of each curve and shaded region is set according to the policy scenario, TcType.

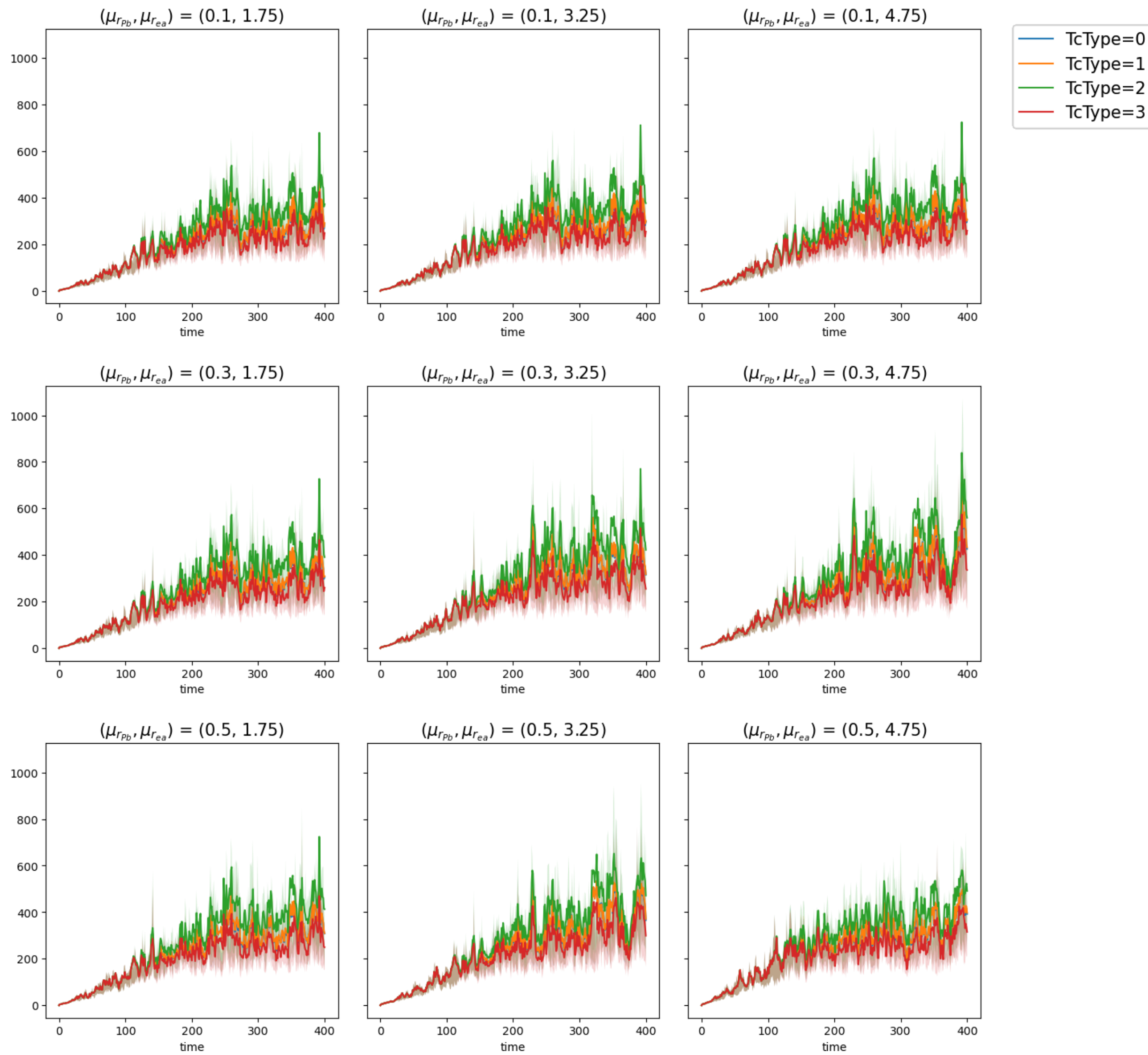

Figure A.7: Time series of max S from $t = 0$ to 400 with $\mu_{rin} = 0.867$. The curve and the upper and lower bound of the shaded region in each plot are the mean and the 25th and 75th percentiles of the data from 10 simulations for each parameter setting, respectively. The color of each curve and shaded region is set according to the policy scenario, TcType.

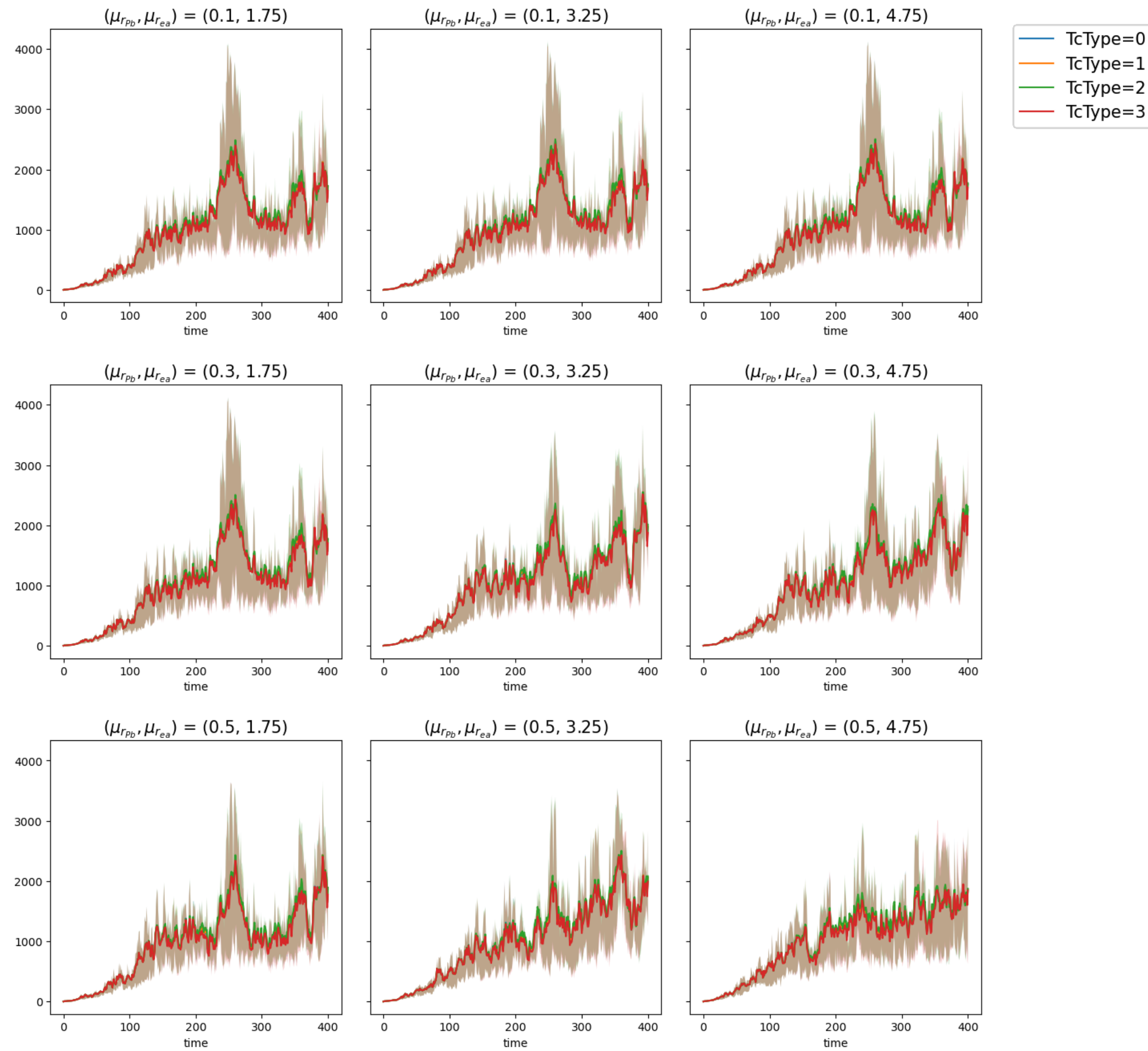

Figure A.8: Time series of max S from $t = 0$ to 400 with $\mu_{rin} = 1.0$. The curve and the upper and lower bound of the shaded region in each plot are the mean and the 25th and 75th percentiles of the data from 10 simulations for each parameter setting, respectively. The color of each curve and shaded region is set according to the policy scenario, TcType.

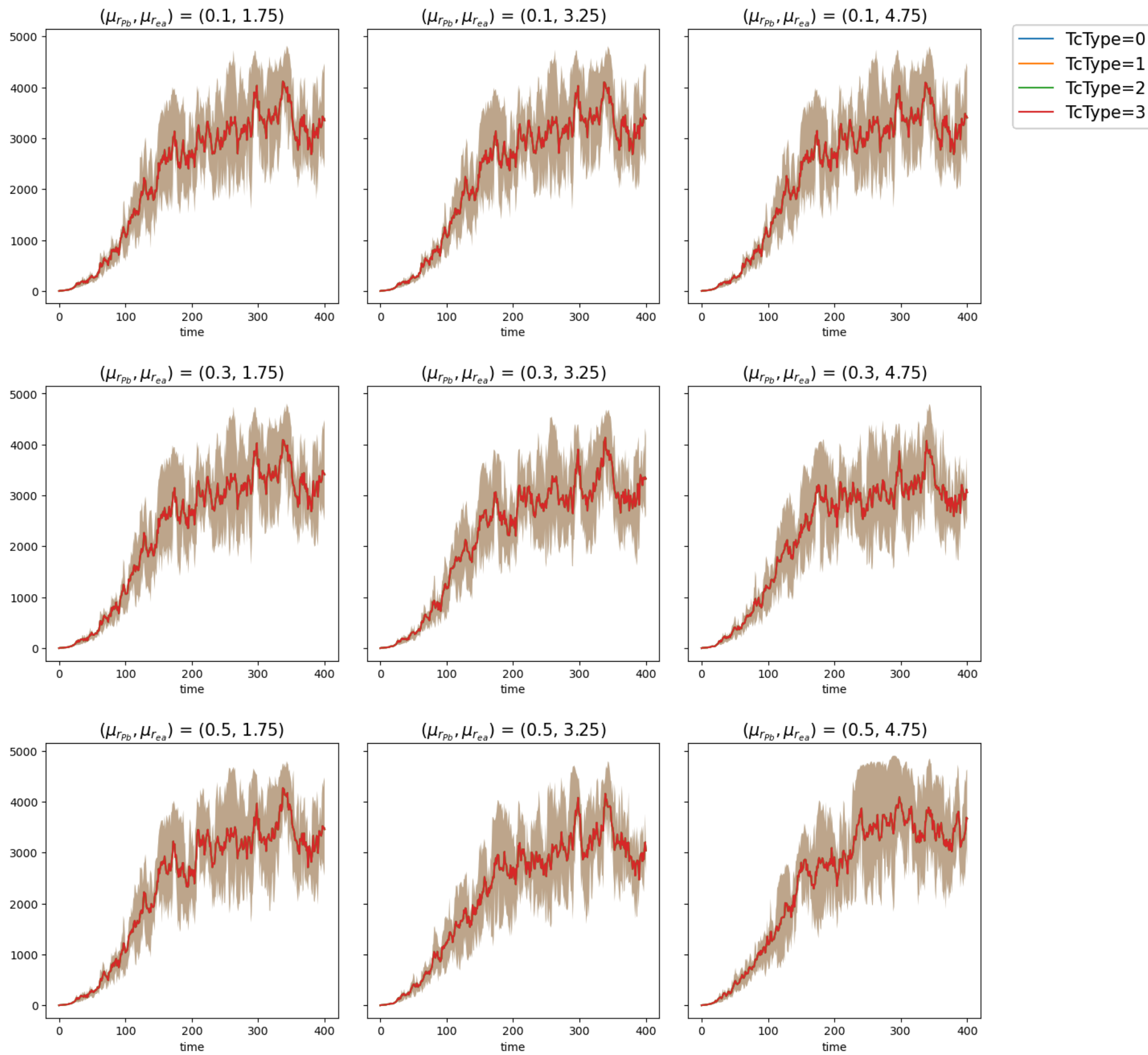

Figure A.9: Time series of $\max S$ from $t = 0$ to 400 with $\mu_{rin} = 1.133$. The curve and the upper and lower bound of the shaded region in each plot are the mean and the 25th and 75th percentiles of the data from 10 simulations for each parameter setting, respectively. The color of each curve and shaded region is set according to the policy scenario, TcType.

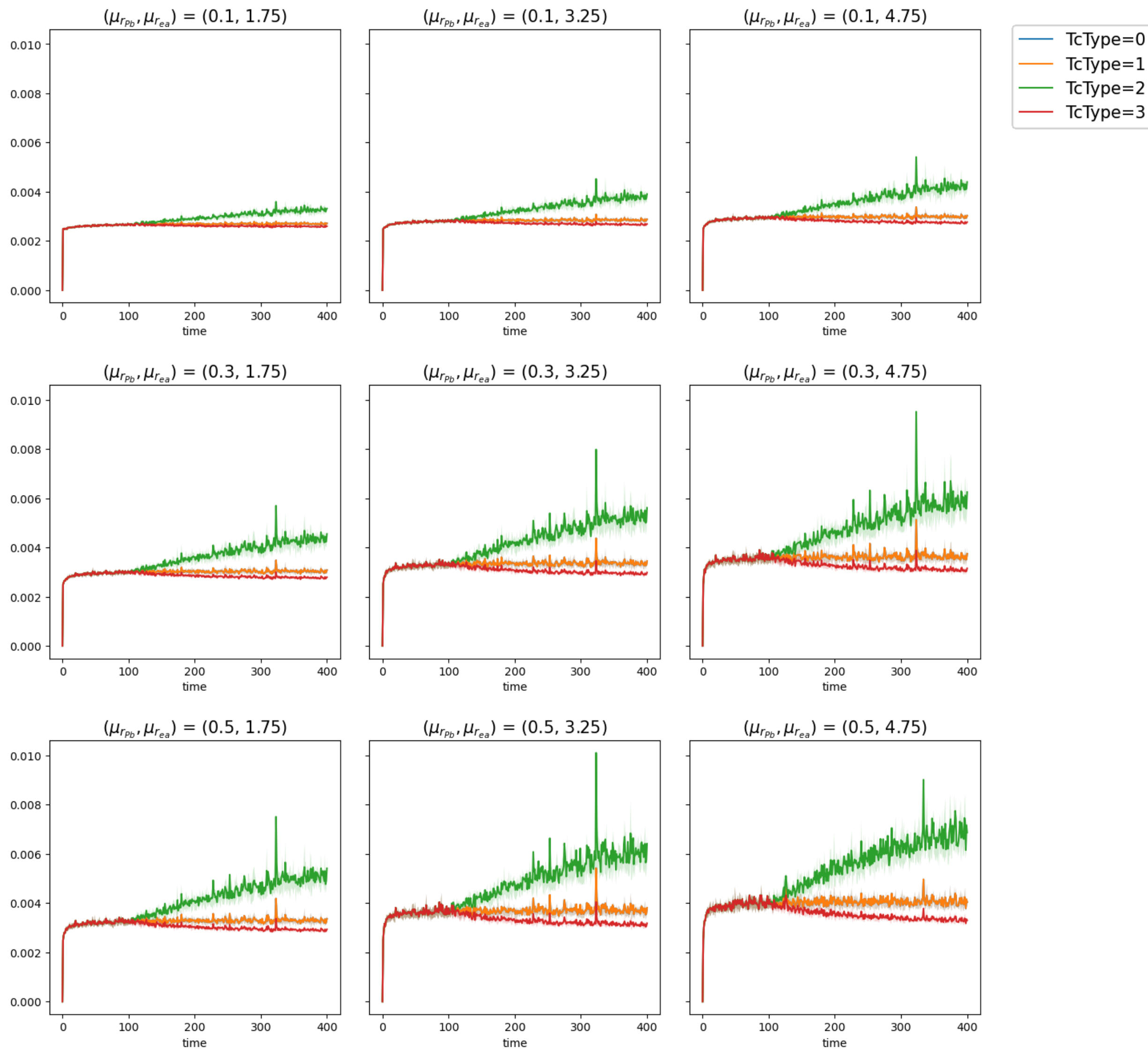

Figure A.10: Time series of hhi from $t = 0$ to 400 with $\mu_{rin} = 0.067$. The curve and the upper and lower bound of the shaded region in each plot are the mean and the 25th and 75th percentiles of the data from 10 simulations for each parameter setting, respectively. The color of each curve and shaded region is set according to the policy scenario, TcType.

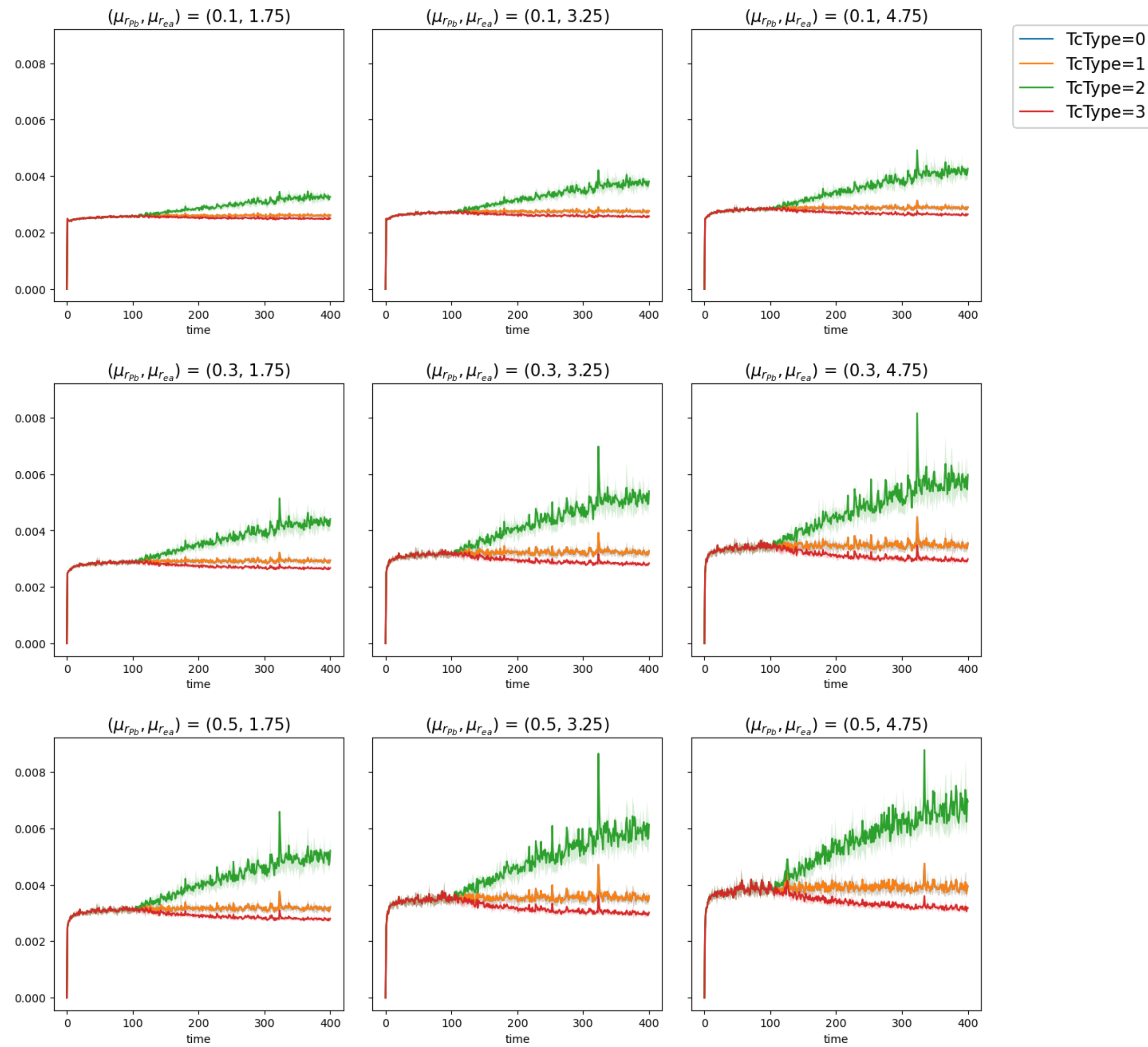

Figure A.11: Time series of hhi from $t = 0$ to 400 with $\mu_{rin} = 0.2$. The curve and the upper and lower bound of the shaded region in each plot are the mean and the 25th and 75th percentiles of the data from 10 simulations for each parameter setting, respectively. The color of each curve and shaded region is set according to the policy scenario, TcType.

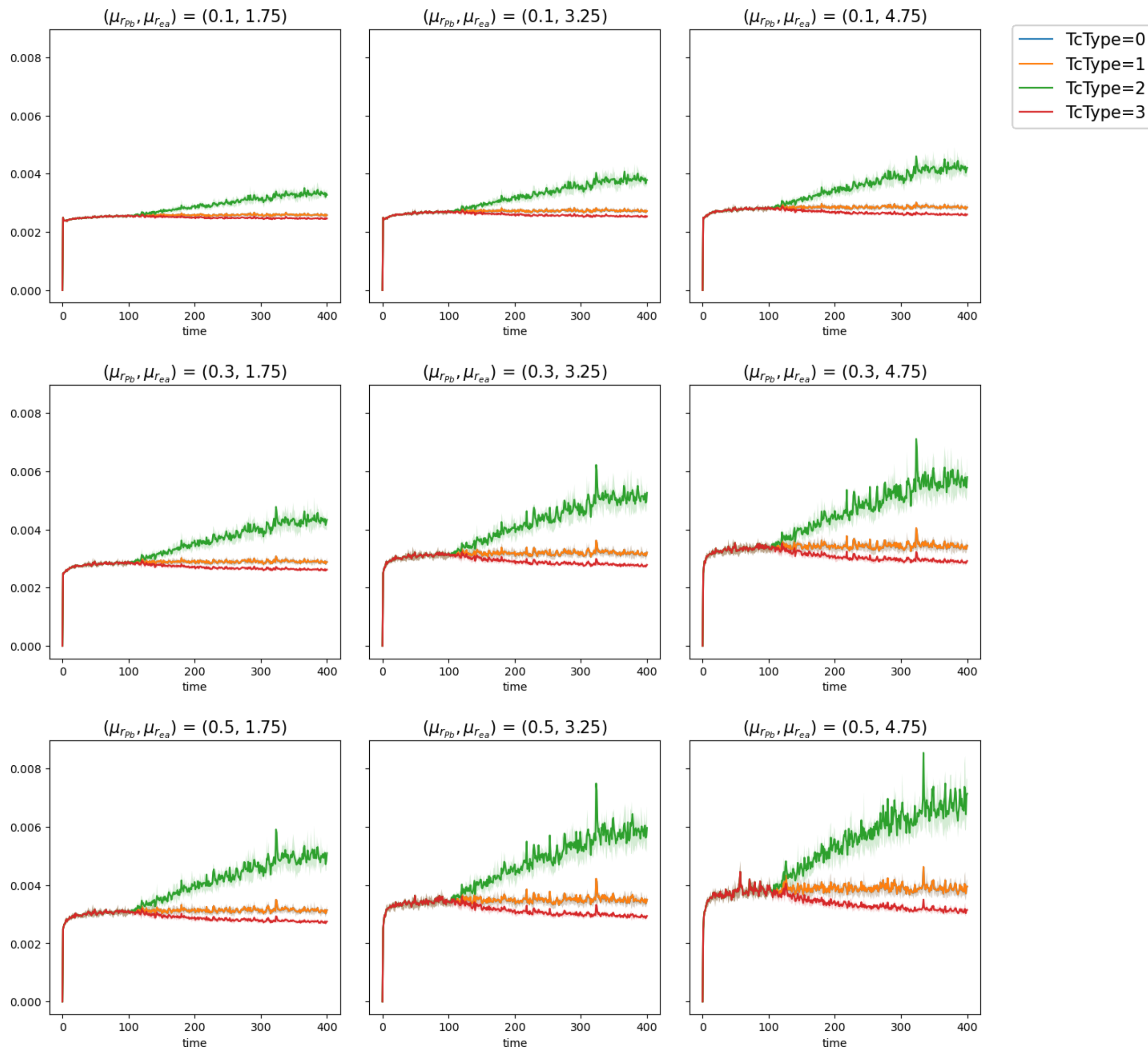

Figure A.12: Time series of hhi from $t = 0$ to 400 with $\mu_{rin} = 0.333$. The curve and the upper and lower bound of the shaded region in each plot are the mean and the 25th and 75th percentiles of the data from 10 simulations for each parameter setting, respectively. The color of each curve and shaded region is set according to the policy scenario, TcType.

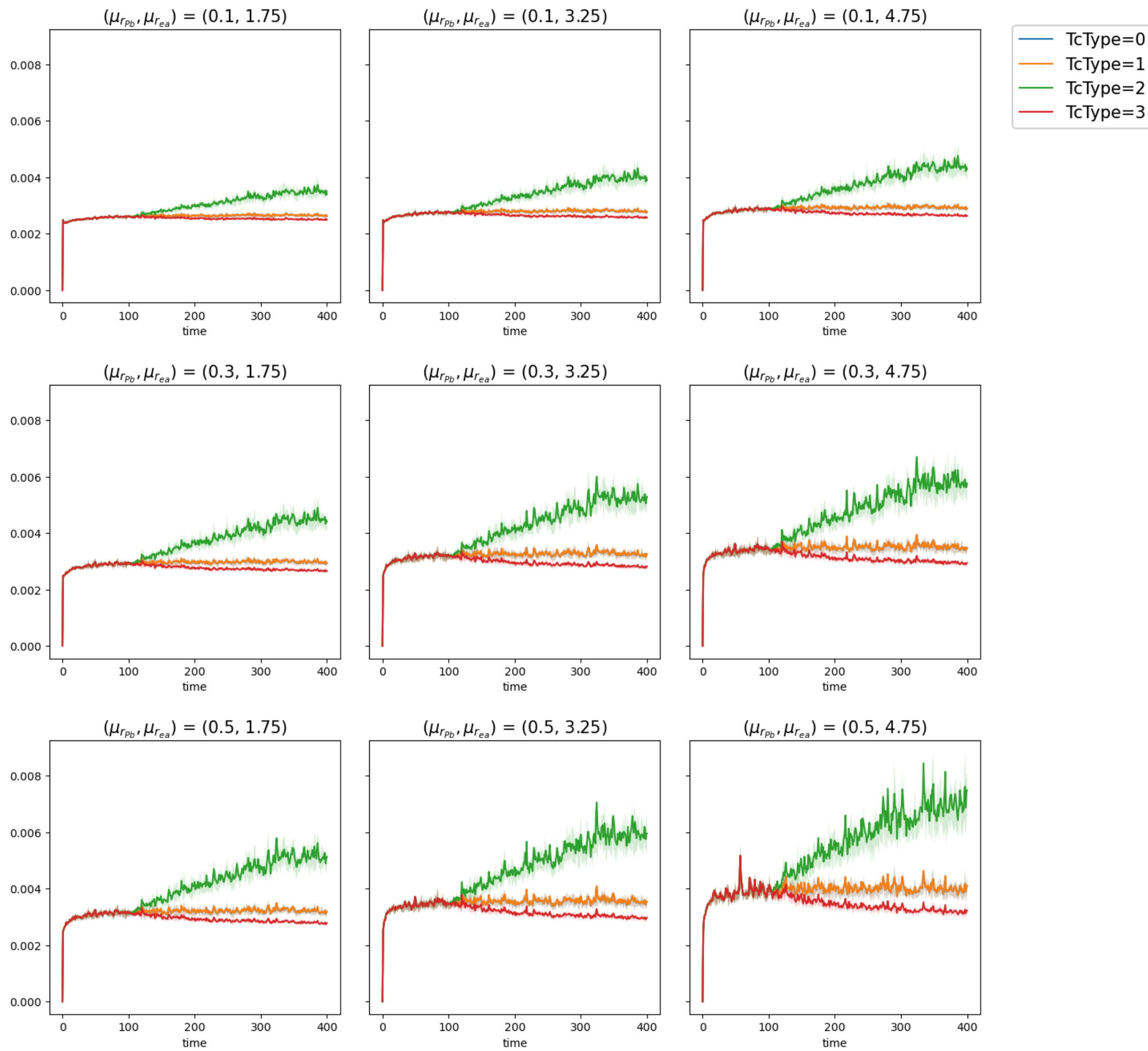

Figure A.13: Time series of hhi from $t = 0$ to 400 with $\mu_{rin} = 0.467$. The curve and the upper and lower bound of the shaded region in each plot are the mean and the 25th and 75th percentiles of the data from 10 simulations for each parameter setting, respectively. The color of each curve and shaded region is set according to the policy scenario, TcType.

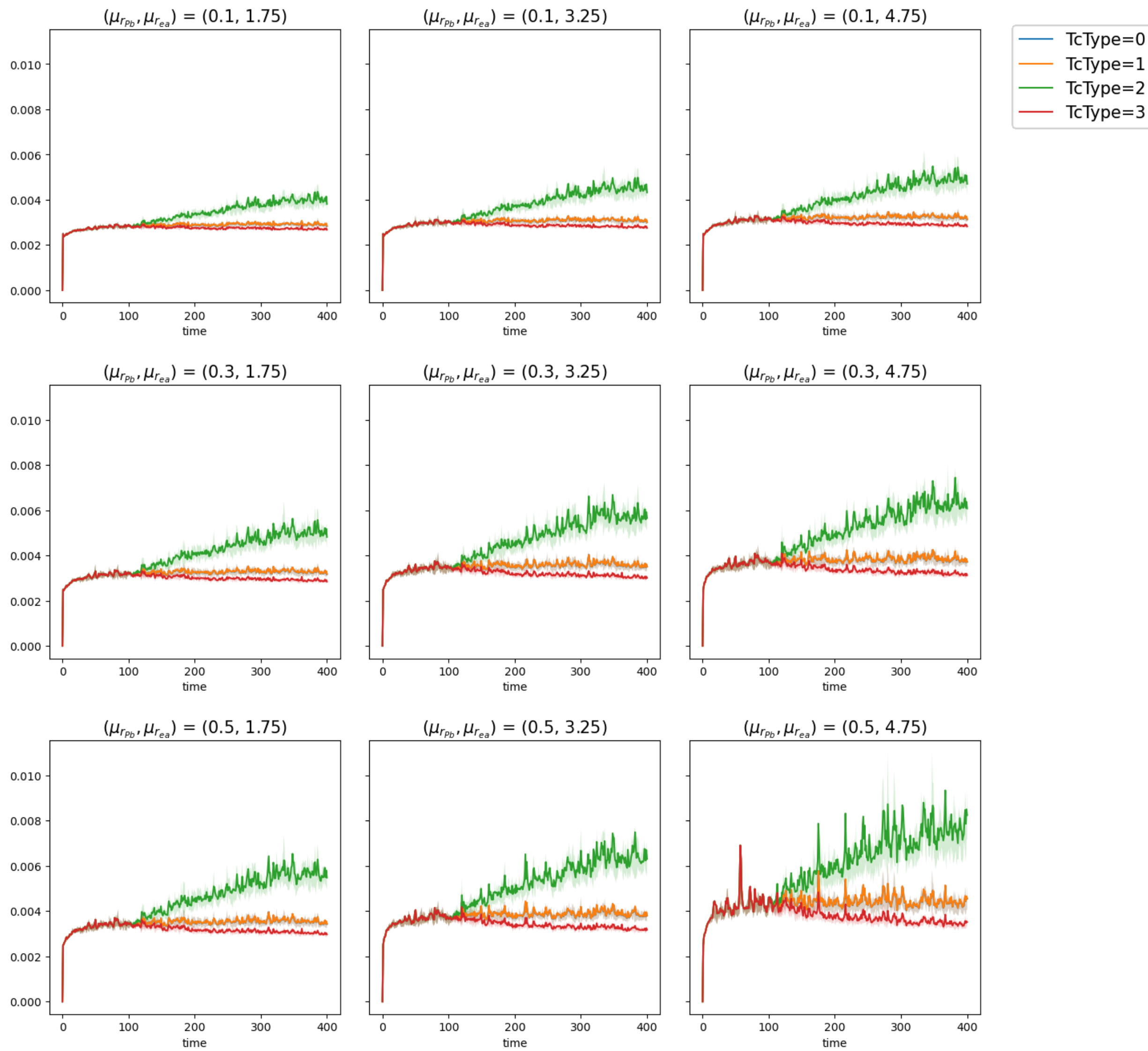

Figure A.14: Time series of hhi from $t = 0$ to 400 with $\mu_{rin} = 0.6$. The curve and the upper and lower bound of the shaded region in each plot are the mean and the 25th and 75th percentiles of the data from 10 simulations for each parameter setting, respectively. The color of each curve and shaded region is set according to the policy scenario, TcType.

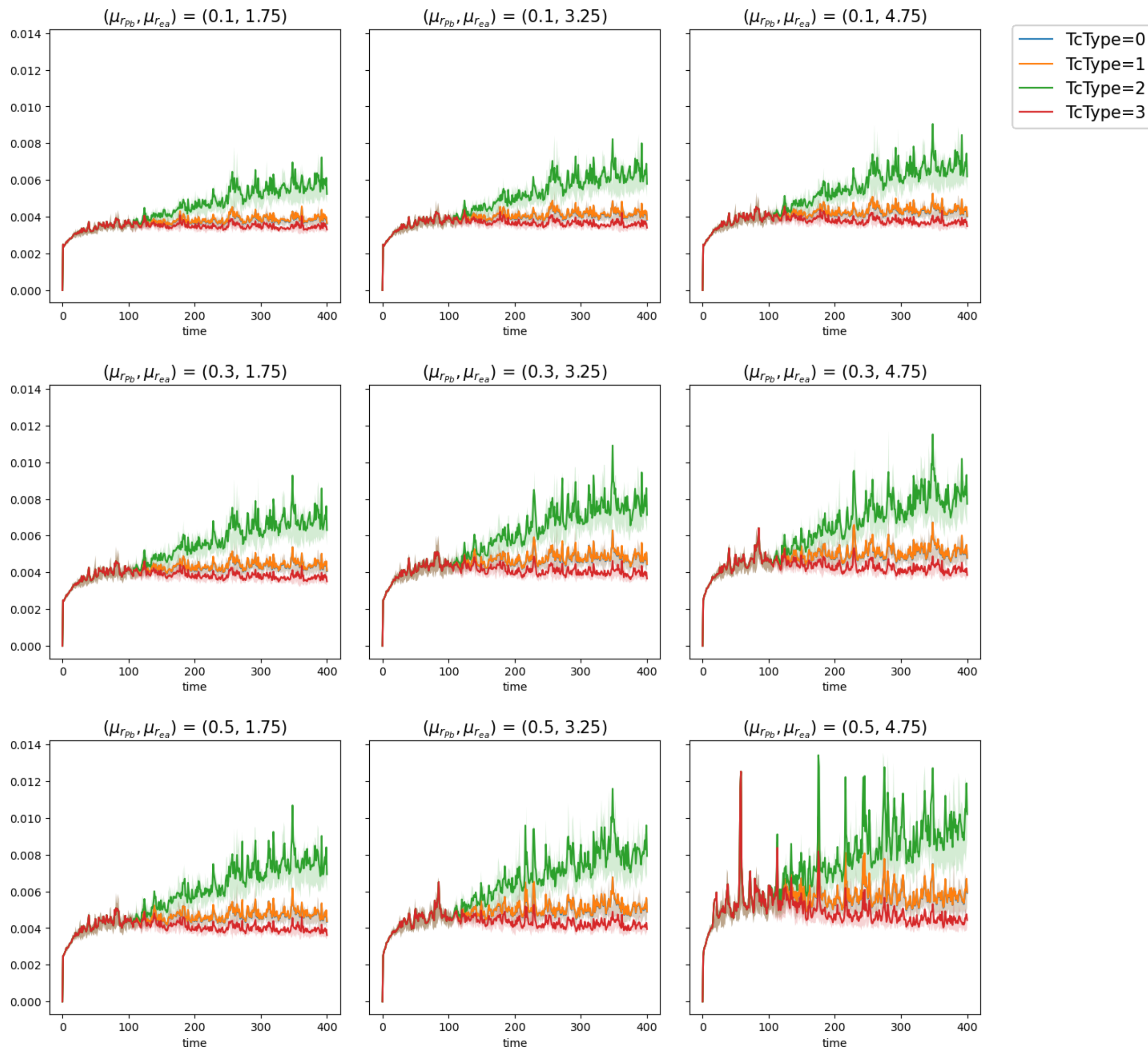

Figure A.15: Time series of hhi from $t = 0$ to 400 with $\mu_{rin} = 0.733$. The curve and the upper and lower bound of the shaded region in each plot are the mean and the 25th and 75th percentiles of the data from 10 simulations for each parameter setting, respectively. The color of each curve and shaded region is set according to the policy scenario, TcType.

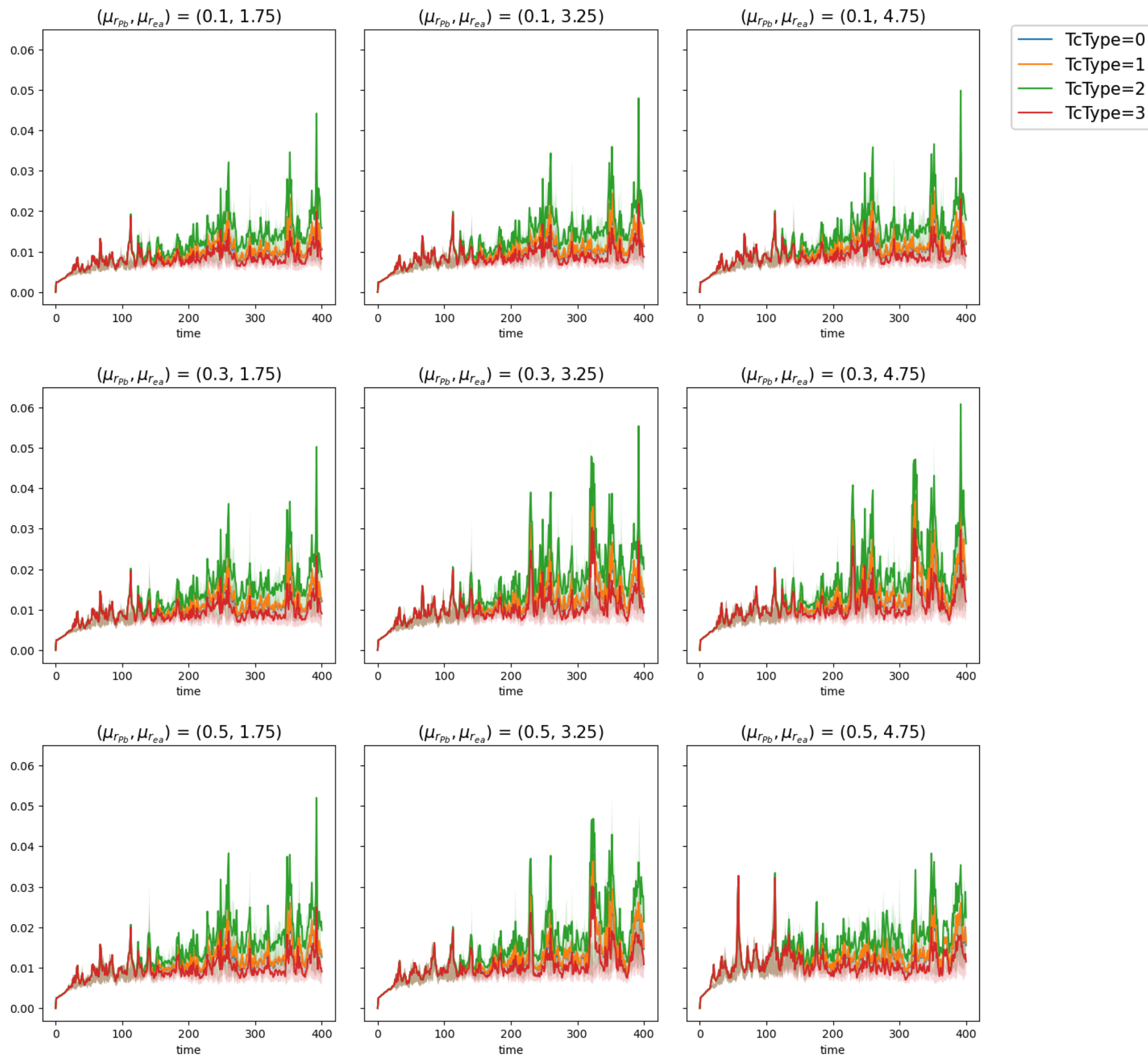

Figure A.16: Time series of *hhi* from $t = 0$ to 400 with $\mu_{rin} = 0.867$. The curve and the upper and lower bound of the shaded region in each plot are the mean and the 25th and 75th percentiles of the data from 10 simulations for each parameter setting, respectively. The color of each curve and shaded region is set according to the policy scenario, TcType.

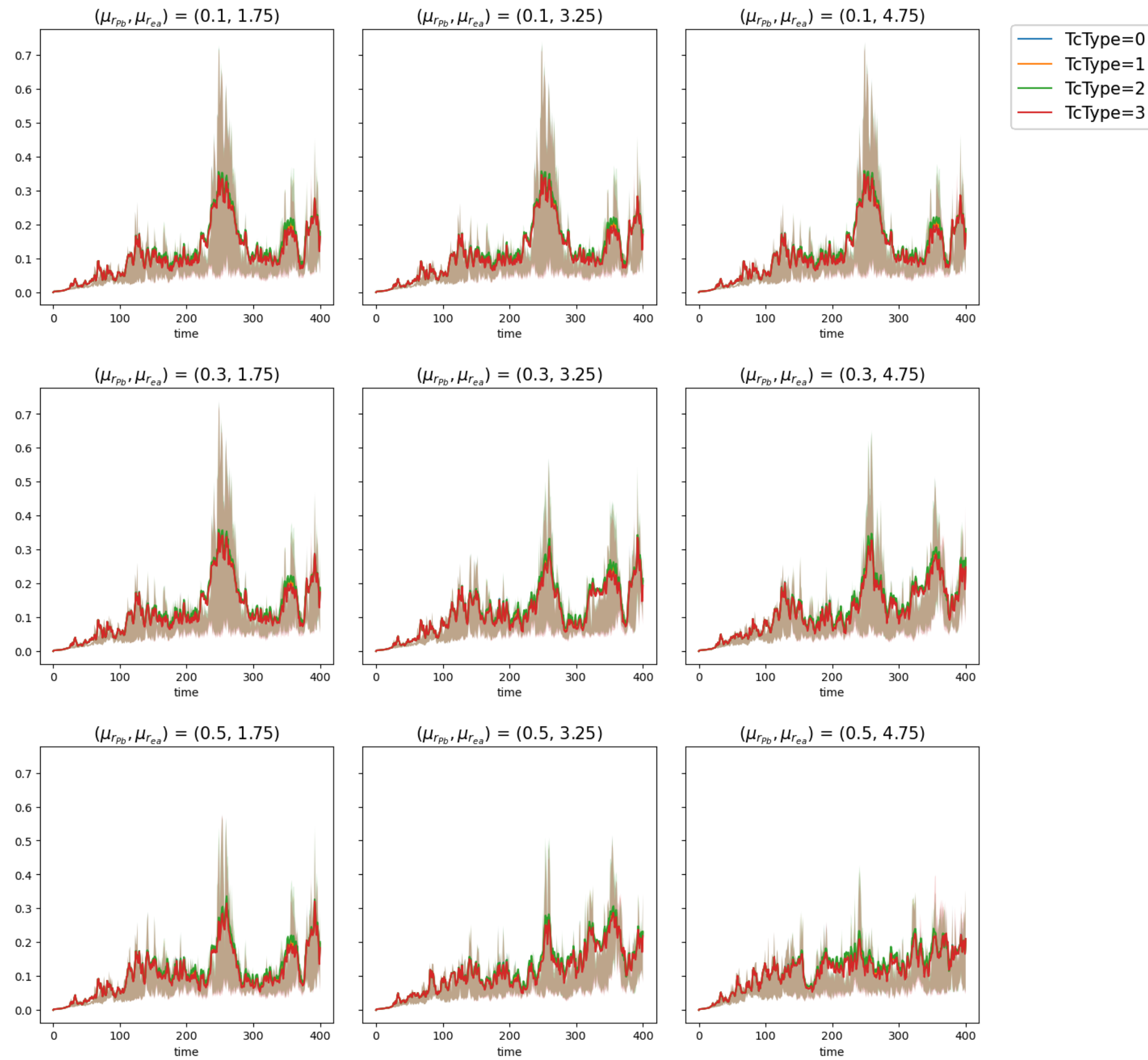

Figure A.17: Time series of *hhi* from $t = 0$ to 400 with $\mu_{rin} = 1.0$. The curve and the upper and lower bound of the shaded region in each plot are the mean and the 25th and 75th percentiles of the data from 10 simulations for each parameter setting, respectively. The color of each curve and shaded region is set according to the policy scenario, TcType.

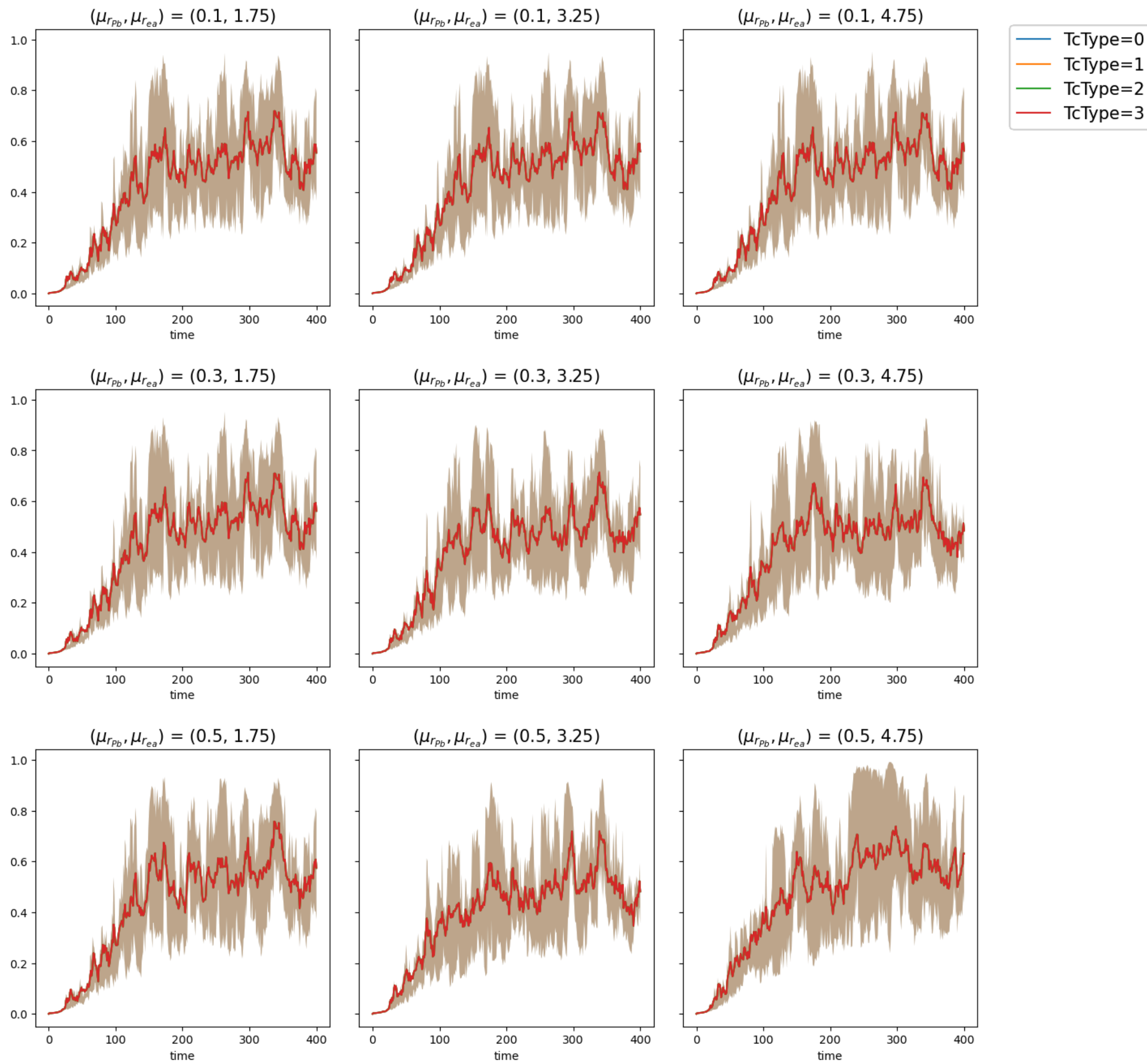

Figure A.18: Time series of hhi from $t = 0$ to 400 with $\mu_{rin} = 1.133$. The curve and the upper and lower bound of the shaded region in each plot are the mean and the 25th and 75th percentiles of the data from 10 simulations for each parameter setting, respectively. The color of each curve and shaded region is set according to the policy scenario, TcType.

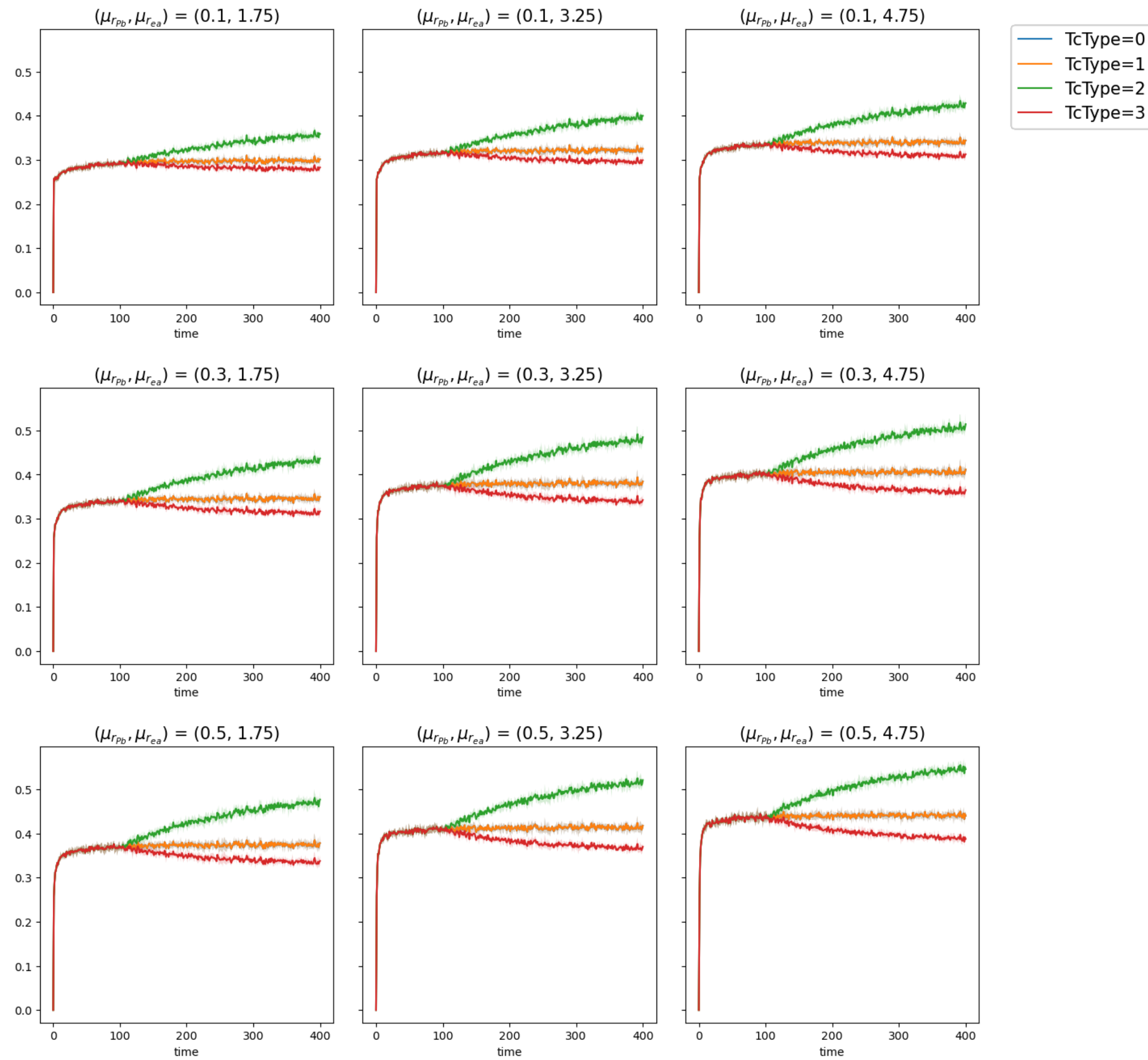

Figure A.19: Time series of *gini* from $t = 0$ to 400 with $\mu_{rin} = 0.067$. The curve and the upper and lower bound of the shaded region in each plot are the mean and the 25th and 75th percentiles of the data from 10 simulations for each parameter setting, respectively. The color of each curve and shaded region is set according to the policy scenario, TcType.

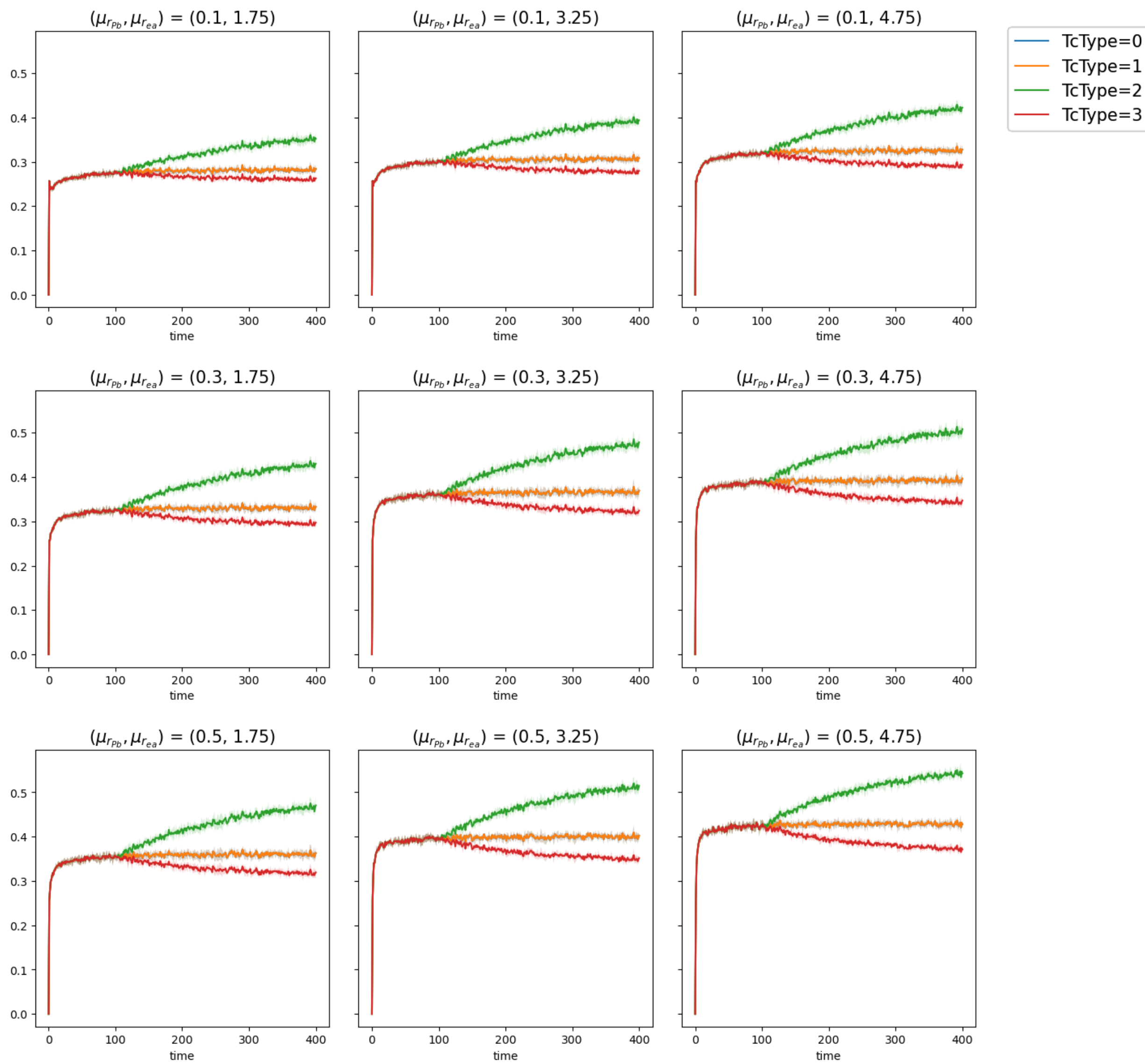

Figure A.20: Time series of *gini* from $t = 0$ to 400 with $\mu_{rin} = 0.2$. The curve and the upper and lower bound of the shaded region in each plot are the mean and the 25th and 75th percentiles of the data from 10 simulations for each parameter setting, respectively. The color of each curve and shaded region is set according to the policy scenario, TcType.

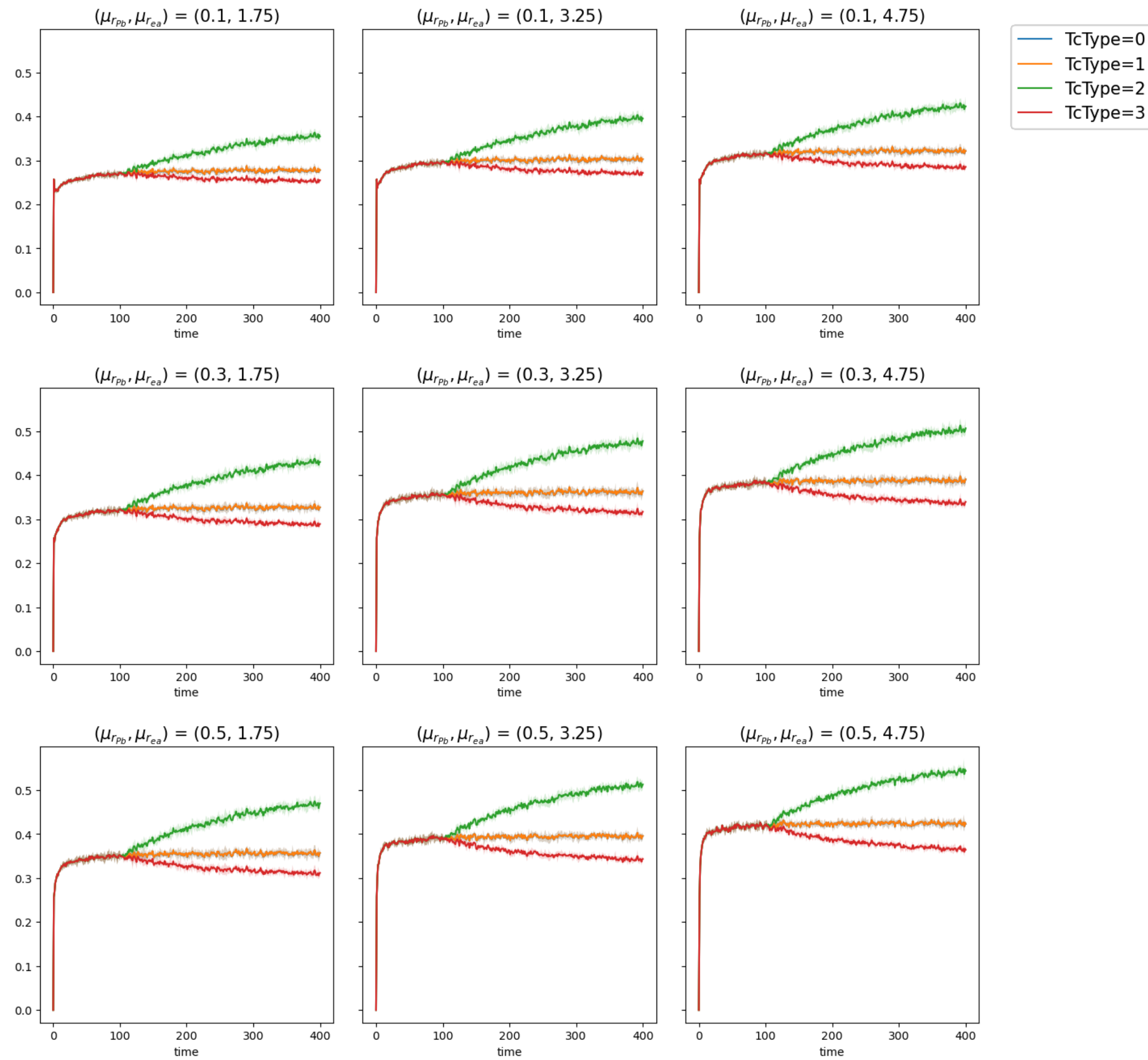

Figure A.21: Time series of *gini* from $t = 0$ to 400 with $\mu_{rin} = 0.333$. The curve and the upper and lower bound of the shaded region in each plot are the mean and the 25th and 75th percentiles of the data from 10 simulations for each parameter setting, respectively. The color of each curve and shaded region is set according to the policy scenario, TcType.

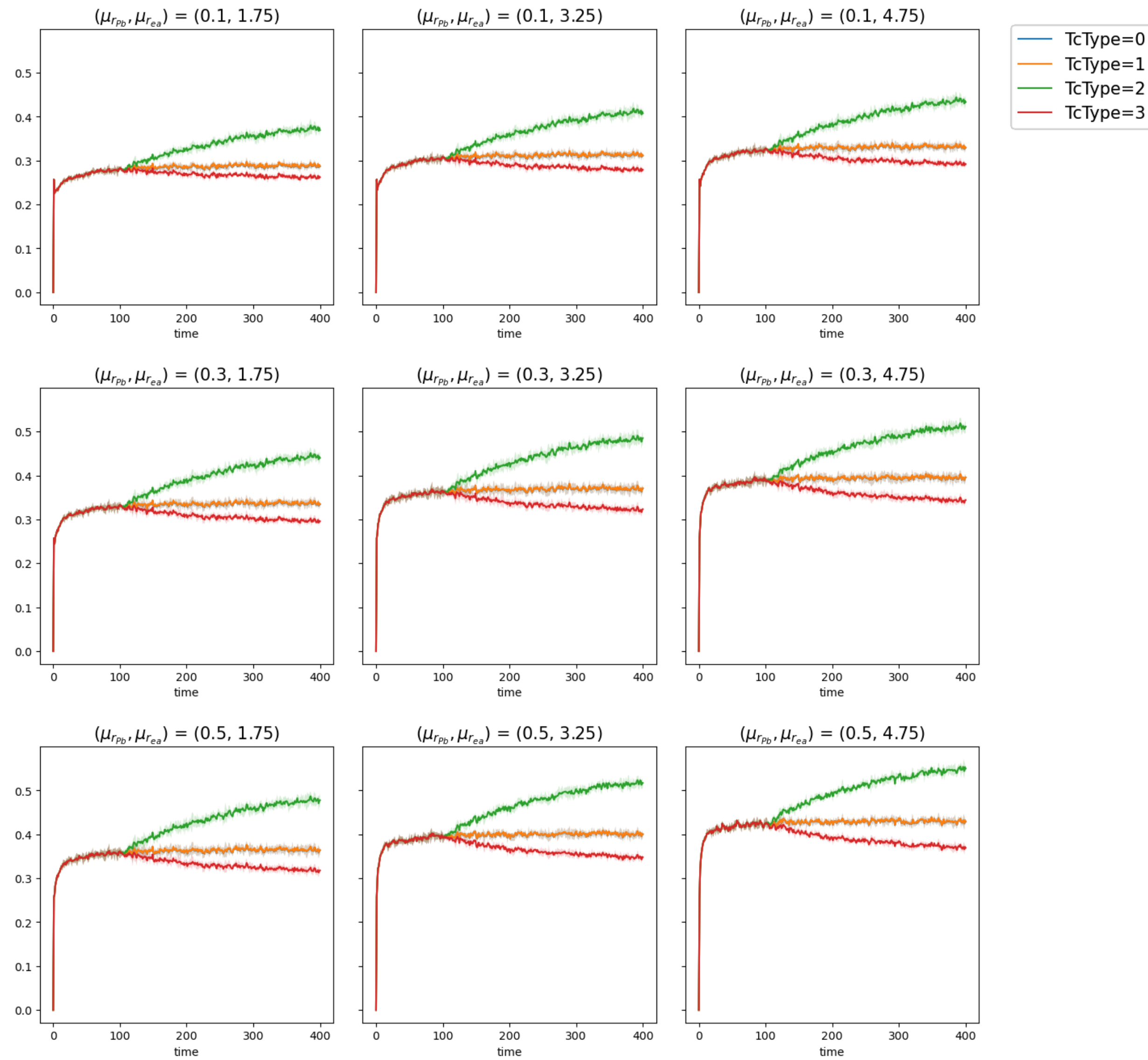

Figure A.22: Time series of *gini* from $t = 0$ to 400 with $\mu_{rin} = 0.467$. The curve and the upper and lower bound of the shaded region in each plot are the mean and the 25th and 75th percentiles of the data from 10 simulations for each parameter setting, respectively. The color of each curve and shaded region is set according to the policy scenario, TcType.

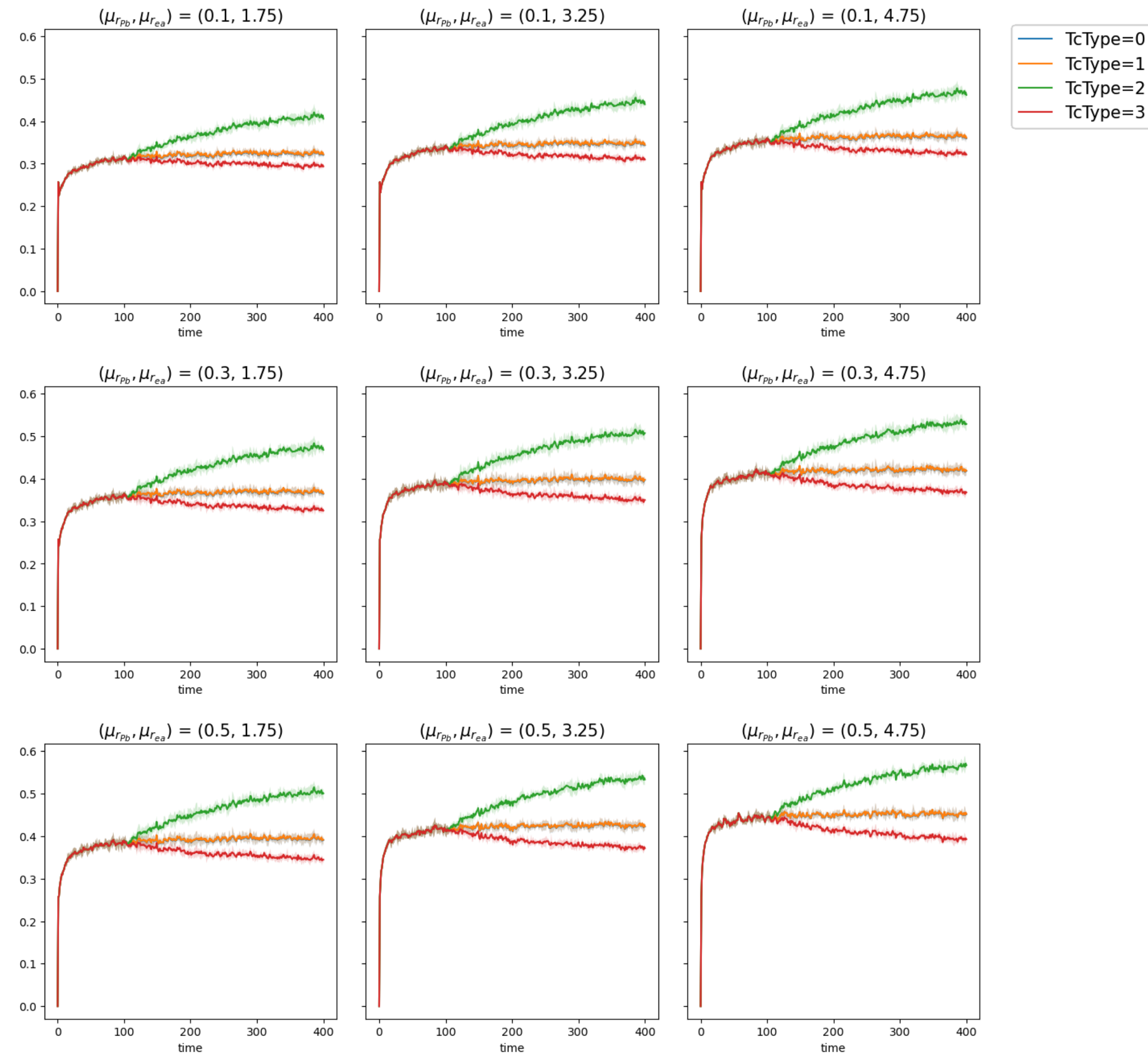

Figure A.23: Time series of *gini* from $t = 0$ to 400 with $\mu_{rin} = 0.6$. The curve and the upper and lower bound of the shaded region in each plot are the mean and the 25th and 75th percentiles of the data from 10 simulations for each parameter setting, respectively. The color of each curve and shaded region is set according to the policy scenario, TcType.

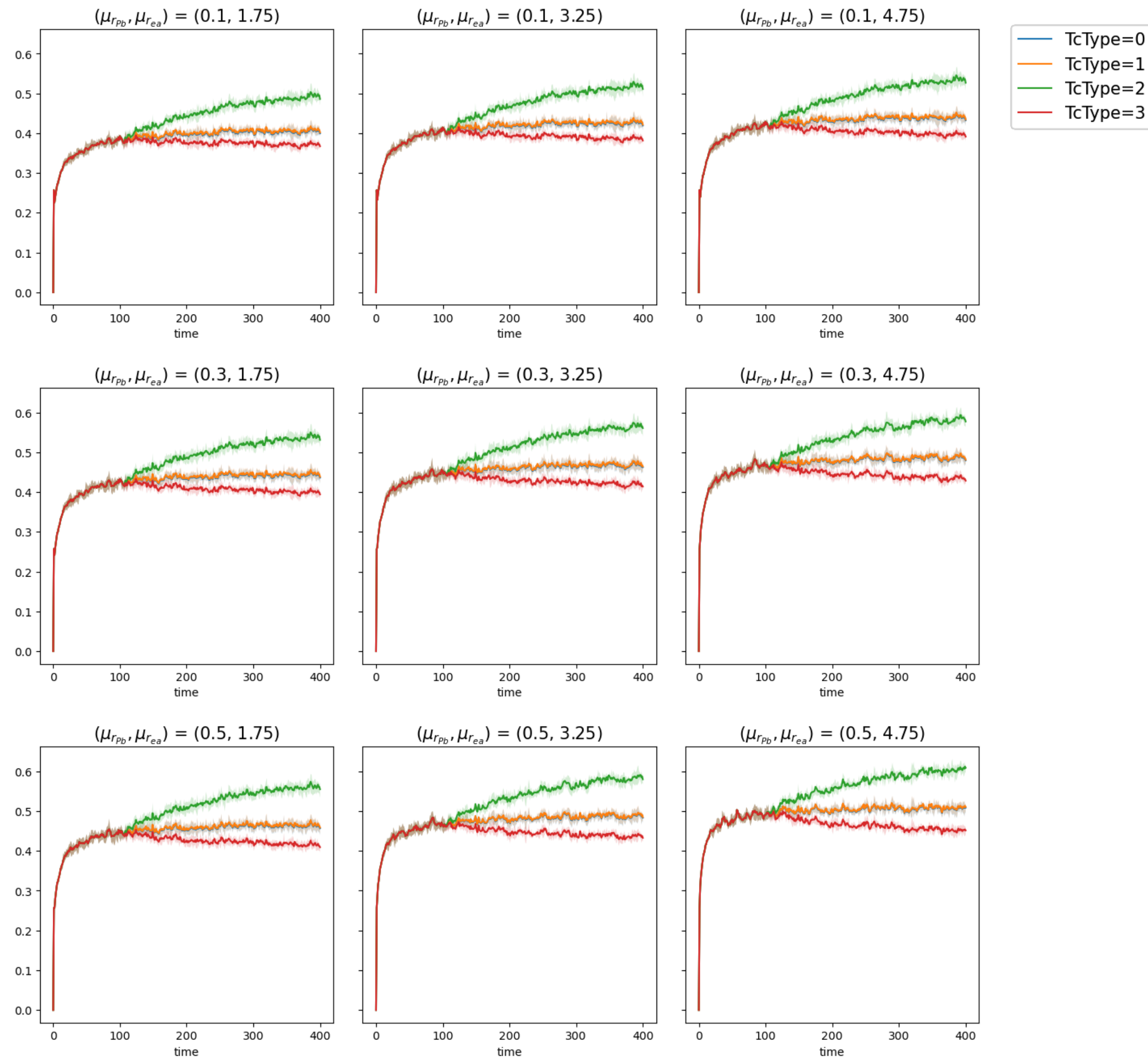

Figure A.24: Time series of *gini* from $t = 0$ to 400 with $\mu_{rin} = 0.733$. The curve and the upper and lower bound of the shaded region in each plot are the mean and the 25th and 75th percentiles of the data from 10 simulations for each parameter setting, respectively. The color of each curve and shaded region is set according to the policy scenario, TcType.

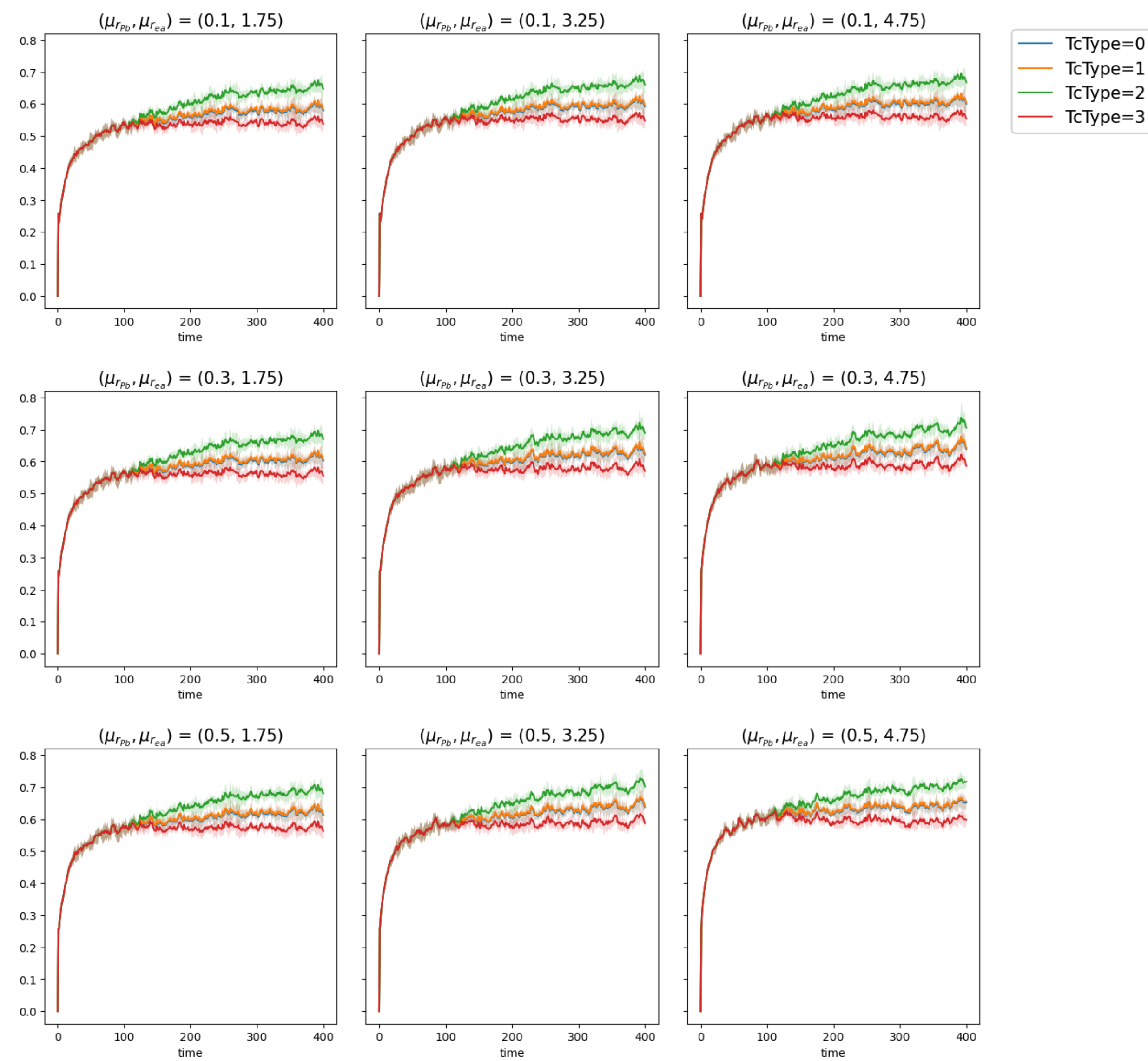

Figure A.25: Time series of *gini* from $t = 0$ to 400 with $\mu_{rin} = 0.867$. The curve and the upper and lower bound of the shaded region in each plot are the mean and the 25th and 75th percentiles of the data from 10 simulations for each parameter setting, respectively. The color of each curve and shaded region is set according to the policy scenario, TcType.

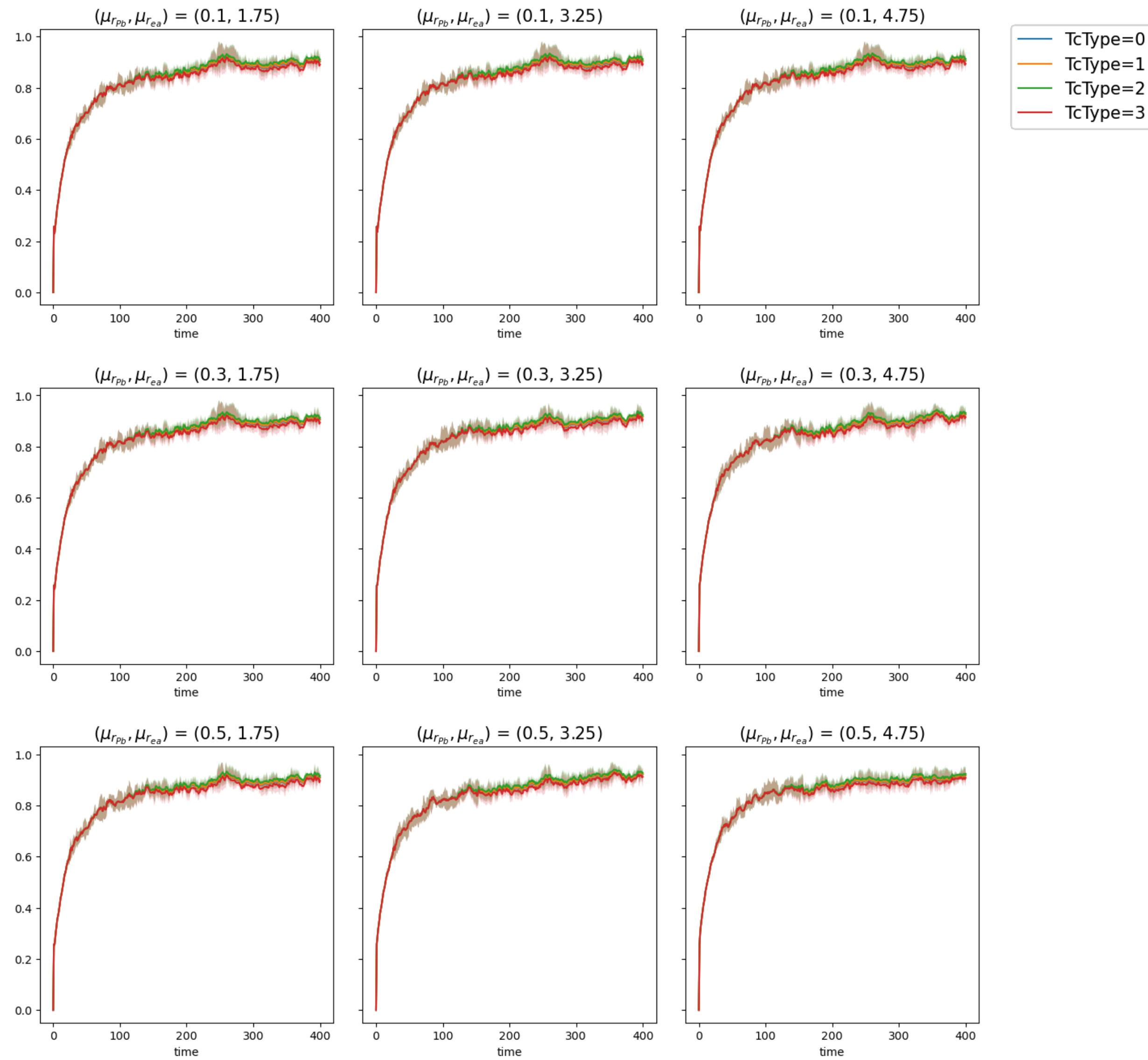

Figure A.26: Time series of *gini* from $t = 0$ to 400 with $\mu_{rin} = 1.0$. The curve and the upper and lower bound of the shaded region in each plot are the mean and the 25th and 75th percentiles of the data from 10 simulations for each parameter setting, respectively. The color of each curve and shaded region is set according to the policy scenario, TcType.

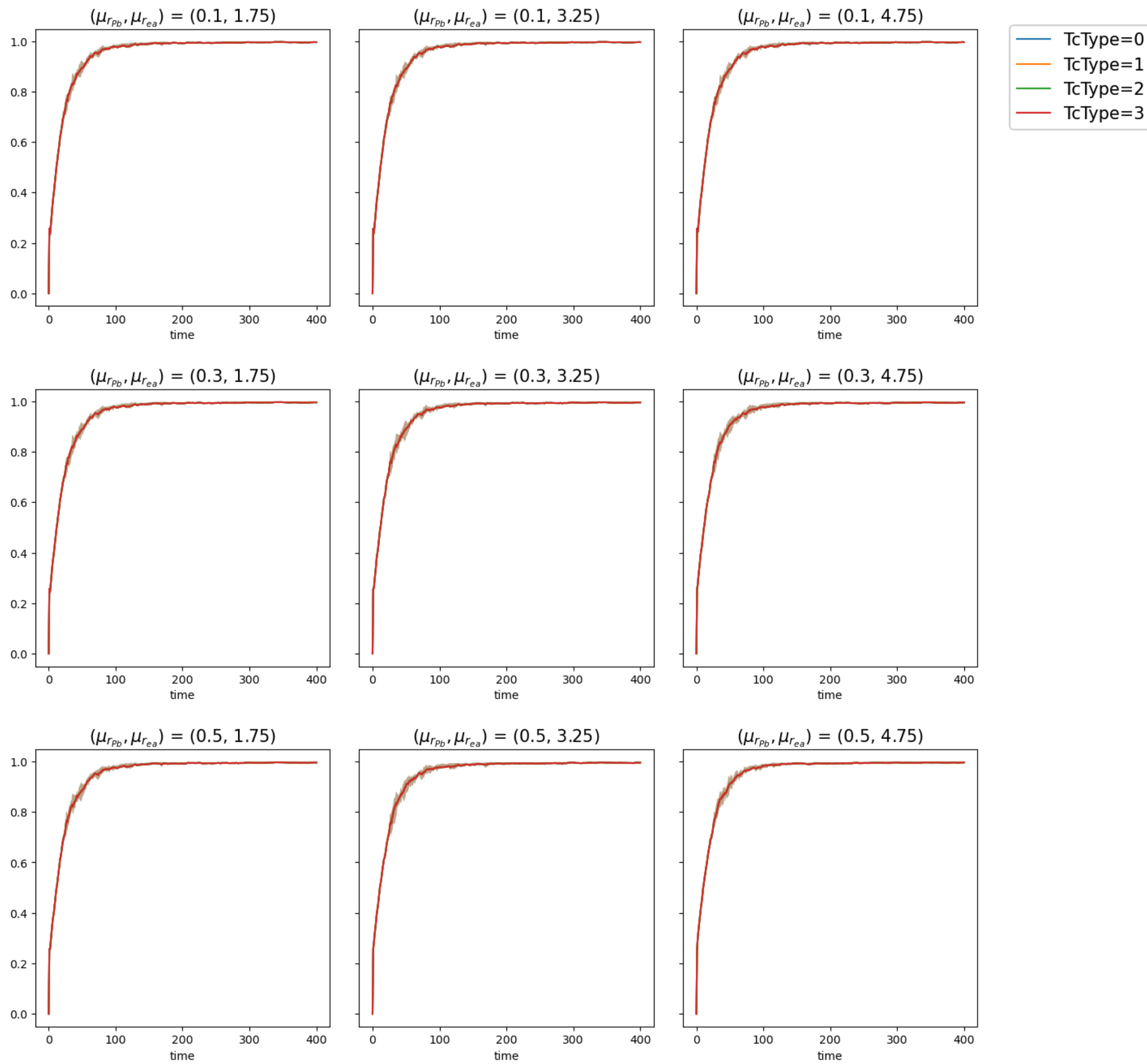

Figure A.27: Time series of *gini* from $t = 0$ to 400 with $\mu_{rin} = 1.133$. The curve and the upper and lower bound of the shaded region in each plot are the mean and the 25th and 75th percentiles of the data from 10 simulations for each parameter setting, respectively. The color of each curve and shaded region is set according to the policy scenario, TcType.

A.2 Relations between Industry Indicators and Pareto Front

In Chapter 4, the values of μ_{rea} and μ_{rPb} were set to the median values in the respective parameter ranges. The following figure shows the relations between the two industry indicators for a total of nine parameter settings consisting of three levels equally spaced across the range of each of the two probability distribution parameters. Although the shape of the Pareto front in each plot is different, we can see a similar trend shown in Chapter 4: the impact of each policy scenario is clear for values of μ_{rin} between 0.067 and 0.733, while for values of μ_{rin} greater than or equal to 1.0, the effects of such policies disappear.

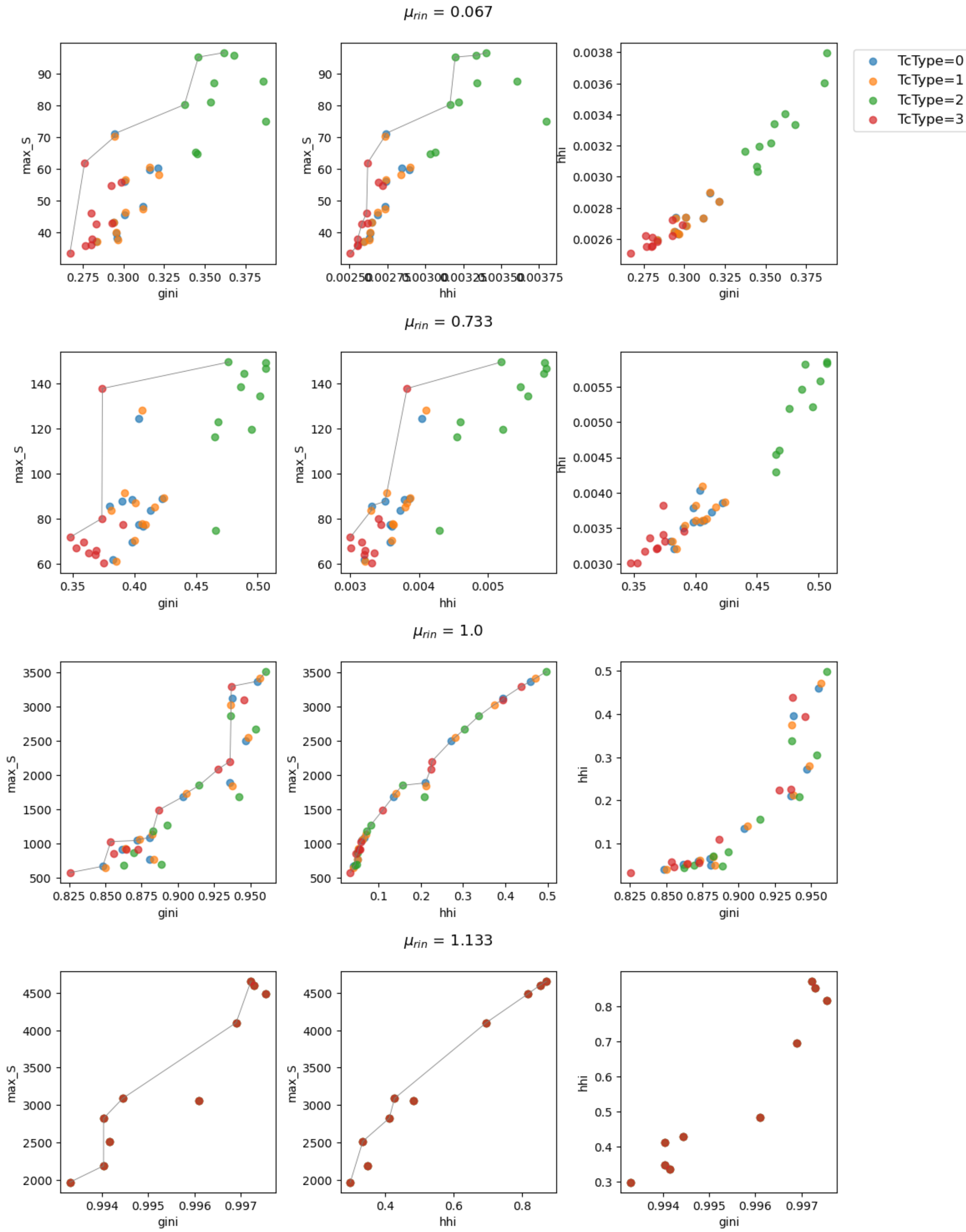

Figure A.28: Relations between max S and hhi, max S and $gini$, and hhi and $gini$ at $t = 400$. The plots in the same row are scatter plots of the two industry indicators under the same μ_{rin} value. The values of μ_{rea} and μ_{rPb} are fixed to 1.75 and 0.1 in all plots, respectively. The color of each data point is set according to the policy scenario, TcType. The gray broken line in each plot is the Pareto front.

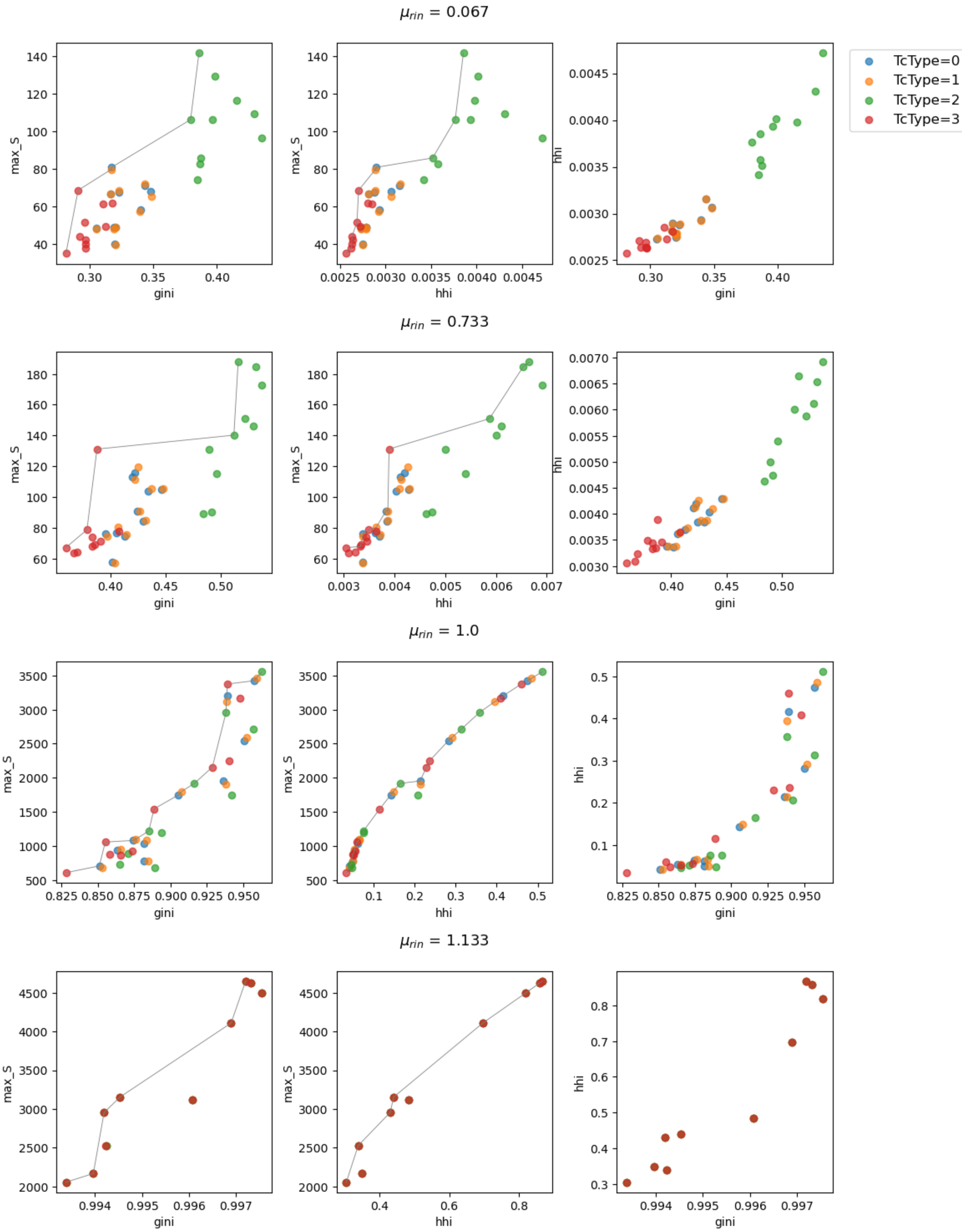

Figure A.29: Relations between $\max S$ and hhi, $\max S$ and $gini$, and hhi and $gini$ at $t = 400$. The plots in the same row are scatter plots of the two industry indicators under the same μ_{rin} value. The values of μ_{rea} and μ_{rPb} are fixed to 3.25 and 0.1 in all plots, respectively. The color of each data point is set according to the policy scenario, TcType. The gray broken line in each plot is the Pareto front.

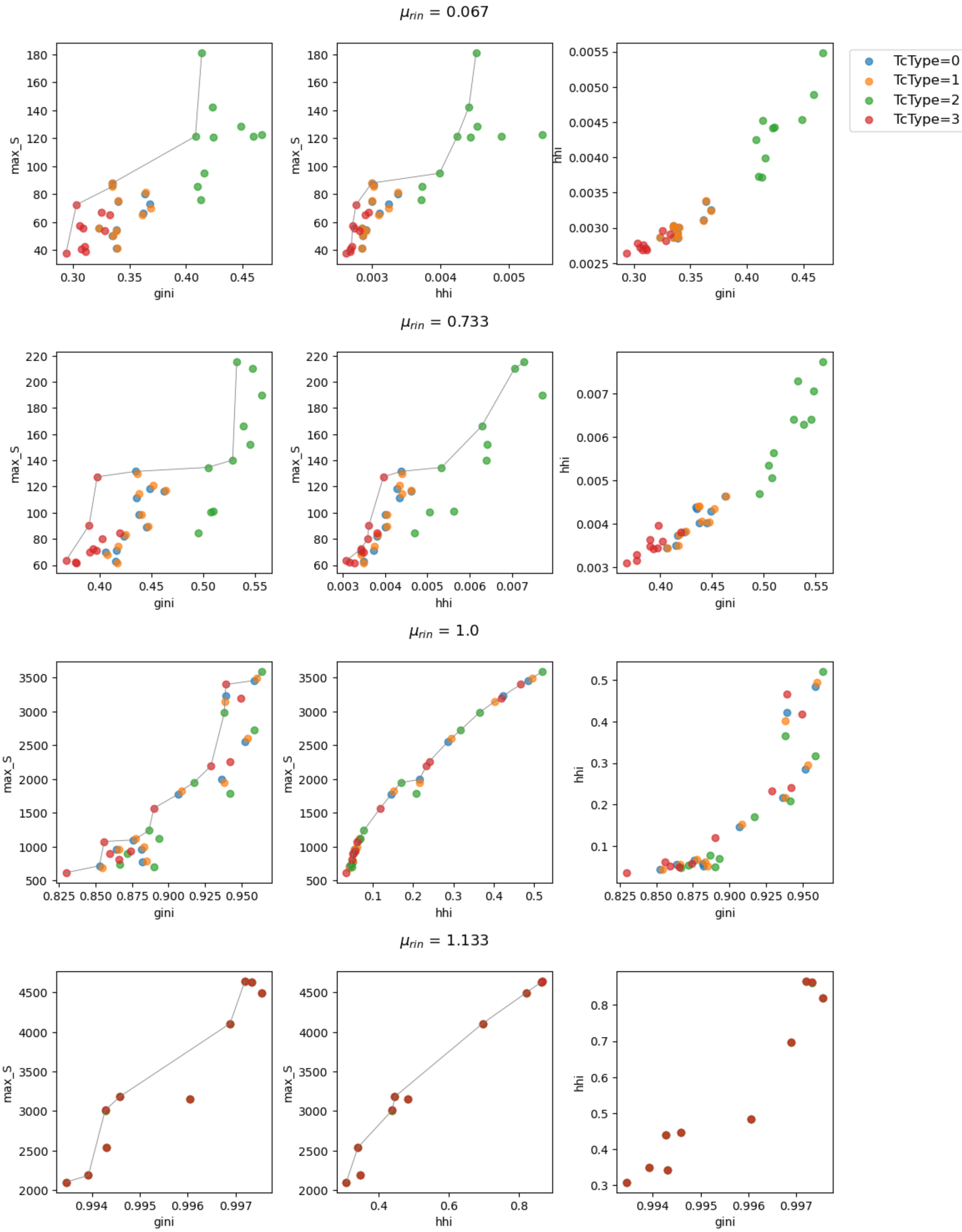

Figure A.30: Relations between $\max S$ and hhi, $\max S$ and $gini$, and hhi and $gini$ at $t = 400$. The plots in the same row are scatter plots of the two industry indicators under the same μ_{rin} value. The values of μ_{rea} and μ_{rPb} are fixed to 4.75 and 0.1 in all plots, respectively. The color of each data point is set according to the policy scenario, TcType. The gray broken line in each plot is the Pareto front.

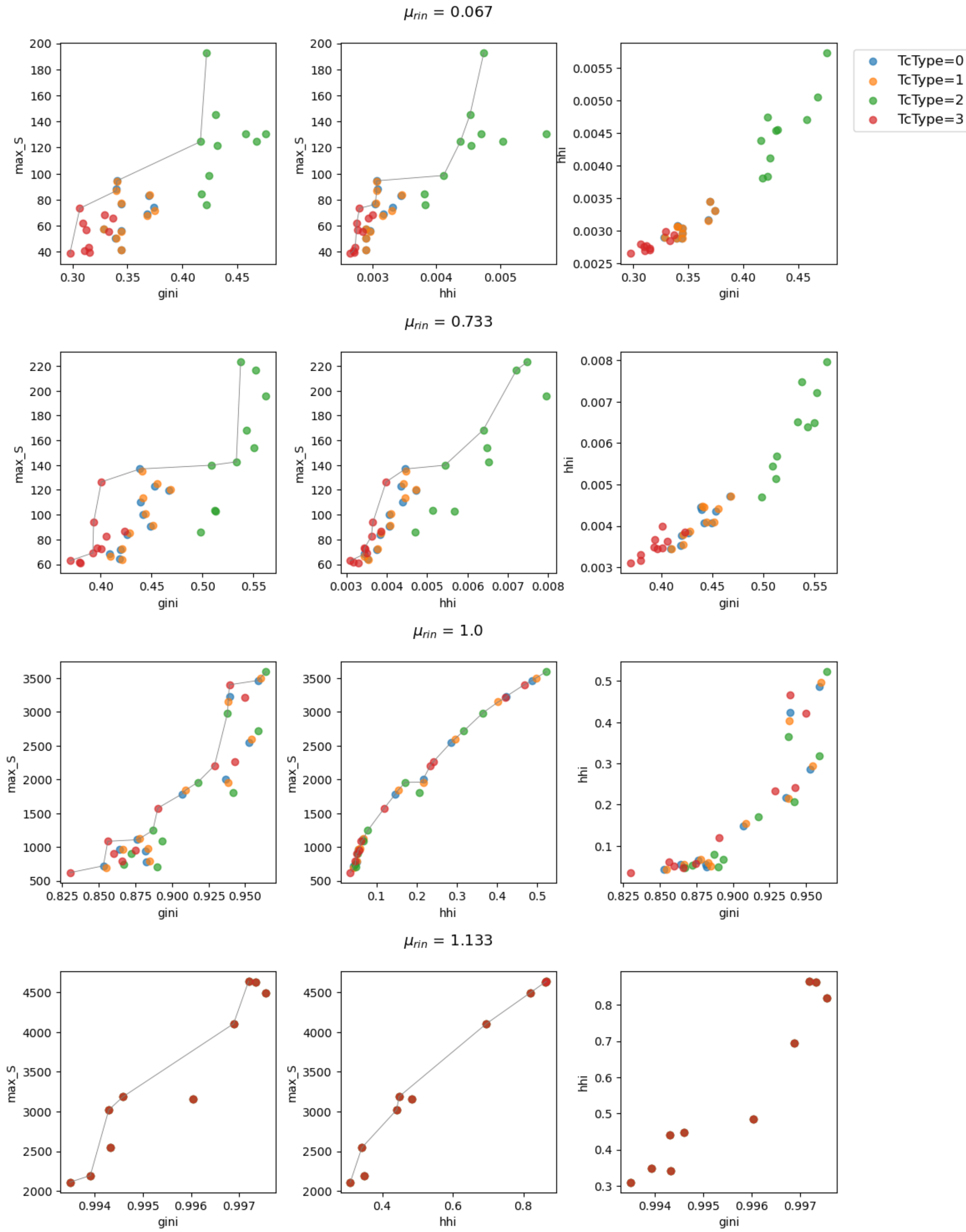

Figure A.31: Relations between $\max S$ and hhi, $\max S$ and $gini$, and hhi and $gini$ at $t = 400$. The plots in the same row are scatter plots of the two industry indicators under the same μ_{rin} value. The values of μ_{rea} and μ_{rPb} are fixed to 1.75 and 0.3 in all plots, respectively. The color of each data point is set according to the policy scenario, TcType. The gray broken line in each plot is the Pareto front.

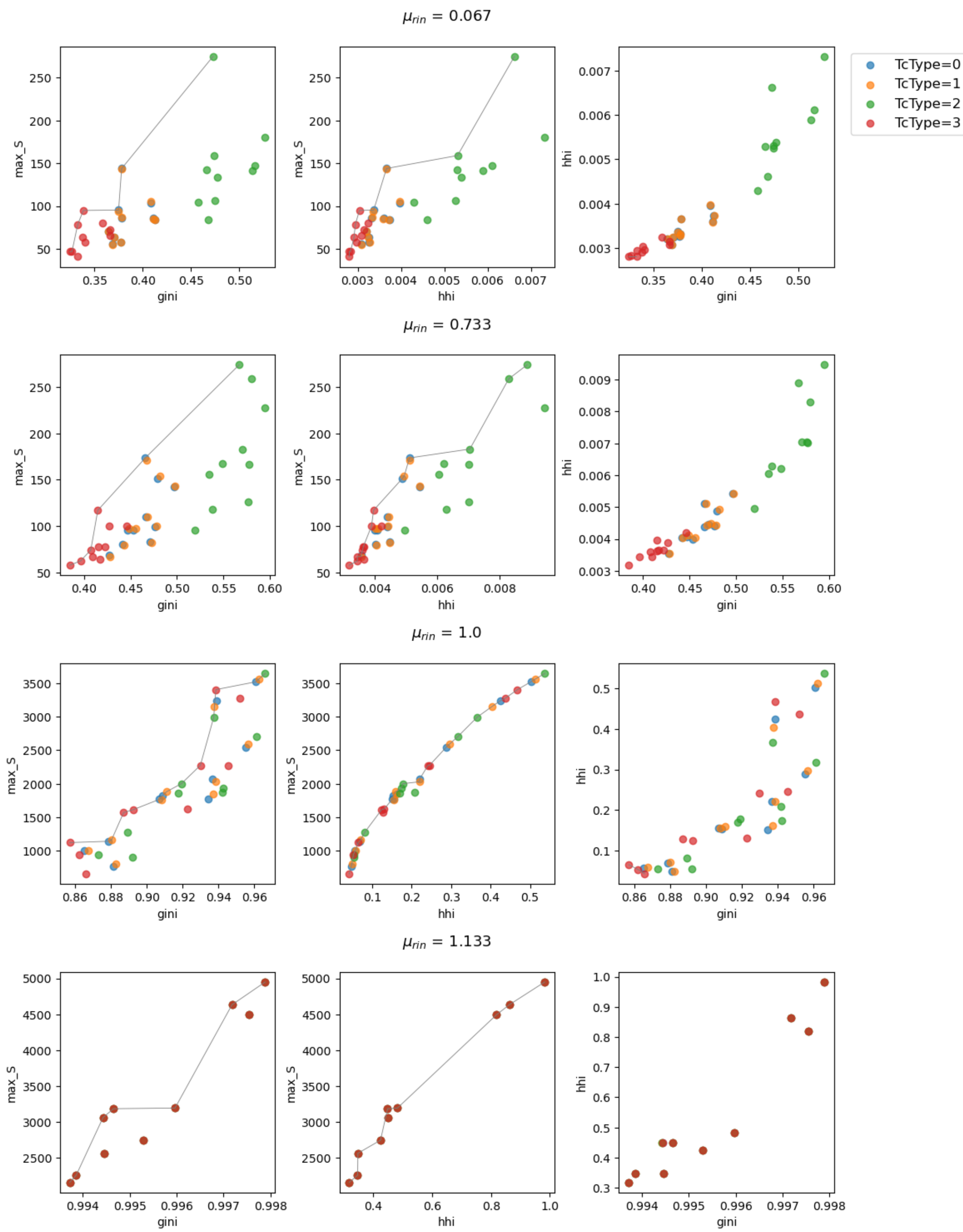

Figure A.32: Relations between $\max S$ and hhi, $\max S$ and $gini$, and hhi and $gini$ at $t = 400$. The plots in the same row are scatter plots of the two industry indicators under the same μ_{rin} value. The values of μ_{rea} and μ_{rPb} are fixed to 3.25 and 0.3 in all plots, respectively. The color of each data point is set according to the policy scenario, TcType. The gray broken line in each plot is the Pareto front.

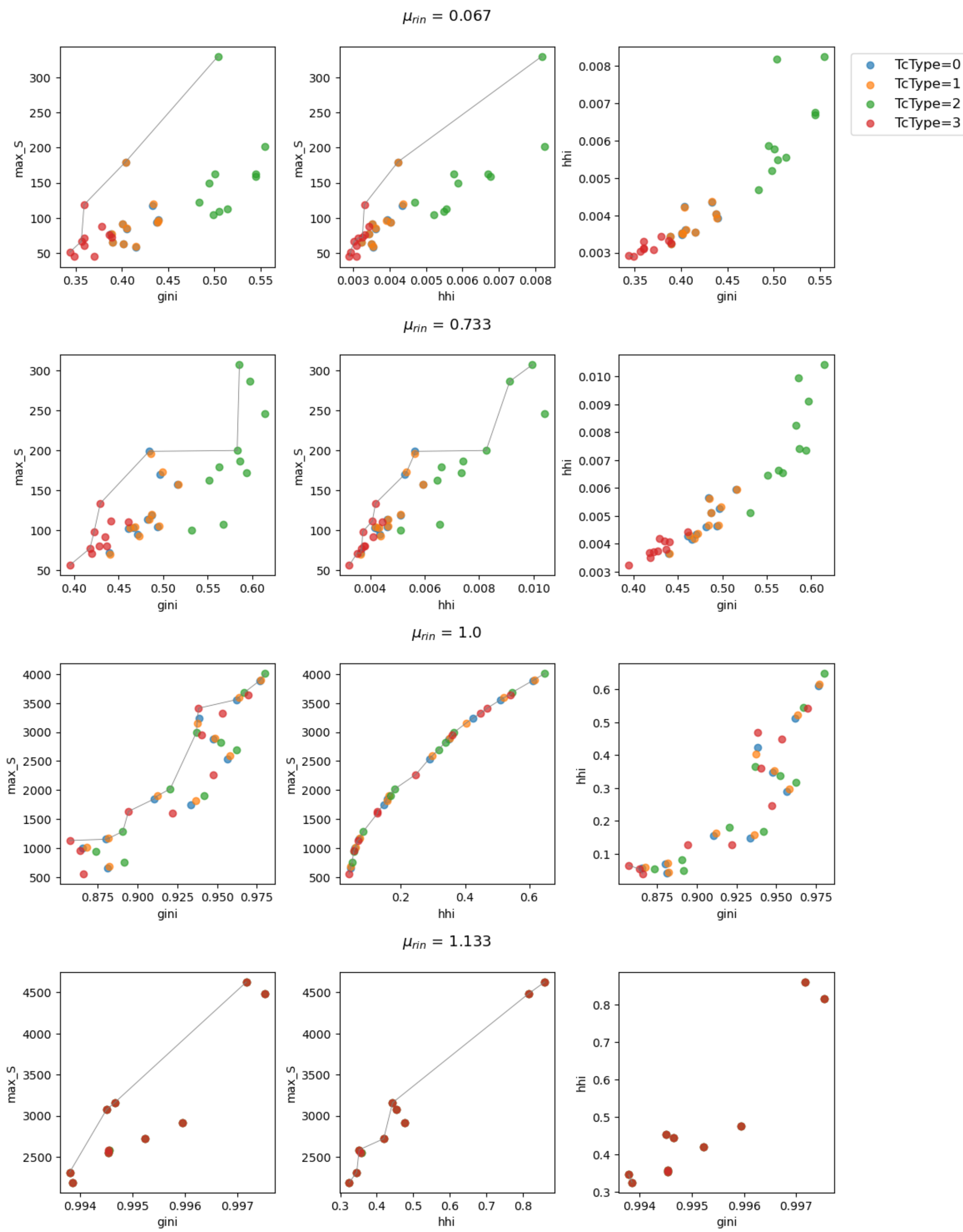

Figure A.33: Relations between $\max S$ and hhi, $\max S$ and $gini$, and hhi and $gini$ at $t = 400$. The plots in the same row are scatter plots of the two industry indicators under the same μ_{rin} value. The values of μ_{rea} and μ_{rPb} are fixed to 4.75 and 0.3 in all plots, respectively. The color of each data point is set according to the policy scenario, TcType. The gray broken line in each plot is the Pareto front.

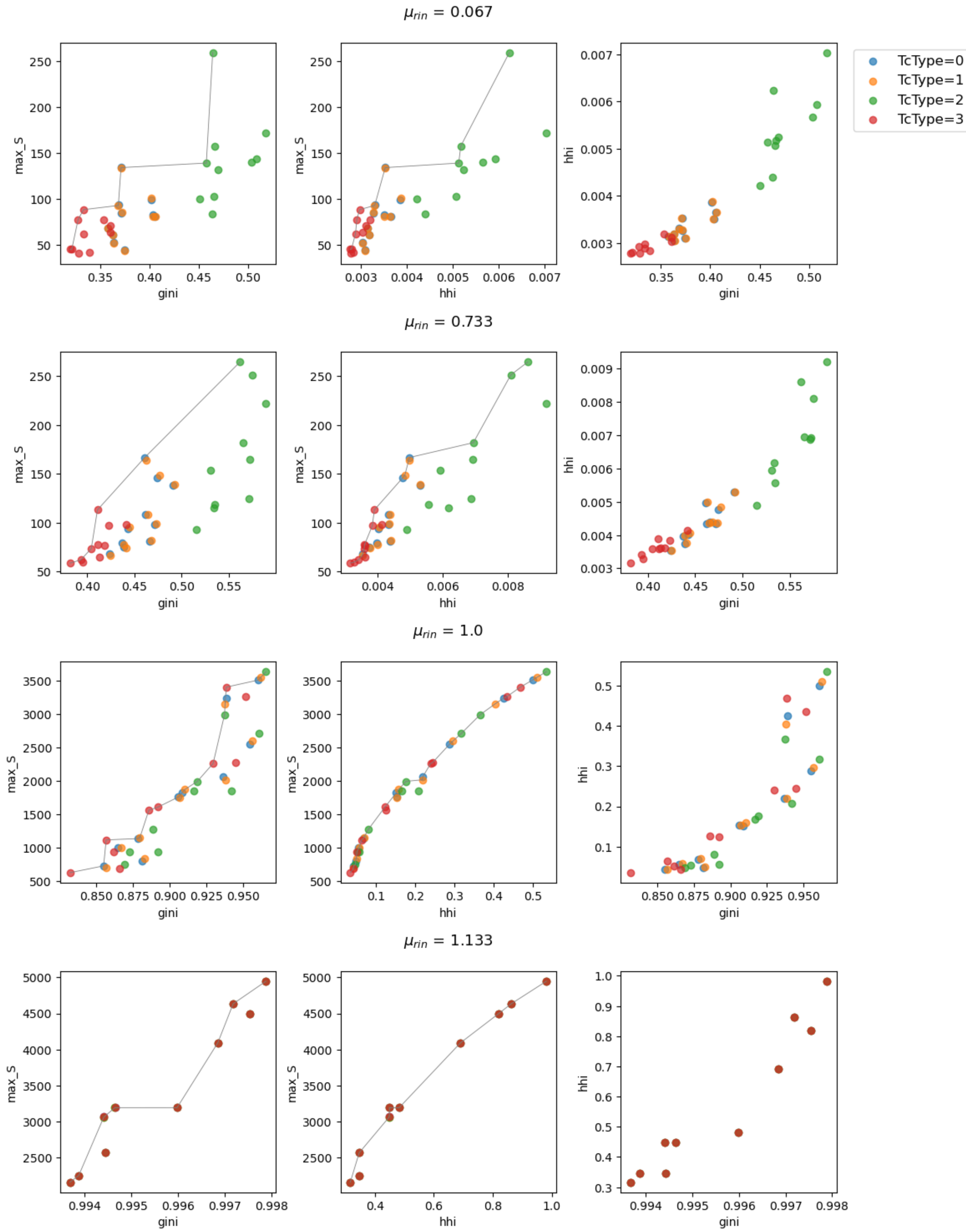

Figure A.34: Relations between $\max S$ and hhi, $\max S$ and $gini$, and hhi and $gini$ at $t = 400$. The plots in the same row are scatter plots of the two industry indicators under the same μ_{rin} value. The values of μ_{rea} and μ_{rPb} are fixed to 1.75 and 0.5 in all plots, respectively. The color of each data point is set according to the policy scenario, TcType. The gray broken line in each plot is the Pareto front.

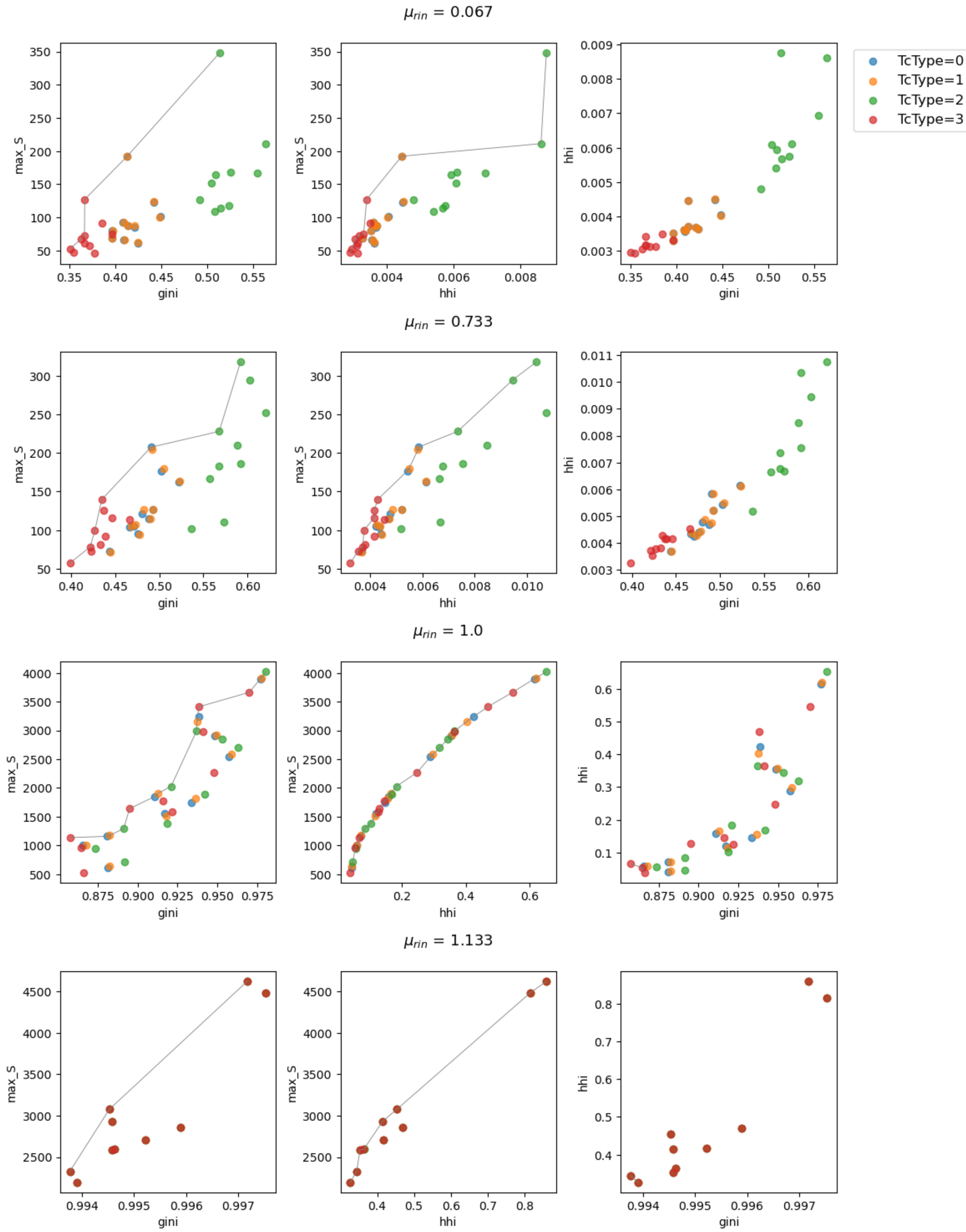

Figure A.35: Relations between $\max S$ and hhi, $\max S$ and $gini$, and hhi and $gini$ at $t = 400$. The plots in the same row are scatter plots of the two industry indicators under the same μ_{rin} value. The values of μ_{rea} and μ_{rPb} are fixed to 3.25 and 0.5 in all plots, respectively. The color of each data point is set according to the policy scenario, TcType. The gray broken line in each plot is the Pareto front.

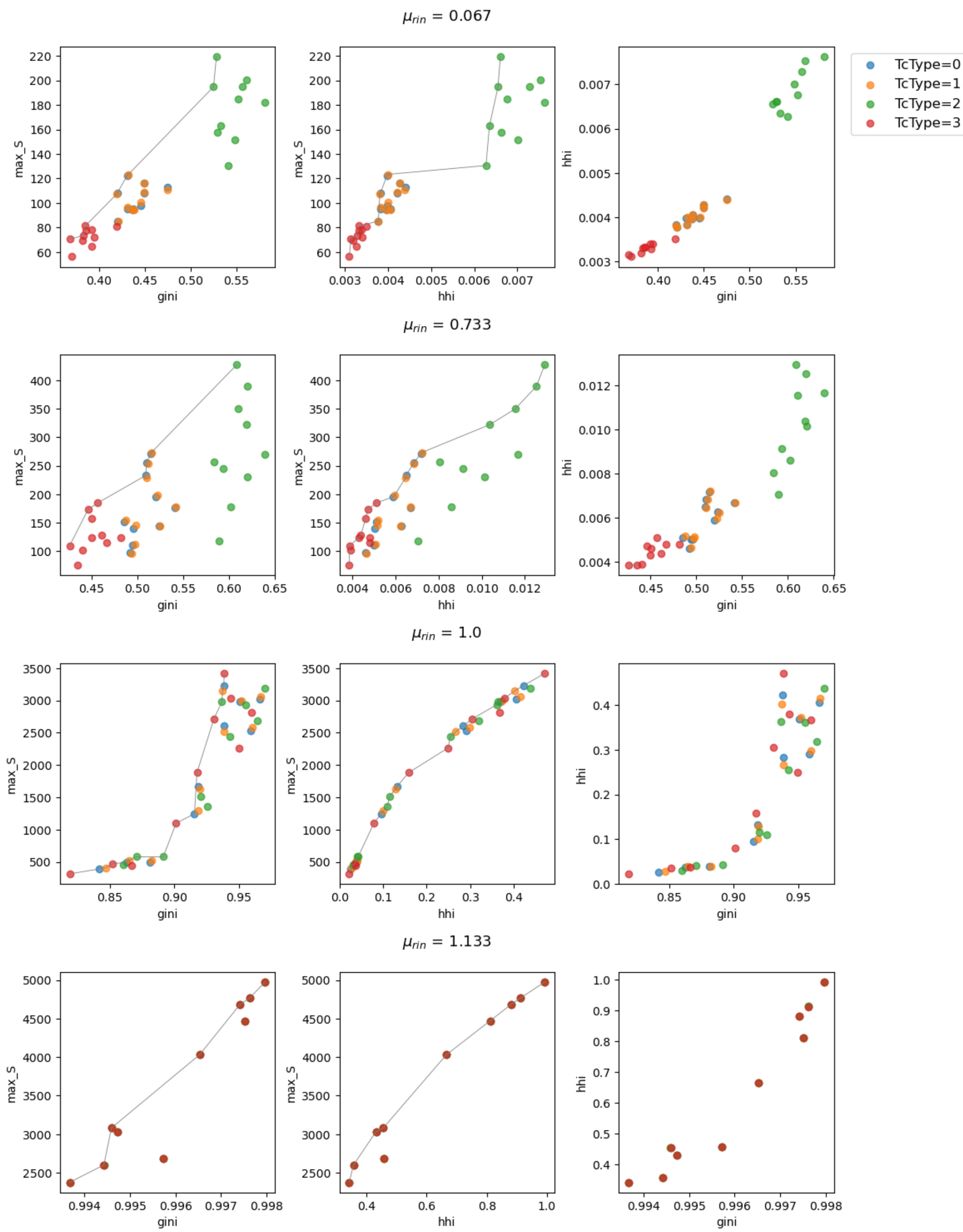

Figure A.36: Relations between $\max S$ and hhi, $\max S$ and $gini$, and hhi and $gini$ at $t = 400$. The plots in the same row are scatter plots of the two industry indicators under the same μ_{rin} value. The values of μ_{rea} and μ_{rPb} are fixed to 4.75 and 0.5 in all plots, respectively. The color of each data point is set according to the policy scenario, TcType. The gray broken line in each plot is the Pareto front.

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